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Haptic Feedback of Rigid Tool / Soft Object Interaction in Medical Training and Robot-Assisted Minimally Invasive Surgery

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Haptic Feedback of Rigid Tool / Soft Object Interaction in Medical Training and Robot-Assisted Minimally Invasive Surgery



by

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Submitted for the degree of

Doctor of Philosophy in Robotics

Department of Informatics, King's College London

2014

Abstract

Sense of touch is crucial for surgeons to effectively identify tumours and boundaries, and, thus to achieve successful cancer resections. To overcome the touch information loss which occurs during robotic-assisted surgical procedures, researchers have proposed methods capable of acquiring partial haptic feedback and mimicking the physical interaction which takes place between surgical tools and human tissue during palpation. This thesis proposes and evaluates haptic palpation systems and suggests the combination of different feedback methods for tumour identification in medical training and robot-assisted minimally invasive surgery using tissue models based on rolling indentation.

A real-time visual tissue stiffness feedback method is proposed and compared to the performance of direct force feedback using tumour identification performance based on user studies with human subjects.

The trade-off problem between system transparency and stability, which is caused by direct force feedback using a tele-manipulation system, is circumvented with the introduction of an intra-operative haptic tissue model generation method capable of representing tissue stiffness distribution of the examined soft tissue. During palpation, force feedback is exerted based on this model. This thesis proposes pseudo-haptic feedback and visualization of tissue surface deformation as an effective method to provide realistic palpation experience, which does not require the use of expensive haptic devices and is capable of handling three-dimensional haptic information. The tumour identification results are compared using different input devices: a computer mouse, a 3-DOF motion tracking input device and force-sensitive 2D haptic surface input devices. Furthermore, it is shown that the performance of haptic systems can be improved beyond the performance of force-feedback-only haptic systems by intelligently combining force feedback and pseudo-haptic feedback.

Multi-fingered palpation is more effective in detecting differences in stiffness in the examined tissue than single-fingered palpation methods. Two approaches of multi-

fingering palpation are proposed, studied and evaluated in this thesis: (1) methods using pseudo-haptic feedback and (2) those that use stiffness actuators. The performance of these methods is compared with the performance of single-fingering palpation approaches.

Acknowledgements

I am grateful to all the people who helped me in the various stages of this project. I would like to express my sincere gratitude to my supervisor Professor Kaspar Althoefer for his support, encouragement and patient guidance throughout this research. I am also thankful to my second supervisor Professor Lakmal Seneviratne for the many useful discussions and comments. I would like to thank my third supervisor Professor Prokar Dasgupta for his support.

I am very grateful to my friends and colleagues at King's College London, especially, Jelizaveta Konstantinova, Allen Jiang, Dr. Hongbin Liu, Dr. Sina Sareh, Dr. Emanuele Secco, Angela Faragasso, Dr. Helge Wuerdemann, Dr. Vahid Aminzadeh, Dr. Guowu Wei, Dr. Jichun Li, and Shan Luo for their friendship and the valuable discussions and suggestions. Also, I would like to express my thanks to all the other colleagues in our robotics office for the fun and supportive environment they created all these years.

I would like to thank the participants in my user study. Without their contribution, I could not have been able to finish the evaluation part of my haptic palpation systems. My thanks are also due to Tommaso Ranzani for his help during the fabrication process of the granular jamming stiffness feedback actuator. I need to thank Maisarah Binti Ridzuan for her help in the programming of the Android system.

I owe my gratitude to my husband Liandong Wang, my parents and my parents-in-law for their consistent, encouragement and support.

The financial support by the K. C. Wang Education Foundation, by the China Scholarship Council (CSC), and by GSTT at Guy's Hospital in collaboration with the Centre for Robotics Research at King's College London is also gratefully acknowledged. I am very thankful to the two financial guarantors, Professor Wenting Han and Associate Professor Gerong Dang, for my application for the CSC scholarship.

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Nomenclature

1D	One-dimensional
2D	Two-dimensional
3D	Three-dimensional
<i>ACC</i>	Accuracy
<i>CI</i>	Combined interval
<i>Crt</i>	Current cursor position
d_{in}	Indentation depth
DOF	Degrees of freedom
<i>Ds</i>	Difference between the current and the last stiffness levels
<i>E</i>	Elastic modulus
ER	Electro-rheological
FEA	Finite element analysis
FE	Finite element
FEM	Finite element modelling
f_l	Force level
<i>FN</i>	False negative
<i>FP</i>	False positive
F/T	Force/Torque
f_t, f_n	Tangent and normal force
f_x, f_y, f_z	Force components in x, y and z directions
<i>in-vivo</i>	Experimentation using a living organism
<i>Lst</i>	Last cursor position
MIS	Minimally invasive surgery
MR	Magneto-rheological
MRI	Magnetic resonance imaging
PCA	Principal component analysis
PCL	Point cloud library
<i>PPV</i>	Positive predictive value

R_0	Original avatar display ratio
RGB	A colour model based on red, green and blue values
R_m	Modified avatar display ratio
RMIS	Robot-assisted minimally invasive surgery
SD	Standard deviation
Se	Sensitivity
Sp	Specificity
t_d	Delay time
TP	True positive
TN	True negative
US	Ultrasound
VR	Virtual reality
VF	Virtual force
μ	Shear modulus
λ_m	Locking stretch
χ^2	Pearson's test statistic
Δp	Probability difference

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Chapter 1 Introduction

1.1. Motivation of the thesis

1.1.1. Palpation in surgery

Palpation, which is utilized in many medical procedures, is a process where a clinician presses a patient's skin or soft tissue with their fingers to detect abnormalities beneath (hand / soft tissue interaction) [1]. During this interaction, tactile and kinaesthetic receptors inside the skin, muscles, tendons and joints allow clinicians to acquire haptic information [2] about mechanical stimulation or pressure, and gather information about the limbs and their movements [3]. Acquiring information about spatially distributed tissue stiffness is significant for abnormality identification. Tissue areas that have higher stiffness than the surrounding tissue can be recognized as possible tumours [4]. Intra-operative palpation is a commonly used method to detect abnormal tissue regions during surgery [5]. During open surgery, which is carried out through a single, large incision, intra-operative palpation is easy to conduct by hand / soft tissue interaction. Abnormality distribution information of the soft tissue is perceived from the force/pressure distribution of the perceptive area. This allows the clinicians to identify tumours and boundaries through manual palpation to ensure entire removal of tumours and a successful cancer excision.

Minimally Invasive Surgery (MIS), where surgeons perform surgical procedures through small incisions ranging from 3 to 12 mm [6], started in the mid-1980s, and has become increasingly popular worldwide ever since. In MIS, specially designed tools and miniature video cameras are inserted through those small incisions and surgical instruments are used to probe tissue surface (rigid tool-soft tissue interaction). By means of these instruments some force can be transmitted to the surgeons enabling them to acquire tissue abnormality information. Compared to open surgery, MIS

offers many benefits, including improved therapeutic outcome, shortened postoperative recovery, lessened immunological stress response of the tissue, and reduced tissue trauma, postoperative pain, and scarring. Therefore, it shortens hospital stay and reduces hospital expenses. However, compared to open surgery, MIS is more demanding as far as the clinicians' technical skills are concerned because of the limited vision of the operative site, reduction of intuitiveness, motion constraints, and the absence of direct hand / soft tissue interaction.

Surgical robots with a master-slave configuration, which achieve a complete separation between surgeons and the patient, were introduced to solve motion constraint problems and to reduce the need for more advanced technical skills required of surgeons performing MIS. This is because the distal dexterity of the surgical tools has been augmented. The surgeon manipulates a robotic interface at the master side and the position or force commands are transmitted to a slave robot at the patient side through a communication medium, thus the slave robot mimics the motion of the master manipulator. Using this type of surgical robots, surgeons are able to carry out remotely precise surgical procedures that are different in scale by guiding the tip of the tool with their fingertips using the master console, whilst being aided by high-definition 3D vision, multiple degrees of freedom robot devices allowing accurate movements, and an intuitive user interface. Robot-assisted Minimally Invasive Surgery (RMIS) enables surgeons to achieve more successful outcomes and has been utilized in a variety of operations, including cholecystectomy, cystectomy, prostatectomy, coronary artery revascularization, and mitral valve repair [7]–[11].

However, the sense of touch – kinaesthetic and tactile information is still missing [12] and this may cause incomplete tumour excising. Most current robotic surgical systems, such as Titan Medical Amadeus and da Vinci, do not provide haptic feedback [13]; adding transparent, mechanical haptics to these existing surgical systems would require a fundamental redesign of the whole system [13]. Therefore, creating a RMIS real-time intra-operative tumour localization method, which is sterilizable, safe, stable, effective, user-friendly, easily integrated in existing systems and which allows the surgeon to conduct the palpation procedure at the master side of the RMIS system would be clinically beneficial.

Researchers have proposed a variety of methods, which can obtain either kinaesthetic or tactile partial haptic information, to mimic the function of palpation during robot-assisted surgical procedures [14]. Acquired soft tissue stiffness information can be displayed to surgeons for in-vivo purposes via different feedback modalities, including vision illusion, graphical display, force feedback, tactile feedback, and combination of tactile and force feedback. However, the combination of different feedback modalities needs more investigation.

1.1.2. Palpation in medical training using haptic feedback

Palpation requires the practitioner to have practical experience, anatomical knowledge, and the sense of touch to identify tissue abnormality and anatomical structures. Ethical issues and patient safety may prevent medical students from practicing on live human bodies, but due to improved computer and graphical techniques during the last decade, Virtual Reality (VR) palpation training has become available. VR-based palpation simulation has several advantages over practicing on real patients, including exchangeable scenarios, fully controllable environments, unlimited repetitions, automated assessment, and no ethical issues and patient safety problems [15]. Many palpation simulators were developed for knee palpation training [16], abdominal palpation to identify liver tumours [17], prostate tumour detection palpation [18], horse ovary palpation [19], feline abdominal palpation [20], and palpation in cardiovascular surgery [5]. However, models based on indentation data from tests on the real organ are not used very often. Moreover, most of the aforementioned palpation simulators provide single-point force feedback during palpation. Multi-fingered haptic palpation would be beneficial compared to the current commonly used single-point haptic palpation simulation, but should be reduced in cost and size of feedback actuators [15].

1.1.3. Link between palpation in medical training and intra-operative palpation using haptic feedback

Mahvash et al. [21] pointed out that if intra-operative tissue models can be created, force display should be based on the tissue model instead of using the current sensed or estimated force. Although this idea has not been validated by Mahvash et al., it

links the research of medical simulation and intra-operative haptic feedback. It is possible to generate patient-specific tissue models for exploring tissue stiffness and following this, a virtual organ for palpation with haptic feedback based on in-vivo tests on the real organ can be created. Force display could be based on this tissue model linking medical simulation research to intra-operative haptic feedback. There were some early attempts pointing to this direction. Khaled et al. [22] created haptic-actuated virtual organs based on the results of real-time ultrasound elastography using Electro-Rheological (ER) fluids-based haptic actuators. Hamamoto et al. [23] attempted to use haptic displays to present elasticity information in real time for virtual palpation systems, which was measured by ultrasonic elasticity imaging equipments. Stalfors et al. [24] created a palpation simulator of malignancy in the human head and neck area using a PHANToM Desktop haptic device (Sensable Technologies) and a 3D tissue model generated from CT data.

1.1.4. Aim of PhD research

The investigation of the performance of different feedback modalities of soft tissue stiffness information and the combination of those modalities is useful for palpation training and mimicking the function of manual palpation in RMIS. The aim of this thesis is the creation and evaluation of rigid tool / soft tissue interactions with combination of different feedback methods, including visual stiffness feedback, force feedback, pseudo-haptic feedback, and multi-fingered haptic feedback, for tumour identification in medical training and RMIS using tissue models based on indentation tests. The application areas of the research results can be extended to general rigid tool-soft object interaction in virtual reality environments, such as video games.

1.2. List of contributions

The main contributions of the research are as follows:

- The first contribution is the creation and evaluation of novel visual feedback methods of soft tissue stiffness information including a real-time visual tissue stiffness feedback method for a tele-manipulation environment (Chapter 3) and pseudo-haptic tissue stiffness simulation methods (Chapter 4).

- The second contribution is the creation and evaluation of a multi-fingered palpation simulation method using novel stiffness feedback actuators (Chapter 5). This multi-fingered palpation simulation method allows a user to carry out palpation of soft tissue experiencing haptic sensations at multiple fingers during medical training, MIS, and RMIS. The efficiency advantage of multi-fingered palpation over single-fingered palpation is proven through user studies. In one of the proposed stiffness feedback actuators, granular jamming is, for the first time, used for haptic feedback.
- The third contribution is the combination of different feedback methods to improve on what can be achieved using a single feedback method including the combination of visual tissue deformation feedback and pseudo-haptic feedback (Chapter 4), the combination of force feedback and pseudo-haptic feedback (Chapter 4), the combination of multi-fingered feedback and pseudo-haptic feedback (Chapter 5).

The work presented in this thesis has resulted in the following peer reviewed publications:

Journal papers

M. Li, H. Liu, A. Jiang, L. D. Seneviratne, P. Dasgupta, K. Althoefer, and H. Wurdemann, “Intra-operative tumour localization in robot-assisted minimally invasive surgery: a current review”, *Proceedings of the Institution of Mechanical Engineers Part H: Journal of Engineering in Medicine*, 228(5):509-522, doi:10.1177/0954411914533679.

M. Li, T. Ranzani, S. Sareh, L. D. Seneviratne, P. Dasgupta, and K. Althoefer, “Multi-fingered haptic palpation utilizing granular jamming stiffness feedback actuator”, *IOP Science: Smart Materials and Structures*, 23(9):095007, doi:10.1088/0964-1726/23/9/095007.

M. Li, M. B. Ridzuan, S. Sareh, L. D. Seneviratne, P. Dasgupta, and K. Althoefer, “Pseudo-haptics for rigid tool/soft object interaction feedback in virtual environments”, *Mechatronics*, accepted.

M. Li, J. Konstantinova, A. Jiang, H. Liu, T. Nanayakkara, L. D. Seneviratne, P. Dasgupta, K. Althoefer, and H. Wurdemann “Using visual cues to enhance haptic feedback for palpation on virtual model of soft tissue”, *Medical & Biological Engineering & Computing*, under review.

M. Li, S. Luo, T. Nanayakkara, L. D. Seneviratne, P. Dasgupta, and K. Althoefer, “Multi-fingered haptic palpation utilizing pneumatic feedback actuators”, *Sensors & Actuators A: Physical*, under review.

J. Konstantinova, M. Li, G. Mehra, P. Dasgupta, K. Althoefer, and T. Nanayakkara, “Behavioral characteristics of manual palpation to localize hard nodules in soft tissues”, *IEEE Transactions on Biomedical Engineering*, 2014, 61(6):1651-1659.

H. Liu, K. Sangpradit, M. Li, P. Dasgupta, L. D. Seneviratne, “Inverse finite-element modelling for tissue parameter identification using a rolling indentation probe”, *Medical & Biological Engineering & Computing*, 2014, 52:17-28.

Conference papers

M. Li, H. Liu, J. Li, L. D. Seneviratne, and K. Althoefer, “Tissue stiffness simulation and abnormality localization using pseudo-haptic feedback,” in *IEEE International Conference on Robotics and Automation (ICRA)*, 2012, pp. 5359–5364.

M. Li, A. Faragasso, J. Konstantinova, V. Aminzadeh, L. D. Seneviratne, P. Dasgupta, and K. Althoefer, “A novel tumour localization method using haptic palpation based on soft tissue probing data”, in *Proceedings of IEEE International Conference on Robotics and Automation (ICRA)*, 2014, pp. 4188-4193.

M. Li, J. Konstantinova, V. Aminzadeh, T. Nanayakkara, L. D. Seneviratne, P. Dasgupta, and K. Althoefer, “Real-time visual stiffness feedback for soft tissue palpation in a tele-manipulation environment”, in *Hamlyn Symposium on Medical Robotics*, 2013, pp 77-78.

M. Li, S. Luo, L. D. Seneviratne, T. Nanayakkara, P. Dasgupta, and K. Althoefer, “Haptics for multi-fingered palpation”, in *Proceeding of IEEE International Conference on System, Man and Cybernetics (SMC)*, 2013, pp 4184-4189.

M. Li, S. Sareh, M. Ridzuan, L. D. Seneviratne, P. Dasgupta, H. A. Wurdemann, K. Althoefer, “Multi-fingered palpation using pseudo-haptic feedback”, Hamlyn 2014, accepted.

M. Li, L. D. Seneviratne, P. Dasgupta, K. Althoefer, “Simulated haptics for minimally invasive surgery”, World Congress of Endourology (WCE), Istanbul, September 2012.

M. Li, L. D. Seneviratne, P. Dasgupta, K. Althoefer, “Virtual palpation system”, International Conference on Intelligent Robots and Systems (IROS) workshop “Learning and Interaction in Haptic Robots” in Vilamoura, Algarve [Portugal], October 2012.

J. Konstantinova, M. Li, V. Aminzadeh, P. Dasgupta, K. Althoefer, and T. Nanayakkara, “Force-velocity modulation strategies for soft tissue examination,” in 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) November 3-7, 2013. Tokyo, Japan, 1998-2003.

J. Konstantinova, M. Li, V. Aminzadeh, K. Althoefer, T. Nanayakkara, P. Dasgupta, “Evaluating manual palpation trajectory patterns in tele-manipulation for soft tissue examination”, IEEE International Conference on System, Man and Cybernetics (SMC), 4190-4195.

1.3. Outline of the thesis

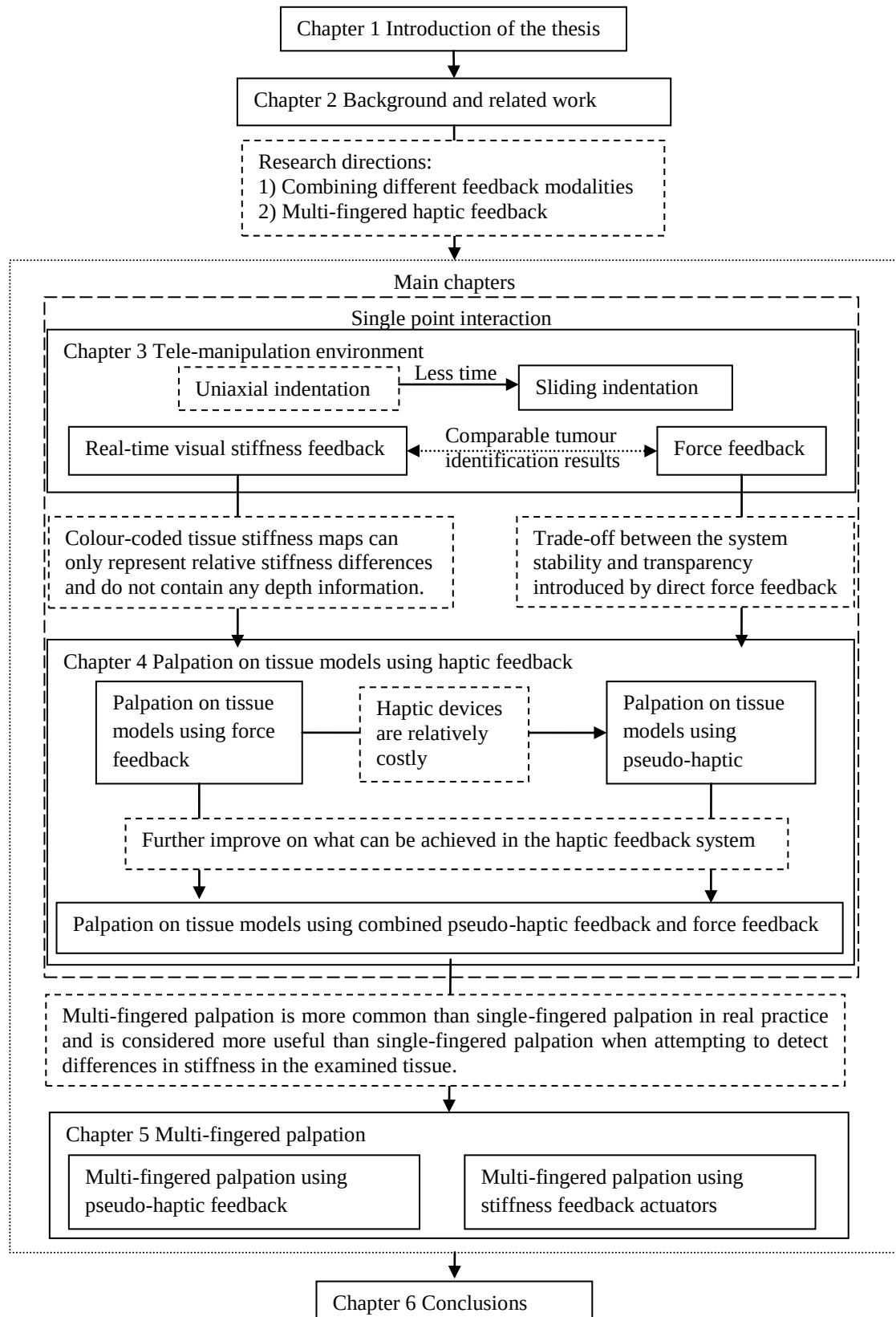


Figure 1-1 Thesis structure

Chapter 2 Background and Related Work

Robot-assisted Minimally Invasive Surgery (RMIS) provides many advantages compared to conventional open surgery such as small incisions via Trocar ports and, less operative trauma for the patient. However, it does not enable the direct hand / soft tissue interaction inside the patient's body for tumour localization. This hinders effective identification of tumours and their boundaries in RMIS. The objective of this review chapter is to summarize the state-of-the-art in intra-operative tumour localization in RMIS in order to account for the limitations of existing systems and identify future directions of research. The reviewed intra-operative methods are divided into several categories according to sensing methods including force-based sensing, tactile-based sensing, and medical imaging techniques, which are already in use or have the potential to be used for mimicking the function of intra-operative hand / soft tissue interaction. The limitations and challenges of the current state-of-the-art are addressed and discussed. Research directions of this thesis are addressed.

Aim: to present a survey of recent research achievements in intra-operative tumour localization methods for RMIS in order to identify existing limitations and research directions

Section 2.2 Literature survey on tumour size, stiffness, and depth

Section 2.3

Literature survey on tumour localization using force-based sensing overview

Direct force feedback architectures

Force sensing strategies

Tissue property acquisition

Feedback modalities

Section 2.4

Literature survey on tumour localization using tactile-based sensing

Tactile information visualization

Tactile feedback devices

Section 2.5

Literature survey on tumour localization using medical imaging and elastography

Medical imaging registration

Real-time elastography

Section 2.6

Literature survey on combination of force feedback and tactile feedback for tumour localization

Section 2.7

Literature survey on multi-fingered palpation for tumour localization

Section 2.8

Conclusion:

Research is needed to address the main problem of how to acquire accurate tissue stiffness data and display useful information to the surgeon; solutions include multi-fingered actuators and combining different feedback modalities.

Figure 2-1 Structure of Chapter 2.

2.1. Introduction

The aim of adding haptic feedback of rigid tool/soft object interaction in medical training and RMIS is to enable palpation and to help surgeons to identify tumours. The tumour size, stiffness and depth properties are investigated first. Feedback modalities are closely related to sensing methods. Therefore, in the following sections, the state-of-the-art feedback methods in intra-operative tumour localization using force-based sensing, tactile-based sensing, and medical imaging techniques are reviewed. Then, the combination of force and tactile feedback modalities is investigated. At the end of this chapter, a more intuitive multi-fingered palpation is discussed.

2.2. Literature survey on tumour size, stiffness, and depth

According to the 2003 American joint committee on cancer staging, T1 stage tumours are 20 mm or less in greatest dimension; T2 stage tumours are more than 20 mm but not more than 50 mm in greatest dimension; T3 tumours are more than 50 mm; T4 tumours are of any size with direct extension to the chest wall or/and skin [25]. The overall survival curves show a decreasing trend through stages [25]. Therefore, identifying the T1 stage tumours is very significant to increase the survival rate.

Although the quantitative measurements of tumour stiffness suggest a wide variability between tumour types [26], cancerous formations are typically stiffer compared with the surrounding healthy soft tissues [27], [28]. The research of Wellman et al. [27] show that the ratios of elastic modulus of cancerous breast tissues (gland, phyllodes tumour, papilloma, lobular carcinoma, fibroadenoma, infiltrating ductal carcinoma, ductal carcinoma in situ) to fat tissue are ranging from 4 to 124. Although some tumours may have fat containing regions that appear less stiff [29], many tumour identification methods, for example, elastography, are based on the fact that most cancerous tissue is stiffer than normal tissue [30]. Cancerous soft tissues may also have different inner structures such as harder shells or softer surfaces. To simplify the question, tumours are commonly modelled to be homogeneous [31]–[34].

Tumour depth is suggested to be a useful predictor for upstaging for cancers [35], [36]. A threshold can be assigned to distinguish between low risk and high risk for upstaging for cancers [35]. Williams et al. [36] and Lee et al. [35] show tumour depths greater than 4 mm are associated with greater risk of upstaging for cancers in the oral cavity, head and neck.

2.3. Literature survey on intra-operative tumour localization using force-based sensing

2.3.1. Direct force feedback architectures

Implementation of direct force feedback in RMIS requires the surgeon who gives commands to the master system to be able to discern material properties of soft tissue when probing soft tissue using a surgical tool at the slave side. In order to benchmark the performance, the term transparency has been defined as a matching level between the master and slave forces as well as the master positions and slave positions [37]. A fundamental redesign of the whole system would be required to integrate completely transparent haptic interactions to existing complex surgical systems (such as the da Vinci and the Titan Medical Amadeus) [13].

Bilateral control is a common method to integrate haptic feedback to robotic surgery [38], [39]. Instead of a simple two-port model, bilateral control has been extended to a four channel architecture, considering not only the master and slave forces but also the difference between the master and slave positions. DLR (German Aerospace Centre) developed a 7-DOF MiroSurge surgical robotic system providing bimanual force feedback based on a bilateral control scheme [40]. Manipulation and force feedback are provided by two Sigma.7 (Force Dimension Inc.) input devices on the master side. Using this system, the user can clearly distinguish between instrument collisions and tool-tissue interactions [40]. In other studies, Tavakoli et al. [39] developed and evaluated a force feedback method which provided users with the ability to distinguish tissue stiffness when probing them remotely. They used strain gauges and a load cell attached to the end of a surgical tool. Employing a PHANToM 1.5A force feedback device (Sensable Technologies Inc.) and implementing a bilateral tele-operation control scheme, the researchers provided direct force feedback of

bending and torsional moments and the contact force between the tool and tissue. However, system instability can be caused by uncontrollable jitters generated by small errors and delays when the transparency increases [41]. Surgery has a low tolerance for this type of inaccurate behaviours. The trade-off between force feedback transparency and system stability is a significant barrier of direct force feedback since it is not possible to successfully apply both position and force control using the aforementioned bilateral control scheme [41]. Instead, acceleration-based bilateral control provides a way to prevent this trade-off and achieve high transparency and manoeuvrability by performing the position and force control simultaneously using the common variable between force and position, i.e. acceleration [38], [42]. Here, force sensor is not necessary for acceleration control. This control type has been applied to a 1-DOF master-slave forceps robot for surgical applications [43] and multi-DOF haptic surgical robot [38]. In order to distinguish between different tissue stiffness, further research regarding this application is needed.

2.3.2. Force sensing strategies

Currently, no commercially available multiple DOF force sensor meets the dimensional constraints for potential use in MIS through Trocar ports (less than 12 mm in diameter) [6] [44]. Although the Nano-17 (ATI, Industrial Automation), a commercial 6-DOF sensor system with a diameter of 17 mm, can be sterilized, it cannot be used in standard MIS. However, this sensor is frequently utilized in MIS-related research studies [45]–[48]. Other specialized force sensors include a 6-DOF Force/Torque (F/T) sensor for the DLR tele-surgery scenario MiroSurge, for instance. An additional 1-DOF gripping force sensor is integrated to the gripper, which has a annular cross section with a diameter of 10 mm. Sargeant et al. [49] developed an MR-compatible 6-DOF F/T sensor based on the Steward Platform that obtains intensity modulated light using linear polarizer materials and fibre optic guided light. This sensor has a diameter of 11 mm, height of 10 mm and weight of 0.6 g, all of which meets MIS requirements.

If the force sensor is positioned outside the patient, there would be no size limits and sterilizability problems. However, the sensor measurement maybe influenced by joint actuation or by the friction between the tool and the Trocar. Alternatively, the

problems related to MR-compatibility, size, sterilizability, and cost can be avoided by measuring contact forces without any force sensor [50]. For snake-like robots, force sensing could be achieved by the kinematic analysis [51]. In another context, Mahvash et al. [21] estimated contact forces by using the current that is applied to the actuators of the slave robot during a remote palpation experiment. However, the sensitivity of these methods is lower than force sensor implementations [21]. Recently, Beccani et al. [52] proved the feasibility of a wireless uniaxial indentation palpation method using a 1-DOF magnetic device. By introducing this method, there is no direct physical connection through the Trocar port, and, thus, the force data will not be distorted by friction or joint actuation. Acceleration-based bilateral control as mentioned before is one example of another option – estimating forces and providing direct force feedback using a further developed bilateral teleportation controller [33]. Force sensing strategies for tumour localization are summarized in Table 2-1.

Table 2-1 Summary of force sensing strategies for tumour localization

Approach	Challenges	Example	Properties	Reference
Measuring contact forces with force sensors	Size, sterilizability, cost, and MR-compatibility. On the one hand, size limitations and sterilizability of the used sensor are negligible, if the sensor is positioned outside the patient. On the other hand, friction between the Trocar and the tool or by joint actuation affects the measurement.	Nano-17 (ATI, Industrial Automation)	Does not meet the dimensional constraints for potential use in MIS through Trocar ports (less than 12 mm in diameter) [6] [44].	Liu et al., Yamamoto et al., Samur et al., and Sangpradit et al. [45]–[48]
		A 6 DOF F/T sensors for the DLR tele-surgery scenario MiroSurge	An additional 1-DOF gripping force sensor is integrated to the gripper, which has a annular cross section with a diameter of 10 mm.	Konietschke et al. [40]
		An optical multi-axis F/T sensor	6-DOF F/T MR-compatible sensor. Diameter: 11 mm, height: 10 mm weight:0.6 g	Sargeant et al. [53]
		A wireless indentation palpation approach using a magnetic device	Since a direct physical connection through the Trocar port is redundant, the force data is not distorted by friction or joint actuation.	Beccani et al. [52]
Measuring contact forces without force sensor	Sensitivity and accuracy	An state observer is used to estimate contact force using the current applied to actuators	Not as accurate as force sensor.	Mahvash et al. [21]
		Bilateral	Transparency achieved is	Gwilliam et

Approach	Challenges	Example	Properties	Reference
		teleportation controllers	limited.	al. [33]
		Acceleration based bilateral control	High transparency and manoeuvrability Further research regarding distinguishing between different tissue stiffness is needed.	Tanaka et al. and Katsura et al. [43], [38]
		Kinematic analysis of a snake-like robot	The flexible continuum robot has intrinsic force sensing ability. Average force sensing errors: 0.34 g, standard deviation: 0.83 g.	Xu and Simmaan [51]

2.3.3. Tissue property acquisition

Instead of providing force feedback directly, indenter displacements and applied forces can be acquired in real time and combined with tissue mathematical models to estimate tissue property.

2.3.3.1. Soft tissue modelling and parameters estimation methods

Several constraints such as computational time, tools, sensors, and required measurement accuracy need to be considered to establish a mathematical model for soft tissue. The contact behaviour of soft tissue is modelled as a function of the applied strain. Thus, soft tissue mathematical models connect the main displacement parameters (such as position, velocity, and acceleration) to dynamic parameters (such as force and torque) [54]. Researchers have been working on this area for many years to find the balance between real-time computations and accuracy.

Human biological tissue exhibits nonlinear properties and consists of non-homogeneous structures [45]. Linear elasticity is valid only for small strains ranging from 1% to 2% [55], but principles of linear elasticity are used in many simulation applications to describe soft tissues in order to simplify analysis and reduce computational time. Linear elastic materials can be simulated and modelled by a spring that generally follows the Hooke's law.

Elastic modulus E , also named Young's modulus, is commonly used to describe the soft tissue behaviours [56]. If indentation force and tissue deformation are known, and if the tissue geometry can be approximated by a semi-infinite body undergoing

normal indentation by a circular punch, then the parameters are related by equation (2.1) [57].

$$E = K \frac{3f_z}{8a\delta_z}, \quad (2.1)$$

where δ_z and f_z are the displacement and force normal to the surface, a is the cylindrical indenter radius, and E is Young's modulus. For a semi-infinite body, K is unity, but if the elastic material is a layer of thickness h bonded to a flat, rigid surface, K increases with increasing a/h and δ_z/h .

If using a rigid hemispherical indenter and applying small indentation, the elastic modulus of tissue can be estimated as

$$E = \frac{3f(1+\nu)}{8d_{in}\sqrt{rd_{in}}}, \quad (2.2)$$

where E is the Elastic or Young's modulus, f is the normal tissue reaction force, d_{in} is the indentation depth, r is the radius of the sphere and ν represents the Poisson ratio [58]. Many soft tissues are nearly incompressible. For an incompressible material, ν is 0.5.

Most of these soft tissue simulations have a response based on both velocity and position and are inherently viscoelastic. Rheological models with linear dashpots (viscous elements with a constant damping) and springs (elastic elements with a constant stiffness) in serial or parallel combinations are used to represent viscoelasticity properties of soft tissue [59]. There are three basic linear viscoelasticity models to represent solids, including the Maxwell (spring and dashpot in parallel), Kelvin-Voigt (or Voigt) (spring and dashpot in series), and Zener standard linear solid (or Kelvin) (spring in parallel with a Maxwell) models. Mass-damper-spring, which is the most popular non-continuum mechanics-based soft tissue modelling method, adds a mass to Kelvin-Voigt model in series. Those models are frequently employed in research regarding tool / soft tissue interaction [60]–[62]. In existing surgical simulators, mass-spring models are used as the standard models for simulations of deformable objects. It is usually fast enough for real-time computation and easy to implement. However, the indenter is not haptic activated, that is the diameter of tool tip is not considered, which makes the display unrealistic.

Nonlinear elasticity theories are commonly used to model biological tissues with large strains [59]. The formulations of the strain energy density function include Neo-Hookean models, Mooney-Rivlin, Ogden, Blatz-Ko, and St. Venant-Kirchhoff [63]. Mooney-Rivlin and Ogden strain energy density formulations can represent the constitutive laws of many biological tissues accurately [64]. Some nonlinear models are extensions of the linear models. The Hunt-Crossley model [65] is one example. It considered the energy loss and was proposed with the aim to overcome the non-zero initial value and discontinuity of contact force of the Kelvin-Voigt linear model. Diolaiti et al. [66] compared the Hunt-Crossley model with the Kelvin-Voigt model. The result showed that the Hunt-Crossley was much better than the Kelvin-Voigt linear model for the silicone gel, while the advantages were more limited for a stiff material. Some researchers tried to add nonlinear elasticity factors to linear models. Liu et al. [67] proposed a nonlinear viscoelastic soft tissue model by adding two nonlinear elasticity factors to a dual Maxwell model and the factors were generated from ex-vivo experimental tests on ovine liver. According to their comparison between the experimental data and simulation results, both static and dynamic indentation conditions could be modelled by this robust model. Other proposed nonlinear models mainly describe the contact behaviour of soft tissue as logarithmic or polynomial functions of strain and stress [45], [68]. The main disadvantage is that, except for the stiffness coefficient, the model parameters (coefficients, coefficient of the exponential function, and degree of the polynomial) have no biological or physical meaning.

Linear elasticity-based Finite-Element (FE) models are widely used to describe the contact behaviour of soft tissue in surgical simulators. Good agreement between the experimental and the simulation results was found for small strains (1% - 2%), but the comparison results were not impressive for large strains [69]. To achieve better fidelity, hyperelastic finite element models can be used [48]. Several studies have been conducted to validate the coefficients of the strain energy function using experimental data. Visco-hyperelastic FE models were introduced because real soft tissue also presents viscoelastic properties. Although FE modelling can provide superior tissue modelling, its demand for a large amount of computational resources has limited its usage in real-time applications. The 2D nonlinear Arruda-Boyce FE

model was used to describe soft tissue rolling indentation, and was found to have good prediction accuracy of interaction forces, but the computational time of each FE test was about 8 minutes for porcine kidney and 10 minutes for silicone phantom [48].

Other innovative methods have been developed to simulate soft tissue in real time. One method involves non-physical models such as those using free-form deformation technique and parametric surfaces defined by curves or splines. Baur et al. [70] displaced the surface nodes using 3D profile functions tuned by experts. Basdogan et al. [71] used second order polynomial functions, fitted to empirical data, to redefine the heights of vertices of organs near the contact point along the direction of the virtual tool. However, cutting could not be simulated using this method, so the applications were limited to palpation simulation. When soft tissue was simulated by using those non-physical models, forces were calculated from the force-deflection curve of the material or Hook's law [72]. Another soft tissue modelling method is volumetric haptic models. Balaniuk and Salisbury [73] presented the Long Element Method (LEM) to model deformable objects. The deformable object was simulated by filling the interior of the volume with rectangular solid (long elements) and defining the equilibrium equation using bulk variables. The number of elements is less than in a finite element method by one order of magnitude. The homogeneous and non-homogeneous volumetric model can be rendered haptically in real time by employing the Shape Retaining Chain Linked Model (S-chain model) algorithm [74]. One disadvantage was the dependence of the resulting deformation shape on the sequence of the applied forces. Park et al. [74] presented a method to conquer this drawback. The deformations were always computed from the rest shape of the object, which retained the rest shape of the modelled geometry when the applied displacement was reversed.

There are several online real-time estimation methods for unknown parameters of a model, including Recursive Least Squares (RLS) [66], [75], [76], adaptive identification [77], Kalman filter approaches [60]–[62], and multi estimator techniques [78]. Yamamoto et al. [78] evaluated the performance of the estimation of unknown parameters of the Kelvin-Voigt model for medical applications using adaptive identification, RLS, and the multi-estimator technique. RLS and the multi-

estimator were recommended for real-time tissue parameter estimation. Inverse FE modelling for tissue parameter estimation is another novel way [48] (see Figure 2-2). The FE model is established with an initial guess of the soft tissue parameters. Then the force-displace curve generated in the FE model is compared to measured data. The Newton-Raphson method is used to change tissue parameters until error is small enough. The accuracy of this method is high, but each simulation takes several minutes.

2.3.3.2. Tissue property acquisition using uniaxial indentation

Separate point uniaxial compression tests are commonly used to acquire the tissue properties. During the process, a F/T sensor is used, either underneath the tissue [45] or attached to the probe [46], [79] (Figure 2-3 and Figure 2-4). Deformation and corresponding interaction force data are recorded. During this type of test, the instrument is restricted to up and down motions.

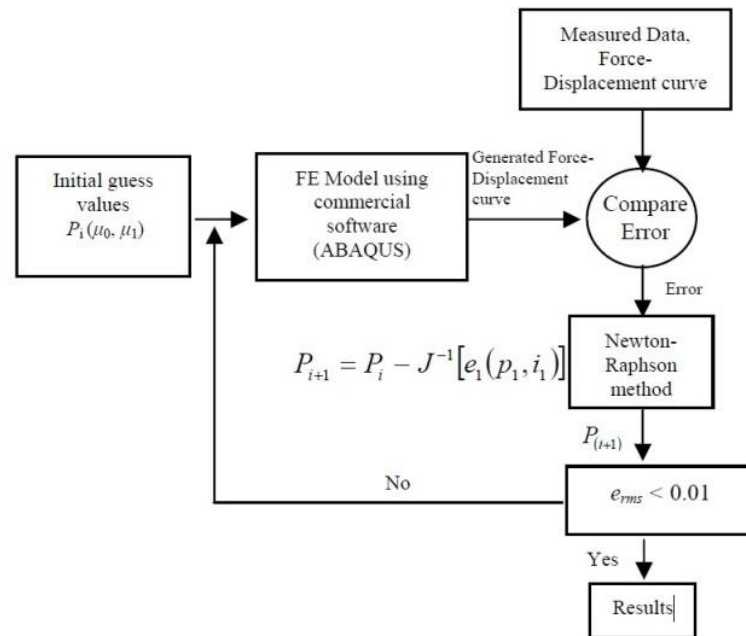


Figure 2-2 Schematic of inverse analysis procedure [48]

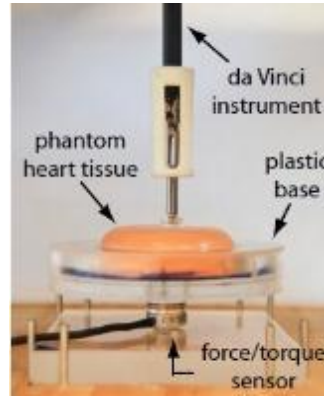


Figure 2-3 Separate point uniaxial compression test [45]

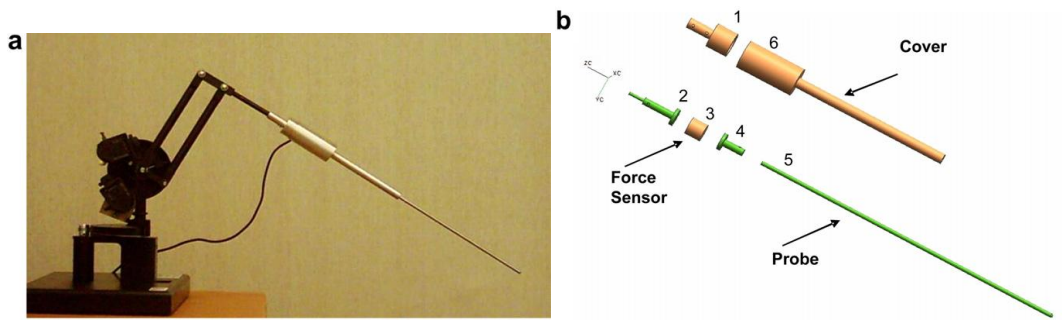


Figure 2-4 Robotic indenter (a) and its components (b) [46]

The feasibility of conducting separate point uniaxial compression to identify lung tumours utilizing a force-sensitive probe based on tissue stiffness distribution was discussed in [80]. In order to get a proper tissue model and estimation technique to assess soft tissue properties at each indentation point with recorded deformation and interaction force data pairs, Yamamoto et al. [45] compared Kelvin-Voigt, mass-damper-spring, 2nd to 4th order polynomial, and 2nd order polynomial + velocity-dependent models, with the Hunt-Crossley model ($\hat{f} = \hat{x}_0 + \hat{k}x^{\hat{n}} + \hat{\lambda}x^{\hat{n}}\dot{x}$). The Hunt-Crossley model was chosen and RLS was employed to estimate the unknown parameters ($\hat{x}_0, \hat{k}, \hat{n}, \hat{\lambda}$) in real time, where $\hat{f}$ is the estimated contact force between the tool and the tissue, and x and $\dot{x}$ are position and velocity of the tool, respectively. Stiffness $\hat{k}$ was then displayed to surgeons [45]. Later, it was improved to an interoperable interface which provides augmented visual feedback using 3D graphical material property overlays as well as virtual fixtures via haptic feedback [32]. Tissue was modelled as linear elastic, homogeneous, isotropic, and incompressible in TeMPeST 1-D [79] and in uniaxial robotic tissue indentation described in [46]. Elastic (or Young's) modulus E was used to describe the material.

2.3.3.3. Rolling and sliding indentation approach

The rolling indentation approach for the localization of tumours has been proposed by [47], [81], [82] (see Figure 2-5). Conducting a rolling indentation on a soft tissue using a force-sensitive probe can acquire the stiffness variations more rapidly than a separate point uniaxial compression test. The air-cushion force-sensitive probe [83] - a concept similar to rolling indentation- was designed to discriminate between hard and soft tissues (see Figure 2-6).

A force distribution matrix can be obtained with the rolling indentation probe and is effectively showing a tissue's elastic (or Young's) modulus E at a given indentation depth assuming that tissue is linear elastic, isotropic, homogeneous, and incompressible [84]. As described in [58], using a rigid hemispherical indenter and employing a small indentation and slow rolling speed, E can be estimated by equation (2.1). However, the probe with the wheeled indenter needs to be rotated when the rolling direction changes. To that effect, a sliding indentation probe was proposed [85]. A round-shaped end effector, which was fixed inside the tip of the probe, replaced the indentation wheel of rolling indentation probe. In order to reduce the friction during sliding over the tissue, the tissue surface was lubricated.

For rolling indentation palpation, it is essential to maintain a constant indentation depth throughout the palpation activity. This could be achieved by pre-registration of the surface. However, pre-registration might be time consuming and the accuracy may be affected by introduced errors. In real applications, instead of maintaining a constant indentation depth during the scan, a tissue stiffness probe, which measures indentation depth and reaction force at the same time, will be needed. Wanninayake et al. [86], [87] proposed an air-float stiffness probe, which fulfilled the requirement. Indentation depth and surface profile variations can be measured. However, some improvements should be undertaken to fulfil the requirements of RMIS with respect to miniaturization for instance. Sangpradit et al. [48], [88] developed an Inverse FE modelling method for tissue parameter estimation using rolling indentation. The FE model was established with an initial guess of the soft tissue parameters. The force-displace curve generated by the FE model was compared to real data. The Newton-Raphson method was applied to adjust tissue parameters and minimize the error. The

results showed that locations and depths of embedded nodules could be identified accurately. Ahn et al. [89] used mechanical property characterization with FEM-based inverse estimation for a robotic sweeping palpation method. The comparatively long computational time was the main disadvantage of this method.

3D reconstruction techniques could be used in tissue surface contour acquisition for indentation depth measurement. In [90], a moving Microsoft Kinect was used for real-time 3D reconstruction and interaction. To make it more suitable for minimally invasive intra-operative purposes, endoscopic cameras should be used for 3D reconstruction. Once the original, unindented surface is reconstructed, the indentation depth can be calculated based on the distance between the current indenter position and the closest triangle planar on the mesh of the original reconstructed contour. To compensate for any tissue shift or deformation, the surface reconstruction process can be repeated several times during the procedure.

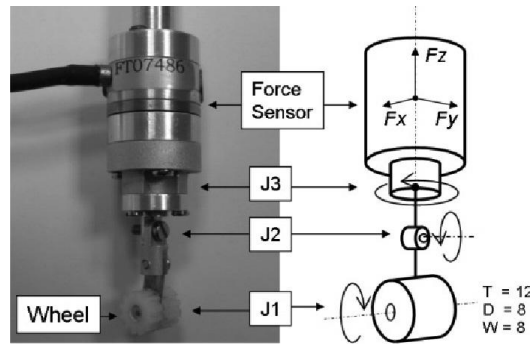


Figure 2-5 Rolling indentation force-sensitive probe with a wheel end-effector [47]

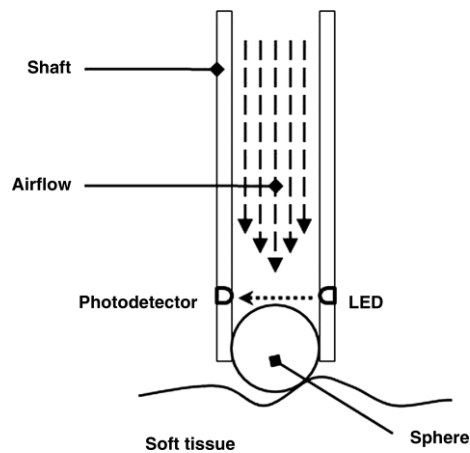


Figure 2-6 Structure of the air-cushion sensor [83]

2.3.4. Feedback modalities

2.3.4.1. Graphical feedback

For intra-operative palpation, the most commonly used way to convey force information is through a graphical display, which is much cheaper and simpler, and especially suitable for diagnosis applications. Graphical feedback does not inject energy into the system, and, thus, it is not likely to break the closed-loop dynamics of the bilateral tele-operator and cause stability issues. Moreover, it can be easily combined with other feedback modalities.

Mahvash et al. [21] compared the performance of graphical force display and direct force feedback, and demonstrated that direct force feedback was better than graphical force displays. A bar, whose height and colour was set to relate to the environment force, which was estimated by monitoring the current applied to the actuators of the patient-side robot instead of using force sensors, was displayed (see Figure 2-7) [21]. A position controller with local dynamic compensators was used to provide force feedback.

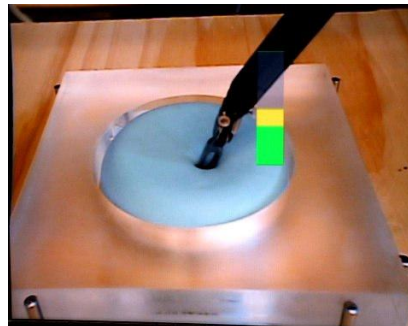


Figure 2-7 The image of the user interface of graphical force display: a colour bar changes height and colour depending on the level of applied force [21]

Compared to the contact force graphical display, spatially distributed tissue stiffness display can be more useful for tissue abnormality localization. A real-time graphical overlay method was used in [45] [32] to help the surgeon distinguish hard and soft tissues using a HSL representation on the tissue surface. A simple interpolation technique has been introduced to create a continuous stiffness colour map (see Figure 2-8). Using rolling indentation approach, the resultant forces f_r acquired by an F/T sensor (f_x , f_y , and f_z) at each sampled point were used to generate the Rolling

Mechanical Image (RMI), which indicated the geometrical stiffness distribution over the tissue surface as shown in Figure 2-9.

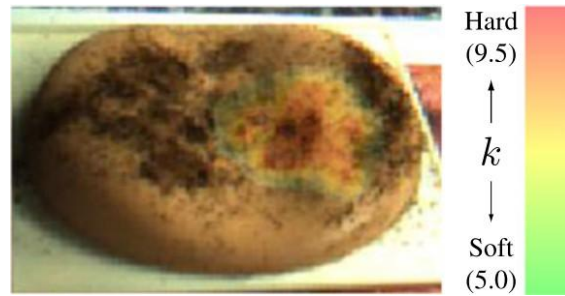


Figure 2-8 A coloured stiffness map indicates an artificial calcified artery hidden in a phantom tissue [32].

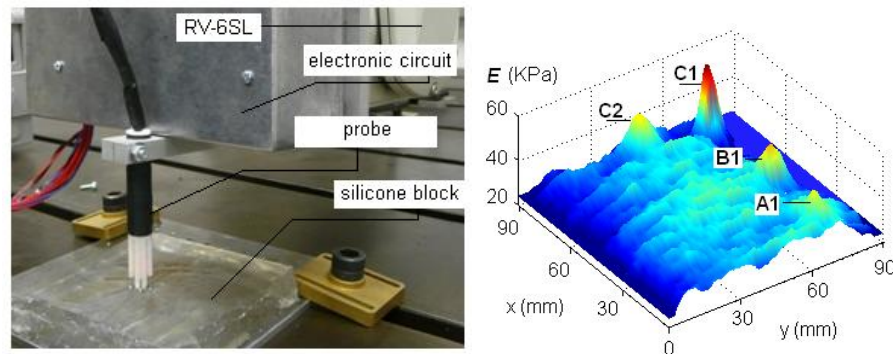


Figure 2-9 The rolling indentation experiment setup (left) and the produced stiffness map (right) [47].

2.3.4.2. Force feedback

Haptic technology is a feedback technology that applies vibrations, motions, or forces to the user in order to enable them to get a sense of touch remotely. The term “tactile” usually refers to mechanical stimulation of the skin (distributed tactile receptors in the human skin which enable us to feel the texture of things) while “kinaesthetic” is force based, referring, for instance, to the force that we can feel with our arm muscles [3], [91]. Generally, users hold the end effecters of haptic devices, and the devices respond to users’ movements or applied forces with corresponding forces or movements. In this way, humans communicate with machines via haptic devices through touch and kinaesthesia. Table 2-2 shows some currently used haptic devices.

A number of haptic devices have been typically employed in rigid tool / soft tissue interaction simulations. Impedance-based haptic devices track the hand motion of the

user and exert a force on the hand actively, creating illusions of interaction with real objects. The force displayed by the device is computed in a haptic loop usually at a rate of about 1000 Hz based on the location of the stylus and the state of the virtual scene [92]. PHANToM is one of the most widely used haptic devices (Sensable Technology Inc.) [93]. The PHANToM device series has three different configurations: Omni (6-DOF of movement and 3-DOF of haptic feedback), Desktop (6-DOF of movement and 3-DOF of haptic feedback) and Premium (6-DOF of movement and 6-DOF of haptic feedback). These devices weigh approximately 1.79 kg, 2.86 kg, and 31.3 kg (control console included), respectively.

The Delta, Omega and Sigma haptic systems from Force Dimension Inc. [94] are based on a particular parallel mechanism concept. Both Delta. 3 and Omega. 3 are capable of performing three active translations. Omega. 6 adds three passive rotations, while Delta. 6 adds three active rotations. Omega. 7 introduces another grasping motion. The most recent Sigma. 7 has a uniquely redesigned delta base introducing a more precision-active grasping capability. These devices are about 270×300×350 mm in dimension. The mechanical structure of the Falcon haptic system from Novint Technologies, Inc. [95] is very similar to the Delta haptic device, but of a lower price. It has a size of 229×229×229 mm and weight of 2.72 kg.

An opposed-type multi-fingered haptic interface – a Haptic Interface Robot (HIRO) device developed by Kawasaki et al. [96] – has been used for breast palpation simulation [72]. It consists of a force actuated 6-DOF arm and three fingers, with 3-DOF force output, which has been later upgraded to a five-fingered HIRO III device [97]. It has a weight of about 3.8 kg with a 23 kg control apparatus (a box size of 443×222×464 mm). The above devices need to be placed on a flat surface, e.g. a desk, when they are in use. The Rutgers Master II force feedback glove [16] is a light-weight (Exoskeleton weight only 80 g) device that can provide force feedback of up to 16 N to each finger. Nevertheless, apart from the glove itself, it has extra components such as pneumatic servovalves and air supply. Pneumatic actuators are used to apply forces to all of the fingertips except for the little finger. However, the glove limits the range of motion of the fingers because of the placement of the cylinders.

Those haptic devices have been applied in training for knee palpation [16], abdominal palpation to detect liver tumours [17], prostate cancer palpation simulation [18], horse ovary palpation simulation [19], feline abdominal palpation simulation [20], palpation simulation in cardiovascular surgery [5], and haptic palpation [15]. One drawback of these haptic devices is their relatively high cost [98]. Moreover, they are bulky and need to be connected to a power supply when they are in use.

Table 2-2 Existing haptic devices

Category		Devices and Companies	Illustrations of Haptic Devices	Properties
Active haptic devices: <i>Can generate a force in any direction, but they are sometimes unstable during operation</i>	Impedance based haptic devices: they sense the displacement of the haptic mechanism as input (position/velocity) and react with force as output--read position and send force	PHANToM [93]	 Figure 2-10 PHANToM Omni, Desktop and Premium 3.0 [93].	Omni (£2,000*) and Desktop (\$16,000*) models have 6-DOF of movement and 3-DOF of haptic feedback. Only the Premium (\$ 56,000*) model can provide 6-DOF of haptic feedback. It has been used for palpation simulation [99]–[102]
		The Delta, Omega and Sigma haptic systems from Force Dimension Inc. [94]	 Figure 2-11 3-DOF and 6-DOF Delta haptic devices [94].  Figure 2-12 3-DOF, 6-DOF, and 7-DOF Omega haptic devices [94].  Figure 2-13 7-DOF Sigma haptic device [94].	Particular parallel mechanism concept, Delta.3 and Omega.3 have 3 active translations. Omega.6 adds 3 passive rotations, while Delta.6 adds 3 active rotations. Omega.7 introduces 1 active grasping. The most recent Sigma.7 (\$52,000*) has 7 unique active DOFs and is based on a redesigned delta base introducing active grasping capability.

Category		Devices and Companies	Illustrations of Haptic Devices	Properties
		Falcon haptic system from Novint Technologies, Inc. [95]	 Figure 2-14 Falcon haptic device [95].	Mechanical structure similar to the Delta (\$200*) haptic device, price is lower, only 3-DOF and cannot be extended. It has been used for palpation simulation [103].
		Maglev 200 magnetic levitation haptic device from Butterfly Haptics LLC.[104]	 Figure 2-15 Maglev 200 haptic device [104].	Since it is based on magnetic levitation and there are no motors, gears, bearings, cables, or linkages, the device is friction-free and provides almost ideal impedance. It has 6 or 7-DOF. The bandwidth is big that maximum and minimum impedance are 50.0 N/mm and 0.002N/mm. It also has high position resolution (2μm).
		Mantis tension-based haptic device from Mimic Technologies, Inc. [105]	 Figure 2-16 Mantis tension-based haptic device [105].	Based on tensioned wires connecting the user handle to the frame of the device, which is a different mechanical structure. The advanced version allows 6-DOF motion tracking and provides 3-DOF of force feedback.

Category		Devices and Companies	Illustrations of Haptic Devices	Properties
	Admittance based haptic devices: A reverse of impedance control. read force signals and send position commands	The HapticMaster device from MOOG Inc. [106]	 Figure 2-17 HapticMaster haptic device [107].	Simulate higher stiffness and larger reaction forces than impedance based haptic devices.
Passive haptic devices: <i>Stable, but can only generate a force against the motion</i>	Use passive actuators (e.g. brakes and constraints) can reflect much larger forces; cannot simulate an energy storage element like a spring [108].	Passive arm with dynamic constraints (PADyC)	 Figure 2-18 PADyC 3-DOF prototype and computer-assisted trajectory execution [109].	Restrict user induced motion on a plane. The drawback is the mechanical complexity.
		Cobot	 Figure 2-19 Cobot [109].	Restrict the motion of the end-effector on a plane. They are complex and not robust.

*Prices quote from products retailers at the time of writing.

2.4. Literature survey on intra-operative tumour localization using tactile-based sensing

2.4.1. Tactile sensing and visualization systems

Tactile information is significant in palpation as it conveys the properties of tissue regions [91]. Tactile sensors comprise an array of force sensing elements which can detect spatially distributed forces within the array and gather a range of palpation information of soft tissue including variations in stiffness [14]. Ideal tactile sensors should be sensitive, reliable, firm, small, light-weight, and low-cost. Some tactile sensor arrays from Pressure Profile Systems Inc., Los Angeles, USA, or Tekscan Inc., Boston, USA, , for instance, are commercially available [110]. Several novel tactile sensing devices for tumour localization have been developed, including Tactile Imaging [111], Tactile Imaging System [56], PVDF-sensing grippers [112], and Tactile Sensing Instrument [113].

2.4.1.1. Grasping palpation

A common approach for tumour localization is to grab tissue with a grasper or hand (prehensile motions). Schostek et al. [114] integrated a 32-element tactile sensor in a 10 mm disposable laparoscopic grasper. Sensed tactile information was displayed visually and the sensor used was low-cost, entirely encapsulated in silicone rubber, and able to withstand high grasping forces. In-vitro and in-vivo exploratory experiments were performed for a subjective evaluation of the usability and feasibility of the system in a clinical environment. Najarian et al. [115] and Dargahi et al. [112] equipped endoscopic graspers with miniaturized PVDF-sensing elements with a graphical visualization. Their system was able to acquire tissue stiffness distribution on the tissue/grasper interface. An average discrepancy of around 10% was achieved between the evaluation experimental outputs and the known tactile properties [112]. However, the developed sensing array of 8 elements constrained by the size of the grasper and could only cover a small tissue area. It was not able to acquire internal stiffness information for big organs.

2.4.1.2. Non-grasping palpation

Egorov et al. [116], [117] developed a mechanical imaging system for breast and transrectal prostate examination. The feedback provided a real time 2D pressure response pattern and a summary mode with a 3D reconstruction.

The Breast Mechanical Imager (BMI) was designed with a 16×12 array of pressure sensors (Pressure Profile Systems, Inc., Los Angeles, CA) covering $40 \times 30 \text{ mm}^2$ and was used on the contact surface of the scan head. Obviously, further miniaturization is needed in order to make it suitable for RMIS.

Two pressure sensor arrays were integrated in the Prostate Mechanical Imaging (PMI) transrectal probe: probe head pressure sensor array for prostate imaging and a probe shaft pressure sensor array for sphincter imaging. The probe head pressure sensor array consisted of 16×8 sensors (Pressure Profile System) covering $40 \text{ mm} \times 16 \text{ mm}$. The shaft pressure array had also 16×8 sensors with a total size of $60 \text{ mm} \times 20 \text{ mm}$. In 84% of studied cases, the system was able to reconstruct 2D cross-sectional and 3D images of the prostate. The PMI system detected malignant nodules in 10 out of 13 patients with biopsy-confirmed malignant inclusions.

Trejos et al. [113] and Perri et al. [118], [119] developed and enhanced the Tactile Sensing Instrument (TSI) to a more advanced Tactile Sensing System (TSS) by adding a visualization interface. This system now visualized an active pressure map of the palpated tissue surface between the tactile sensor (4×15 elements) and the organ surface. Both the interaction force data (kinaesthetic data) and the colour-contour pressure distribution (tactile data) were provided to the clinician. This study concluded that if the sustained applied forces exceeded 6 N, visible and irreversible bulk damage would be caused to the soft tissue.

Using a capacitive sensor array, Miller et al. [56] constructed a similar Tactile Imaging System (TIS) for the localization of tumours during MIS. The advantage of this system was its vision-based algorithm localizing the probe and a live video was overlaid with a registered pseudo-colour map of the measured pressure distribution (3×12 sensing elements) at the tracked probe location. The surgeon could locate tumours by scanning the surface of the organ using the probe and observing the

change in pseudo-colours of the distribution map overlaid on the laparoscopic image (Figure 2-20).

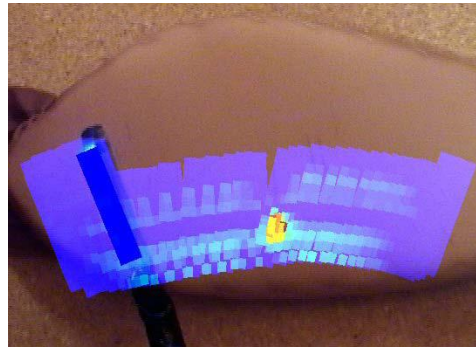


Figure 2-20 Overlaid pressure data on the laparoscopic image [56]

2.4.2. Palpation using tactile feedback devices

Using tactile feedback devices to interpret the stiffness distribution of the soft tissue may provide a more intuitive reception of tissue stiffness information [114]. However, our understanding of human tactile receptors is still limited and research of tactile interfaces in its early stages [1], which makes the development of tactile feedback devices challenging. Currently, tactile feedback display is done by employing several types of techniques including pins tactile display [91], vibrotactile [120], [121], pneumatic activated tactile display [122], microfluidic activated tactile display [123], surface acoustic waves [124], focused ultrasound [125], [126], ER (Electrorheological) [22], and MR (Magneto-rheological) fluid [127]. Existing tactile technologies and devices are mostly expensive, large, and imprecise, while their lack of portability makes them unsuitable for use as tactile feedback devices in a real haptic interaction, especially in MIS and in training scenarios [1], [128], [129]. The lack of commercially available tactile interfaces also limits current research of intra-operative palpation in RMIS. Two main simulation types are available for utilizing tactile feedback devices for tumour identification which will be summarized in the next sections.

2.4.2.1. Tactile feedback using movable components

Ottermo et al. [130] presented a remote palpation system equipped with a tactile sensor ($2 \times 2 \times 0.5 \text{ mm}^3 \times 30$ piezoelectric sensor elements in a 3×10 pattern and a total size of $24 \times 8 \text{ mm}^2$) and a tactile display (with 4×8 tactels (TACTil Element)

mounted). Since the height modification of the tactels creates skin deformation, reflecting force distribution was simulated. A comparison study of the grasper with and without tactile feedback was conducted proving that the grasper with tactile feedback can achieve stiffness discrimination. Kim et al. [91] developed a planar distributed tactile display for organ palpation. It had a 5×6 pin array with a total size of $40 \times 20 \times 23$ mm. 30 piezoelectric bimorphs actuators were used. Equivalent to Ottermo et al. [130], the height modification was used to simulate force distribution. The experimental results showed that by adding this tactile feedback display, precision of perception of the shape and stiffness of objects improved significantly.

2.4.2.2. Tactile feedback using materials with variable stiffness

The use of rigid movable elements to simulate force distribution in palpation may improve tumour identification results, but it does not give the user a direct stiffness feeling. Hence researchers have investigated approaches to simulate stiffness directly.

The viscosity of ER fluid can be controlled by the application of an electric field. Similarly, the rheological properties of MR fluid change when subjected to an external magnetic field. Khaled et al. [22] developed a tactile actuator array using ER fluid. Liu et al. [127] created a single MR fluid-based tactile element. The changes of the sensed profile followed the variations of the applied electric field or magnetic field.

Mansour et al. [131] presented a device which can display both the stiffness distribution and the surface shape of an object. It consisted of an Elongation Spring (ES) for displaying shape and a Stiffness Spring (SS) for displaying stiffness. A FEA of selected parameters proved and validated the design concept. Pneumatic and micro fluidic activated tactile displays also illustrated shape and stiffness at the same time.

Culjat et al. [122] developed a pneumatic balloon tactile display. Balloon deflections display the shape/height. This device could be easily attached to existing commercial robot-assisted surgery systems such as the da Vinci. Culjat used commercial single-element piezoresistive force sensors (FlexiForce, Tekscan) in their psychophysics experiments. The results revealed that the pneumatic balloon tactile display can reduce grasping force in robot-assisted surgery. Although it has not been applied in tumour localization, there is a high potential for this application. Larger balloons, in

theory, provide more tactile information. However, the limited mounting space on the robotic master control restricts the number of elements and the size of the balloons.

Similar to pneumatic activated tactile displays, microfluidic activated displays also exert the force on the fingertip by using the inflation of a tactile layer. Tactus Technology, Inc. [123] developed a deformable tactile layer panel which can be integrated in a touch-screen device to provide transparent physical buttons. Those buttons can be disabled and will recede into the screen where they become invisible. This has potential to be used in tactile feedback for palpation. Tactile-based sensing used for tumour localization is summarized in Table 2-3.

Table 2-3 Summary of tactile-based sensing used for tumour localization

Approach	Sensor	Feedback	Properties	In-vitro palpation experiments		In-vivo palpation experiments	Reference
				Phantom organ	Animal organ		
<i>Disposable laparoscopic grasper with tactile sensing</i>	10 mm disposable laparoscopic grasper with a 32-element tactile sensor	Graphical visualization	Low-cost, entirely encapsulated in silicone rubber, able to withstand high grasping forces.	No	Yes	Yes	[114]
<i>Endoscopic grasper with tactile sensing</i>	Endoscopic graspers are equipped with miniaturized PVDF-sensing elements with a graphical visualization	Graphical visualization	The developed sensing array of 8 elements, which is limited by the size of the grasper, only covers a small tissue area.	Yes	No	No	[115], [112]
<i>Breast Mechanical Imager (BMI)</i>	A 16 ×12 array of pressure sensors (Pressure Profile Systems) covering 40 mm×30 mm	Graphical visualization	Further miniaturization is needed in order to make it suitable for RMIS	Yes	No	No	[49]
<i>Prostate Mechanical Imaging (PMI) transrectal probe</i>	Probe head pressure sensor array: 16×8 sensors (Pressure Profile System) covering 40 mm×16 mm. Shaft: 16× 8 sensors covering 60 mm× 20 mm.	Graphical visualization	Probe shaft pressure sensor array for sphincter imaging and probe head pressure sensor array for prostate imaging.	Yes	No	Yes	[50]
<i>Tactile Sensing System (TSS)</i>	Tactile sensor (4×15 elements)	Graphical visualization	Provides both interaction force data (kinaesthetic data) and the coloured pressure map (tactile data).	No	Yes	No	[113], [118], [119]

Approach	Sensor	Feedback	Properties	In-vitro palpation experiments		In-vivo palpation experiments	Reference
				Phantom organ	Animal organ		
<i>Tactile Imaging System (TIS)</i>	3×12 sensing elements (Pressure Profile System)	Graphical visualization	A live video overlaid with a registered pseudo-colour map of the acquired pressure distribution.	No	Yes	No	[56]
<i>A remote palpation instrument</i>	2×2×0.5 mm ³ ×30 piezoelectric sensor elements in a 3×10 mm ² pattern and a total size of 24×8 mm ²	A tactile display (a tactile display with 4×8 tactels (TACTil Element))	Using rigid movable elements to simulate force distribution in palpation.	Yes	No	No	[130]
<i>Area-based haptic palpation simulator</i>	Null	A 5×6 pin array with a total size of 40×20×23 mm piezoelectric bimorphs	Designed for training residents how to perform diagnosis or surgery	Yes	No	No	[91]
<i>Haptic Sensor Actuator System (HASASEM)</i>	Ultrasound real-time elastography	A tactile actuator array using ER fluid	Simulates stiffness directly; allows users to conduct palpation while imaging and making a biopsy	No	No	No	[22]
<i>MR fluid based tactile display</i>	Null	A single MR fluid-based tactile element	Simulates stiffness directly. Miniaturization is needed.	No	No	No	[127]
<i>A multi-modal tactile display device</i>	Null	Two springs: the Elongation Spring and Stiffness Spring	Displays both surface shape and stiffness.	No	No	No	[131]
<i>Pneumatic balloon actuators</i>	Commercial single-element piezoresistive force sensors (FlexiForce, Tekscan)	A pneumatic balloon tactile display	Can be directly mounted onto the hand controls of the da Vinci surgical robotic system	No	No	No	[122]

2.5. Literature survey on intra-operative tumour localization using medical imaging and elastography

2.5.1. Medical imaging registration

Sophisticated pre-operative imaging techniques such as Magnetic Resonance Imaging (MRI), Ultrasound imaging (US) and Computed Tomography (CT) are often utilized for preoperative tumour identification and provide accurate and highly detailed multi-dimensional images. However, sometimes they are not able to distinguish between tumour and oedema fluid, especially in the case of small size formations [132]. Moreover, due to the likely movement of organs and the deformability of the soft tissue during surgery, the position of a tumour is often different from that registered during the preoperative scan. Image registration is commonly used to transform pre-operative images to the intra-operative tumour positions. As mentioned earlier, the accurate rigid registration of the tumour position is challenging due to organ deformability during the surgical procedure [133], [134].

Non-rigid transformations, which have a high degree of freedom and are capable of accommodating the most likely local deformations that occur during surgery, have therefore been introduced as a way of mapping the pre-operatively acquired information into the intra-operative space. Deformable tissue models have been developed such as specialized non-linear FE algorithms and solvers for real-time computation of soft tissue deformation [135]. Compared to intra-operative palpation, the performance of pre-operative imaging techniques is moderate. Schipper et al. [136] compared the tumour detection rates between intra-operative lung palpation and pre-operative CT imaging. The results show that a significant number of malignant pulmonary nodules which were detected intra-operatively were not identified on preoperative imaging.

Intra-operative imaging helps to identify any residual tumour tissue and leads to a significant increase in tumour removal rates and survival times. However, the quality of intra-operative images is often degraded compared to that of pre-operative images. Thus, co-registering pre- and intra-operative images is a solution albeit difficult to

achieve due to tissue deformation, different acquisition parameters, resolutions, plane orientations, and computational time constraints [137]. Challenges include discontinuities and missing data in the registration algorithms due to retraction and resection, and time requirements of intra-operative registration. Rigid registration is more common because it is relatively faster compared to non-rigid registration [137]. Non-rigid registration methods are still at an experimental stage and not fit for use in practical applications as yet. Registration uncertainty has also been considered [138]. Providing registration uncertainty information may increase the confidence level of surgeons in the registered image data and, thus, would be helpful in decision making.

2.5.2. Real-time elastography

Elastography is a technique to calculate and visualize various elastic parameters of soft tissue from different tissue stimuli, such as US, CT, MRI, or optics [139], [140]. Elastography involves mapping the strain of the soft tissue induced by applied stress [141]. Stiffer tissues experience lower strains. In palpation, Young's modulus E , or shear modulus μ , the parameter expressing the elastic properties, is assessed. For most soft tissues, there is a simple relational expression for the Young's modulus and the shear modulus: $E=3\mu$, which means that the shear modulus or Young's modulus contains the same information. US elastography can evaluate tissue stiffness in real time, and has been applied to tumour identification for breast [142], prostate [143], liver [144], and pancreas [141]. However, a certain expertise is still needed for the surgeon to understand the image.

To this effect, remote palpation can be conducted by combining real-time elastography with haptic actuators [22], [23]. Khaled et al. [22] developed an integrated haptic sensor/actuator system based on US real-time elastography and ER fluids and combined the results of elasticity images to reconstruct virtual objects on the haptic actuator array. The haptic display allows users to palpate the patient's organ while imaging. With this method, specialized personnel are not necessary to interpret the images. However, disadvantages include the high computational expense [140], limited acquirable characteristics of linear elasticity such as Young's elasticity and Poisson's ratio [55]. Also, there is a limited depth for measurements of ultrasound.

2.5.3. Other Methods

Active Strobe Imager [145] (ASI) consists of a nozzle for supplying a pulsating air jet to the soft tissue surface, a strobe system for visualizing the dynamic behaviour of the tissue, a camera for capturing the image when strobe flashes, and a monitor for displaying the dynamic deformation of soft tissue. It has been used to detect tumours in lungs.

2.6. Literature survey on combination of force feedback and tactile feedback

Real palpation involves both force and tactile feedback. Sang-Youn KIM et al. [91] developed an area-based haptic rendering approach for palpation simulation which can provide distributed pressure and force feedback at the same time (see Figure 2-21). Comparison study of point-based haptic rendering and area-based haptic rendering was conducted. The results showed that the perception of the shape and stiffness of tumours with area-based haptic feedback was more precise than with point-based haptic feedback.

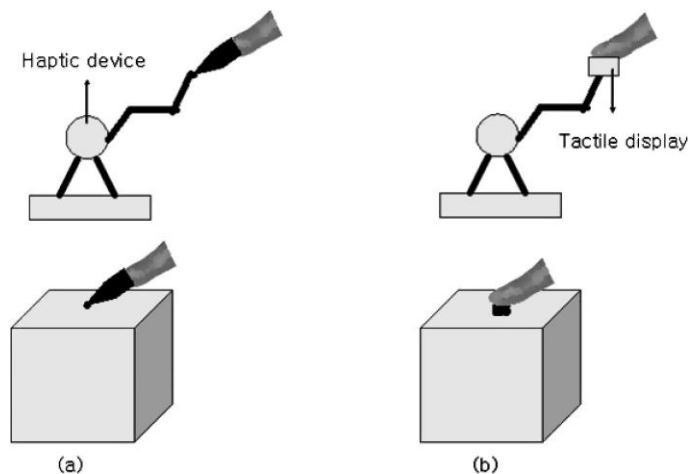


Figure 2-21 Point-based and area-based haptic rendering [91]

One palpation simulator for a pulse specifically for palpation of the femoral artery has been reported [103]. Piezoelectric pads, a pin array and micro speakers were mounded onto a low-cost Falcon end effector and evaluated separately (see Figure 2-22). The displacement of piezoelectric material was controlled by voltage changes.

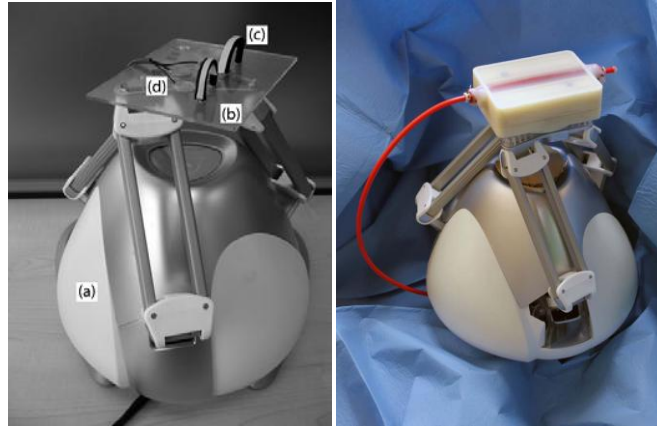


Figure 2-22 Modified Falcon force feedback device with piezoelectric pads (left) and modified with pneumatically actuated tactile end effector (right) [1]

2.7. Literature survey on multi-fingered palpation

Multi-fingered palpation is more common than single-fingered palpation in real practice and is considered more useful than single-fingered palpation when attempting to detect differences in stiffness in the examined tissue [17].

A light-weight Rutgers Master II glove (only 80 g) [16] can provide force feedback up to 16 N to each finger. It uses pneumatic actuators to apply forces to all of the fingertips except for the small finger. However, the glove limits the range of motion of the fingers because of the placement of the cylinders. The haptic Interface Robot (HIRO) device developed by Kawasaki et al. [96] consists of a robot arm with 6-DOF force output and three fingers with 3-DOF force output and then later and has been upgraded to the five-fingered HIRO III device [97]. This is the first five-fingered opposed-type haptic feedback device providing force feedback including weight perception to the user. Control of this device is still complex since each finger has more than one joint. Therefore, not only its cost is relatively high but the device is also bulky with a weight of about 3.8 kg and a 23 kg control apparatus box size of 443×222×464 mm.

Those haptic devices have been applied in knee palpation training [16], the abdominal palpation to detect liver tumours [17], and breast palpation [72][146]. If multi-fingered palpation is used in intra-operative palpation on real-time generated virtual tissue, the stiffness distribution can still be attained by using single point force sensing.

Alternatively, a specialized multi-fingered probe and corresponding feedback actuator needs to be developed to inspect the surface stiffness of tissues for direct force feedback.

2.8. Discussion and Conclusion

2.8.1. Discussion

2.8.1.1. *Tactile-based sensing*

The methods and technologies discussed above provide support to surgeons during tumour removal procedures. However, two factors prevent the application of tactile-based sensing in real surgical applications:

- 1) The small mounting surface of surgical tools put limits on the size of sensing arrays leading in relative data variations over large tissue areas. As a result, multiple discrete indentations need to be performed which increases the palpation time.
- 2) The tumour detection result may be affected by the higher contact stress which appears at the edge of the sensor array when it is indented on the soft tissue. It is noted that this issue has been largely ignored in the research presented in the literature review.

2.8.1.2. *Indentation depth measurement*

Indentation depth measurement is crucial for stiffness calculation. For rolling indentation palpation, it is essential to maintain a constant indentation depth throughout the palpation activity. This could be achieved by pre-registration of the surface, a time consuming process prone to inaccuracies caused by introduced errors. Thus, a real-time indentation depth measurement is needed. Although some sensors with the capability of indentation depth measurement have been developed, e.g. air-float palpation probe [87], some improvements should be undertaken to fulfil the requirements of RMIS with respect to miniaturization, for instance.

Three-dimensional (3D) reconstruction techniques could be used in tissue surface contour acquisition for indentation depth measurement. In [90], a moving Microsoft Kinect was used for real-time 3D reconstruction and interaction. To make it more

suitable for minimally invasive intra-operative purposes, endoscopic cameras should be used for 3D reconstruction. Once the original, unindented surface is reconstructed, the indentation depth can be calculated based on the distance between the current indenter position and the closest triangle planar on the mesh of the original reconstructed contour. To compensate for any tissue shift or deformation, the surface reconstruction process can be repeated later.

2.8.1.3. Tactile actuators and graphical sensory substitution

Using tactile feedback devices to interpret the stiffness distribution of the soft tissue may lead to a more intuitive tactile information reception than using graphical sensory substitution techniques [114]. However, existing tactile feedback devices are mostly expensive, large, and non-portable which makes them unsuitable for use as tactile feedback devices for intra-operative palpation [1]. Graphical sensory substitution techniques are more common than other relatively complex tactile actuators. However, colour-coded tissue stiffness maps only represent local relative stiffness differences and do not transfer absolute stiffness information to the surgeon. Hence, surgeons should rely on their expertise of haptic properties in order to correctly judge the corresponding tissue using this system [114].

2.8.1.4. Combination of feedback modalities

In real palpation, both force and tactile feedback are involved. Direct force feedback does not convey tactile information and thus is not useful for identification of exact tumour boundaries. There are currently not many research studies regarding both force and tactile feedback in intra-operative palpation in RMIS. Besides, the combination of direct haptic feedback and visual force feedback may result in getting benefits from both sides [33]. A study comparing the direct force feedback to visual force feedback reported an error reduction of distinguishing areas of stiffness when feedbacks were combined [33].

Graphical material property overlays could be beneficial for tumour identification, while the combination of direct force feedback and visual force feedback or visual stiffness distribution feedback could enhance the perception and improve the performance of tumour localization in future research.

2.8.2. Research directions

2.8.2.1. *Feedback modality combinations*

Mahvash et al. [21] pointed out that force displays could be based on real-time intra-operative patient-specific tissue models rather than on the current measured contact force. Tumour identification during RMIS can rely on intra-operative palpation of virtual tissue which is generated by rapid tissue property estimation based on in-vivo tests. Also, force displays based on such tissue models would enable the acquisition of quantitative information for localization of abnormal tissues. Palpation with haptic feedback on a virtual tissue is superior to direct haptic feedback as it avoids the complex control during force feedback between the master robot side and the slave robot side. Based on this virtual tissue, pseudo-haptic feedback can be used to enhance the perception of palpation on the virtual tissue.

Pseudo-haptic feedback has already been used in medical applications. Bibin et al. [147] introduced a medical simulator called SAILOR for training of Loco-Regional Anaesthesia with neurostimulation based on VR technique. Pseudo-haptic feedback was utilized to give touch feedback of organs beneath the skin and can be easily combined with other haptic feedback approaches without affecting the control performance of the system [148]. Therefore, augmenting haptics with pseudo-haptics and its use for intra-operative palpation is promising.

2.8.2.2. *Multi-fingered palpation*

Among clinicians, multi-fingered palpation is more common than single-fingered palpation. There are some attempts at multi-fingered palpation simulation [16], [17], [72], [96], [97]. However, those multi-fingered palpation simulations used complex and expensive feedback systems. Moreover, a comparison study between single-fingered palpation and multi-fingered palpation has not been conducted yet. Multi-fingered palpation feedback can also be adapted to intra-operative palpation using real-time generated virtual tissue.

2.8.3. Conclusion

Overall, most existing engineering methods for intra-operative tumour localization are still at an experimental stage and have not been tested in-vivo. Further research in this field is needed on ways of mimicking the function of hand / soft tissue interaction by acquiring accurate tissue stiffness data and displaying useful information to the surgeon. Up to now, no robust and fast intra-operative solution has been proposed. In order to improve user experience and develop a method as close as possible to manual palpation, the research directions that have been addressed include using multi-fingered actuators and combining different feedback modalities, namely pseudo-haptic and real haptic feedback, graphical and haptic displays.

Chapter 3 Force Feedback and

Novel Visual Stiffness Feedback in a

Tele-Manipulation Environment

Providing haptic information in robotic surgery could significantly improve clinical outcomes and help to detect hard inclusions within soft tissue indicating potential abnormalities. Visual representation of tissue stiffness information is cost effective while direct force feedback remains a more intuitive method of displaying tissue stiffness information to surgeons. It is interesting to observe the difference in tumour detection performance between visual representation of soft tissue stiffness distribution and force feedback in a tele-manipulation environment.

In this chapter, a real-time visual stiffness feedback method for RMIS using sliding indentation is proposed, validated, and compared with force feedback in an experimental tele-manipulation environment. This environment and an associated experimental study involving human subjects were designed and created as part of this PhD research. Dynamically updates of the colour map depicting the stiffness of probed soft tissue is provided via a graphical interface. The force feedback is provided with the help of a master haptic device using the data acquired from an F/T sensor that is attached to the end-effector of the tele-manipulated robot. The tumour detection performance is evaluated for the different modes of stiffness feedback on a soft-tissue phantom containing buried stiff nodules.

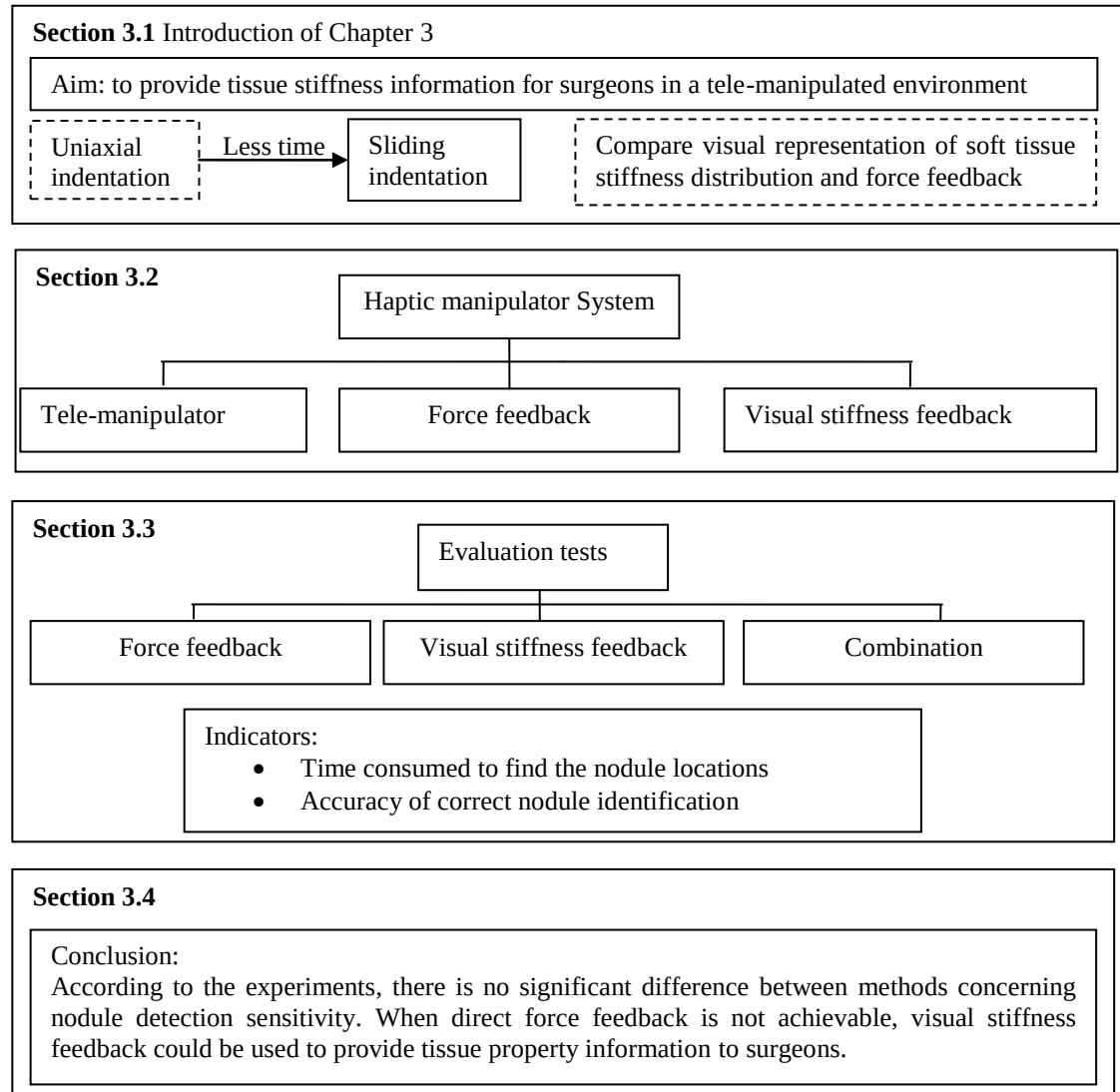


Figure 3-1 Structure of Chapter 3.

3.1. Introduction to a novel visual stiffness feedback in a tele-manipulation environment

Tumours in soft tissue are often localized by conducting intra-operative manual palpation during open surgery. Manual palpation identifies hard nodules through direct touch sensation with haptic feedback enabling surgeons to gather information of about the reaction force and helping them to understand the material properties of the soft tissue. Stiffer tissues typically indicate the locations of tumours [149]. Force and tactile sensing technologies allow for the detection of tumours not otherwise visible outside the soft tissue, as well as for the determination of an adequate resection margin. RMIS has been widely performed in recent years. However, surgeons often report the lack of haptic feedback as a major drawback of current surgical tele-manipulators [149].

In conventional MIS, palpation can be conducted indirectly via a surgical instrument, namely “instrument palpation” [56]. If the RMIS system is equipped with direct force feedback, the “instrument palpation” can also be utilized. Haptic perception through direct force feedback is bi-directionally related to the exploratory movements. Research described in [21] shows a priority of direct force feedback over visual force feedback using a bar that changes height and colour depending on the level of the applied force.

A combination of direct haptic feedback and visual force feedback was introduced by Gwilliam et al. to get benefits from the both sides [33]. In their comparison study an error reduction of distinguishing areas of stiffness was reported in a combination mode of direct force and visual force feedback.

Instead of providing discrete force information, a straightforward mapping of stiffness information produced by using the distributed visual representation method was proposed, for instance, a tissue stiffness distribution graphical overlay in [32], [56]. Visual representation of tissue stiffness information is cost effective. In this chapter, a novel real-time visual stiffness feedback method for RMIS is proposed. A sliding indentation, which can acquire the stiffness distribution faster, replaces the separate point uniaxial indentation behaviour as shown in [47] and [72]. A graphical interface

displays a dynamically updating colour map depicting the stiffness of probed soft tissue.

However, force feedback remains a relatively more intuitive means of relaying tissue stiffness information to surgeon. Colour-coded tissue stiffness maps only represent relative stiffness differences and do not contain any depth information of tumours. In addition, the graphical overlay may block a portion of the field view of the surgeon [33]. It is interesting to observe how well visual representation of soft tissue stiffness distribution performs in tumour detection by comparing it to force feedback in a tele-manipulation environment. Therefore, experimental tests were conducted to evaluate the usefulness of the three modes of feedback using an experimental surgical tele-manipulator: (1) force feedback, (2) visual stiffness feedback, and (3) combined force and visual stiffness feedback. The purpose was to observe the influence of various types of haptic feedback on the performance of tumour detection during palpation in tele-manipulation.

The contribution of this chapter is the creation and validation of a real-time visual stiffness feedback method for RMIS using sliding indentation behaviour with force feedback for tumour identification in an experimental tele-manipulation environment.

3.2. Haptic manipulator

3.2.1. Overview of the experimental haptic manipulator

The experimental platform, which provided force and visual stiffness information feedback and was designed and created as part of this PhD study, consisted of the following main components: tele-manipulators (a slave robot and a master robot), a vision system and a visual stiffness display. Figure 3-2 displays the schematic diagram of the system design. The right column shows the hardware at the slave side: a camera, a robot arm, a rolling indentation probe [47], [81], [82] (for details see Chapter 2), and a silicone phantom tissue. The left column shows the configuration at the master side: live camera image, visual stiffness display, and force feedback via a haptic device. The middle column lists the software. According to the different functions, software was classified into three main parts: camera image viewer, virtual soft tissue surface reconstruction and stiffness visualization and tele-manipulation.

Sensor measurements including force and position were transmitted from the slave side to enable the virtual soft tissue surface reconstruction, visual stiffness feedback, and force feedback on the master side. Real-time images of palpation site were also provided using a camera. The details of the methodology are presented below.

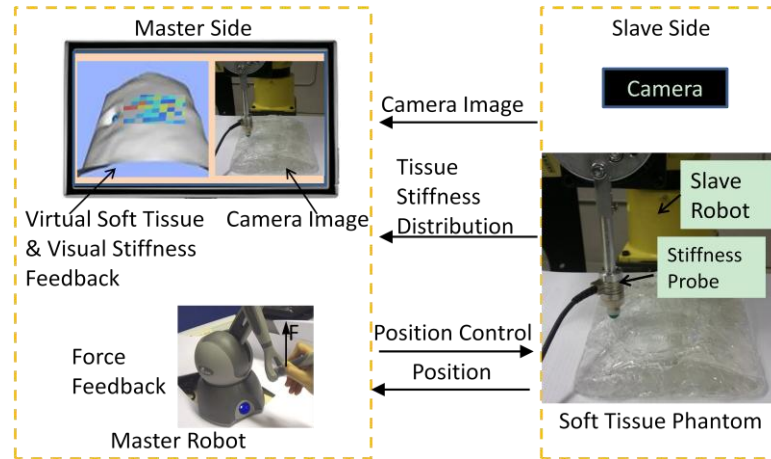


Figure 3-2 Schematic diagram of the experimental haptic manipulator.

3.2.2. Tele-manipulator

3.2.2.1. Control architecture

A master-slave tele-manipulation configuration was created and utilized to simulate the tele-manipulation environment of RMIS. A block diagram of the tele-operation architecture is shown in Figure 3-3. PHANToM Omni (SensAble Technologies Inc.) and FANUC robot arm (M-6iB, FANUC Corporation) were used as the master robot and slave robot, respectively. The software framework is shown in Figure 3-3. A TCP/IP communication link was used between the master and slave sides. Both the main loops of the master and slave sides were synchronized at a frequency of 21.3 Hz. The position of the master robot end-effector was transmitted to the slave side as an input of the slave robot control loop. At the same time, the position information of the slave robot was transmitted to the master side for the display of visual indenter avatar. Haptic and graphics rendering was performed concurrently in separate threads. The haptic device servo thread ran at a frequency of 1000 Hz in order to give the kinaesthetic sense of stiff contact. A force sensor was located at the slave side, but the force data acquisition program was in the master side software. The frequency of the

graphics rendering and force data acquisition was the same as in the master side main loop.

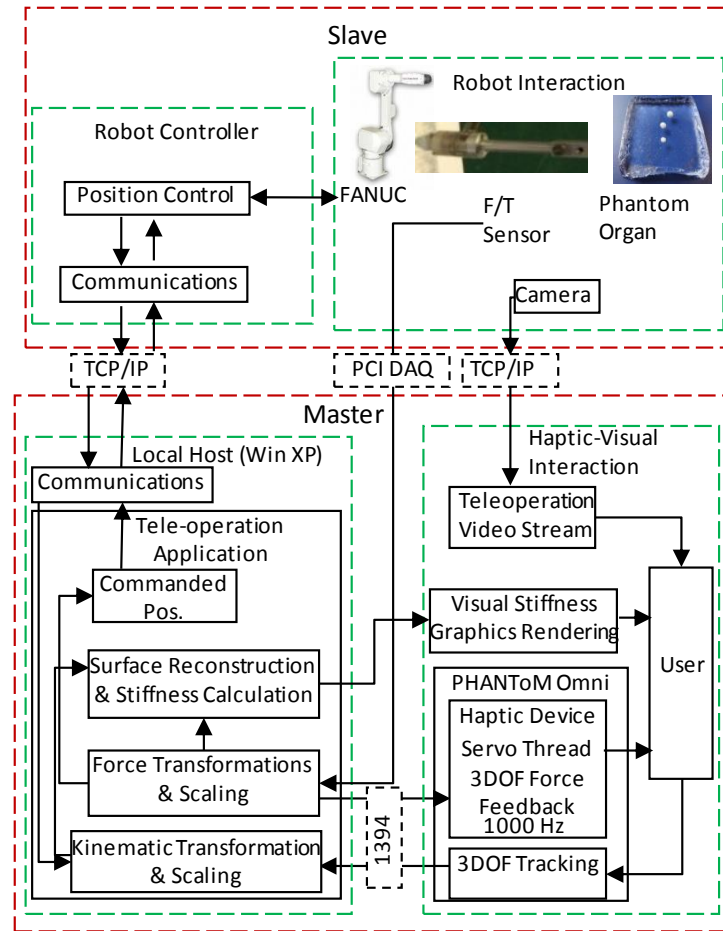


Figure 3-3 Tele-operation architecture.

3.2.2.2. Robot controller

FANUC was equipped with R-J3iC controller which consisted of embedded kinematic and dynamic controller optimized for M-6iB robot. The sequence of the positions provided by the master was passed directly to the trajectory generator of the robot; however, in order to avoid discontinuity between the points, the trajectory generator was set to work in a linear interpolation mode.

In the linear interpolation mode, the trajectory generated followed the Hermite curve (see Figure 3-4) with the following equation.

$$\begin{aligned}
\mathbf{p}(t) = & \mathbf{p}_{ci}(1-3(t_i-t_c)^2t^2+2(t_i-t_c)^3t^3) \\
& + \mathbf{p}_{e(i)}(3(t_i-t_c)^2t^2-2(t_i-t_c)^3t^3) \\
& + \alpha(\mathbf{p}_{e(i-1)}-\mathbf{p}_{ci})(t-2(t_i-t_c)^2t^2+(t_i-t_c)^3t^3) \\
& + \alpha(\mathbf{p}_{ci}-\mathbf{p}_{e(i-1)})((t_i-t_c)^2t^2+(t_i-t_c)^3t^3)
\end{aligned} \tag{3.1}$$

where $\mathbf{p}_{ei}$ and $\mathbf{p}_{e(i-1)}$ are two consecutive points passed to the trajectory generator, $\mathbf{p}_{ci}$ is the current location of the robot at the time of receiving the update of the position $\mathbf{p}_{ei}$ and α is a scalar which determines how strongly should the motion of the robot align to the intermediate point. This means that by adjusting the scalar parameter α to a high value, the trajectory of the motion of the robot starting from $\mathbf{p}_{ci}$ is parallel to the vector $\mathbf{p}_{e(i-1)}-\mathbf{p}_{ci}$ and ends parallel to the vector $\mathbf{p}_{ei}-\mathbf{p}_{e(i-1)}$. This allows online continuous imitation of the motion of the master in the slave manipulator. The choice of parameter α is a trade-off between the vibration caused by the robot at higher values and the positioning error at smaller values, and was chosen empirically based on the trajectories generated at $\alpha=3.5$ here.

The position response during random motion was tested to show the performance of the controller. The master and slave position responses were recorded when the master robot was manipulated in random motion with and without force feedback applied. Figure 3-5 and Figure 3-6 show the experimental results of the recorded master and slave trajectories of the random motion, with and without force feedback. The mean delay of the trajectories without force feedback was 0.25 s with a standard deviation of 0.03 s while the mean delay was 0.25 s with a standard deviation of 0.04 s when force feedback was applied. The slave trajectories matched the master trajectories generally. There was no big difference between the trajectory tracking with (mean position error 0.48 mm) and without force feedback (mean position error 0.53 mm).

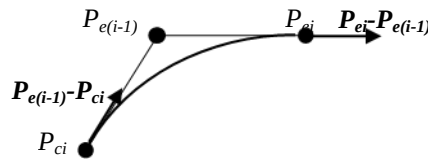


Figure 3-4 Hermite curve interpolation trajectory generation.

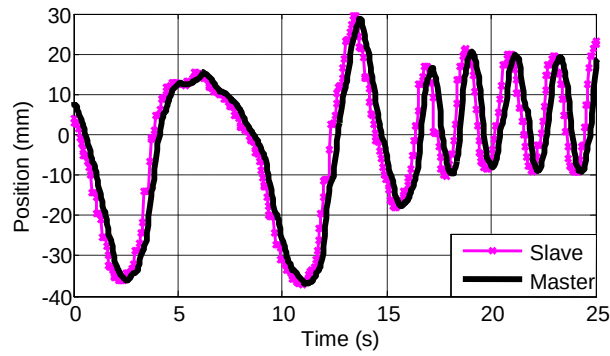


Figure 3-5 Position response when no force feedback is applied

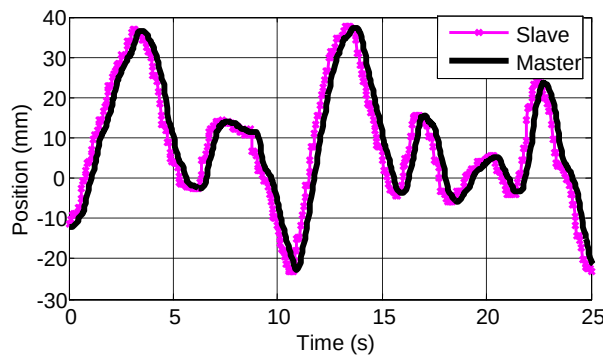


Figure 3-6 Position response when force feedback is applied

3.2.3. Force feedback

In the proposed design, force feedback was provided to help the operator to form an instinctive impression of the magnitude of tissue stiffness. Instead of using force sensors, some researchers used bilateral tele-operation controllers and patient-side arm actuator electric currents to estimate force [21]. However, these methods were not as sensitive as using force sensors [33]. Here, an ATI Nano 17 force sensor (SI-12-0.12, resolution 0.003N with 16-bit data acquisition card) was used for force measurement. Because the separate point uniaxial indentation may have difficulties for rapid soft tissue scanning over a large tissue area [47], the rolling indentation approach using a force-sensitive wheeled probe for the localization has been proposed by [47], [81], [82] (for details see Chapter 2). The rolling indentation can acquire the stiffness distribution rapidly along fixed trajectories. However, the probe with the wheeled indenter needs to be rotated when the rolling direction changes. Thus, a similar sliding indentation probe was proposed [85]. A round-shaped end effector,

which was fixed inside the tip of the probe, replaced the indentation wheel of rolling indentation probe. In order to reduce the friction during sliding over the tissue, the tissue surface was lubricated (Boots Pharmaceuticals Intrasond Gel). A force distribution matrix can be obtained using the sliding indentation probe, which shows the tissue's elastic modulus at a given indentation depth assuming that the investigated tissue is linear elastic, isotropic, homogeneous, and incompressible [84]. Liu et al. [84] has validated the linear elastic assumption. They have concluded that this assumption achieved accurate estimated elastic modulus when the indentation depth d_{in} was small ($d_{in} < 3.5$ mm). It was also found that the indentation speed did not have significant impact on the estimated elastic modulus. Therefore, equation (2.2) was used to calculate elastic modulus E in their indentation experiments.

Force feedback was applied via a haptic device according to the force sensor measurements at the slave side. The maximum executable force at nominal (orthogonal arms) position of this 3-DOF of force feedback device PHANTOM Omni was 3.3 N. Force data contained three components f_x , f_y , and f_z . The perpendicular reaction force was generated from the value of f_z . The horizontal force was the resultant of f_x and f_y , and the force direction was calculated based on the difference between the previous updated position and the current position (see equation (3.2)). The horizontal component vector of the force direction was then transformed to a unit vector with the same direction. The tangent force was generated in the same direction of that tangent unit vector (see equation (3.3)).

$$\mathbf{V}_h \equiv \overrightarrow{P_l P_c}, \quad (3.2)$$

$$\hat{\mathbf{V}}_h = \frac{\mathbf{V}_h}{|\mathbf{V}_h|}, \quad (3.3)$$

where P_l is the previous position (x_l, y_l), P_c is the current position (x_c, y_c), $\hat{\mathbf{V}}_h$ is force direction unit vector. If the force value exceeded the maximum output (3.3 N), it was kept at this value.

3.2.4. Novel visual stiffness feedback

To help an operator acquire a clear view of the stiffness distribution, a deformable virtual soft tissue surface with a real-time updating stiffness map was displayed through a graphical interface. This section describes the establishment of virtual soft

tissue surface, visualization of tissue deformation, real-time soft tissue stiffness estimation, and real-time visualization of the stiffness distribution.

A live camera image of the palpation site and a separate virtual soft tissue surface were rendered in a graphical interface in this system. Augmented visual feedback has been proposed as an efficient tool in tumour identification [32]. A semi-transparent stiffness map generated by uniaxial-indenting was overlaid on soft tissue image. To maintain the clearness and quality of camera image of the operation site, visual stiffness feedback was overlaid on a separate virtual soft tissue surface here. This virtual soft tissue surface was displayed on a graphical interface using a mesh of triangles, whose positions can be acquired from a scan of tissue contour. During the contour scan, the indenter needs to be controlled just to contact the tissue surface. This tissue contour scan will be discussed in Section 4.3 in detail. Here, a phantom tissue with a flat surface was used. The tissue surface height was assumed to be constant.

Deformation of the virtual soft tissue during palpation was displayed in real time using a geometrical deformable soft tissue model considering the influence of the indenter diameter based on predefined FE modelling. The specifics of this model will be discussed in Section 4.4. If a node of the mesh is pressed by the indenter, the perpendicular vertex of this node is redefined according to the depth of the indenter. At the same time, the perpendicular vertices of other nearby nodes on the mesh are affected by the indentation and are adapted according to the geometrical model to display the tissue displacement. The number of the affected nodes increases as the indentation depth increases.

A real-time soft tissue stiffness calculation method using the equation (2.2) was applied. Indentation depth was calculated using the distance between the indenter position ($\mathbf{P}_0$) and the nearest triangle planar of the original contour (vertices: $\mathbf{P}_1$, $\mathbf{P}_2$, $\mathbf{P}_3$). The normal vector of the planar $\mathbf{n}$ was acquired from the cross product $(\mathbf{P}_2 - \mathbf{P}_1) \times (\mathbf{P}_3 - \mathbf{P}_1)$. This distance was calculated using the absolute value of the dot product $\mathbf{v} \cdot \mathbf{n}$, where $\mathbf{v}$ is the vector from $\mathbf{P}_0$ to $\mathbf{P}_1$. Using this indentation depth calculation method, not only the indentation depth on a planar surface can be acquired, but also indentation depth on curved surfaces. Real-time indentation depth and reaction force

were the two inputs of this method. The elastic modulus E calculated in equation (2.2) was the output.

A real-time visualization of the stiffness distribution was created using the calculated stiffness data. The calculated E was stored with its palpated location. Then this value was converted to a RGB value using the minimum and maximum stiffness values in the current storage space (see Figure 3-7). These pairs of RGB value and palpated location were used to dynamically update the stiffness map. Colour blue represented the minimum stiffness and colour red represented the maximum stiffness (see Figure 3-8).

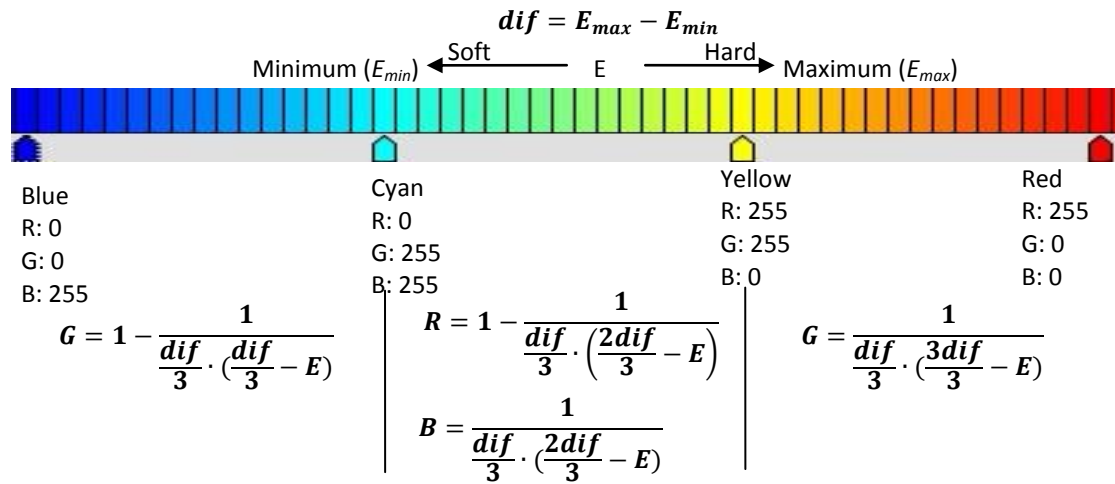


Figure 3-7 Mapping stiffness data to RGB value.

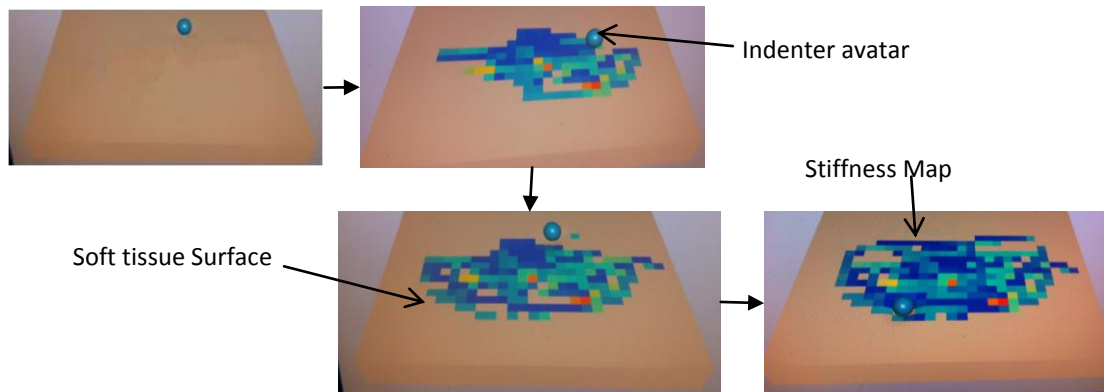


Figure 3-8 Stiffness map generation process.

3.3. Evaluation Tests of the proposed visual stiffness feedback

3.3.1. Phantom tissue

The aim of the experiment was to locate the position of a stiff nodule buried under the flat surface of the silicone phantom tissue. The phantom was $120 \times 120 \times 30 \text{ mm}^3$ and contained three embedded spherical nodules (A, B, C) (Figure 3-9). The silicone block had a flat surface. As shown in Chapter 2, the recognition and identification of T1 stage tumours (measuring 20 mm or less at their widest point [25]) is very significant to increase the survival rate. In this study, T1 stage tumours are simulated using artificial tumour models in silicone phantom tissues. Cancerous formations are typically stiffer compared with healthy soft tissues [27]. In the scope of this thesis, tumours are assumed to be homogeneous and stiffer than surrounding healthy soft tissues. The phantom was fabricated using RTV6166 (TECHSIL Limited, UK) (A : B = 4 : 6, Young's modulus 7.63 kPa [150]). The nodules were made from STAEDTLER Mars plastic 526 50 (47-50 ShoreA, Young's modulus about 1.59 MPa). The diameters of the used spherical nodules were 10 mm, 8 mm, and 6 mm. Tumour depth is suggested to be a useful tool for cancer staging [35], [36]. A 4 mm threshold has been assigned to distinguish between low risk and high risk in the context of cancer staging the oral cavity, head and neck [35], [36]. Therefore here all nodules were buried at a depth of 6 mm, measured from the top of the nodules to the silicone surface.

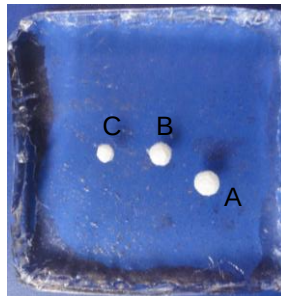


Figure 3-9 Silicone soft-tissue phantom: the locations of the three embedded nodules are highlighted (A, B, C).

3.3.2. Stiffness map generation test

In order to test the robustness of the proposed real-time stiffness calculation and visual feedback generation, the master robot was repeatedly manipulated to palpate the phantom silicone organ along one straight trajectory which covers nodules A and B, using variable velocities. From trials 1 to 7, the researcher used different levels of velocities from the slowest to the fastest achievable speed. Position and force data was recorded. Figure 3-10 displays the trajectory of motion, which covered Nodule A and Nodule B during this test. Figure 3-11 shows the stiffness map calculated from the perpendicular reaction force along the same trajectory, in multiple trials of remote palpation, with increasing velocity from trials 1 to 7. Although palpation velocity and indentation depth were not constant in the different trials, the stiffness maps produced were similar. This proves the robustness of the presented method in calculating real-time stiffness.

3.3.3. User study of the proposed visual stiffness feedback

3.3.3.1. Participants and experimental Procedure

One left-handed and nine right-handed subjects aging from 23 to 42 were asked to perform a palpation task with the tele-operation system, using three feedback modes described earlier. Three out of them had previous experience with this system and most users had little or no experience with haptic feedback devices. None of them had palpation experience or a medical background. The details of the participants are presented in Table 3-1.

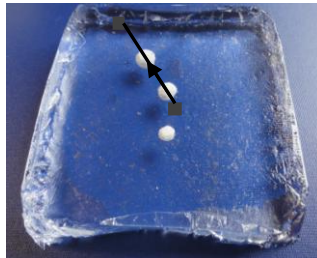


Figure 3-10 An operator remotely palpated the phantom tissue using the same trajectory, which covers nodule A and nodule B, guided by the two black tags.

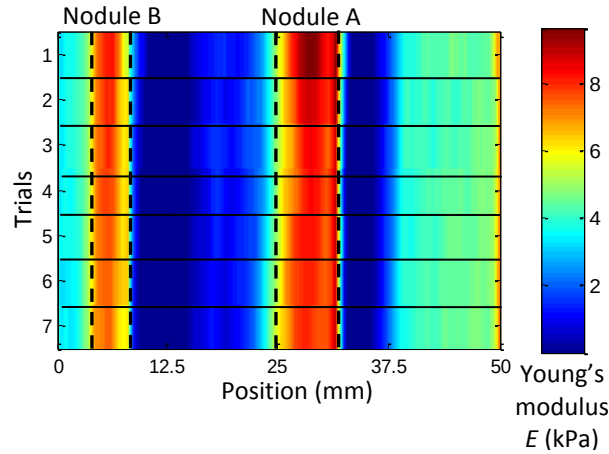


Figure 3-11 Stiffness map estimated from perpendicular reaction force along the same trajectory in multiply trials of remote palpation (shown in Figure 3-10) with increased velocity from trials 1 to 7. Nodule A and B are presented with colour red or orange, while other areas are blue or cyan.

Table 3-1 Overview of demographics and experience of the participants in the palpation experiment with the tele-operation system

Item	Detail
<i>Age range</i>	23-42
<i>Average age</i>	27.8
<i>Gender</i>	♀: 3; ♂: 7
<i>Handedness</i>	R: 9; L: 1
<i>Tele-manipulator</i>	3
<i>Palpation experience</i>	0
<i>Engineering background</i>	10
<i>VR simulator</i>	0

All trials were performed by participants controlling the slave robot to palpate the silicone phantom tissue through the stylus of the PHANToM Omni. In order to prevent tissue damage during palpation, a limit on the indentation depth (6 mm) was stipulated to keep the palpation force within a safe range based on the tissue surface. The participants viewed the environment through a graphical interface on a computer monitor. The surface of the phantom tissue was lubricated to reduce the effect of friction and dragging forces (Boots Pharmaceuticals Intrasond Gel). The surface of the phantom was palpated in a continuous fashion to allow fast scanning and stiffness

representation. The palpation trials were conducted continuously using the sliding indentation probe (see Figure 3-12).

Each of the following three feedback conditions were distributed pseudo-randomly and equally among the trials: (1) force feedback, (2) visual stiffness feedback, and (3) the combination of force and visual stiffness feedback. The visual stiffness feedback consisted of a representation of a deformable virtual soft tissue surface with a dynamically updated coloured stiffness map overlaid, as described in Section 3.2.4. Prior to the first trial, participants were allowed a trial on a different phantom tissue. Force data and time consumed during each trial were recorded for each participant. The orientation of the phantom tissue was changed for each trial.

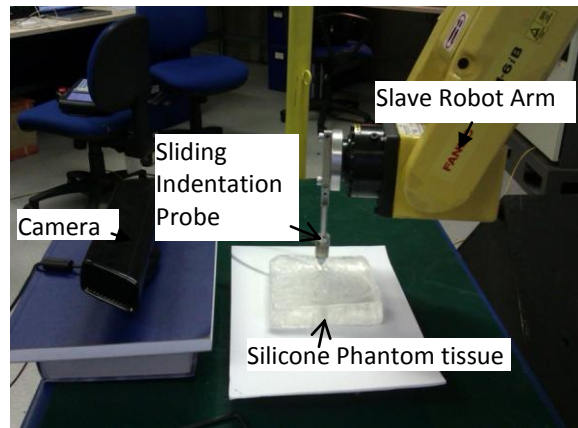


Figure 3-12 Experimental platform of slave side hardware, including a slave robot arm, a silicone phantom tissue, and a camera.

3.3.3.2. Results

Figure 3-13 shows two stiffness maps obtained during a palpation trial using visual stiffness feedback and a palpation trial using a combination of force and visual stiffness feedback. As indicated by the colour stiffness maps, the three nodules were detected at the correct locations. The largest nodule, nodule A, was marked by red colour; the middle sized nodule, nodule B, was marked by orange colour; the smallest, nodule C, was marked by yellow colour.

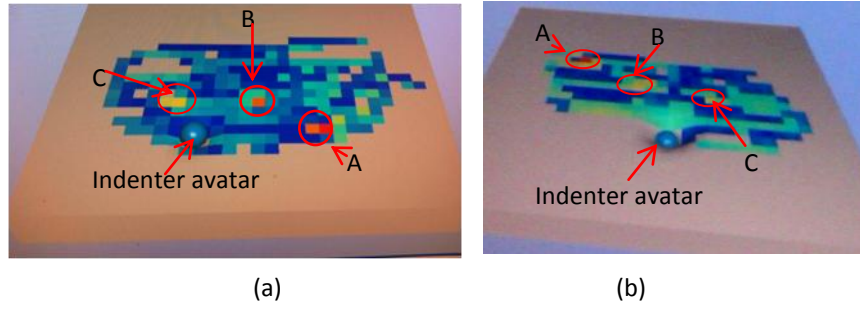


Figure 3-13 Visual stiffness feedback: a stiffness map acquired during a trial using visual stiffness feedback, shown in (a); a stiffness map acquired during a trial using force and visual stiffness feedback together, shown in (b).

The magnitude of the palpation force recorded by the system was within the range of 0 – 3.24 N. The average highest palpation force of those trials was 2.27 N. The Sensitivity Se [151], which relates to the test's ability to identify positive results, was defined as sum over all the n trials of the True Positives TP divided by the sum of False Negatives FN and TP , namely:

$$Se = \sum_{i=1}^n TP_i / \sum_{i=1}^n (TP_i + FN_i). \quad (3.4)$$

Figure 3-14 presents the nodule detection sensitivities using the different feedback methods. Wilson score intervals [152], which have good properties even for a small number of trials (less than 30), were calculated at a 95% confidence level.

$$\frac{1}{1 + \frac{z^2}{n}} \left[\hat{p} + \frac{z^2}{2n} \pm z \sqrt{\frac{\hat{p}(1 - \hat{p})}{n} + \frac{z^2}{4n^2}} \right], \quad (3.5)$$

where $\hat{p}$ is the proportion of successes estimated from the statistical sample; z is the $1-\alpha/2$ percentile of a standard normal distribution; α is the error percentile and n is the sample size. Here, since the confidence level was 95%, the error α was 5%. The sample size was 30 (3 nodules $\times$ 10 participants). The nodule detection Se values were 66.7% (95% confidential interval: 48.8 – 80.8%), 76.7% (95% confidential interval: 59.1 – 88.2%), and 73.3% (95% confidential interval: 55.5 – 85.8%), for visual feedback, force feedback, and visual + force feedback, respectively. Figure 3-15 presents the nodule detection sensitivities of nodule A, B and C. It appears that the middle-sized nodule B was easier to be detected using visual feedback than using force feedback (visual vs. force: 90% vs. 60%), while force feedback was more

suitable for the largest and the smallest nodules (visual/force: 80% vs. 100%, 30% vs. 70%), respectively. The visual + force feedback method combines the characteristics of both feedback modes ($A = 80\%$, $B = 90\%$, $C = 50\%$). The significance of the difference of sensitivity Se between paired tests was examined. It was conducted by comparing the observed probabilities (p_1 and p_2) with a combined interval CI , which was calculated by the following formula [153]:

$$CI = \sqrt{(P_1 - p_1)^2 + (P_2 - p_2)^2} \quad (3.6)$$

where if $p_1 < p_2$, P_1 is the upper bound of p_1 and P_2 is the lower bound of p_2 . If $|p_1 - p_2| > CI$, there is a significant difference between the two tests. From Table 3-2, one can conclude that there was no significant difference among methods concerning nodule detection Se .

Figure 3-16 shows the time consumed for nodule detection. In general, the proposed tele-manipulator was time efficient for tumour identification – the average time for all trials being 107.6 s. Wicoxon matched-pairs signed-rank test [154], [155] was used to compare the time consumed by each pair of feedback method modes. Using this test, one can decide whether the sample size distributions are identical without checking the normal distribution [156]. The test involves the calculation of a statistic, usually called W , which is given by:

$$W = \left| \sum_{i=1}^{n_r} [\text{sgn}(x_{2,i} - x_{1,i}) \cdot R_i] \right| \quad (3.7)$$

where n is the sample size; $i = 1, \dots, n$; sgn is the sign function; n_r is the reduced sample size without pairs that $|x_{2,i} - x_{1,i}| = 0$; R_i is the rank. When the sample size is larger than 20, a p -value can be calculated from enumeration of all possible combinations of W given n_r . When the sample size is lower, W needs to be compared to a critical value from a reference table. The significance level 0.05 was checked. Table 3-3 shows the test results. From Table 3-3, one can conclude that regarding the time needed for nodule detection, there was no significant difference between the three tests.

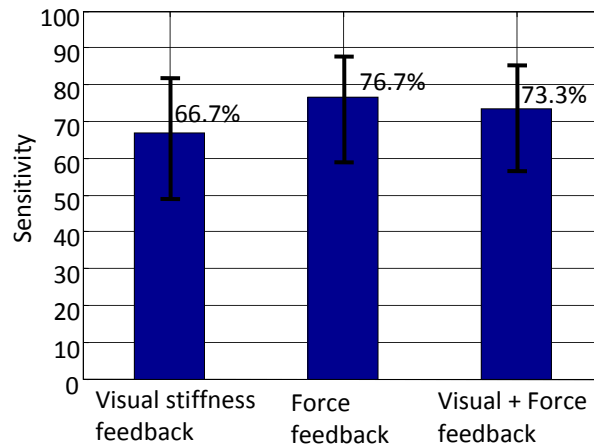


Figure 3-14 Nodule detection sensitivities of visual stiffness feedback and force feedback in a tele-manipulation environment and Wilson score intervals at a 95% confidence level are shown.

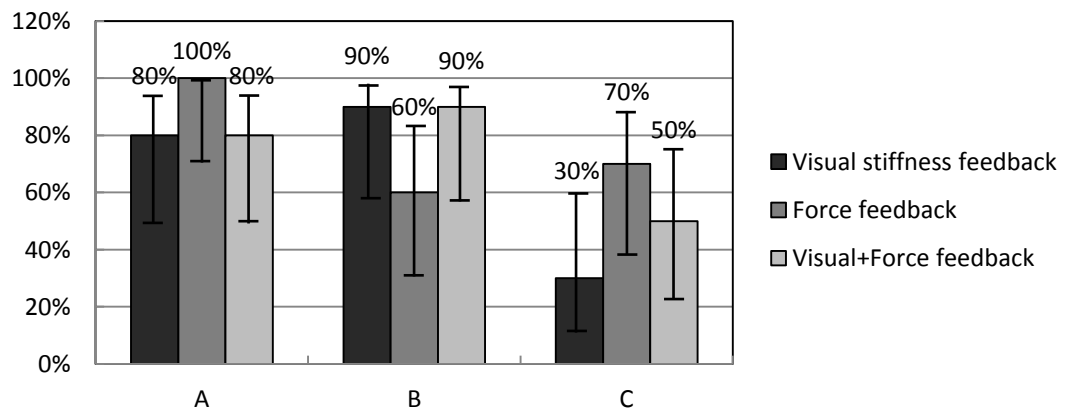


Figure 3-15 Nodule identification sensitivities from visual stiffness feedback, force feedback, and combination of visual stiffness feedback and force feedback with Wilson score intervals at a 95% confidence level.

Table 3-2 Comparison of sensitivities of visual stiffness feedback and force feedback in a tele-manipulation environment

Item	Combined interval (CI)	Probability difference (Δp)	Significance
<i>Force & visual feedback</i>	0.225	0.100	$CI > \Delta p$, No
<i>Force & combination feedback</i>	0.216	0.066	$CI > \Delta p$, No
<i>Combination & visual feedback</i>	0.218	0.034	$CI > \Delta p$, No

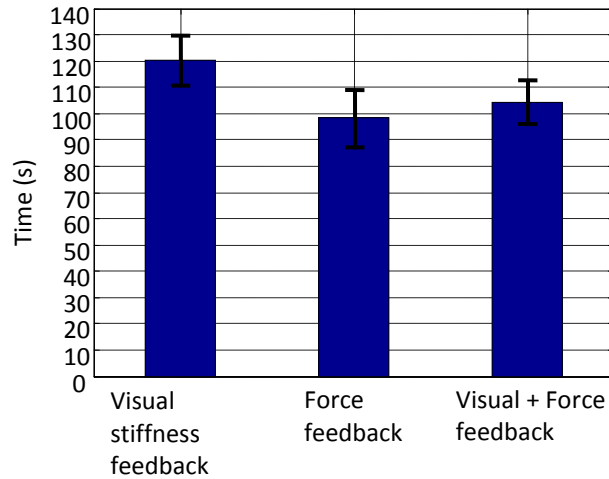


Figure 3-16 Time consumed to find the nodule locations of visual stiffness feedback and force feedback in a tele-manipulation environment: data is averaged over all ten subjects, and standard error bars are shown (Standard error of mean is the standard deviation of the sampling distribution of a statistic [157], and is an indicator of result precision).

Table 3-3 Wilcoxon signed-rank tests for nodule detection time of visual stiffness feedback and force feedback in a tele-manipulation environment

Item	n_r	W	$W_{critical}$	Significance
<i>Force & visual feedback</i>	10	12	8	$W > W_{critical}$, No
<i>Force & combination feedback</i>	10	27.5	8	$W > W_{critical}$, No
<i>Combination & visual</i>	10	15	8	$W > W_{critical}$, No

3.3.4. Discussion

Liu et al. [84] found that indentation speed did not have significant impact on the estimated elastic modulus in their rolling indentation experiments. Here, the stiffness map generation test has proved that calculated stiffness is similar for different palpation velocities and confirmed their findings.

Force feedback or force control in palpation was reported to be helpful in preventing tissue damage [158]. It was found that palpation pressure greater than 100 kPa [159] and palpation force above 6 N [158] could cause visible damage to the tissue. The palpation force range result has shown that the applied limit of the indentation depth kept the palpation force within a safe range in this experiment. Thus, compared to

visual feedback, force feedback did not have the advantage of preventing tissue damage. The maximum stiffness of PHANToM Omni was regarded as insufficient for haptic palpation simulation in [15]. However, the palpation force range result in this study has shown that PHANToM Omni (maximum 3.3 N) was sufficient to provide force feedback for palpation procedures as long as a limit of the indentation depth was applied. Thus, the hardware requirements and the cost of haptic devices in medical simulators could be reduced.

The proposed haptic tele-manipulator provides more flexibility of tissue stiffness feedback modes. The conducted experiments have shown no significant difference among methods concerning nodule detection rate. Hence, when direct force feedback is not achievable, for instance, when haptic feedback devices cannot be integrated in the surgical tele-operator, visual stiffness feedback can be used to provide tissue property information for surgeons as long as the indentation depth is controlled to keep the palpation force at a safe range.

The accuracy of the soft tissue contour could affect the estimation of indentation depth and further influence the accuracy of the stiffness. In this study, a tissue silicone phantom with a flat surface was used. For uneven tissue surfaces, the soft tissue surface can be generated from a manual tissue contour scan using a motion tracking device. A binocular camera can also be used to provide 3D reconstruction of the soft tissue. These two ways will be discussed in the next chapter.

As reviewed in Section 2.2, the ratios of elastic modulus of cancerous breast tissues to fat tissue are ranging from 4 to 124 [27]. In this thesis, a wide range of tumour stiffness is modelled. The stiffness ratio between the manufactured hard nodules and the silicone phantom tissue is about 208. In the next chapter, smaller stiffness ratios will be applied.

The experiment results in [33] have shown that surgeons with more da Vinci experiences performed better when using force feedback in tele-operated palpation, which supported previous findings that the benefits of force feedback depends on surgeon's experience in RMIS [160], [161]. Most participants did not have any

experience with haptic feedback or tele-manipulators here, so there would be a further performance improvement with more practice.

However, robots often become unstable when contact with stiff environments during force control [21]. Moreover, colour-coded tissue stiffness maps can only represent relative stiffness differences and do not contain any depth information of tumours [56]. If haptic feedback can be provided to the surgeon during palpation on a tissue model which represents the specific tissue status of a real tissue based on an intra-operative indenting approach, the two problems mentioned above can be avoided. This will be discussed in the next chapter.

3.4. Conclusion

This chapter evaluated the performance of the visual representation of soft tissue stiffness distribution method in tumour detection by comparing it to force feedback in a tele-manipulation environment. Three stiffness feedback modes of a haptic tele-manipulator for soft tissue palpation were investigated: (1) force feedback, (2) visual stiffness feedback, and (3) combined force and visual stiffness feedback. The force feedback was provided by a haptic device using the measurements from an F/T sensor attached to a sliding indentation probe, with which the user could probe the surface continuously. The visual stiffness feedback was provided by refreshing the colour of the representation of a reconstructed soft tissue surface on a graphical interface using soft tissue stiffness data estimated in real time. Ten participants used the tele-manipulator to palpate an artificial organ with hard nodules embedded. Results showed that stiffness maps could be successfully generated; subjects could localize nodules using all feedback modes; the proposed tele-manipulator was time-efficient for tumour identification with an average time to explore the whole surface of the artificial organ for all trials of 107.6 s; there was no significant difference among methods concerning nodule detection Se and the time consumed for tumour detection; the limit of the indentation depth was beneficial for preventing tissue damage and reduced the requirements of the haptic feedback device stiffness. To conclude, displaying visual stiffness is a useful means to provide surgeons with additional feedback from the operating site, especially where force feedback is not available.

Chapter 4 Palpation on Tissue

Models using Novel Feedback

Modalities

Current surgical tele-manipulators do not provide explicit haptic feedback during soft tissue palpation. Haptic information could improve the clinical outcomes significantly and help to detect hard inclusions within soft-tissue organs indicating potential abnormalities. However, system instability is often caused by direct force feedback. In this chapter, a new method for tumour localization is introduced. Virtual-environment tissue models are created based on the reconstructed surfaces of silicone phantom soft tissues using a tissue contour scan and the organ's stiffness distribution acquired during rolling or sliding indentation measurements. The reaction forces during virtual rigid tool / soft tissue model interaction are haptically fed back to the user. In contrast to the previous work reviewed in Chapter 2, this method avoids the control issues inherent to systems that provide direct force feedback. The feasibility of this method is demonstrated by evaluating the performance of the proposed tumour localization method on soft tissue phantoms containing buried stiff nodules using various feedback modalities, including visualization of tissue deformation, force feedback, pseudo-haptic feedback, and the combination of force feedback and pseudo-haptic feedback.

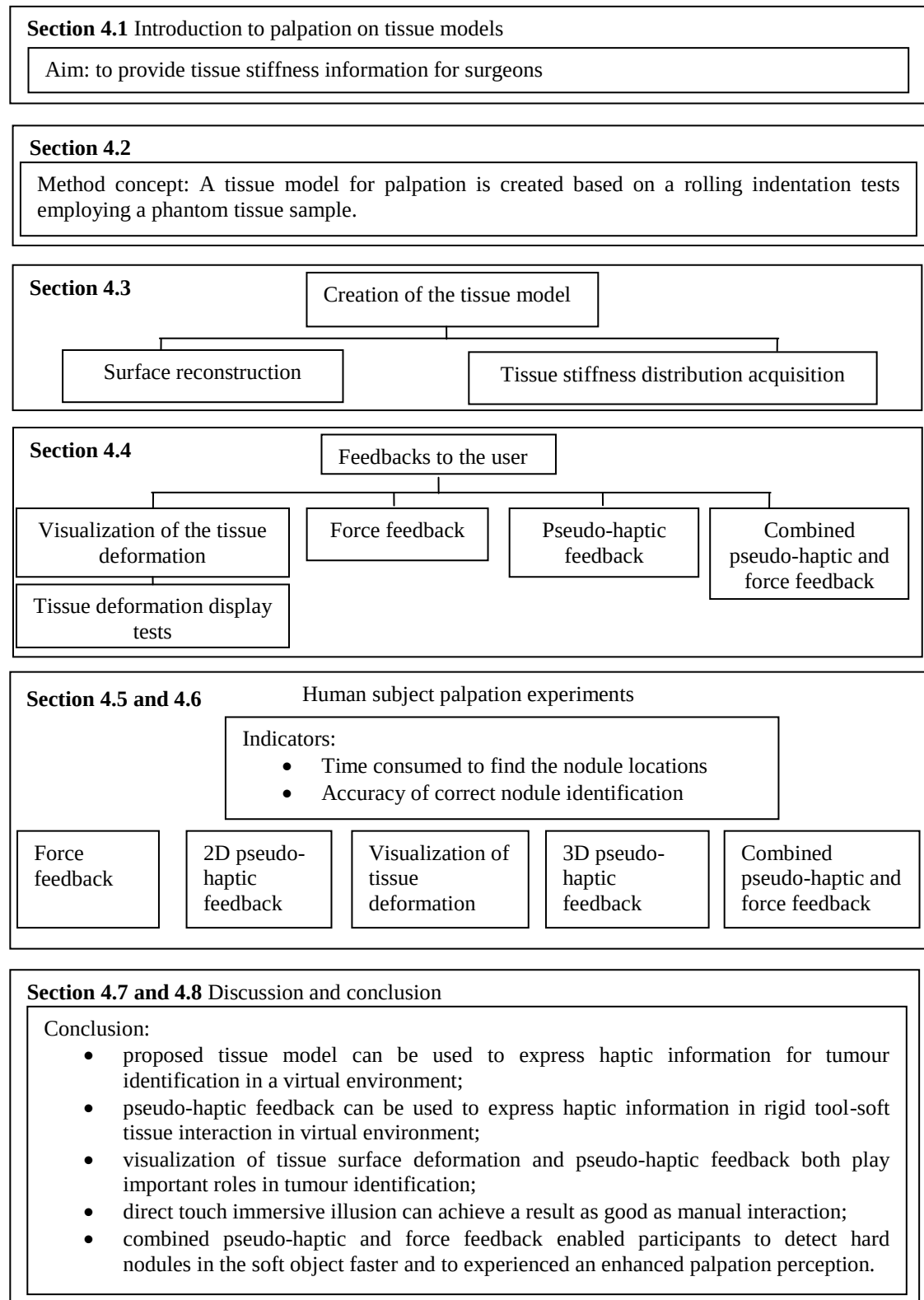


Figure 4-1 Structure of Chapter 4.

4.1. Introduction to palpation on tissue models

The inclusion of haptic palpation in training simulators could be beneficial for the acquisition of practical experience. VR simulators for palpation training commonly use deformable soft tissue models, such as mass-spring models, but the parameters of those models are not acquired from tests on specific soft tissues. Haptic palpation will be more realistic and meaningful if the soft tissue stiffness distribution is generated based on tests on real tissue and can represent specific tissue status, namely patient-specific tissue models. Data-driven tissue models can overcome the drawbacks of the parametric method which cannot run in real-time mode and in which non-linear material behaviours and complex objects are difficult to model [162]. Moreover, measuring stiffness by employing an intra-operative indenting approach and providing haptic feedback to the surgeon is another solution for tumour detection in RMIS.

Direct force feedback conveyed to the surgeon's hands by programming the motors in the master manipulator to recreate the forces measured by the patient-side robot is a most obvious way of exploring tissue stiffness distribution exploration. However, robots often become unstable when in contact with stiff environments during force control [21]. Conducting palpation on a soft tissue model based on the measured tissue surface contour and stiffness distribution would not cause system instability as is the case with direct force feedback.

Visual force feedback using a colour bar [33] and material property distribution graphical overlay [32], [56] have also been introduced as another solution for tumour identification in RMIS. A drawback of visual force feedback is that it is time consuming because cognitive processing is needed by the user to get the explicit information about soft tissue mechanical property distribution [39]. Instead of providing discrete force information, the distributed visual representation – colour-coded tissue stiffness maps – has been introduced to provide straightforward mapping to stiffness information [32], [56] and has been discussed in Chapter 3. However, the colour-coded tissue stiffness maps can only represent relative stiffness differences and the location projection of tumour on the surface, but do not contain any tumour depth information [56].

In this chapter, a novel palpation method with haptic feedback for use in medical training and during RMIS is introduced. Instead of using empirical mathematic models, the proposed data-driven tissue model is based on stiffness distribution acquired from tests on silicone phantom tissue with artificial tumours embedded. Virtual force feedback is provided by interpolation of the recorded contact forces during interaction with the soft objects. This method avoids the control issues of direct force feedback in RMIS.

Normally, haptic devices are required to provide haptic feedback. One of the disadvantages of using haptic devices to provide force feedback is that haptic devices are relatively costly. This chapter also presents a new tissue stiffness simulation technique for surgical training and RMIS using pseudo-haptic feedback, a technique which eliminates the need for real haptic devices. To the best knowledge of the author, this is the first time 2D pressure-sensitive touchpads and tablet computers are combined with pseudo-haptic feedback to convey 3D haptic information.

In addition, with the aim to improve on what can be achieved in a haptic feedback system, a new method is introduced which combines pseudo-haptic feedback with force feedback in order to enhance the haptic perception of the user while interacting with a soft tissue and embedded hard inclusions.

This chapter makes the following contributions:

1. Introduction of a novel intra-operative haptic tissue model generation method that is capable of representing the tissue surface contour and the tissue stiffness distribution of the examined soft tissue. By avoiding the control issues of direct force feedback this method gives the user a direct impression of reaction force magnitude during palpation.
2. Introduction of a 2D pseudo-haptic tissue stiffness simulation method in which tangent reaction force of sliding behaviour and normal reaction force of indentation behaviour during palpation are simulated separately using pseudo-haptic feedback and other auxiliary feedback strategies with the aid of a computer mouse utilized as an input device. The roles of these two behaviours in tumour identification are examined.

3. The creation of a geometrical soft tissue deformation computation method to provide visual feedback of tissue deformation during haptic palpation considering the influence of the indenter diameter on tissue deformation and the roles of the visualization of tissue surface deformation and pseudo-haptic feedback in tumour identification.
4. The creation and validation of a pseudo-haptic feedback method, which in contrast to previous approaches that were limited to 2D haptic information, is capable of handling 3D haptic information that can be applied in soft tissue stiffness simulation using different input devices including a pressure-sensitive touchpad and two tablet computers.
5. The combination of force feedback and pseudo-haptic feedback to further improve on what can be achieved in the haptic feedback system for tumour identification.

4.2. Method concept of palpation on tissue models using novel feedback modalities

A tissue model for palpation was created based on an experimental study employing a phantom tissue sample. The generated tissue model makes the exploration of stiffness distribution possible without a need for a tissue sample. This method avoids the control issues linked to direct force feedback and makes it possible for the user to receive an intuitive sense of touch through force feedback.

Figure 4-2 depicts the flow chart of the validation test of the proposed method. First, a soft tissue model was generated from the parameters of a tissue sample using a tissue surface reconstruction process and a rolling / sliding indentation probing process. The tissue surface was reconstructed from a tissue contour scan using a motion tracking device or from a stereoscopic image acquired from a depth sensor. A rolling / sliding indentation trajectory with a certain indentation depth was generated based on the reconstructed tissue surface coordinates. Next, a robot arm was programmed to conduct the rolling / sliding indentation following the trajectory. During the indentation probing, indentation depth / reaction force pairs were obtained enabling the acquisition of tissue stiffness distribution. The reconstructed tissue surface was

used to ensure that the indentation depth during the rolling / sliding indentation was kept constant. A soft tissue model was then established based on the reconstructed tissue surface and tissue stiffness distribution. Visualization of soft tissue deformation and / or pseudo-haptic feedback and / or force feedback was provided. The force calculation was based on a look-up table and a linear interpolation of the measured indentation depth / force pairs during rolling / sliding indentation. Thus, the virtual tissue could be palpated with real-time tissue deformation and force feedback.

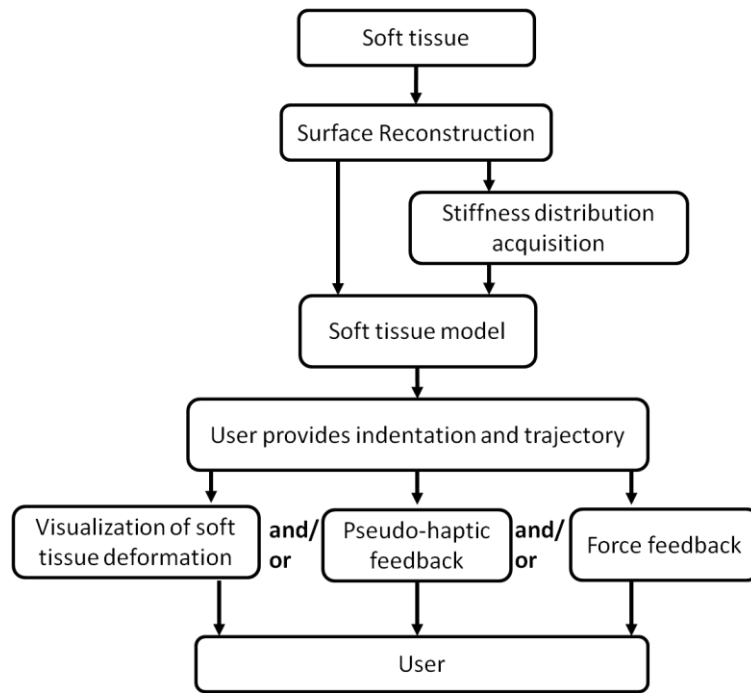


Figure 4-2 Flowchart of the validation test of the concept of intra-operative tumour localization using intra-operative generated tissue model.

4.3. Creation of the tissue model

4.3.1. Tissue surface reconstruction

In this study, two ways of tissue surface reconstruction were investigated including a tissue contour scan using a motion tracking device and 3D reconstruction using a Kinect sensor.

4.3.1.1. Tissue contour scan using a motion tracking device

A PHANToM Omni was used to track the motion when scanning the surface of a silicone phantom tissue sample with a curved surface (see Figure 4-3) along

trajectories parallel to the x -axis with an interval of 10 mm along the z -axis to get the contour of the phantom tissue (see Figure 4-4). The stylus was controlled manually to scan the surface line by line with the help of a coordinate paper underneath. The process was time consuming and took half an hour. The acquired matrix of the y -axis was then converted to 31×31 nodes using linear interpolation. The organ surface was reconstructed and displayed on the screen as 1800 small, distributed triangles with the 31×31 nodes using Open GL in VC++.

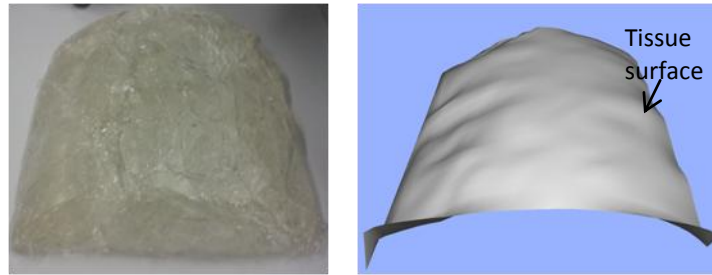


Figure 4-3 Phantom tissue surface (left) and reconstruction result (right)

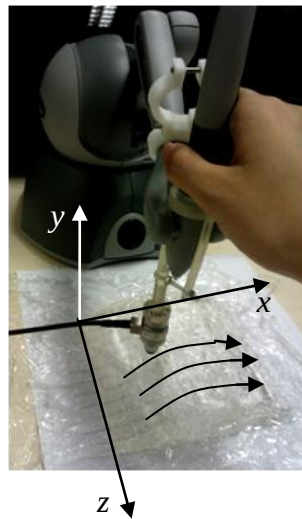


Figure 4-4 Phantom tissue contour scanning

4.3.1.2. 3D reconstruction using a Kinect sensor

3D reconstruction is widely used in many fields including robotics, security, biomedical industries, virtual and augmented reality, and entertainment [163]. Here, the target was to achieve satisfactory 3D tissue surface reconstruction results without heavy computational effort. A Kinect depth sensor was used. The Kinect depth sensor has been used in many research projects to obtain real-time 3D models of physical

scenes. A comparison of the 3D reconstruction produced by the KinectFusion algorithm with ground truth data obtained from high-precision 3D scanner is given in [164]. That work demonstrated that KinectFusion was a new low-cost solution to resolve object details with a minimum curvature of 10 mm.

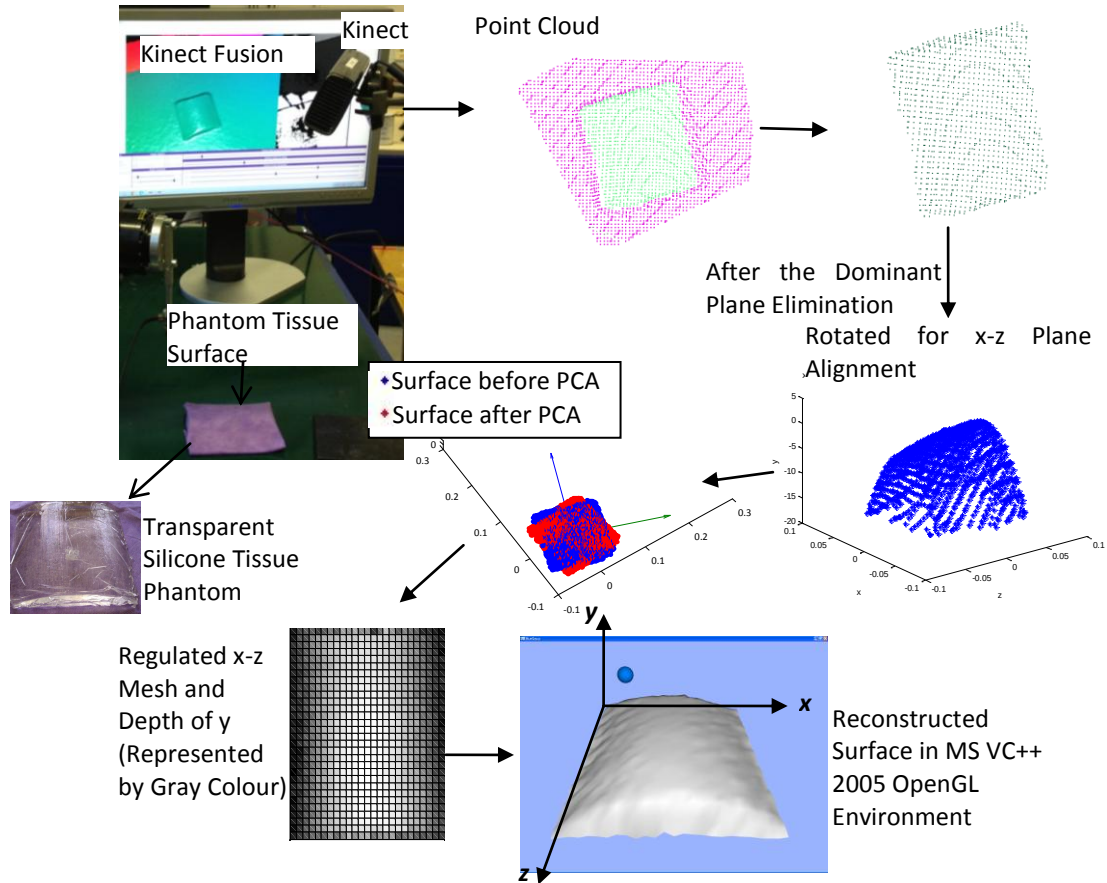


Figure 4-5 Real-time 3D reconstruction and point cloud processing, using Principal Component Analysis (PCA).

Figure 4-5 shows the real-time tissue surface reconstruction and point cloud processing. Firstly, a real-time 3D reconstruction of the scene was obtained using KinectFusion. This interactive system allows the creation of a single high-quality, geometrically accurate 3D model [90]. The artificial soft tissue was made from transparent silicone RTV6166 (TECHSIL Limited, UK). A hand-held Kinect sensor was slowly moved at about 1 m distance around the phantom tissue sample, which was located on a planar table. During the process, the transparent phantom tissue (see Figure 4-5) was covered by a piece of purple cloth. The 3D model of the scene obtained from the Kinect depth camera was then used to extract the point cloud. Only

the point cloud representing the soft tissue surface and the planar table were selected manually; the remaining part of the scene was cut out. The plane representing the planar table and the tissue surface were separated using a segmentation program with PCL (Point Cloud Library). The centroid of the points representing the surface was then used to translate the points while the normal of the table plane was used to rotate these points and make them parallel to the x - z plane. In the next step, the eigenvectors of the covariance matrix were calculated by using the principal component analysis PCA (Principal Component Analysis) transformation, and used to rotate the side of the surface and make it parallel to the z -axis. Linear interpolation was applied to regulate the points. Finally, the organ surface was reconstructed and displayed on the screen as 1500 small, distributed triangles with 31×26 nodes using OpenGL in VC++.

4.3.2. Tissue stiffness distribution acquisition

4.3.2.1. Phantom tissue I

According to the 2003 American joint committee on cancer staging, T1 stage tumours are 20 mm or less at the widest point [25]. Cancerous formations are typically stiffer compared to healthy soft tissues [27]. The phantom tissue sample (Phantom tissue I), used for the experimental study described later, was a $120 \times 120 \times 25 \text{ mm}^3$ rectangular cuboid with three differently-sized spherical nodules (A, B, C) embedded inside simulating abnormal formations: the nodules' diameters were A: 10 mm, B: 8 mm, and C: 6 mm (see Figure 4-6). The nodules were buried with a depth of 6 mm measured from each sphere's top to the silicone surface. The phantom was made from RTV6166 (TECHSIL Limited, UK) (ratio 3 : 7, the viscosity 900 mPa·s, density 1100 kg/m³, Young's modulus 15.3 kPa [165], [166]). The nodules were made from a rubber eraser – STAEDTLER Mars plastic 526 50 (47-50 ShoreA, Young's modulus about 1.59 MPa). The phantom tissue sample has a flat surface. To correctly match the coordinate systems of the robot, the three points of the tissue surface (centroid of the surface, and one point in x and z directions) on the robot structure were measured. Based on these points, homogenous transformation matrices were created which transformed the points of the point cloud into the robot coordinate frame. To obtain a stiffness map, 59 straight trajectories (121 mm long and parallel to the x -axis with a shift of 2 mm along the z -axis between trajectories) were defined. A robot arm was

then programmed to move the sliding indentation probe along the defined 59 straight-line trajectories at a speed of 30 mm/s with a constant indentation depth. During the process, the surface of the phantom tissue was lubricated with Boots Pharmaceuticals Intrasond Gel to reduce the effect of friction and dragging forces. Tissue interaction forces were recorded with a Nano 17 (ATI) F/T sensor (SI-12-0.12, resolution 0.003 N with 16-bit data acquisition card). The normal and horizontal reflected forces were recorded at 100 Hz. The experiments were repeated at different indentation depths. The indentation depths were varied between 2 mm and 7 mm at intervals of 1 mm. Thus, six 159×59 sets of force data (f_x , f_y , f_z) were recorded, which allowed the acquisition of stiffness distribution maps for the whole phantom tissue surface to be used for the experimental studies. When the probe was perpendicular to the tissue surface, the redundant force of f_x and f_z was the tangent force (f_t), while f_z was the normal force (f_n).

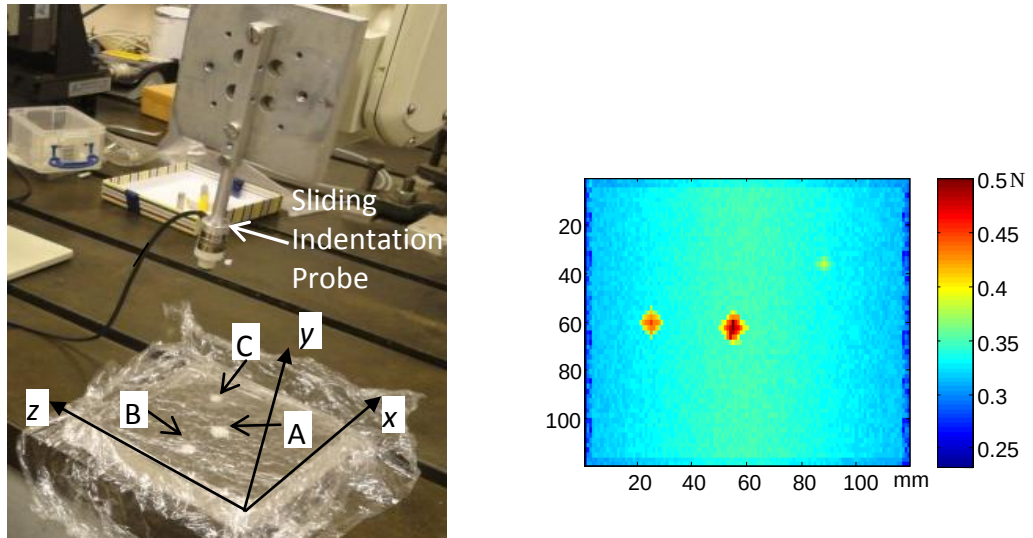


Figure 4-6 Experimental set-up of tissue stiffness distribution acquisition of the Phantom tissue I (left) and the reaction force matrix (right).

4.3.2.2. Phantom tissue II

A silicone phantom tissue with a curved surface (Phantom tissue II, see Figure 4-7) was also used for the experimental study. A sliding indentation trajectory was generated based on the surface reconstruction result using the Kinect sensor. A robot arm was programmed to conduct the sliding indentation following the trajectory. During the indentation, indentation depth/reaction force pairs were obtained enabling

tissue stiffness distribution acquisition. The phantom tissue sample contained two embedded spherical nodules (A and B) at a depth of 3 mm, measured from the top of the nodules to the silicone surface. The phantom was fabricated using RTV6166 (TECHSIL Limited, UK) (ratio 4 : 6 and the viscosity 900 mPa·s). The nodules (15 mm in diameter) were made from RTV615 (TECHSIL Limited, UK) (ratio 10 : 1 and the viscosity 4000 mPa·s).

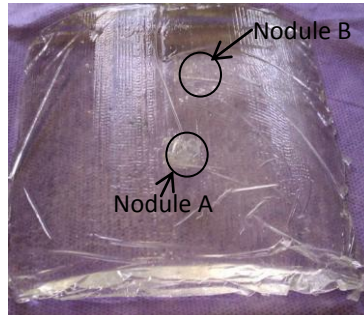


Figure 4-7 Phantom tissue II with the locations of two embedded hard inclusions.

To correctly match the coordinate systems of the robot, three points of the point cloud (centroid of the surface, and one point in x and z directions) on the robot structure were measured. Based on these points, homogenous transformation matrices were created which transformed the points of the point cloud into the robot coordinate frame. To validate the accuracy of the tissue surface reconstruction result, the robot was first programmed to follow the reconstructed tissue surface with an indentation depth of 0. Force data was recorded. The maximum force was 0.041 N. The average force was 0.009 N with a standard deviation of 0.008 N. The result demonstrated the indenter was barely touching the reconstructed surface – hence, following the curvature of the tissue surface accurately during the entire scan process. One can conclude that the tissue surface reconstruction can be used for indentation depth control during indentation scans that aim at acquiring a tissue's stiffness distribution. Three sliding indentation process were conducted with the indentation depths of 2 mm, 4 mm and 6 mm. During the process, the soft tissue surface was lubricated with Boots Pharmaceuticals Intrasond Gel. Normal reaction force data was recorded (see Figure 4-8). From the force matrices, one can see that the two nodules, A and B, are recognisable in the colour-coded representation of the force matrix – the two nodules are shown as high force peaks (distinct red and yellow areas in an otherwise blue (low

value) force distribution). In Figure 4-8 (b), (c) and (d), there is an area with relative high reaction forces (top right yellow area). This change in stiffness may stem from a localised inhomogeneity of the two silicone components used for creating the phantom.

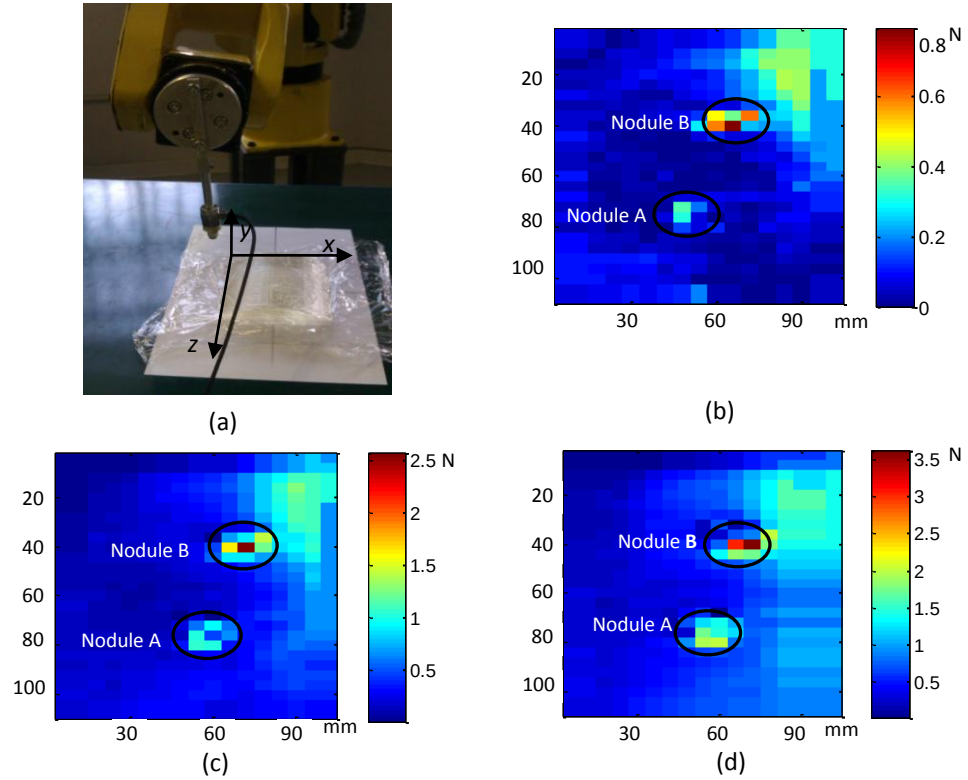


Figure 4-8 Tissue stiffness distribution acquisition experiment setting up and the reaction force matrices of Phantom tissue II at the indentation depth of (b) 2 mm, (c) 4 mm and (d) 6 mm.

4.3.2.3. Phantom tissue III

The silicone phantom tissue sample (Phantom tissue III) was $150 \times 150 \times 17$ mm³ with nine embedded simulated tumours (see Figure 4-9 and Table 4-1). The silicone phantom was made from RTV6166 (TECHSIL Limited, UK) (A : B = 1 : 2). The elastic modulus was 14.7 kPa; Poisson's ratio was 0.45; mass density was 980 kg/m³. The nodules were made from a rubber eraser with elastic modulus of 219 kPa, Poisson's ratio of 0.49, and mass density of 1000 kg/m³ (material properties were obtained from uniaxial compression tests [48]). To obtain a rolling stiffness map, 36×150 mm trajectories parallel to the x-axis with a shift of 4 mm along the y-axis

between each two trajectories were defined. The start point of the first trajectory was (0, 0) on the silicone phantom. A robot arm was then programmed to move the rolling indentation probe along the middle 34 trajectories at a speed of 45 mm/s with a constant rolling indentation depth. It took 2.5 minutes to cover the entire area. The sampling rate of reflection forces was 100 Hz. The rolling indentation depth was 3 mm. These procedures were repeated ten times. A force distribution matrix with 135×34 elements was generated.

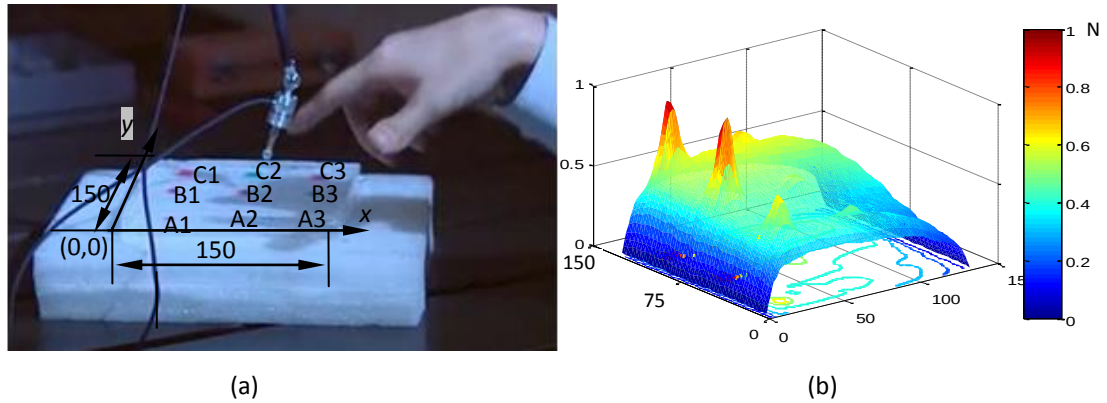


Figure 4-9 (a) Phantom tissue III with the locations of nine embedded hard inclusions and (b) force distribution acquired from rolling indentation.

Table 4-1 Dimensions and locations of simulated tumours within the Phantom tissue III (all dimensions are in millimetres).

Hard inclusions and coordinates	Cross sections of hard inclusions	Thickness	Depth
<i>A1</i> (25,25)		12	5
<i>A2</i> (75,25)		8	7
<i>A3</i> (125,25)		4	13
<i>B1</i> (25,75)		12	5
<i>B2</i> (75,75)		8	7
<i>B3</i> (125,75)		4	13
<i>C1</i> (25,125)		12	5
<i>C2</i> (75,125)		8	7
<i>C3</i> (125,125)		4	13

4.4. Feedback modalities

4.4.1. Visualization of the tissue deformation

4.4.1.1. *Deformable tissue models*

This section describes the proposed reproduction of the deformation of soft tissue during palpation on the soft tissue computer model. For a biomedical simulation, the computation of soft tissue behaviour is vital. The key trade-off to be considered is the real-time capability and the deformation accuracy, which are two main requirements for surgical simulation. Numerous approaches have been proposed to model the deformation behaviour of soft tissue, including FE methods, the boundary element method [167], [168], the long element method [73], tensor-mass models [169], [170], mass-spring models [171], [172], meshless methods [173]–[175], geometrical methods [70], [71], and ChainMail algorithms [74]. FE methods can provide different levels of accuracy for simulation of tissue deformation including linear elastic and non-linear systems. However, their high computation time is a barrier for real-time applications [48]. The boundary element method reduces the computational complexity [167], [168] but it is not suitable for large displacements since it is based on linear elasticity. The long element method also reduces computational complexity [73] but it only generates accurate results when the deformation is small. Mass-spring models are a type of lumped parameter models [74] and have been a standard tool to model deformable objects in surgical simulations because of their conceptual simplicity and computational speed. However, the deformation of an elastic object can only be roughly approximated by using these methods. In FE or mass-spring models, the deformation and feedback force are computed simultaneously since the force and position are dynamically coupled at all nodes [176]. Tensor-mass models are a simplification of FE techniques and are incorporated to mass-spring models [169], [170]. It has been modified to accommodate large deformations by using anisotropic material laws and, or, non-linear strain tensors [169]. For those models, it is difficult to determine the parameters of so many springs, tensors, and masses to represent tissue stiffness distribution especially when nonlinear behaviour is to be captured [174]. Meshless methods support not only the simulation of large deformations but

also the topology modifications, such as cutting [173], [174]. The Point-Associated Finite Field (PAFF) approach is one example. However, it is computationally intensive [175]. Localized solutions have been introduced to solve this problem [174]. Geometrical methods were used in early applications which modelled the behaviour of soft bodies based on geometrical modifications of the surface mesh. For example, Baur et al. [70] used 3D profile functions tuned by experts to model deformed tissue surface while Basdogan et al. [71] used second order polynomial functions, fitted to empirical data, to translate the vertices of organs in the vicinity of a contact point along the direction of the virtual tool. But none of them compared the simulated deformations with real deformations. ChainMail algorithms model deformations of volumetric objects by the motion of linked elements similar to chains. These algorithms are fast to calculate propagation velocity of the deformation but the deformed model cannot be easily reshaped back to its original state. Thus, ChainMail algorithms were improved to a shape-retaining chain linked model or S-chain model [74]. Different from the simultaneous force and deformation computation process of mass-spring and FE models, the S-chain model computes force after the computation of displacements. In order to apply to volumetric medical image data, the physical meaning of the parameters in this model needs more investigation. As the force computation was recognized as “not intuitive”, a force-voltage analogy concept was introduced to resolve the confusion later [176]. It was concluded in [74] that displaying deformed shapes precisely may not be so critical as long as they are within the acceptable range of our haptic sense.

Different from all the methods reviewed above, the reaction force in this research came from the stiffness distribution of the tissue model based on the indentation tests on soft tissue sample. Therefore, the deformation of soft tissue and the reaction force were computed separately.

4.4.1.2. 3D finite element modelling

The influence of different hyperelastic material properties on the relationship between the curvature of the tissue surface and other factors, such as indentation depth and diameter of indenter, were studied. In this experimental study, the indenter’s diameter was varied between 6 mm and 10 mm and different material properties (Table 4-2)

including shear modulus μ , locking stretch λ_m and mass density were investigated. This approach was applied to two different materials: Silicone (RTV6166 gel) and porcine kidney whose respective material properties were obtained from uniaxial compression tests [48]. 3D finite element modelling (using hyperelastic Arruda-Boyce equations) of soft tissue rolling indentation was conducted. The rolling friction was ignored, assuming that the contact between the indenter and simulated soft tissue was defined as “frictionless”. The bottom of the soft tissue was defined as fixed. The results show that the investigated hyperelastic material properties had virtually no impact on the displacement curvature of the tissue surface (Figure 4-10 and Figure 4-11). In the scope of this thesis, it is assumed that it can be applied to any other hyperelastic materials.

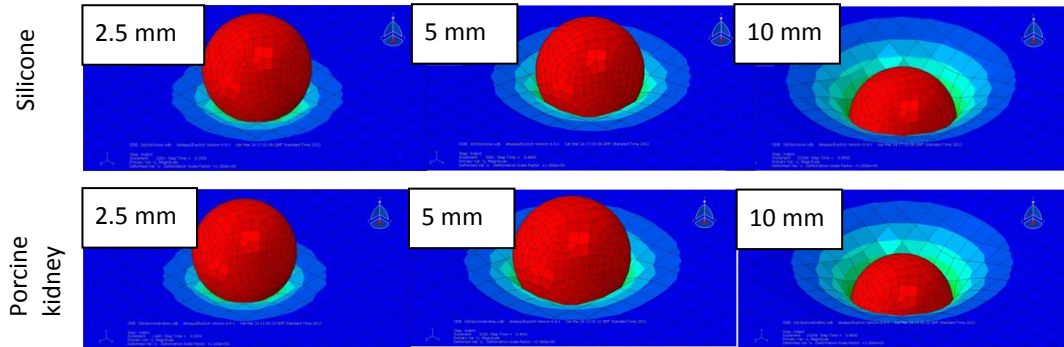
Table 4-2 Property of the Test materials

Item	μ Shear modulus (kPa)	λ_m Locking stretch	Mass density (kg/m ³)
<i>Silicone (RTV6166 gel)</i>	4.98	1.05	980
<i>Porcine kidney</i>	1.85	1.05	800

4.4.1.3. A geometrical soft tissue deformation computation method

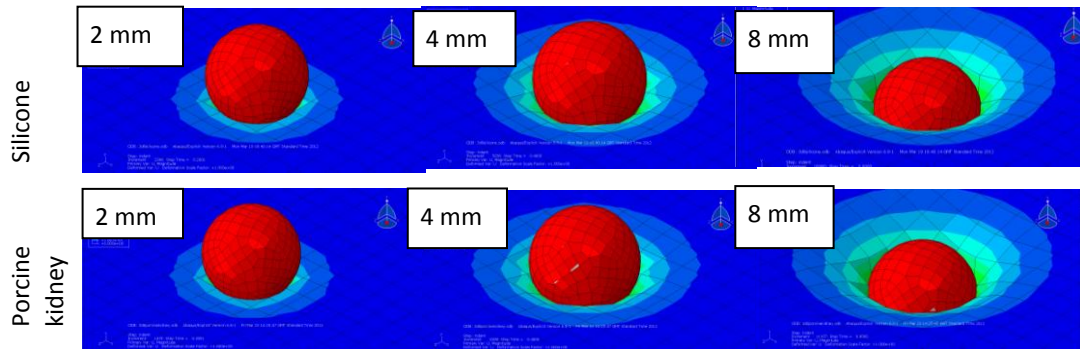
The result of 3D finite element modelling shows that the investigated material properties had no obvious impact on the displacement curvature of the tissue surface. The simplified model of the displacement curvature of the tissue surface, which can be used for redefinition of nodes' heights, is summarized for a planar surface (see Table 4-3). In the scope of this thesis, it is assumed the model can be applied to any other hyperelastic material. To extend the applications of this tissue displacement model on curved surface soft tissue, the small area around the indentation centre can be considered as planar. The modifications of nodes' heights according to the model of the displacement curvature can be converted to normal to this planar.

Indenter diameter 10 mm



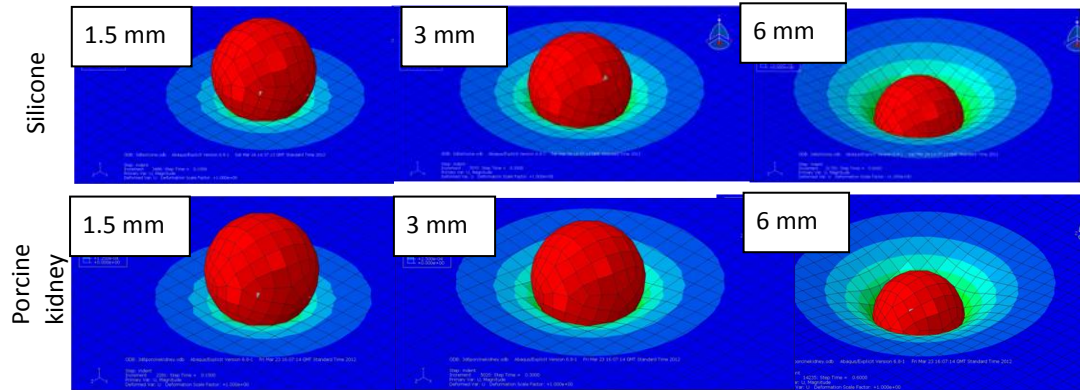
(a)

Indenter diameter 8 mm



(b)

Indenter diameter 6 mm



(c)

Figure 4-10 3D finite element simulation of indentation: silicone (RTV6166 gel) and porcine kidney using (a) 10 mm, (b) 8 mm, and (c) 6 mm indenter with indentation depths equal to a quarter of indenter diameter, half of indenter diameter, and indenter diameter; at the same indentation depth, the deformation of the tissue surface of each pair is comparable.

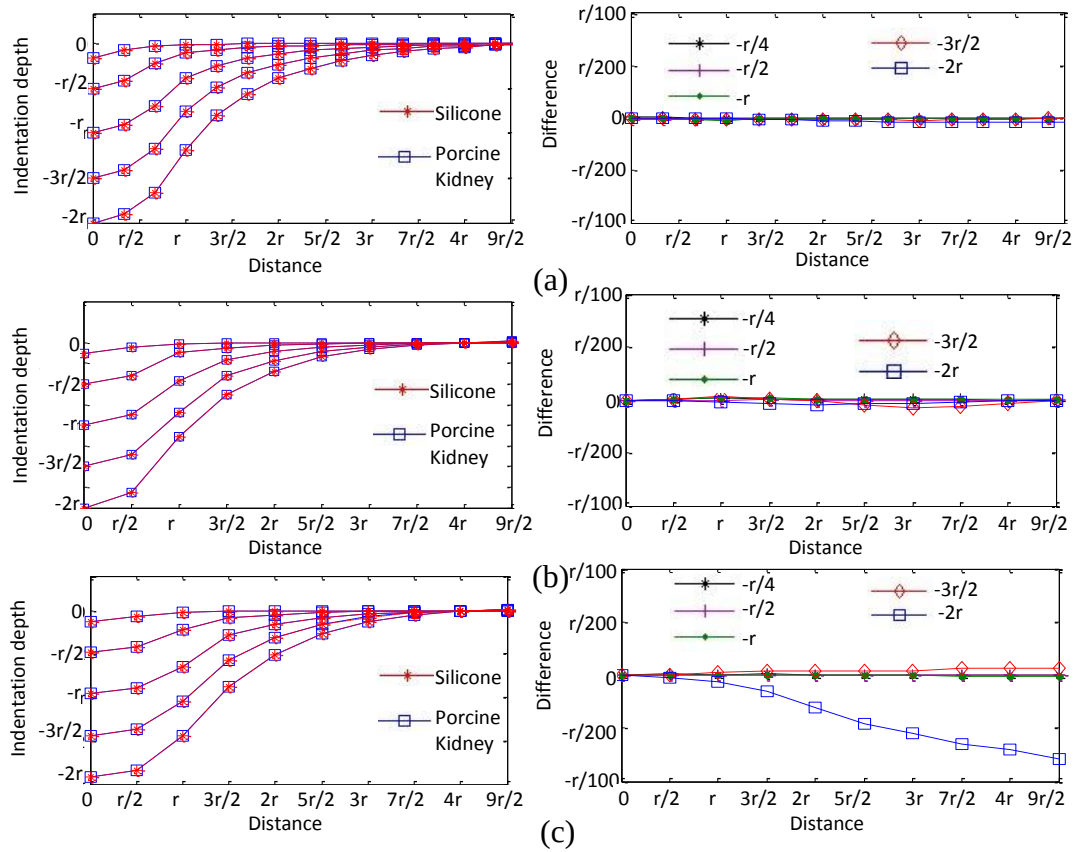


Figure 4-11 On the left panels: the deformation curvature of silicone (RTV6166 gel) and porcine kidney at different indentation depths using 6 mm (a), 8 mm (b), and 10 mm (c) indenter in 3D finite element simulation; on the right panels: the difference between the displacement curvatures.

Employing the above models, the tissue surface was displayed graphically using a mesh of connected triangles whose vertices form a graph of nodes (Figure 4-12). For a node i at the centre of an indentation caused by a sphere, its perpendicular vertex was updated as a function of the indentation depth. The perpendicular vertices of other affected nodes on the mesh (such as node $i-1$, $i+1$, $i-x$ and $i+x$, in Figure 4-12) were updated as a function of distance from node i and the tissue deformation presented in Table 4-3, where indentation depth d_A was defined as the distance between the tissue surface and the largest displacement point (bottom point of the indenting sphere). In this model, the indentation depth was divided into four ranges: the demarcation points were $(2-\sqrt{3}) \cdot r/2$, r , and $2r$ for case a), b), c), and d), respectively, as shown Table 4-3. As the indentation depth increases, the number of the affected vertices of triangle increases. The depths of subsequent neighbouring points (d_B , d_C , d_D , d_E , d_F , and d_G

where they are at a distance of $r/2$ apart) were defined as functions of d_A . For soft tissue samples with a curved surface, the proposed model can still be used under the assumption that the relevant area around the indentation centre is planar.

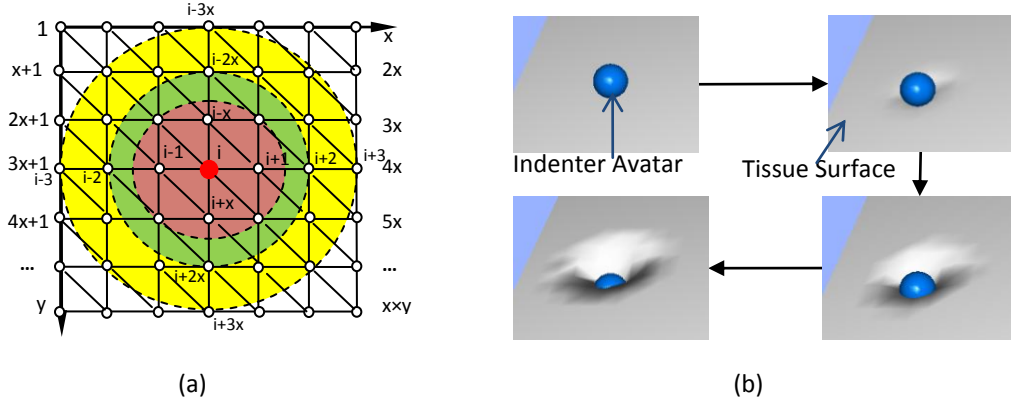


Figure 4-12 Number of vertices of triangles of tissue surface is $x \times y$; node i is at the centre of an indentation and other affected nodes are presented in (a); as the indentation depth increases, the affected tissue surface area becomes larger, shown in (b).

When the tissue surface was uneven, the indentation depth (d_A) was calculated using the distance between the indenter position (P_0) and the nearest triangle planar on the mesh of the original tissue surface contour (vertices: P_1 , P_2 , P_3). The unit normal vector of the planar n was acquired from $(P_2 - P_1) \times (P_3 - P_1) / |(P_2 - P_1) \times (P_3 - P_1)|$, where v was the vector from P_0 to P_1 . This distance was $|v \cdot n|$. The coordinates of the mesh were then adapted according to the tissue indentation and the geometrical soft tissue deformation computation method described before. The depth of the closest node was set to be the value of the indentation depth (d_A) (Figure 4-13).

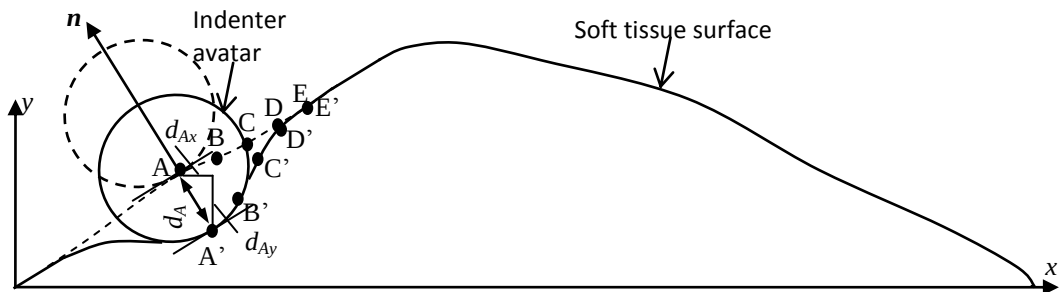
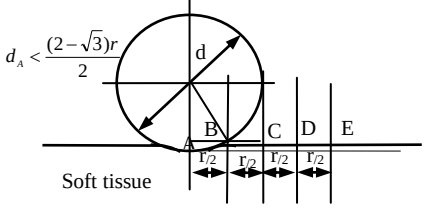
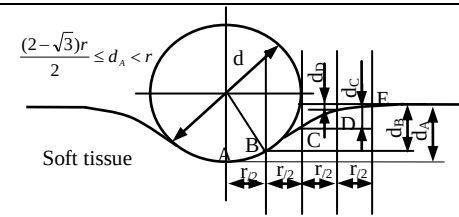
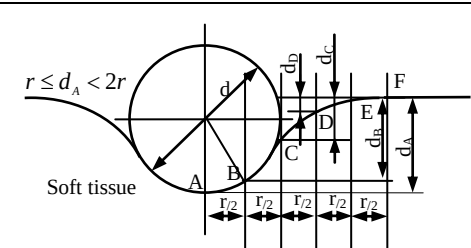
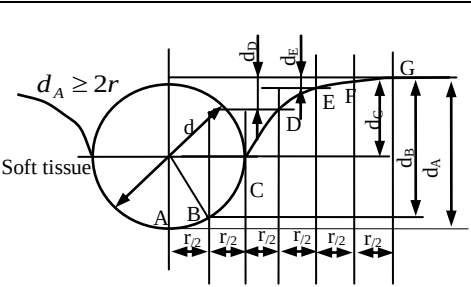


Figure 4-13 Adaptation of the coordinates of the mesh.

Table 4-3 Simplified model of displacement curvature of tissue surface and nodes height redefinition

 $d_A < \frac{(2-\sqrt{3})r}{2}$ Soft tissue	$d_B = d_C = d_D = d_E = 0$
 $\frac{(2-\sqrt{3})r}{2} \leq d_A < r$ Soft tissue	$d_B = d_A - \frac{(2-\sqrt{3})r}{2}$ $d_C \approx d_B / 2$ $d_D \approx d_C / 3$ $d_E = 0$
 $r \leq d_A < 2r$ Soft tissue	$d_B = d_A - \frac{(2-\sqrt{3})r}{2}$ $d_C \approx d_B / 2$ $d_D \approx d_C / 2$ $d_E \approx d_D / 3$ $d_F = 0$
 $d_A \geq 2r$ Soft tissue	$d_B = d_A - \frac{(2-\sqrt{3})r}{2}$ $d_C \approx d_A - r$ $d_D \approx d_C / 2$ $d_E \approx d_D / 2$ $d_F \approx d_E / 2$ $d_G = 0$

4.4.2. Force feedback

Force feedback was provided via a haptic device to enable the user to “palpate” the created tissue computer model. The current indenter position ($\mathbf{P}_c$ which represents the stylus position shows as a blue sphere on graphic display) and the last indenter position ($\mathbf{P}_l$) were read by the haptic rendering program and compared with the soft tissue surface continuously. If the current indenter position was within the original contour of soft tissue, it meant that the tissue was touched. The indentation depth was calculated using the distance between the indenter position ($\mathbf{P}_c$) and the nearest

triangle planar on the mesh of the original tissue surface contour (vertices: $\mathbf{P}_1, \mathbf{P}_2, \mathbf{P}_3$). The unit normal vector of the planar $\mathbf{n}$ was acquired from $(\mathbf{P}_2 - \mathbf{P}_1) \times (\mathbf{P}_3 - \mathbf{P}_1) / \|(\mathbf{P}_2 - \mathbf{P}_1) \times (\mathbf{P}_3 - \mathbf{P}_1)\|$, $\mathbf{v}$ was the vector from $\mathbf{P}_c$ to $\mathbf{P}_1$. This distance was $|\mathbf{v} \cdot \mathbf{n}|$. According to the calculated indentation depth, the reaction forces were acquired from a look-up table and linear interpolation of measured tissue reaction force matrices of different indentation depths. When the force in the look-up table exceeded the max force (3.3 N) of PHANTOM Omni, the force was set to be 3.3 N. Although the tangent force (f_t) was very small compared with normal force during the rolling indentation with lubrication, it was recreated and fed back to the user in order to create a similar feeling of tangent resistance during palpation with finger and make the user feel more clearly the motion direction. The direction of the normal reaction force (f_n) was defined by a contact normal $\mathbf{n}$. The tangent force was the same direction of the unit vector $\mathbf{k}$, which was acquired from $(\mathbf{P}_t - \mathbf{P}_c) / \|\mathbf{P}_t - \mathbf{P}_c\|$. The forces f_n and f_t were decomposed and converted into forces along x, y, z axes of the haptic device (see Figure 4-14). Since the reaction force data acquired from rolling indentation with a constant velocity, the proposed haptic palpation method assumed a constant palpation velocity along the tissue surface and the user needed to palpate with a fairly constant velocity during the experiments.

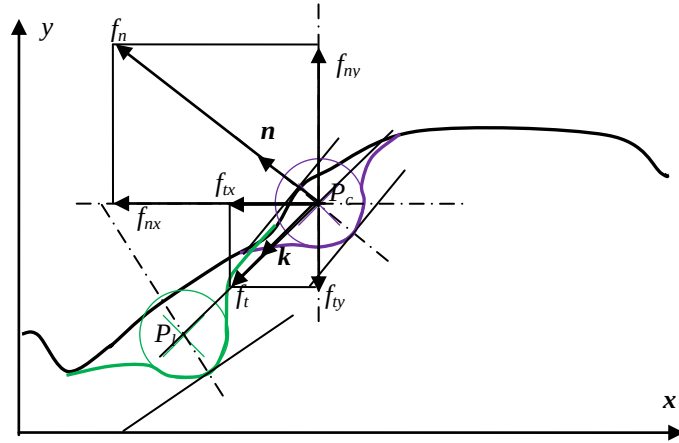


Figure 4-14 Force directions of haptic feedback.

4.4.3. 2D Pseudo-haptic tissue stiffness simulation

4.4.3.1. *Pseudo-haptic feedback*

Pseudo-haptic feedback creates a haptic feedback illusion [177] and generates virtual force through only visual feedback. For example, if the velocity of the cursor when moving a computer mouse on a smooth and flat surface is modified as a function of its location on the graphical interface in correlation with other displayed items, haptic sensations, such as viscosity, stiffness or surface texture, can be experienced [178]. Pseudo-haptic feedback has been used to simulate several haptic properties [179], including friction [177], stiffness [177], [178], mass [180], texture [181], and force [182].

Anatole Lécuyer et al. from INRA/IRISA have been working on pseudo-haptic feedback for over ten years. They came to the conclusion that isometric input devices can be used to simulate force feedback because visual feedback gave users the illusion of using a non-isometric device [177] (see Figure 4-15). The concepts of isometric input devices and isotonic input devices have been proposed by Zai [183]. When force is applied, isometric devices offer resistance and stay put while isotonic devices offer almost no resistance. For example, when the user is pressing a spring simulated by an isometric stick, the spring on the screen becomes shorter so that the user will have an illusion that the stick is compressed by the user's hand. The stick itself is not compressed, so it is "isometric". Lécuyer et al. [184] presented an approach to simulate textures in computer applications without haptic interfaces by modifying the movement speed of the cursor on the computer monitor. Lécuyer et al. [181] described another strategy to enhance the speed strategy and simulate texture sensations by relating the size of the cursor displayed on the computer monitor to the local height of the texture. Hachisu et al. [148] augmented pseudo-haptic feedback by adding visual and tactile vibrations, which proved that pseudo-haptic feedback can be integrated with other haptic feedback methods to enhance perception.

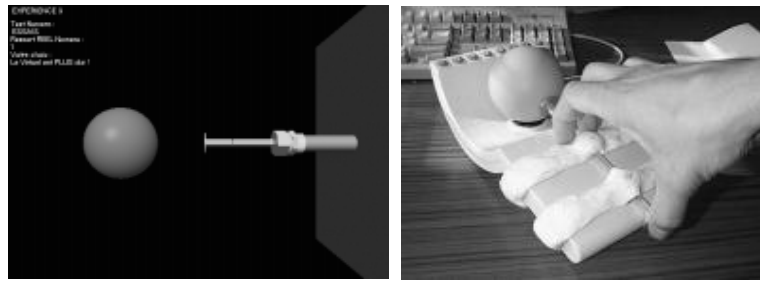


Figure 4-15 Visual display of a virtual spring (left) and “Modified” isometric device (right) [177]

Pusch et al. [182] proposed a method called Hand-displacEMent-based Pseudo-haptics (HEMP) to simulate force fields (see Figure 4-16). In an augmented reality environment, it generated virtual force by dynamically placing the virtual hand at a different position from the user’s hand.



Figure 4-16 Hand-displacement-based pseudo-haptics (HEMP) (left) and the view the users see (right) [182]

Pseudo-haptic feedback is currently used in the areas of tactile images [185], graphical user interfaces [186], data mining [187], and virtual technical trainer [188]. Medical simulation is a new application area for pseudo-haptic feedback. Bibin et al. [147] introduced a medical simulator called SAILOR for training for Loco-Regional Anaesthesia in a virtual environment. They introduced pseudo-haptic feedback to give the touch sensation of the contour of the organs beneath the skin. They used the algorithm described in [184] to change the speed of the cursor as function of the height of the picture pixel. They also modified the size of the cursor as in [181] to improve the pseudo-haptic sensation.

Most of the current pseudo-haptic feedback techniques are applied to express 1D [180], [189] or 2D haptic information [148], [181]. Pseudo-haptic feedback also has the potential to convey 3D haptic information.

4.4.3.2. Concept of 2D pseudo-haptic tissue stiffness simulation

There are two types of non-prehensile relative motion between the rigid tool tip and the soft tissue: sliding and indenting. For superficial sliding, the indenter slides over the soft object surface to experience the soft object stiffness change. When the indenter is approaching a tumour, tangent force f_x increases (see Figure 4-17). For indenting behaviour, the tool is used to press on the soft object surface to feel stiffness of the soft object. Reflected force f_y increases as indentation depth increases (see Figure 4-17). When the areas with hard inclusions underneath are pressed, reflected forces will be bigger than when pressing other areas. In this study, the tangent reaction force of sliding behaviour and the normal reaction force of indenting behaviour were simulated first separately in 2D pseudo-haptic soft tissue stiffness simulation and then simultaneously in 3D pseudo-haptic soft tissue stiffness simulation.

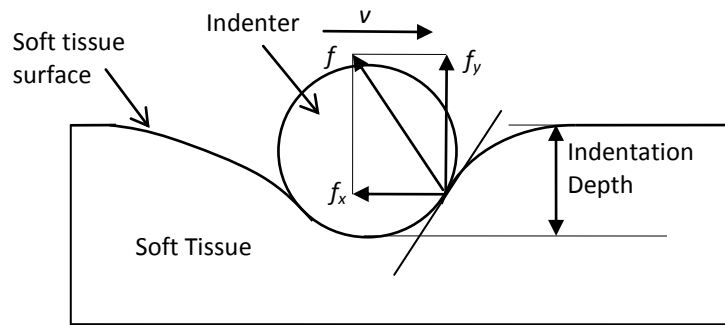


Figure 4-17 Reflecting forces in rigid tool-soft object interaction.

The differences between the conventional haptic feedback method and the pseudo-haptic feedback method proposed are described as follows:

In conventional haptic feedback methods, impedance based haptic devices are used. These sense the displacement of the haptic mechanism (position/velocity) as input and react with force as output. Hand motion (D) is the input as shown in Figure 4-18. When the user manipulates the haptic device, the device tracks the position of the end-effector and conveys its tip position to the computer. When contact between the avatar and the soft tissue takes place, the torque commands to the actuators on the haptic interface are calculated by the computer using the models of virtual objects in real

time. Thus appropriate feedback reaction forces are applied on the user's hand, leading to haptic perception of virtual objects.

In terms of using pseudo-haptic feedback, a motion tracking device is used as the input device. The relationship between the input device movement and the movement of the slave indenter avatar is introduced. The avatar display ratio is the relationship between the indenter avatar displacement distance (d) and the input device displacement distance (D) ($R = d/D$). Therefore, the movement speed of the indenter avatar can be reduced by changing the avatar display ratio when it is approaching a hard inclusion. The user can experience a corresponding resistance when the speed of indenter avatar is slower. If the user moves the input device towards a relative hard area over a certain distance (D), the indenter avatar display ratio will be modified to be smaller than the original ratio ($R_m < R_o$, R_m is the modified ratio and R_o is the original ratio), thus the modified avatar displacement distance d_m will be smaller than the original indenter avatar displacement distance d_o ($d_m = R_m \cdot D$, $d_o = R_o \cdot D$), and a resistance to motion will be experienced compared to the originally applied avatar display ratio. Thus, virtual forces (VF) are perceived through visual perception along the movement direction. The indenter avatar will move faster when moving away from the hard area.

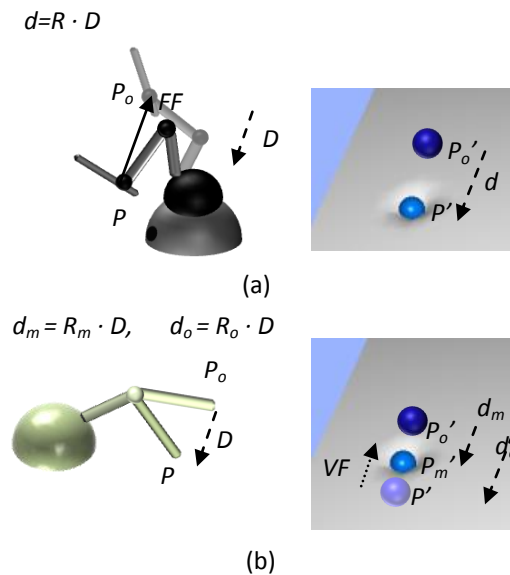


Figure 4-18 Conventional haptic feedback method (a): the input displacement distance D ; the avatar display distance d ; FF is the force feedback exerted on the

hand; Pseudo-haptic feedback using a 3-DOF motion tracking device (b): the avatar display distance d_m ; VF is the virtual force generated by using pseudo-haptic feedback algorithm.

In this study, the tangent reaction force of sliding behaviour and normal reaction force of indenting behaviour were simulated separately using a 2-DOF input device – a computer mouse. Figure 4-19 illustrates the tangent virtual force of the sliding behaviour pseudo-haptic simulation. The rectangle represents a tissue surface viewed from the top. A round cursor was controlled by a computer mouse to explore the tissue surface. A virtual resistance occurred when the cursor moved less while the mouse displacement remained the same. Figure 4-20 illustrates the normal virtual force of the indenting behaviour. The rectangle represents the cross section of a soft organ. When the cursor moved downwards, the tissue surface was deformed. A virtual upwards resistance occurred when the tissue surface deformed less while the mouse displacement remained the same. To press the cursor down to the same indentation depth, the user's hand needed to move a longer distance manipulating the computer mouse at stiffer tissue locations than at softer locations to create a feeling that extra efforts are needed to “palpate” on stiffer tissue locations.

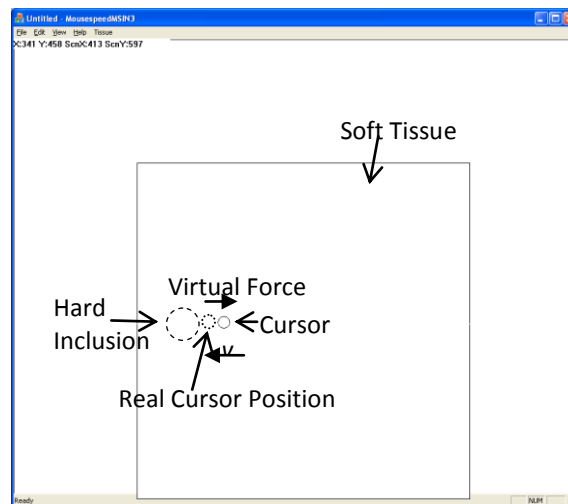


Figure 4-19 Tangent virtual force of the sliding behaviour palpation on soft tissue pseudo-haptic simulation.

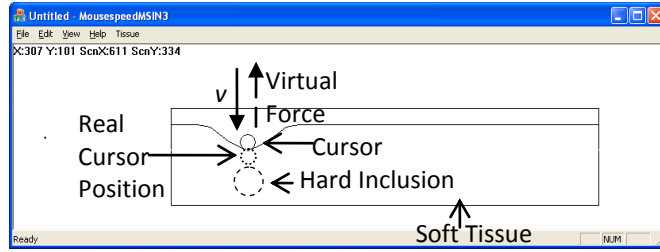


Figure 4-20 Normal virtual force of the indenting behaviour.

4.4.3.3. Basic strategy of simulation of sliding behaviour

- Mouse cursor speed changing strategy

The pseudo-haptic simulation of sliding behaviour was 2D, where the tangent reaction force during palpation was simulated. To simplify the calculation of the program, stiffness data was linearly mapped to integer numbers between 1 (stiffest) and 20 (softest) and were stored in a 2D array. In sliding behaviour pseudo-haptic simulation, when a mouse-movement event was triggered, the current cursor position and last cursor position were obtained and corresponding stiffness levels (Crt and Lst) were read from the 2D stiffness level array. The mouse movement speed was mapped to the difference value (Ds) between the current stiffness level (Crt) and the last stiffness level (Lst) (Figure 4-21), with the input device – computer mouse movement speed parameter varying ranging from 1 (slowest) to 20 (fastest) with a default value of 10. This mapping relationship was used instead of linear mapping to augment the difference in mouse speeds between the stiff areas and soft areas. SystemParametersInfo (Windows API Function) was used to set the mouse speed according to the mapping relation between stiffness level difference (Ds) and mouse movement speed parameter ($aMouseInfo$).

$$Ds = Crt - Lst \quad (4.1)$$

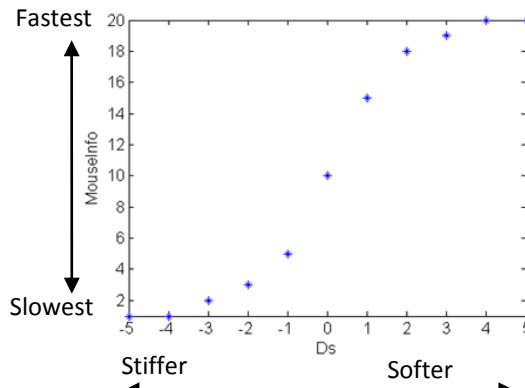


Figure 4-21 Mapping relation between stiffness data difference (D_s) and mouse movement speed parameter ($aMouseInfo$).

4.4.3.4. Auxiliary strategies of simulation of sliding behaviour

- Mouse cursor size changing strategy
- Flashing cursor strategy
- Shaking background strategy

Auxiliary strategies were proposed to strengthen perception for superficial palpation simulation, which can be used as a teacher signal during medical training. Employing the mouse cursor size changing strategy, the mouse cursor radius (r) changed from 1 to 20 pixels as a function of stiffness level difference (D_s):

$$r = r_0 - k \cdot D_s \quad (4.2)$$

Here, $r_0 = 1$ and $k = 1$. A flashing cursor was used in flashing cursor strategy, and when the stiffness change exceeded a predetermined threshold of stiffness level difference (D_{s0}), the cursor started flashing. For shaking background strategy, the window shook when the D_{s0} became larger than the threshold. Shaking background simulated vibration sensory stimuli without vibration actuators. In flashing cursor strategy and shaking background strategy, the threshold stiffness level stiffness D_{s0} was -3.

4.4.3.5. Simulation of indenting palpation behaviour

The indenting behaviour pseudo-haptic simulation where the normal reaction force was simulated was 1D. When soft object areas with a high stiffness were encountered, the cursor speed decreased and the maximum-achievable indentation depth became smaller. The phantom soft object cross section was a white rectangular 2D area of 540×100 pixels. In this test, parameter k in equation (4.4) was 1. The mouse

movement speed parameter ($aMouseInfo$) and maximum indentation depth (Md_{in}) setting were according to current soft object stiffness level (Crt):

$$aMouseInfo = Crt, \quad (4.3)$$

$$Md_{in} = Md_{in0} - k \cdot Crt. \quad (4.4)$$

4.4.4. Combined pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation

Tissue stiffness can be estimated via visual feedback of the tissue deformation when the applied force is controlled. As described in the previous section, tissue surface deformation was not displayed in this 2D pseudo-haptic soft tissue stiffness simulation. To provide to the user a more realistic feedback of the tissue behaviour during palpation, visual feedback of tissue surface deformation is needed. Ridzuan et al. [190] proposed to convey stiffness information of soft objects by changing the visual deformation depth of the virtual object on a force-sensitive tablet in accordance with the pressing force and the stiffness property of the soft objects. Their method can produce a stiffness sensation similar to the one perceived from real soft objects. During their experiments, homogeneous stiffness property was assigned to each virtual sample and only vertical interaction (indentation behaviour) with the virtual object was enabled. Non-homogeneous stiffness property of soft tissue can be expressed and both the indentation behaviour and sliding behaviour of palpation can be simulated by integrating the sliding behaviour simulated by pseudo-haptic feedback-simulated sliding behaviour (described in Section 4.4.3) with visualization of soft tissue deformation (see Figure 4-22). Moreover, it would be interesting to examine the role of visualization of tissue surface deformation and of sliding resistance simulated by pseudo-haptic feedback in tumour identification: determining which one of these plays a more important role in tumour identification may provide guidelines for the further development of palpation simulators. In this section, the investigation process of the role of visualization of tissue surface deformation and pseudo-haptic feedback in tumour identification is presented.

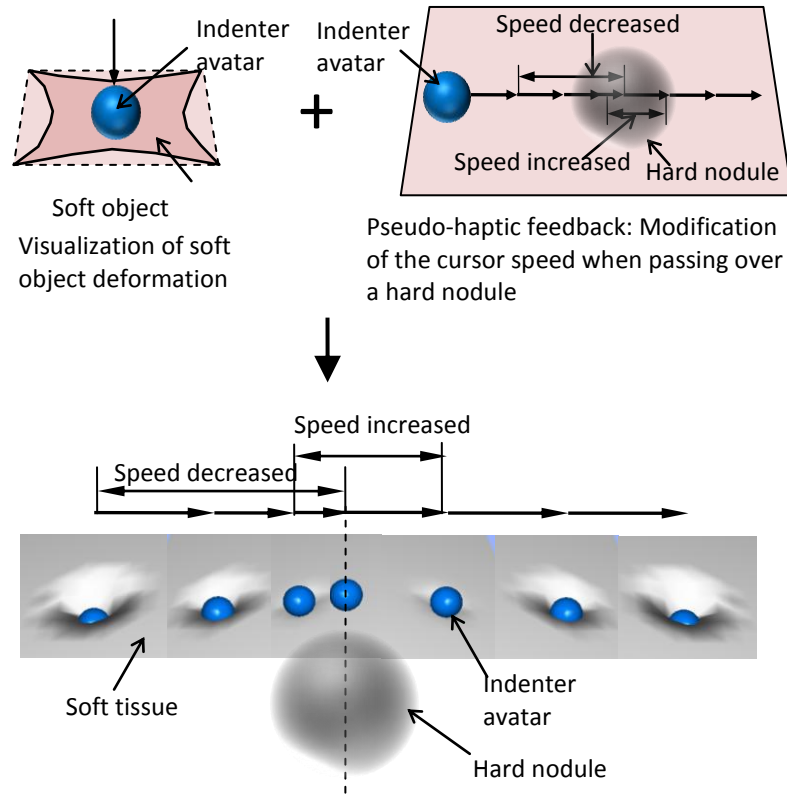


Figure 4-22 Combined pseudo-haptic feedback and visualization of tissue surface deformation.

As was the case in 2D pseudo-haptic soft tissue stiffness simulation described in Section 4.4.3, a computer mouse was used as an input device here. A virtual model of a tissue block with a flat surface was displayed on a graphical interface with an angle of 45° towards the user. The coordinates of the window were linearly mapped to the tissue surface. When the computer mouse moved on the window, the mouse cursor was set to be a blue sphere of 8 mm in diameter and was moving on the displayed tissue surface. When the cursor was sliding on the tissue area where the stiffness value was higher than the surrounding tissues, the indentation depth and a smaller tissue surface deformation was displayed since the indentation force was assumed to be the same during the palpation process. Stiffness data of the soft tissue was linearly mapped to indentation depths between 0.1 and 9 mm. Tissue surface deformation was displayed according to the indentation depth values and the method described in Section 4.4.1.

Although the concept was the same, the cursor speed changing algorithm was slightly different from the one described in the last section. When the mouse moved, a mouse-movement event was triggered; the current cursor position and last cursor position were then obtained and corresponding stiffness levels (Crt and Lst) were read from the two-dimensional stiffness level array. The current movement speed parameter ($oMouseInfo$) was read from the computer operation system. `SystemParametersInfo` (Windows API Function) was used to set the mouse speed ($aMouseInfo$) according to the algorithm described in Table 4-4 and the stiffness level difference (Ds , equation 4.1).

Table 4-4 Algorithm of the pseudo-haptic feedback using a computer mouse input device

Condition	Equation for Displacement Distance
<i>Tissue stiffness in current position is the same as the tissue in the previous position</i>	$aMouseInfo = oMouseInfo$
<i>Tissue stiffness in current position is stiffer than the tissue in the previous position</i>	$aMouseInfo = oMouseInfo \times (1.1 - Crt) / (1 + Ds)$
<i>Tissue in current position has the same stiffness or softer than in the previous position</i>	$aMouseInfo = oMouseInfo / (1.1 - Ds)$

4.4.5. Novel 3D Pseudo-haptic tissue stiffness simulation

In the proposed 3D pseudo-haptic soft object stiffness simulation, tangent reaction force of sliding behaviour and normal reaction force of indenting behaviour were simulated simultaneously. Figure 4-23 presents the concept of the modification of the indenter avatar speed to simulate the normal reaction force of indenting behaviour and the tangent reaction force of sliding behaviour when impacting in the neighbourhood of a hard nodule during palpation. For a 3D haptic simulation, a 3-DOF motion input device is needed. One drawback of the current commonly used haptic devices, such as PHANToM Omni, Desktop and Premium, the Delta, Omega and Sigma haptic systems from Force Dimension Inc., and multi-fingered Haptic Interface Robot (HIRO) devices, is their relatively high cost [98]. Moreover, those bulky devices need to be connected to a power supply when they are in use. In recent years, the new pressure sensitive technology has improved the touch experience of users on

touchpads and laptops. The system can produce a reaction corresponding to the force level the user applies on the surface. Compared to the aforementioned haptic devices, pressure-sensitive touchpad and tablet computers are smaller, lighter (less than 1 kg in weight), less complex in structure, cheaper, and portable. Therefore, 3D haptic information was conveyed using a force-sensitive touchpad or a tablet computer combined with the pseudo-haptic feedback technique.

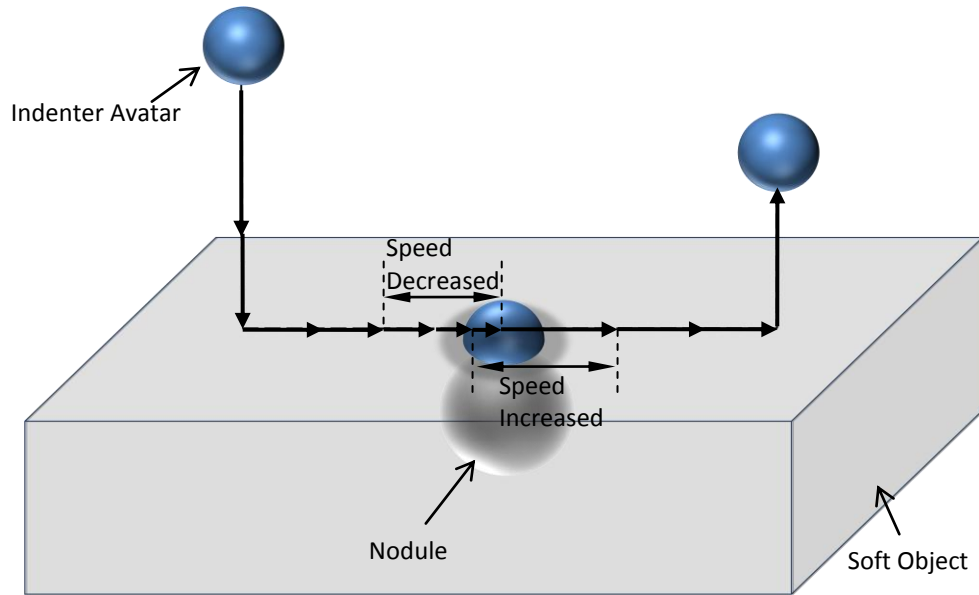


Figure 4-23 Modification of the indenter avatar speed when passing over a hard nodule.

4.4.5.1. Using a 3-DOF stylus motion tracking input device

The schematic diagram of the pseudo-haptic soft object stiffness simulation using a 3-DOF stylus motion tracking input device is shown in Figure 4-24. The hand motion was the input. The device tracked the position of the end-effector when the user manipulated and conveyed its tip position to the computer. When the contact between the avatar of the input device tip and the soft object took place, the virtual resistance along the movement direction was generated by using pseudo-haptic feedback and the soft object displacement was shown on the graphical interface. The stiffness value and 3-DOF stylus movement were processed in the pseudo-haptic feedback algorithm described in the next paragraph and generated the indenter avatar movement modification. The tissue curvature was calculated based on the indentation depth and the model of soft object surface displacement curvature.

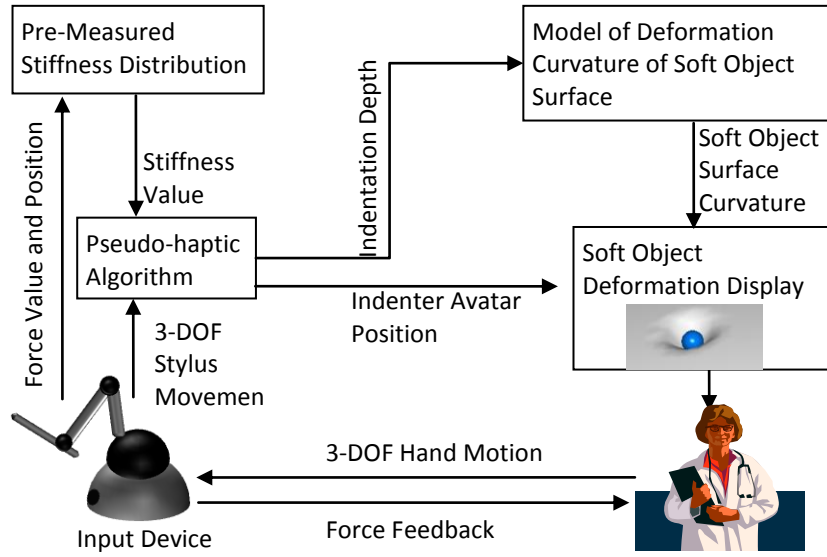


Figure 4-24 Schematic diagram of the pseudo-haptic soft object stiffness simulation using a 3-DOF stylus motion tracking input device

Using a 3-DOF stylus motion tracking device as an input device, the ratio between the normal and horizontal indenter avatar displacement distance and the input device displacement distance (R_n and R_h) were defined in equation (4.5), (4.6), and (4.7). Reaction force values (f_n and f_h) were acquired from the reaction force matrices in rolling indentation. The corresponding indentation depth was used as the maximum indentation depth during palpation. The indenter avatar displacement distance was modified according to the rules in Table 4-5.

$$R_n = R_o / (f_n + 1), \quad (4.5)$$

$$R_h = R_o / (\Delta f_h + 1), \quad (4.6)$$

$$\Delta f_h = f_h - f_{hl}. \quad (4.7)$$

where f_n is the normal reaction force value; f_h is the horizontal reaction force value at the current indenter avatar position; f_{hl} is the horizontal reaction force value at the last indenter avatar position; R_o is the original ratio between the indenter avatar displacement distance and the input device displacement distance (indenter avatar display ratio); R_n is the modified indenter avatar normal display ratio; R_h is the modified indenter avatar horizontal display ratio.

Table 4-5 Algorithm of the 3D pseudo-haptic feedback using a 3-DOF motion tracking input device

Condition	Equation for Displacement Distance
<i>Indentation depth is increasing</i>	$d_m(z) = R_n \cdot D(z)$
<i>Indentation depth is decreasing</i>	$d_m(z) = R_o \cdot D(z)$
<i>Tissue stiffness in current position is stiffer than the tissue in the previous position</i>	$d_m(x, y) = R_h \cdot D(x, y)$
<i>Tissue in current position has the same stiffness or softer than in the previous position</i>	$d_m(x, y) = R_o \cdot D(x, y)$

4.4.5.2. Using a pressure-sensitive touchpad motion input device

Here it will be shown how 3D haptic information was conveyed using a force-sensitive Wacom BAMBOO Pen & Touch touchpad (a 2D haptic input device, 248×176×8.5 mm in dimension, 125×85 mm for touch sensitivity, 360 g weight) and the proposed pseudo-haptic feedback technique.

The schematic diagram of the pseudo-haptic soft object stiffness simulation using a pressure-sensitive touchpad motion input device is shown in Figure 4-25. During the simulation process, the user held a special pen to provide horizontal movement and normal force on the force-sensitive touchpad. The normal force exerted on the touchpad and the 2-DOF movement of the pen tip on the touchpad were the two inputs. The outputs were the normal reaction force from the touchpad, the virtual resistance along the movement direction generated by using pseudo-haptic feedback, and the soft object deformation shown on the graphical interface. The force level extracted from the device was translated to a force value. Then, a stiffness value and an indentation depth were obtained from the measured stiffness distribution according to the force value and the position information. The stiffness value and horizontal movement of the contact point were processed in pseudo-haptic feedback algorithm and generated the indenter avatar movement modification. The soft tissue deformation was calculated based on the indentation depth, the model of soft object surface deformation curvature, and the avatar movement modification. Finally, the soft object deformation was displayed graphically.

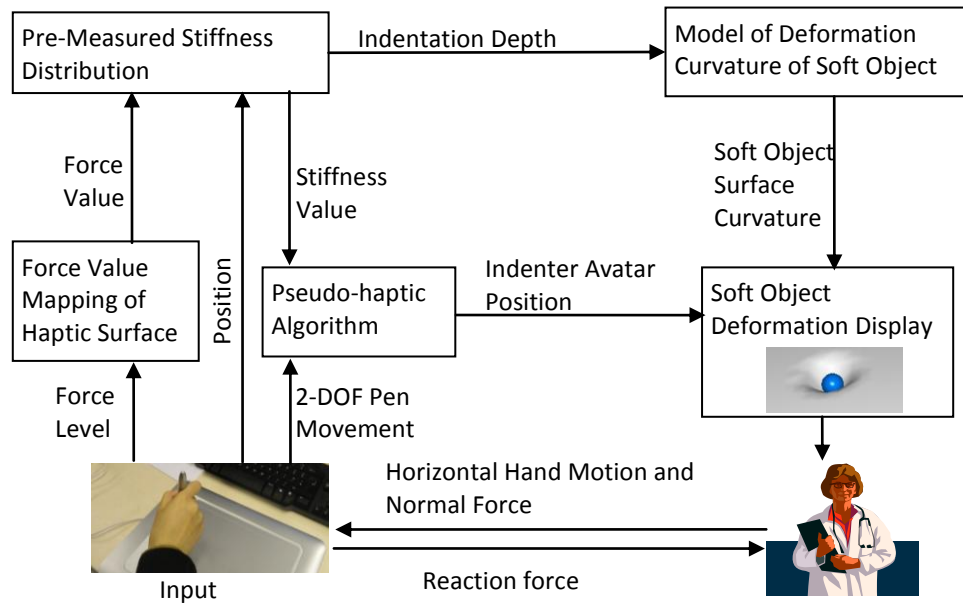


Figure 4-25 Schematic diagram of the pseudo-haptic palpation simulation using a pressure-sensitive touchpad motion input device.

Using a pressure-sensitive touchpad and a special pen as an input device, the return value from the touchpad is force level. It needs to be mapped with force magnitude. An F/T sensor ATI Mini 40 was placed under the touchpad to record the force applied and map the force levels to force values. The touchpad had 1024 force levels. During the experiment, the pen was used to apply normal forces to the touchpad from 0 to a maximum force level 1024. Force levels and force values were recorded. This experiment was repeated four times. 57 sets of data points were obtained. The least square method was used to get the regression equation described in equation (4.8) ($R^2 = 0.9703$, see Figure 4-26).

$$f_n = 0.0827e^{0.0039f_i}, \quad (4.8)$$

where f_n is normal reaction force value acquired from the reaction force matrices in sliding indentation [85]; f_i is the force level read from the touchpad data package.

The coordinates of the touchpad surface were linearly mapped to the soft object surface. The force levels (f_i) read from the touchpad data package were converted to the normal force values (f_n) according to the equation (1) first. The position of the interaction on the surface of the soft object was calculated based on the mapping relationship between the touchpad surface and the soft object surface. Then the indentation depth $d_m(z)$ was calculated as a function of the pressure applied to the

touchpad (f_n) employing a lookup table of force matrices linearly interpolated between stored values.

The tangent reaction force f_t was acquired via the lookup table of force matrices according to the indentation depth $d_m(z)$. Then, the difference of the tangent reaction forces (Δf_t) between the current avatar position and the last avatar position was calculated as:

$$\Delta f_t = f_t - f_{tl}, \quad (4.9)$$

where f_{tl} is the tangent reaction force value at the current avatar position; f_{tl} is the tangent reaction force value at the last avatar position.

When the soft object stiffness in current position was stiffer than the tissue in the previous position ($\Delta f_t > 0$), the movement distance was reduced:

$$d_m(x, y) = R_{mt} \cdot D(x, y), \quad (4.10)$$

$$R_{mh} = R_o / (\Delta f_h + 1), \quad (4.11)$$

where R_o is the original default ratio between the avatar displacement and the input device displacement (avatar display ratio) calculated based on the coordinates mapping relationship between the touchpad surface and the soft object surface; and R_{mt} is the modified avatar tangent display ratio.

When the soft object in current position had the same stiffness or was softer than in the previous position ($\Delta f_t \leq 0$), the position of the indenter avatar was calculated based on the coordinates mapping relationship between the touchpad surface and the soft object surface.

In 3-DOF pseudo-haptic soft object stiffness simulation, deformation of the virtual soft object during indentation was displayed in real time using a geometrical deformable soft object model, which was established based on predefined finite element modelling considering the influence of the indenter diameter. The detail of this model was presented in Section 4.4.1. When a node of the mesh was pressed by the indenter, the normal vertex of this node was redefined according to the depth of the indenter. At the same time, the normal vertices of other nodes nearby on the mesh were affected by the indentation and were adapted according to the geometrical model

to display the tissue displacement. When the indentation depth increased, the number of the affected nodes increased.

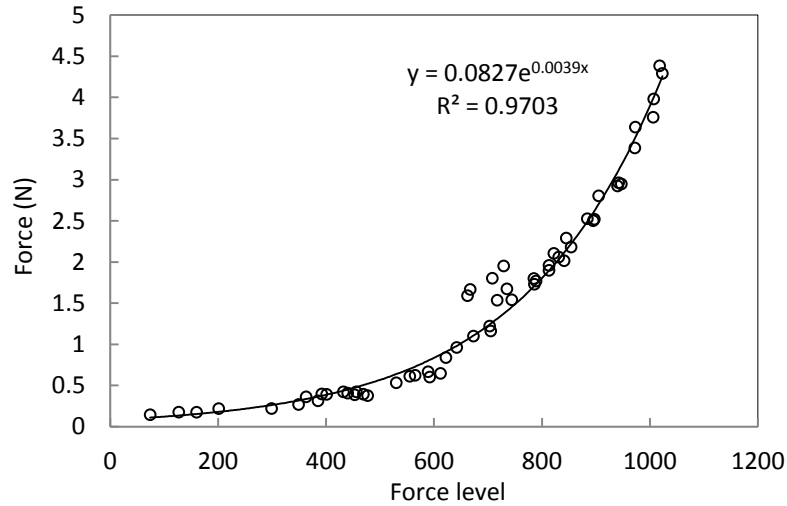


Figure 4-26 Force levels and force value mapping.

4.4.5.3. Using tablet computers

Using a touchpad as an input device, visual and haptic information was presented at different points of interaction – the contact force was exerted from the touchpad via the special pen while the visual information was displayed on a computer screen. To improve the effectiveness of object stiffness identification, haptic and visual information should be presented at the same active point of interaction. Utilizing a tablet computer made the user feel as though the finger or the stylus could penetrate the surface and be extended into the digital world to manipulate virtual tissue behind the screens directly. This was called direct touch and immersive illusion in [190], [191].

Two types of tablet computer were used: Samsung Galaxy Note 10.1 (using an S-pen) and Motorola Xoom (using the user's bare finger) (see Figure 4-27). The Samsung Note used here had a dimension of 262×180×8.9 mm and a weight of 600 g while the Motorola used here was 249×167.8 ×12.9 mm and 730 g. As was the case when using the touchpad, tangent movement and normal force were applied on the force-sensitive tablet by the user holding the pen or using one index finger. The normal force exerted on the tablet and the 2-DOF movement of the pen tip or the fingertip on the tablet were the two inputs. The outputs were the normal reaction force from the tablet, the

virtual resistance along the movement direction generated by using pseudo-haptic feedback, and the soft object deformation shown on the graphical interface. The Samsung Note (using a Wacom S-pen) used here was force-sensitive and had 1024 level of pressure sensitivity. The other tablet computer used in this study – Motorola Xoom – sensed the area of touch to calculate contact force. When the touch area was broader, it recognized the applied force as higher. The force level was mapped with force magnitude by using the same experiment method described in Section 4.4.5.2. The force level and force value relationship was described in equation (4.12) (4.13) (see Figure 4-28), according to which the force levels (f_l) read were converted to the normal force values (f_n) first. Then the indentation depth $d_m(z)$ was calculated as a function of the pressure applied to the tablet (f_n) employing a lookup table of force matrices linearly interpolated between stored values,

$$f_n = 0.1008e^{4.2081f_l}, \quad (4.12)$$

$$f_n = 0.0772e^{3.0727f_l}, \quad (4.13)$$

where f_l is the force level read by using `getPressure()` method in Android SDK; f_n is the corresponding normal force.

The modification of the avatar display ratio R was realized by adding a delay time for the indenter avatar displaying task when the indenter moved towards an area with a higher stiffness. If the indenter has passed over the stiffer area and the delay time has expired, the indenter avatar will continue to follow the interaction point. The delay time was determined by

$$t_d = \Delta f_t \cdot m, \quad (4.14)$$

$$\Delta f_t = f_t - f_{tl}, \quad (4.15)$$

where f_t is tangent reaction force acquired from the reaction force matrices in rolling indentation; f_{tl} is the tangent reaction force value at the last avatar position; Δf_t is the reaction force difference, m is a scalar value. Here, m was set to be 500. The calculated delay time was then added to the program frame interval time.

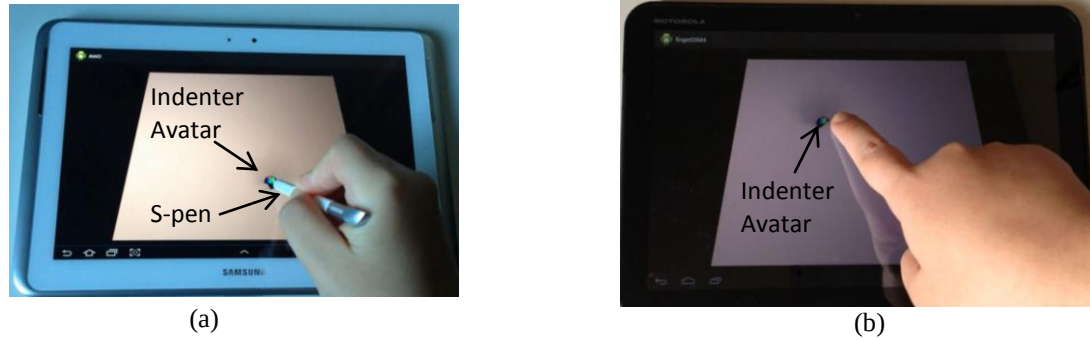


Figure 4-27 Pseudo-haptic soft object stiffness simulation using tablet computers: (a) Samsung Galaxy Note 10.1 (using an S-pen) and (b) Motorola Xoom (using a bare finger of the user).

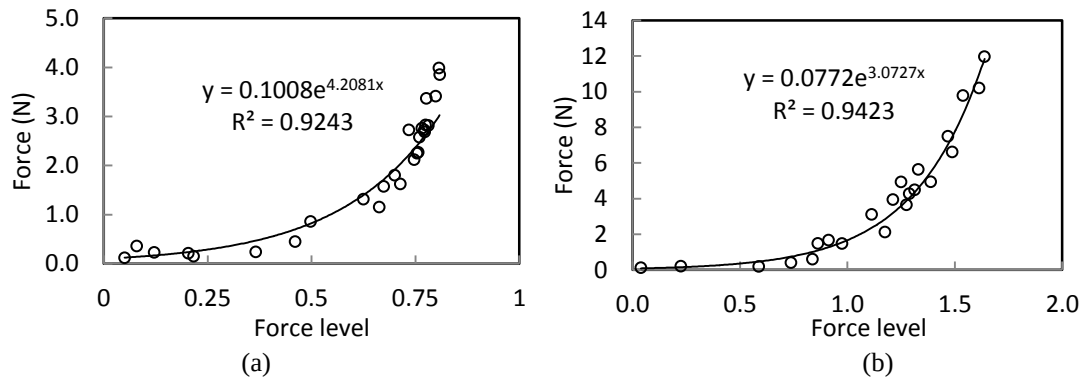


Figure 4-28 Force level and force value mapping of (a) the Samsung Note tablet (using an S-pen) and (b) the Motorola Xoom tablet (using a bare finger of the user).

4.4.6. Combined pseudo-haptic and force feedback

Hachisu et al. has successfully combined pseudo-haptic feedback with tactile vibrations and visual jitters and they claim that the combination of the two different modalities (tactile and visual) strengthened the perception [148]. Some theoretical research has been conducted to investigate the domination of the visual over the haptic modality [192]–[194]. Haptically guided reproduction of mouse movement was observed to be distorted by visual distortion using a cursor [194]. It has been shown that humans integrate visual and haptic information in a statistically optimal fashion that is similar to a maximum-likelihood integrator [192]. Some research has been done on the preference between the two feedback cues. However, the benefits of a

pseudo-haptic and force feedback combination in the context of haptic perception of rigid tool / soft object interaction were studied previously.

Since the two mechanisms, namely the pseudo-haptic feedback and force feedback, are different, they can be easily combined and will not adversely affect each other [148]. Force feedback was fed to the hand of the user through a haptic device, while the pseudo-haptic feedback information was fed through a graphical interface (see Figure 4-29). Therefore, the force perception of the user was expected to result from a combination of sensations based on the proprioceptive and visual sensors of the subject.

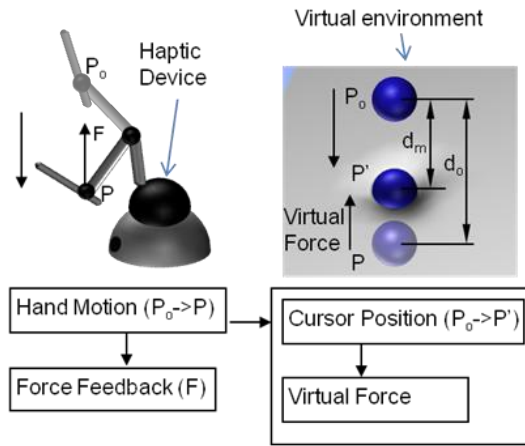


Figure 4-29 Combined pseudo-haptic and force feedback: the left panel is a haptic device, whose stylus is moved from P_0 to P , and the right panel is a virtual environment, in which cursor is supposed to move from P_0 to P but actually moved to P' to create a virtual force.

4.5. Evaluation tests of the proposed palpation feedback modalities

4.5.1. Tissue deformation display test

The tissue deformation display method was tested to validate its feasibility when uneven tissue surfaces are present. Two tissue surfaces were used. They were acquired from the tissue contour scan using a motion tracking device and 3D reconstruction using a Kinect sensor (see Section 4.3.1). The tissue deformation

visualization was tested employing a 2.8 GHz Pentium (R) D computer which had a 3.5 GB RAM in the MS VC++ 2005 programming environment. The indenter avatar was set to move following the stylus of the PHANToM Omni to contact the tissue surface and cause deformation. During the process, screen shot pictures were recorded.

4.5.2. Test protocol of human subject palpation experiment on tissue model using force feedback

An empirical study on the effectiveness of the proposed palpation method was carried out on a phantom tissue with a curved surface (Phantom tissue II). Twenty participants were involved in the palpation test. The details of the participants were presented in Table 4-6.

Table 4-6 Overview of demographics and experience of participants in evaluation tests for palpation on tissue model using force feedback

Item	Detail
<i>Age range</i>	19-42
<i>Average age</i>	29.6
<i>Gender</i>	♀: 5; ♂: 15
<i>Handedness</i>	R: 19; L: 1
<i>Palpation experience</i>	1
<i>Engineering background</i>	19
<i>VR simulator</i>	0

Two tests were conducted: manual palpation employing a silicone block with embedded nodules and haptic palpation with force feedback using the soft tissue model based on the surface reconstruction and the stiffness distribution results (described in Section 4.3). To avoid learning effect which might have biased the results in favour of the last test, the order of the two tests was balanced during the experiment. Before the manual palpation experiment, participants were asked to do a practice trial run palpating a transparent silicone phantom tissue with and without nodules inside. During the manual palpation experiment, participants were asked to manually palpate the silicone phantom tissue which was covered by a purple cloth hiding hard nodules buried inside the silicone phantom. The task of this experiment

was to find the location of the buried nodules employing the haptic feedback and visual tissue deformation. Before the haptic palpation test, participants were asked to do a practice run with hard nodules that were visible. During the haptic palpation experiment, participants were asked to palpate the virtual tissue with no hidden nodules and to pinpoint the nodule positions found.

4.5.3. Test protocol of 2D pseudo-haptic simulation of sliding palpation behaviour

Pseudo-haptic tissue stiffness simulation was evaluated for tissue abnormality localization using a three-button infra-red mouse. The phantom tissue was represented using a white and rectangular 2D surface of 540×544 pixels, displayed on a monoscopic computer screen. One square millimetre of soft tissue was represented by 4×4 pixels. In order to evaluate the different strategies, six tests were conducted. Test 1 was only the basic strategy. In test 2 to test 6, there was a combination of the auxiliary strategies and the basic strategy.

Test 1: Cursor speed changing strategy;

Test 2: Combination of cursor size changing and speed changing strategy;

Test 3: Combination of flashing cursor and speed changing strategies;

Test 4: Combination of flashing cursor strategy, speed and size changing strategies;

Test 5: Combination of shaking background and cursor speed changing strategy;

Test 6: Combination of shaking background, cursor speed, and cursor size changing strategy

Participants were asked to conduct the tests of the study pseudo-randomly. The test protocol of each test was explained to the participants and they were asked to scan the tissue surface with the mouse, and to record coordinates of any located tumours.

4.5.4. Test protocol of 2D pseudo-haptic simulation of indenting palpation behaviour

Participants were asked to scan the tissue surface with the superficial palpation method based on the cursor speed changing strategy. Once an area of potential abnormality was identified, they were asked to right-click the mouse, and then to use the deep palpation method to further explore the cross section in the vicinity of the identified abnormality (Parallel to the x -axis). They were asked to record the identified tumour coordinates.

Fourteen participants consisting of 11 men and 3 women, with normal or corrected vision, participated in both the evaluation studies of the simulation of sliding palpation behaviour and of the indenting palpation behaviour. The details of the participants were presented in Table 4-7.

Table 4-7 Overview of demographics and experience of the participants in the evaluation tests for 2D pseudo-haptic soft tissue stiffness simulation

Item	Detail
<i>Age range</i>	21-32
<i>Average age</i>	27.1
<i>Gender</i>	♀: 3; ♂: 11
<i>Handedness</i>	R: 14; L: 0
<i>Palpation experience</i>	0
<i>Engineering background</i>	12

4.5.5. Test protocol for combined pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation

Three types of feedback were investigated, namely visual feedback of tissue surface deformation only, pseudo-haptic feedback only, and the combination of the two. Cursor speed changing strategy was applied in pseudo-haptic feedback. The stiffness information of hard inclusions A1, B1, and C1 in Phantom tissue III was extracted and used here (see Figure 4-30). The stiffness map was normalized to be in the range

of 0 – 1.0. On each side, there were two types of status – a hard inclusion (A1, B1, or C1 from Phantom tissue III) or no hard inclusion buried inside (see Figure 4-31). The tissue surface was divided into left part and right part (see Figure 4-32). Thirteen groups of stiffness distribution information were used. The participants were asked to explore the virtual tissue surface and figure out whether there was a tumour underneath on each side.

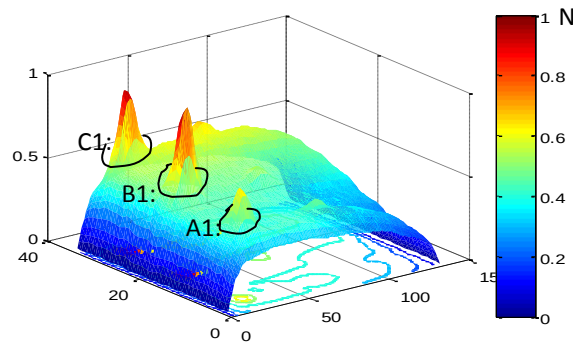


Figure 4-30 Stiffness map of the silicone phantom tissue III.

Fourteen participants were involved in the trials: 1 woman and 13 men. The demographics of the involved participants are presented in Table 4-8. All the tests were performed in sequence but in random order by each participant. During the test a stopwatch was used in order to measure the time required by the participant to detect the nodules. The instrument allowed a precision of the time measurement of ± 1 s.

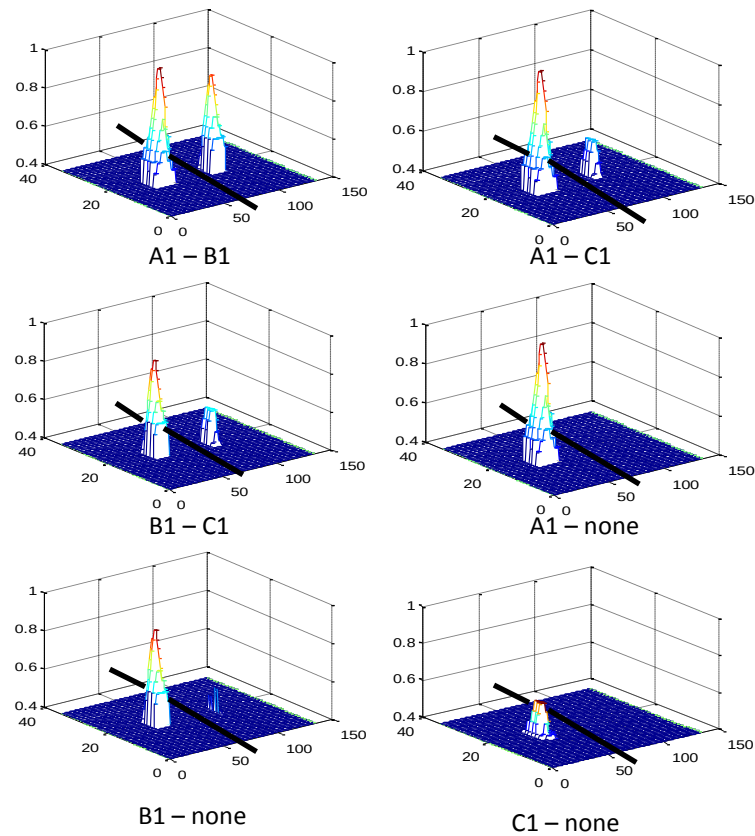


Figure 4-31 Stiffness distribution information used in the experiment of combined pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation: the surface is divided into left and right two parts; four types of status (A1, B1, C1 and none hard inclusion buried inside) are possible for each side; thirteen combinations of the two sides are used.

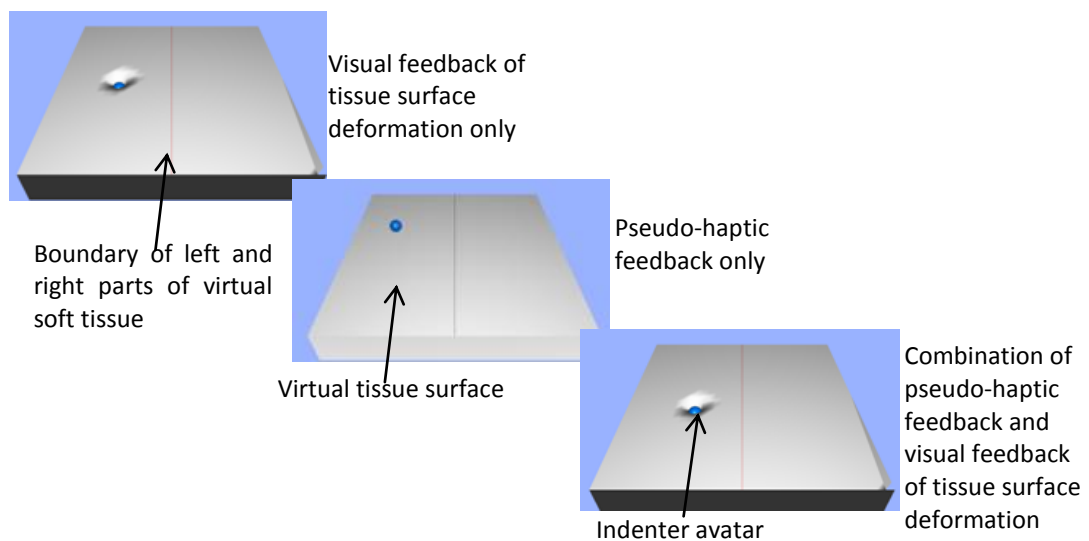


Figure 4-32 Evaluation tests for the combination of pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation.

Table 4-8 Overview of demographics and experience of the participants of the evaluation tests for the combination of pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation

Item	Detail
<i>Age range</i>	21-36
<i>Average age</i>	27.4
<i>Gender</i>	♀: 1; ♂: 13
<i>Handedness</i>	R: 14; L: 0
<i>Palpation experience</i>	0
<i>Engineering background</i>	14
<i>VR simulator</i>	0

4.5.6. Test protocol for 3D pseudo-haptic tissue stiffness simulation

In order to validate the pseudo-haptic soft object stiffness simulation, four tests were conducted using a 3-DOF stylus motion tracking device, force-sensitive 2-DOF haptic surfaces, including a touchpad, a tablet and S-pen input, a tablet and bare finger input. The phantom tissue sample used here was the same one as the Phantom tissue I. Two groups of participants, who had normal or corrected vision, participated in the empirical study (Pseudo-haptic feedback relies on visual display, so people with a vision disability cannot do the test). Group I: Twenty participants (nineteen right-handed, one left-handed, all had engineering background, one subject was a surgeon, and others had no palpation experience) conducted the tests of manual hard inclusions detection and the pseudo-haptic soft object stiffness simulation using a 3-DOF stylus motion tracking device and a force-sensitive touchpad. Group II: Twenty participants (all right-handed, with engineering background and no palpation experience) conducted the tests of manual hard inclusions detection and the pseudo-haptic soft object stiffness simulation using a tablet with an S-pen and a tablet with a bare finger input. During the two sets of tests, participants were first asked to do a practice run with known tumour locations. Then, participants were asked to manipulate the input device to palpate the virtual soft object and observe the change of the ratio between the indenter avatar displacement distance and the input device displacement distance. When they found hard inclusions, they told the researchers the locations. The

researchers recorded the nodule detection rates and time consumed. The order of tests within one group was pseudo-random. For all those tests, the same stiffness distribution was used, but the orientation of the soft object was different from test to test. So the participants would not know the nodules locations from the earlier tests. The details of the participants are presented in Table 4-9.

Table 4-9 Overview of demographics and experience of the Group I and Group II in the evaluation tests for 3D pseudo-haptic tissue stiffness simulation

Item	Group I	Group II
<i>Age range</i>	23-42	20-30
<i>Gender</i>	♀: 6; ♂: 14	♀: 7; ♂: 13
<i>Handedness</i>	R: 19; L: 1	R: 20; L: 0
<i>Palpation experience</i>	1	0
<i>Engineering background</i>	20	20
<i>VR simulator</i>	0	0

4.5.7. Test protocol for combined pseudo-haptic and force feedback

An experimental validation study aiming at assessing the benefits of the proposed method was performed with the aim to (a) define the efficiency of the proposed method, (b) explore the advantages or shortcomings of using a combined pseudo-haptic and force feedback method, (c) evaluate the feasibility of this method as a replacement for manual palpation.

Twenty participants were involved in the trials: 6 women and 14 men. The demographics of the involved participants were presented in Table 4-10. The following four tests were performed in sequence but in pseudo-random order by each participant. For each test, the same stiffness distribution was used, but the orientation of the silicone block or silicone block model was changed randomly from time to time. In this way, it was ensured that the participants did not know the locations of the nodules from the tests conducted earlier. The experimental setting is depicted in Figure 4-33. During the test a stopwatch was used in order to measure the time

required by the participant to detect the nodules. The instrument allowed a precision of the time measurement of ± 1 s.

Table 4-10 Overview of demographics and experience of the participants

Item	Detail
<i>Age range</i>	23-42
<i>Average age</i>	27.5
<i>Gender</i>	♀: 6; ♂: 14
<i>Handedness</i>	R: 19; L: 1
<i>Palpation experience</i>	1
<i>Engineering background</i>	19
<i>VR simulator</i>	0

Test 1: Manual Palpation

At first, participants were asked to do an acquaintance trial run by palpating the transparent silicone block containing or not containing visible hard inclusions. During the real tests, participants were asked to close their eyes and manually palpate the silicone block with hard nodules embedded at unknown locations. Then they were asked to determine at which locations they believed to have sensed hard nodules. The time needed for the detection was recorded until they thought they had found all the nodules.

Test 2: Pseudo-haptic feedback

Participants were again asked to do a practice run with visible hard nodule locations. Then, they were asked to palpate the virtual soft object with embedded hard nodules inside using only pseudo-haptic feedback, and to indicate the positions of the hard nodules they believed to have found. The time taken to detect all nodules was recorded.

Test 3: Force feedback

The procedure was the same as in Test 1 & 2. The participants were asked this time to perform palpation relying on force feedback only and then also asked to indicate the different positions where they believed to have found hard inclusions. Again, the time needed to detect nodules was recorded.

Test 4: Combination of pseudo-haptic feedback and force feedback

A practice run of the test was first conducted. Then, participants were asked to palpate the virtual soft object with embedded nodules by using the combined feedback and then asked to indicate the different positions where they believed to have found hard inclusions. The time needed to detect all nodules was recorded for each participant. Every participant was asked whether there was any difference in perception with combined feedback versus force feedback alone.

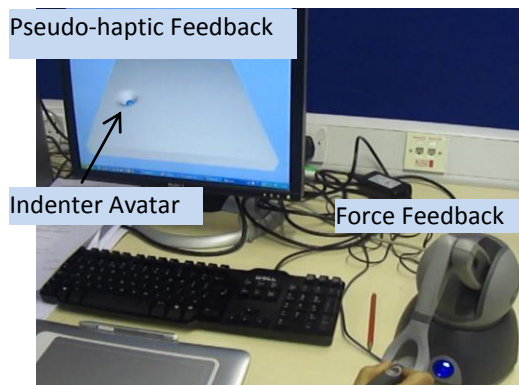


Figure 4-33 Experimental setting of the evaluation tests.

4.6. Test results of the proposed palpation feedback modalities

4.6.1. Results of tissue deformation display tests

The test result showed real-time tissue deformation on a visual display without any noticeable delay. Figure 4-34 presents the phantom tissue surface and the indentation deformation on the reconstructed surface.

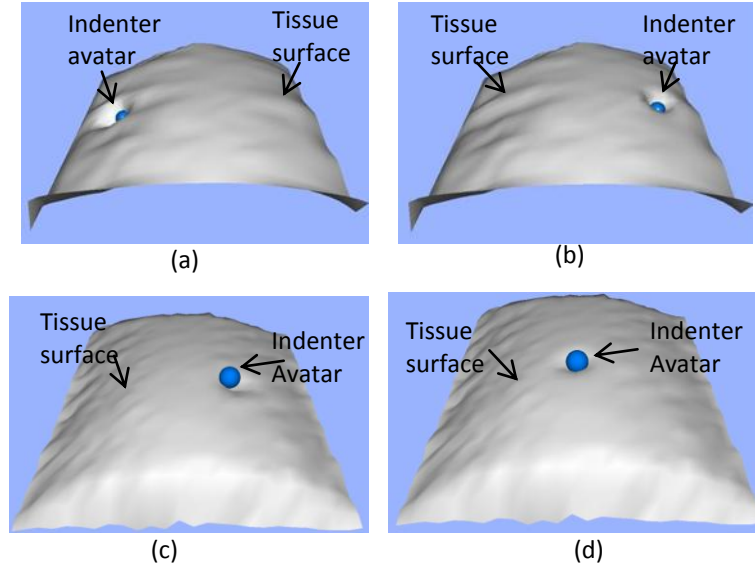


Figure 4-34 Tissue deformation result: (a), (b) from tissue contour scan using a motion tracking device; (c), (d) from 3D reconstruction using a Kinect sensor.

4.6.2. Results of palpation on tissue model using force feedback

During the palpation experiment, all participants found the two embedded nodules (Nodule A: 100%; Nodule B: 100%). It was noted that one participant wrongly identified two additional regions as tissue regions where nodules were buried (see the yellow circles in Figure 4-35). Haptic palpation and manual palpation produced comparable localization results. The average time of the manual palpation experiment was 29.15 s (Standard Error = 2.54 s) while the average time of the haptic palpation was 39.95 s (Standard Error = 4.18 s). A Wilcoxon signed-rank test was conducted to compare the consumed time of these two methods (for details of this method, see equation (3.7)). The significance level 0.05 was checked. No significant difference was found ($W = 46.5$, $W_{critical} = 46$). In this experiment, haptic palpation was as efficient as manual palpation.

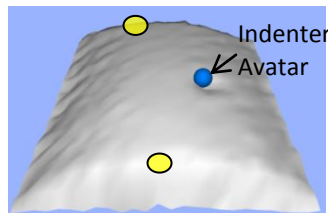


Figure 4-35 Wrongly recognized hard areas (marked by two yellow circles).

4.6.3. Results of pseudo-haptic simulation of sliding palpation behaviour

All participants identified tissue abnormalities in all tests. Figure 4-36 shows the rolling indentation stiffness map and possible stiff points recorded by participants: correctly recognized stiff points are represented by “•” and wrongly recognized stiff points are marked by “☆”. Most wrong points were within the stiffer area around tumours B1, B2, C1, and C2.

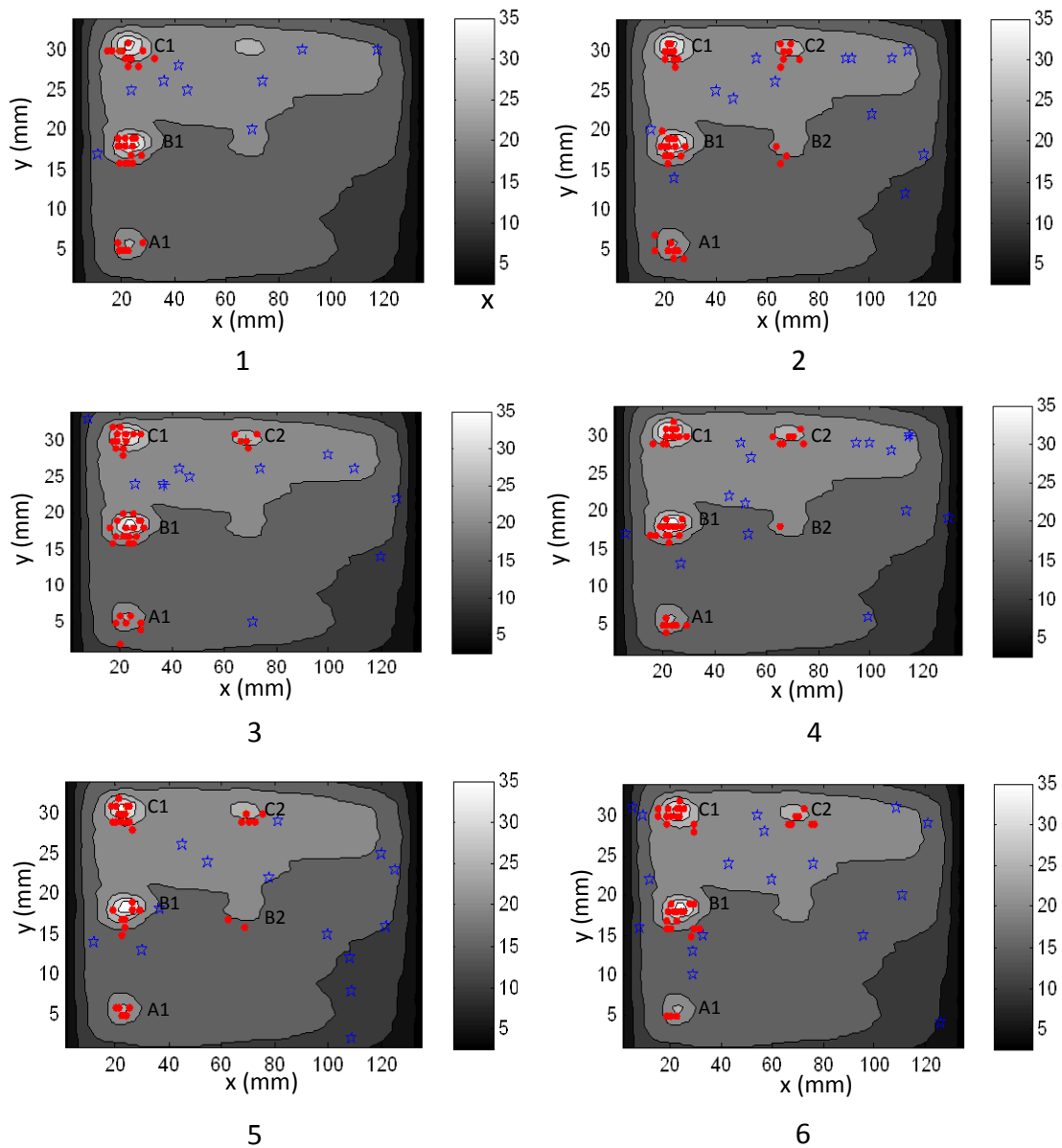


Figure 4-36 Recorded points of tissue abnormalities of each test in rolling indentation stiffness map by participants: correctly recognized points (•) and wrongly recognized points (☆)

Positive Predictive Value *PPV* [195], or precision rate, a measure of the performance of the diagnostic method, was defined as the sum of the True Positives *TP* over all the n trials divided by the test outcome positive or the sum of *TP* and False Positives *FP* (participants claim there was a hard nodule when there was no one), namely:

$$PPV = \sum_{i=1}^n TP / \sum_{i=1}^n (TP + FP). \quad (4.16)$$

Figure 4-37 shows the *PPV* of the tests with Wilson score intervals (see equation (3.5)) at a 95% confidence level. Test 3 got the highest *PPV*. Table 4-11 presents the result of comparison of *PPV* of the six tests. There was no significant difference among the tests regarding *PPV*. Figure 4-38 presents the number of tumours found by participants in each test. In most tests, the recognized tumours number was around 3. The worst performance could be observed in test 5 (71.9%, 95% confidence interval: 45.8% – 88.6%). The short time delay that occurred before the shaking background became active in response to a participant encountering a tumour can explain this slightly poorer performance. *PPV* were compared in pairs using the same method as described in Section 3.3. One can see that there was no significant difference in the tests regarding the *PPV*. Figure 4-39 shows how often individual tumours were recognized by the users. C1 and B1 were most easily recognized, because stiffness gradients around tumour C1 and tumour B1 were the biggest. Since the stiffness gradient around tumour B2 was much lower, tumour B2 was recognized the fewest times. A2, A3, B3, and C3 were not recognized during the tests. The reason could be that the gradients around A2, A3, B3, and C3 were too low to detect. The Sensitivity (*Se*, see equation 3.4) of each test and each nodule, which is the measure of the test's ability to identify positive results, is shown in Figure 4-40. According to this figure, the performance of Test 2 was the best, while Test 5 was the worst. To investigate the significance of the difference on the *Se* among the six tests, a Pearson's Chi-Squared test was conducted on the *Se*. The value of the test-statistic is

$$\chi^2 = \sum_{i=1}^r \sum_{j=1}^c \frac{(O_{i,j} - E_{i,j})^2}{E_{i,j}}, \quad (4.17)$$

where χ^2 is Pearson's test statistic; $O_{i,j}$ is an observed frequency; $E_{i,j}$ is an expected (theoretical) frequency; there are r rows and c columns in the table. The degrees of freedom is $(r - 1)(c - 1)$. The theoretical frequency for a cell is given by

$$E_{i,j} = \frac{(\sum_{n_c=1}^c O_{i,n_c}) \cdot (\sum_{n_r=1}^r O_{n_r,j})}{N}, \quad (4.18)$$

where N is the total sample size.

It was defined that there was a significant effect when the p -value was smaller than 0.05 and there was no significant difference when it was larger than 0.05. The null hypothesis was that they had no significant difference. The test result ($\chi^2 = 18.77$, $df = 20$, $p = 0.537$) accepted the null hypothesis. The Se of the six tests also had no significant difference.

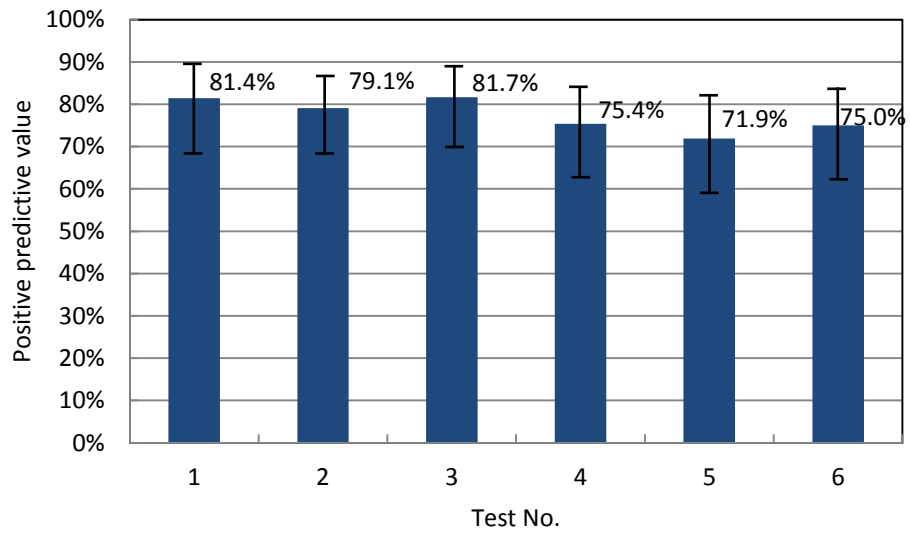


Figure 4-37 Positive predictive value of 2D pseudo-haptic soft tissue stiffness simulation tests with Wilson score intervals at a 95% confidence level.

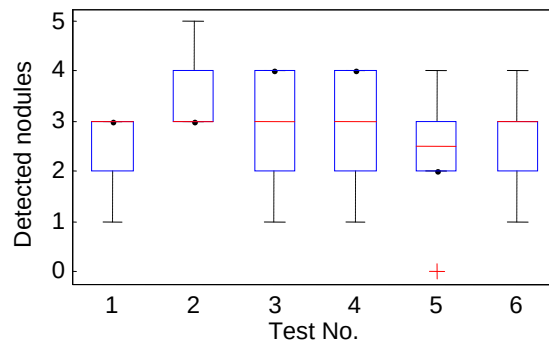


Figure 4-38 Number of nodules the participants found during pseudo-haptic simulation of sliding palpation behaviour.

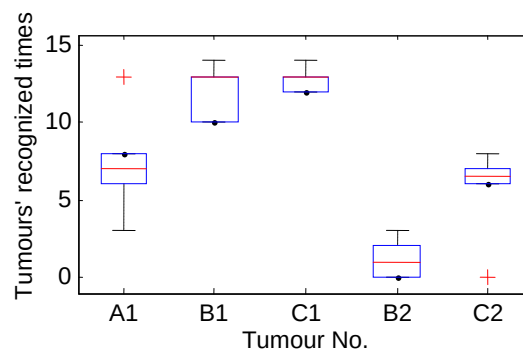


Figure 4-39 Number of times individual tumours were recognized during pseudo-haptic simulation of sliding palpation behaviour.

Table 4-11 Comparison of positive predictive values of 2D pseudo-haptic soft tissue stiffness simulation

Item	Combined interval (CI)	Probability difference (Δp)	Significance	Item	Combined interval (CI)	Probability difference (Δp)	Significance
1 & 2	0.158	0.023	$CI > \Delta p$, No	2 & 5	0.150	0.072	$CI > \Delta p$, No
1 & 3	0.145	0.003	$CI > \Delta p$, No	2 & 6	0.112	0.041	$CI > \Delta p$, No
1 & 4	0.164	0.060	$CI > \Delta p$, No	3 & 4	0.147	0.063	$CI > \Delta p$, No
1 & 5	0.166	0.095	$CI > \Delta p$, No	3 & 5	0.149	0.097	$CI > \Delta p$, No
1 & 6	0.169	0.064	$CI > \Delta p$, No	3 & 6	0.150	0.067	$CI > \Delta p$, No
2 & 3	0.141	0.026	$CI > \Delta p$, No	4 & 5	0.157	0.035	$CI > \Delta p$, No
2 & 4	0.145	0.037	$CI > \Delta p$, No	4 & 6	0.157	0.004	$CI > \Delta p$, No
5 & 6	0.119	0.031	$CI > \Delta p$, No				

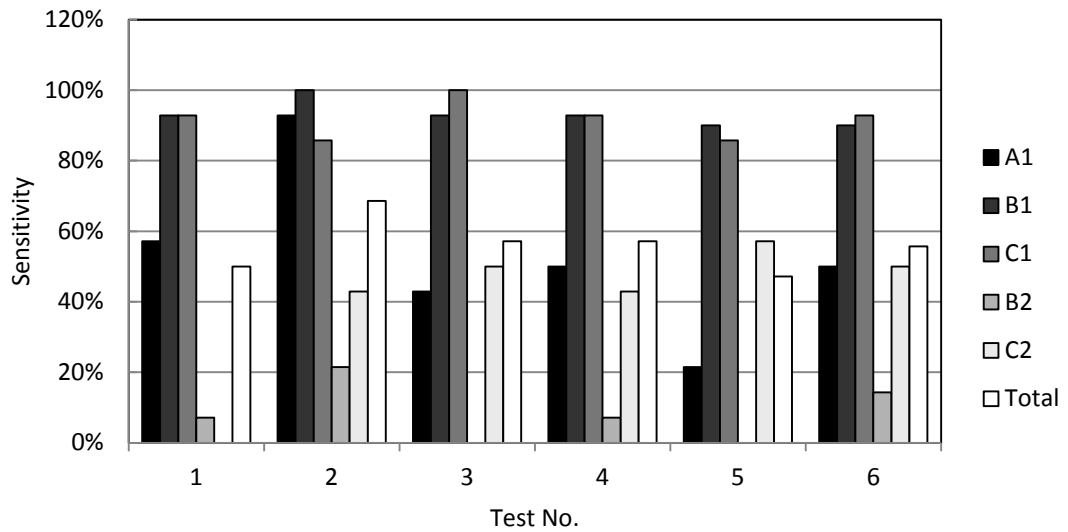


Figure 4-40 Sensitivity of each test and each nodule of 2D pseudo-haptic soft tissue stiffness simulation.

4.6.4. Tangent force simulation vs. normal force simulation

All participants noticed tissue abnormalities in these two tests. In tangent force simulation, the *PPV* of stiff points marked by participants was 81.40% (95% confidence interval: 58.3% – 95.2%). The average numbers of correctly identified nodules of each participant was 2.50 (SD = 0.650). Figure 4-41 shows the possible stiff points recorded by the participants, in which correctly recognized stiff points are represented by “•” and wrongly recognized stiff points are represented by “☆”. As shown in Figure 4-41 (a), hard nodules A1, B1, C1, and B2 were found by the participants. In normal force simulation, the *PPV* of stiff points marked by the participants was 100% (95% confidence interval: 78.5% – 100%). The *CI* of the two tests was 0.242 and the $|p_1 - p_2|$ was 0.159. Thus, there was no significant difference between the two tests regarding *PPV*. The average numbers of correctly identified nodules for each participant was 2.14 (SD = 0.864). The participants showed to find larger numbers of hard inclusions in lateral force simulation while the normal force simulation was shown to be more accurate. As shown in Figure 4-41 (b), hard nodules A1, B1, C1, and C2 were found. In tangent force simulation, most wrong points were within the stiffer area around tumours C1, and C2. The detection rates of C1 and B1 were the highest, because stiffness gradients around tumour C1 and tumour B1 were the biggest. A2, A3, B3, and C3 were not detected by any participant during the tests.

The reason would be that the gradients around A2, A3, B3, and C3 were too low to detect.

The *Se* of each test and each nodule is shown in Figure 4-42. To investigate the significance of the difference between tangent force simulation and normal force simulation regarding sensitivities, a Pearson's Chi-Squared test for count data was conducted on the *Se*. It was defined that there was a significant effect when the *p*-value was smaller than 0.05 and there was no significant effect when it was larger than 0.05. The null hypothesis was that they had no significant difference. The test result ($\chi^2 = 15$, $df = 12$, $p = 0.241$) accepted the null hypothesis. The *Se* also had no significant difference between the two tests.

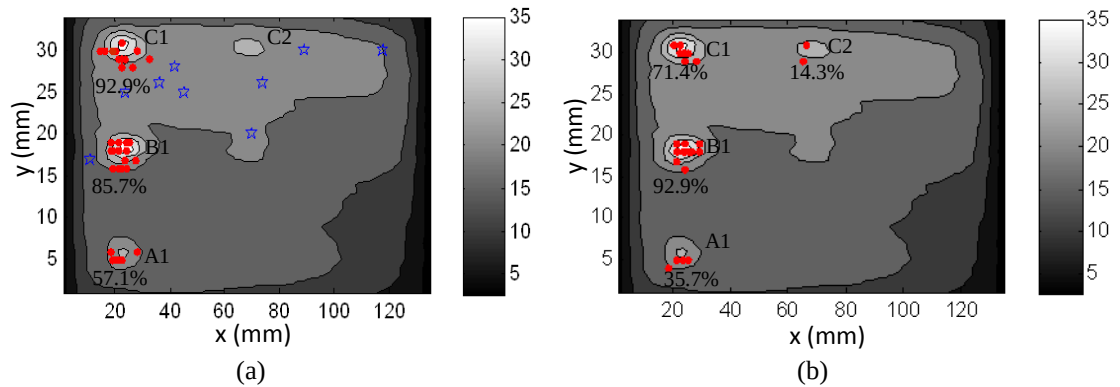


Figure 4-41 Recorded points of hard nodules in lateral force simulation (a) and normal force simulation (b) by participants: correctly recognized points (●) and wrongly recognized points (☆)

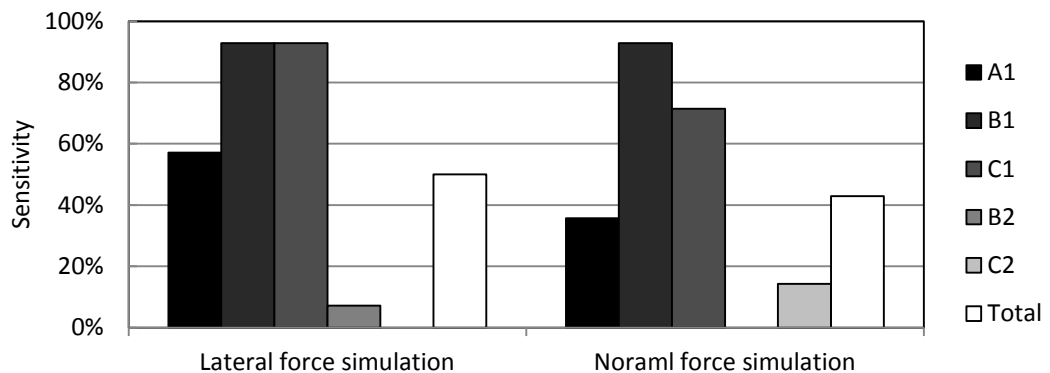


Figure 4-42 Nodule detection sensitivities of each nodule in lateral force simulation and normal force simulation.

4.6.5. Results of combined pseudo-haptic tissue stiffness simulation and visualization of tissue surface

Figure 4-43 presents the nodule detection sensitivities and specificities obtained by using different palpation techniques. The Se – a measure of the test's ability to identify positive results, was defined in equation (3.4). The specificity Sp [151], which relates to the test's ability to identify negative results, was defined as the sum of all the n trials of the True Negatives TN divided by the actual number of hard inclusions (sum of TN and False Positives FP), namely:

$$Sp = \sum_{i=1}^n TN_i / \sum_{i=1}^n (TN_i + FP_i) \cdot \quad (4.19)$$

The Accuracy ACC [195] was calculated as:

$$ACC = \sum_{i=1}^n (TP_i + TN_i) / \sum_{i=1}^n (TN_i + TN_i + FP_i + FN_i) \cdot \quad (4.20)$$

Wilson score intervals (see equation (3.5)), which have good properties even for a small number of trials (less than 30) and/or an extreme probability, were calculated for Se and Sp at a 95% confidence level. The combination of pseudo-haptic feedback and visual feedback of tissue deformation had the highest nodule detection Se , Sp and ACC , namely 94.8% (95% confidence interval: 80.0% – 98.85%), 100% (95% confidence interval: 87.9% – 100%), and 96.4% (95% confidence interval: 82.3% – 99.4%), respectively). Pseudo-haptic feedback using speed changing strategy had higher Se (93.7% vs. 72.6%) and accuracy (94.2% vs. 80.8%) than the visual feedback of tissue deformation. However, the situation was reversed regarding Sp (95.5% vs. 99.1%). The significance of the difference of Se , Sp and ACC between paired tests was examined using the same method as described in Section 3.3. The test result is shown in Table 4-12. One can see that the Se of the tests using speed changing strategy of pseudo-haptic feedback and the combination of the two feedbacks were significantly higher than the test using visual feedback of tissue deformation at a 95% confidence level. Regarding Sp and ACC , there was no significant difference among the tests at a 95% confidence level.

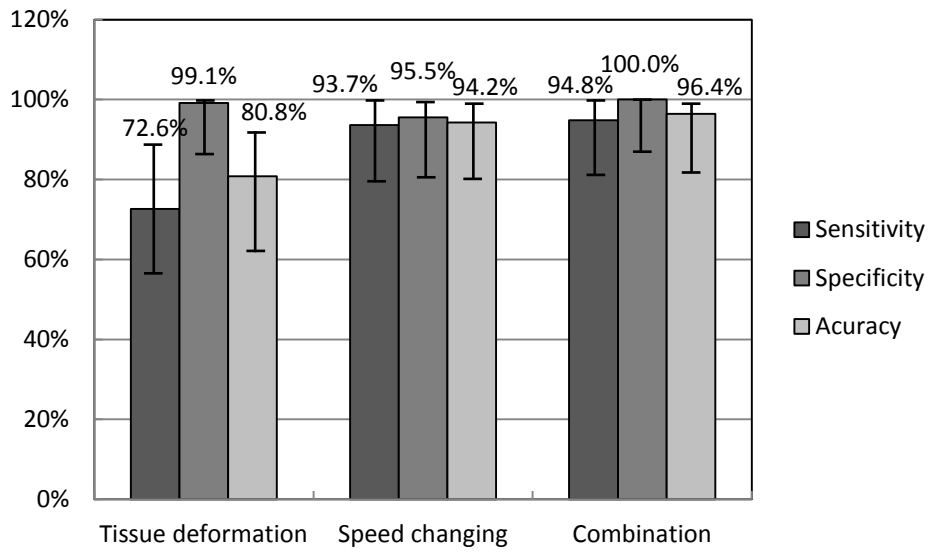


Figure 4-43 Nodule detection sensitivity, specificity and accuracies with Wilson score intervals at a 95% confidence level of visual feedback of tissue deformation, speed changing strategy of pseudo-haptic feedback, and combination of the two feedbacks.

Table 4-12 Comparison of sensitivity, specificity, and accuracy in tests using visual feedback of tissue deformation, speed changing strategy of pseudo-haptic feedback, and combination of the two feedbacks

Statistical measure	Item	Combined interval (CI)	Probability difference (Δp)	Significance
Sensitivity	Tissue deformation & Speed changing	0.200	0.210	$CI < \Delta p$, Yes
	Tissue deformation & Combination	0.197	0.222	$CI < \Delta p$, Yes
	Speed changing & Combination	0.155	0.012	$CI > \Delta p$, No
Specificity	Tissue deformation & Speed changing	0.132	0.035	$CI > \Delta p$, No
	Tissue deformation & Combination	0.121	0.009	$CI > \Delta p$, No
	Speed changing & Combination	0.126	0.045	$CI > \Delta p$, No
Accuracy	Tissue deformation & Speed changing	0.183	0.135	$CI > \Delta p$, No
	Tissue deformation & Combination	0.176	0.157	$CI > \Delta p$, No
	Speed changing & Combination	0.148	0.022	$CI > \Delta p$, No

According to the post-experiment survey, ten participants (71.4%) claimed that the combination method was the best; two (14.3%) claimed that the combination method and the visual tissue deformation feedback were the same and better than the speed

changing method; one (7.1%) preferred the visual tissue deformation feedback; one (7.1%) claimed that the speed changing method was the quickest method. One can see that all the statistic analysis results show that the combination method performed the best.

Figure 4-44 presents the consumed time during nodule identification tests. Since the sample size was 182 (13 trails $\times$ 14 participants), the consumed time was considered as normally distributed and a student t-test was performed to compare the consumed time during the tests. Table 4-13 shows the test results. The combination feedback modality consumed significantly less time than the other two feedback modalities.

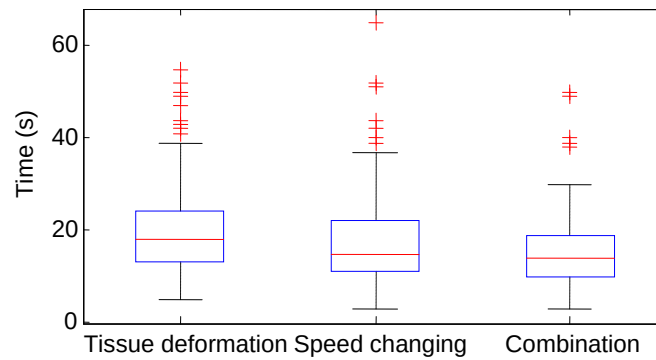


Figure 4-44 Time used for nodule detection using visual feedback of tissue deformation, speed changing strategy of pseudo-haptic feedback, and combination of the two feedbacks.

Table 4-13 Student t-test for consumed time using visual feedback of tissue deformation, speed changing strategy of pseudo-haptic feedback, and combination of the two feedbacks

Item	<i>p</i> -value	Significance
<i>Tissue deformation & Speed changing</i>	$1.74 \times 10^{-4**}$	Yes
<i>Tissue deformation & Combination</i>	$9.51 \times 10^{-9**}$	Yes
<i>Speed changing & Combination</i>	0.016*	Yes

*. Significant at the 5% level; **. Stronger significance than at the 5% level

4.6.6. Results of 3D pseudo-haptic tissue stiffness simulation

4.6.6.1. Nodule detection

Figure 4-45 presents the nodule detection sensitivity Se , which is a measure of the test's ability to identify positive results (defined in equation (3.4)) for nodule A, B and C. Figure 4-46 presents the overall Se . Figure 4-47 presents the positive predictive value PPV , or precision rate (defined in equation (4.16)). Compared with Group II, Group I had a higher Se (88.3% vs. 73.3%). However, the two methods had no significant difference on Se ($CI = 0.148$, $\Delta p = 0.100$, calculated using equation (3.6)), which means the touch perception abilities of these two groups had no significant difference. Using a touchpad as an input device, visual and haptic information were presented at different points of interaction – the contact force was exerted from the touchpad via the special pen while the visual information was displayed on a computer screen. Utilizing a tablet computer made the user feel as though their finger or the stylus could penetrate the pressure-sensitive surface and be extended into the digital world to manipulate virtual tissue behind the screens directly, so called direct touch or immersive illusion. The significance of the difference of Se between each pair of tests was examined. Table 4-14 shows the test results. One can notice that when tablet and S-pen or tablet and bare finger were used both the hard inclusion detection rates were significantly higher than when using touchpad or PHANToM Omni. Thus, direct touch and immersive illusion was proven to be superior to when visual and haptic information did not spatially coincide with each other.

The force-sensitive 2D haptic surface input device had a higher Se (51.7% vs. 50%) and a higher PPV (86.1% vs. 83.3%) compared to pseudo-haptic feedback using the 3-DOF motion tracking input device. In the force-sensitive 2D haptic surface input device, the Se of nodule B was the highest (75%), followed by nodule A (65%). It is interesting to note that nodule B had a higher Se despite being smaller than nodule A. The smallest tumour C had a low Se of 15%. This implied that certain palpating methods suited certain types of nodules. Using the force-sensitive 2D haptic surface input device proved more suitable for detecting middle sized nodules. Three participants (15%) detected all nodules while the same number of participants detected no nodules at all. Eleven participants (55%) detected more than two tumours

correctly. Using the 3-DOF motion tracking input device, bigger nodules had higher detection rates. The lowest *Se* occurred at tumour C (5%). Thus, this method is not suitable for detecting small nodules.

Compared to pseudo-haptic feedback using the tablet with a bare finger, using the tablet with an S-pen had a higher *Se* (91.7% vs. 85%). However, the two methods had no significant difference ($CI = 0.157$, $\Delta p = 0.067$, see equation (3.6)). When using the tablet with an S-pen, both the sensitivities of nodule A and B were 100%. The smallest tumour C had a sensitivity of 75%. Using the tablet with a bare finger, both the *Se* of nodule A and B were 95%. The smallest tumour C had a *Se* of 65%.

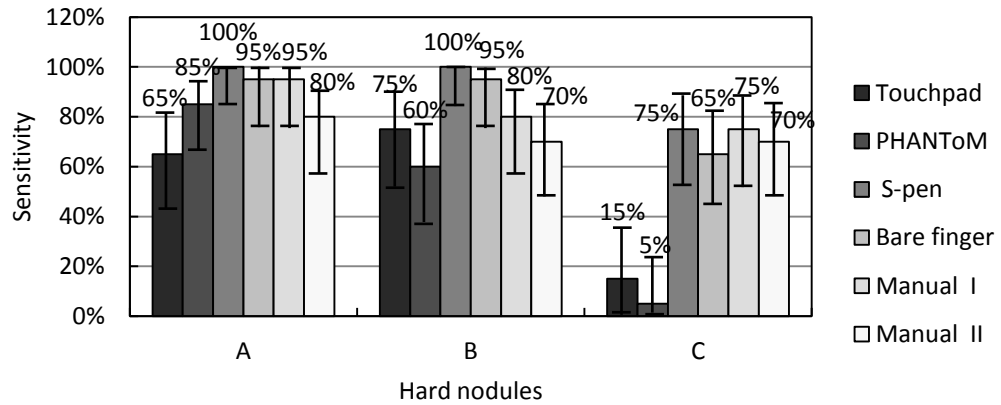


Figure 4-45 Nodule detection sensitivities of nodule A, B and C with Wilson score intervals at a 95% confidence level of 3D pseudo-haptic tissue stiffness simulation.

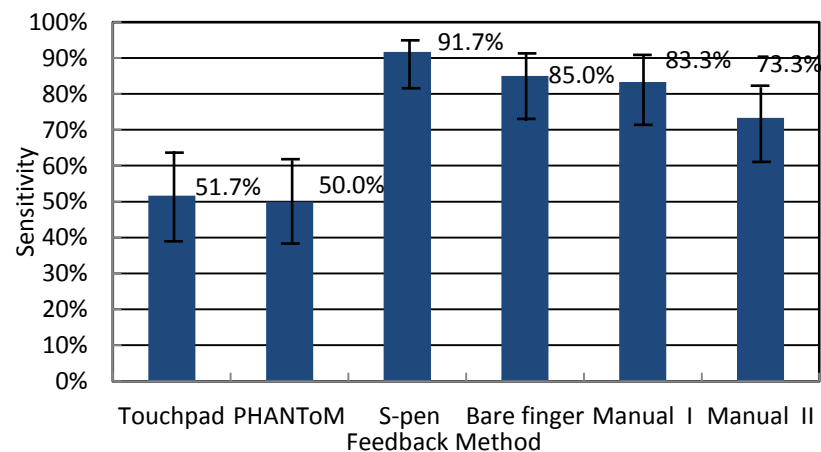


Figure 4-46 Overall nodule detection sensitivities of 3D pseudo-haptic tissue stiffness simulation with Wilson score intervals at a 95% confidence level.

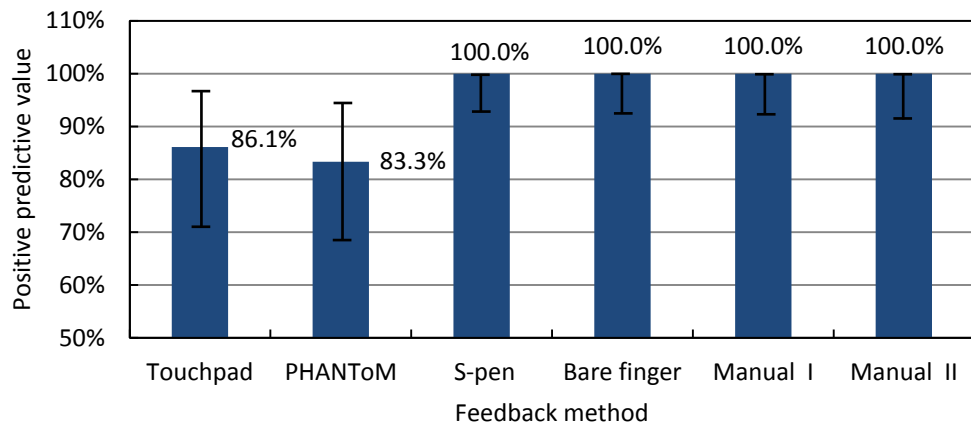


Figure 4-47 Positive predictive values of 3D pseudo-haptic tissue stiffness simulation with Wilson score intervals at a 95% confidence level.

Table 4-14 Comparison of sensitivities in tests of 3D pseudo-haptic tissue stiffness simulation

Item	Combined interval (CI)	Probability difference (Δp)	Significance
<i>Manual Group II & manual Group I</i>	0.148	0.100	$CI > \Delta p$, No
<i>Touchpad & PHANToM</i>	0.174	0.017	$CI > \Delta p$, No
<i>Manual Group I & touchpad</i>	0.167	0.316	$CI < \Delta p$, Yes
<i>Manual Group I & PHANToM</i>	0.167	0.333	$CI < \Delta p$, Yes
<i>Tablet + S-pen & tablet + bare finger</i>	0.157	0.067	$CI > \Delta p$, No
<i>Tablet + S-pen & touchpad</i>	0.156	0.400	$CI < \Delta p$, Yes
<i>Tablet + S-pen & PHANToM</i>	0.157	0.417	$CI < \Delta p$, Yes
<i>Tablet + S-pen & manual Group II</i>	0.136	0.184	$CI < \Delta p$, Yes
<i>Tablet + bare finger & touchpad</i>	0.165	0.333	$CI < \Delta p$, Yes
<i>Tablet + bare finger & PHANToM</i>	0.166	0.350	$CI < \Delta p$, Yes
<i>Tablet + bare finger & manual Group II</i>	0.146	0.117	$CI > \Delta p$, No

4.6.6.1. Time

Figure 4-48 and Figure 4-49 present the consumed time during nodule identification tests done by Group I and Group II. In general, the tests conducted by Group I consumed more time than the tests conducted by Group II. Mann-Whitney U -tests and Wilcoxon signed-rank tests (see equation (3.7)) were performed to compare the consumed time during the tests. For Wilcoxon signed-rank tests, data should be paired

and come from the same population. Using the Mann-Whitney U -test (Wilcoxon rank-sum tests) [196], all the observations from both groups are independent of each other. This test ranks the data for each condition, and then compares the two rank totals. The test involves the calculation of a statistic, usually called U , which is given by:

$$U_i = R_i - \frac{n_i(n_i + 1)}{2} \quad (4.21)$$

where $i = 1$ or 2 ; n is the sample size; R is the sum of the ranks in this sample. The smaller value of U_1 and U_2 is the one used when checking significance. This U reflects the difference between the two rank totals. Table 4-15 shows the test results. For the tests conducted by Group I, manual palpation needed significantly less time than the two pseudo-haptic feedback tests. For the tests conducted by Group II, there was no significant difference concerning time.

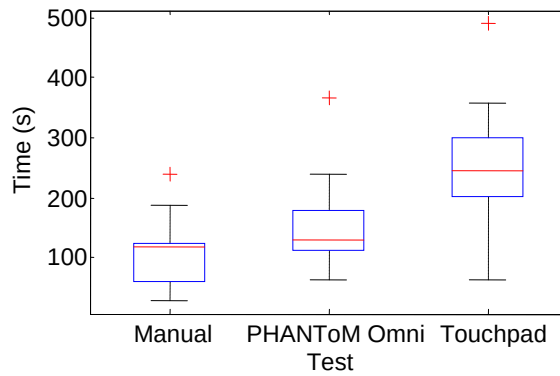


Figure 4-48 Consumed time for hard nodule detection of 3D pseudo-haptic tissue stiffness simulation (Group I).

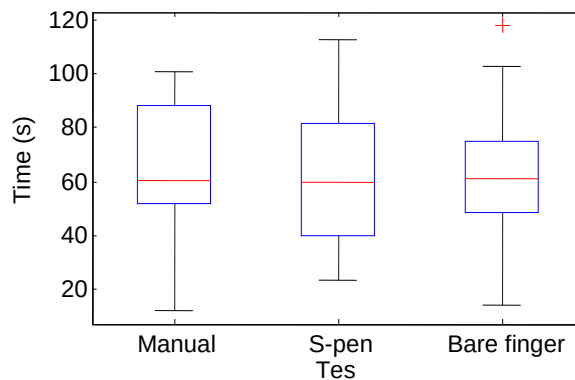


Figure 4-49 Consumed time for hard nodule detection of 3D pseudo-haptic tissue stiffness simulation (Group II).

Table 4-15 Mann-Whitney U-tests (Wilcoxon rank-sum tests) and Wilcoxon signed-rank tests for consumed time for hard nodule detection of 3D pseudo-haptic tissue stiffness simulation

	Item	U	p -value		Significance
Wilcoxon rank-sum tests	Manual Group II & manual Group I	298.5	0.008**		Yes
	Tablet + S-pen & touchpad	382.5	8.47×10^{-7} **		Yes
	Tablet + S-pen & PHANToM	380	1.19×10^{-6} **		Yes
	Tablet + bare finger & touchpad	15.5	6.43×10^{-7} **		Yes
	Tablet + bare finger & PHANToM	22	1.57×10^{-6} **		Yes
	Item	n_r	W	$W_{critical}$	Significance
Wilcoxon signed-rank tests	Manual Group I & touchpad	19	0	46	Yes
	Manual Group I & PHANToM	18	27	40	Yes
	Tablet + S-pen & tablet + bare finger	20	92	52	No
	Touchpad & PHANToM	20	5	52	Yes
	Tablet + S-pen & manual Group II	20	94.5	52	No
	Tablet + bare finger & manual Group II	20	94.5	52	No

*. Significant at the 5% level; **. Stronger significance than at the 5% level

4.6.7. Results of combined pseudo-haptic and force feedback

Figure 4-50 presents the nodule detection sensitivities Se (see Section 3.3 for details) of nodule A, B, and C obtained by using different palpation techniques. In general, there was a positive correlation between the detection sensitivities and nodule size – bigger nodules had higher detection sensitivities (mX represents mean detection sensitivity of X ; $mA = 91.3\%$, $SD = 28\%$; $mB = 76.3\%$, $SD = 43\%$; $mC = 53.75\%$, $SD = 50\%$). Figure 4-51 presents the overall nodule detection sensitivity of each method. The best Se was achieved with the combined technique utilizing both pseudo-haptic and force feedback (83.3% with 95% confidential interval 71.9 – 90.7%). The technique using only pseudo-haptic feedback had a Se of 50% (95% confidential interval: 37.7 – 62.3%) overall. The performance of force feedback was better with a detection rate of 78.3% (95% confidential interval: 66.3 – 86.9%). Compared with force feedback only, the proposed combination technique improved the Se of the middle sized nodule B dramatically from 75% to 90%, but reduced the Se of the largest nodule A slightly from 95% to 90%. This indicates that the combined technique was particularly suitable for detecting middle-sized nodules. Figure 4-52

presents the *PPVs* (see equation (4.16)). Compared to pseudo-haptic feedback and force feedback, the *PPV* of the combination method was larger. *Se* and *PPV* of the tests were compared in pairs. Table 4-16 shows the test results. The combination method had no significant difference from the manual palpation both in *Se* and *PPV*.

Figure 4-53 depicts the difference in the time taken to detect the hard nodules with each technique. It is important to note that the combined technique recorded the shortest detection times, even shorter than manual palpation (73.6 s vs. 106.2 s). Wilcoxon signed-rank tests (see equation (3.7)) were performed to compare the consumed time during the tests. Table 4-17 shows the test results. The combination method needed significantly less time than the Force Feedback and Pseudo-Haptic Feedback tests.

The majority of the participants ($n = 16$, 80%) stated that perception was “better” when using the combination method than when using force feedback alone. Only four participants described the combination methods to be “the same” as the technique based on force feedback alone.

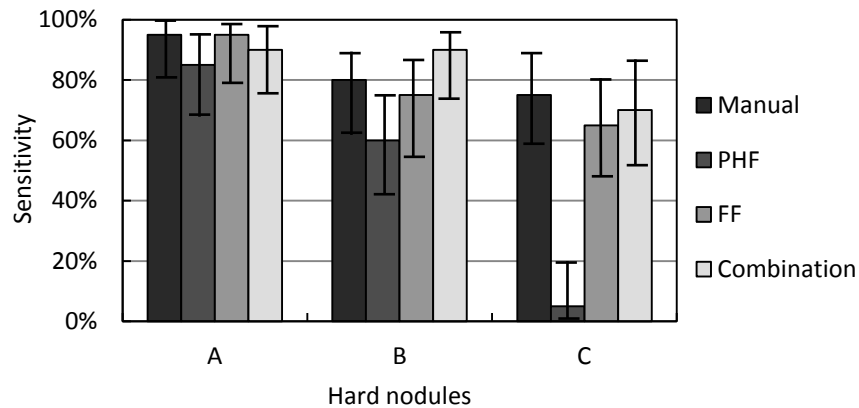


Figure 4-50 Nodule detection sensitivity of nodule A, B and C in the tests for combined pseudo-haptic and force feedback with Wilson score intervals at a 95% confidence level.

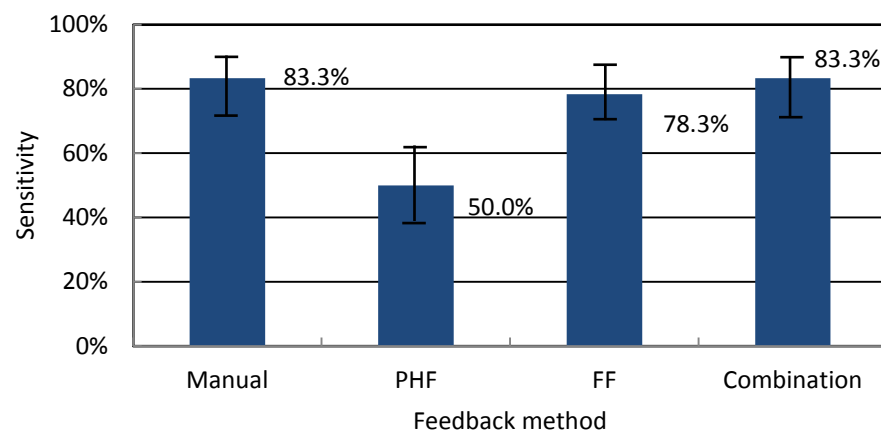


Figure 4-51 Overall nodule detection sensitivities in the tests for combined pseudo-haptic and force feedback with Wilson score intervals at a 95% confidence level.

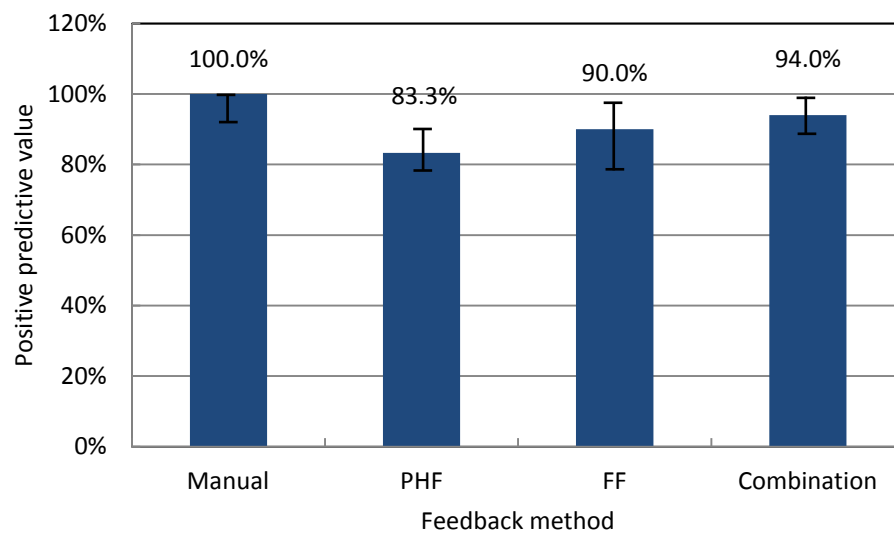


Figure 4-52 Positive predictive values in the tests for combined pseudo-haptic and force feedback with Wilson score intervals at a 95% confidence level.

Table 4-16 Comparison of nodule detection sensitivities and positive predictive values in the tests of combined pseudo-haptic and force feedback

Statistical measure	Item	Combined interval (CI)	Probability difference (Δp)	Significance
Se	Manual & FF	0.142	0.050	$CI > \Delta p$, No
	Manual & PHF	0.167	0.333	$CI < \Delta p$, Yes
	Manual & Combination	NULL	NULL	$CI > \Delta p$, No

Statistical measure	Item	Combined interval (CI)	Probability difference (Δp)	Significance
	FH & PHF	0.171	0.283	$CI < \Delta p$, Yes
	FH & Combination	0.142	0.050	$CI > \Delta p$, No
	PHF & Combination	0.167	0.333	$CI < \Delta p$, Yes
PPV	Manual & FF	0.090	0.100	$CI < \Delta p$, Yes
	Manual & PHF	0.113	0.167	$CI < \Delta p$, Yes
	Manual & Combination	0.081	0.060	$CI > \Delta p$, No
	FH & PHF	0.142	0.067	$CI > \Delta p$, No
	FH & Combination	0.071	0.040	$CI > \Delta p$, No
	PHF & Combination	0.098	0.107	$CI < \Delta p$, Yes

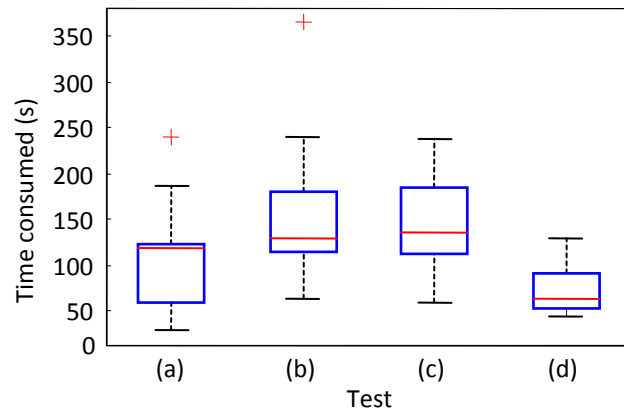


Figure 4-53 Time needed to find nodules using manual palpation, shown in (a); pseudo-haptic feedback, shown in (b); force feedback, shown in (c); combination technique of pseudo-haptic feedback and force feedback, shown in (d).

Table 4-17 Wilcoxon signed-rank tests for consumed time in the tests of combined pseudo-haptic and force feedback

Item	n_r	W	$W_{critical}$	Significance
<i>Manual & FF</i>	19	42	46	$W < W_{critical}$, Yes
<i>Manual & PHF</i>	18	22	40	$W < W_{critical}$, Yes
<i>Manual & Combination</i>	19	47.5	46	$W > W_{critical}$, No
<i>FF & PHF</i>	20	99.5	52	$W > W_{critical}$, No
<i>FF & Combination</i>	19	6	46	$W < W_{critical}$, Yes
<i>PHF & Combination</i>	19	4	46	$W < W_{critical}$, Yes

4.7. Discussion

4.7.1. Soft tissue modelling

In this study, T1 stage tumours (measuring 20 mm or less along their widest section [25]) are simulated using artificial tumour models buried in silicone phantom tissues. As reviewed in Section 2.2, the ratios of elastic modulus of cancerous breast tissues to fat tissue are ranging from 4 to 124 [27]. Therefore, in this research, a wide range of stiffness ratios are used. The stiffness ratio between the hard nodules and the silicone phantom tissues are about 104, 4.4, and 14.9 for Phantom tissue I, II, and III, respectively. The hard nodules are embedded in 3 mm, 6 mm, 8 mm and 10 mm depths covering both the lower and greater risk regions presented in [35], [36].

To employ the proposed 3D tissue surface reconstruction method in a real MIS setting, it is necessary to use a smaller and sterilizable depth sensor or a binocular camera instead of the Kinect. Although there has been no official announcement at the time of writing, Microsoft is actually developing a miniaturized Kinect depth sensor, which will be more suitable for the size requirements of MIS tools. Hopefully in the near future, it can be applied in a real MIS setting. In the proposed method, a flat table surface was used to work as a reference planar to segment and rotate the tissue surface and a centroid of tissue surface was used to register the reconstructed tissue surface to the coordinate frame of the robot. In practice, the tissue will not be sitting on a planar surface *in-vivo*, but rather on and surrounded by other organs. The proposed method needs to be adapted to those conditions. Manually inserted markers or pins would be one solution. Attachment of the depth sensor to the surgical robot to unify the coordinate systems would be another solution.

Data-driven haptic rendering has advantages over conventional parametric methods, but also certain challenges and limitations, such as high data storage requirements for complex objects, large training data size, and multi-points of interaction [162]. The computational effort of data-driven tissue model is related to the number of recorded samples contact forces [197]. Data-driven tissue deformation rendering would require a lot of computational effort. In this study, only contact force of soft tissue was modelled using this data-driven concept and the tissue deformation was rendered by

using a simplified geometrical tissue deformation computation method, which reduced the computational effort. More research is needed to further explore and improve data-driven tissue modelling.

4.7.2. Rolling indentation probe

The rolling indenter and the probe will also need to be small enough to be used internally on the patient. In this research, an ATI Nano 17 force sensor (SI-12-0.12, resolution 0.003N with 16-bit data acquisition card) was used, which has a diameter of 17 mm. However, Trocar ports are normally less than 12 mm in diameter [6] [44]. As reviewed in Chapter 2, other optional force sensors include the 6-DOF Force/Torque (F/T) sensor for the DLR tele-surgery scenario MiroSurge, which has an annular cross section with a diameter of 10 mm and the MR-compatible 6-DOF F/T sensor with a diameter of 11 mm, height of 10 mm and weight of 0.6 g developed by Sargeant et al. [49]. In future research, a miniaturized rolling indentation probe needs to be developed and evaluated so that it can be applied in surgical environments.

4.7.3. Palpation on tissue model using force feedback

The two wrongly recognized nodule locations in the experiment of palpation on tissue model using force feedback were both at the edges of the tissue model. The reason for the wrong detection could be that the particular participant confused the changes of force caused by stiffness differences and the tissue texture. By just observing reaction force maps (like the one shown in Figure 4-8), there is a risk of making mistakes in nodule identification and localization. In Figure 4-8, there is an area with a relative high reaction force (see top right yellow area in Figure 4-8 (a), (b) and (c)), which could be wrongly interpreted as a hard nodule if only the colour coding of the shown force matrix is used in the analysis. In these human subject palpation experiments, users were able to detect the hard nodules correctly with the help of force feedback information. The reason for the slightly lower performance during the haptic palpation experiments compared to the manual palpation performance might be related to the limited tactile information experienced during the haptic feedback experiments.

4.7.4. 2D pseudo-haptic tissue stiffness simulation

The evaluation results of 2D pseudo-haptic tissue stiffness simulation show that users could identify hard nodules using pseudo-haptic soft tissue stiffness simulation. Both the *PPV* and *Se* show that Test 5 (combination of shaking background and cursor speed changing strategy) had the poorest performance. The reason could be the time delay of the shaking background strategy. The six tests of normal force simulation had no significant difference both in *PPV* and *Se*. No auxiliary strategies were used in the following studies to simplify the programme. Regarding *PPV*, the normal force simulation performed better than the lateral force simulation (100% vs. 81.40%). However, the normal force simulation and the lateral force simulation did not have significant difference according to the *PPV* and *Se*. Performance comparison studies of the pseudo-haptic palpation simulation and manual palpation should to be conducted in the next step. Moreover, other input devices which can make palpation simulation more natural should be introduced. Furthermore, this 2D method should be extended to 3D palpation simulations.

4.7.5. Combined pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation

The combination of pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation performed the best at nodule detection *Se*, *Sp*, *ACC*, consumed time, and in the post-experiment survey. Although the difference between the combined method and the other two separate feedback modalities was not significant regarding *Sp* and *ACC*, the combined method showed significantly better performance on *Se*, consumed time, and the post-experiment survey. While using pseudo-haptic tissue stiffness simulation consumed significantly less time and had higher *Se* than using visualization of tissue surface deformation during the nodule detection experiments, they had not significant difference on *Sp* and *ACC*. The test results revealed that the visualization of tissue surface deformation and pseudo-haptic feedback both played important roles in tumour identification. Therefore, the two feedbacks were both provided in the following studies. If a computer mouse is used, only a 2D motion can be captured as the input. However, 3D information input is required for exploration of tissue stiffness. Therefore, a 3D pseudo-haptic tissue

stiffness simulation method was introduced and discussed in the following experiments.

4.7.6. 3D pseudo-haptic tissue stiffness simulation

Using a bare finger to provide the input of indentation and sliding made the contact more natural than using a pen. However, *Se* when using a tablet and a bare finger was lower than when using a tablet and an S-pen. One reason for this could be that the fingertips were larger than the S-pen tip used in this experiment. Touching the screen with a bare finger can sometimes obstruct the vision of the user during the experiments. Another reason could be the saturation problem of the pressure level measurement of this device: estimating the contact force by using the contact surface area is not reliable when the contact area reaches its maximum while the contact force is still increasing. Hence, a better pressure-sensitive touch screen for bare finger interaction is required.

The performance of the proposed pseudo-haptics rigid tool / soft object interaction technique has been assessed using a force-sensitive touchpad with a pen input, a tablet computer with an S-pen input, and a tablet computer with a user's bare finger input. Hard inclusions were detected more effectively on tablet computers. *Se* and *PPV* were lower when the force-sensitive touchpad was used as visual and haptic information was presented at different points of interaction. Notably, the detection of hard inclusions conducted by applying direct touch or immersive illusion on tablet computers was comparable to the performance of the use of direct hand / soft tissue interaction. Pseudo-haptic feedback provides a low-cost method to simulate soft object stiffness and hard inclusions and can be used in many low-budget applications where haptic sensation is required, such as video games.

4.7.7. Combined pseudo-haptic and force feedback

In the user study, by employing the combination of both pseudo-haptic and force feedback technique, both the nodule detection *Se* and *PPV* were higher than when using either the force or pseudo-haptic technique solely (*Se*: 83.3% vs. 78.3% and 50%, *PPV*: 94% vs. 90% and 83.3%). In addition, less time was consumed (73.6 s vs. 143.5 s and 149.5 s). The combination technique performed as well as the gold

standard manual palpation concerning the nodule detection *Se*, *PPV*, and time consumed (*Se*: 83.3% vs. 83.3%, *PPV*: 100% vs. 94%, time: 73.6 s vs. 106.2 s). Further analysis of this combined feedback technique is needed on real soft tissue and *in-vivo* environment.

It has been proven that humans integrate visual and haptic information in a statistically optimal fashion that is similar to a maximum-likelihood integrator [192]. In this study, the combination of pseudo-haptic and force feedback provided a better performance than when using either of them solely. It should also be noted that the problem of cognitive overload of surgeons should be avoided when considering and/or combining feedback modalities.

4.8. Conclusion

Providing direct force feedback to enable palpation via a surgical tele-manipulator can lead to system instability issues whereby using tissue stiffness distribution information provided by a graphical display it is difficult for surgeons to form a reliable impression of the actual tissue stiffness. To fill the research gap, an intra-operative tumour localization method providing force feedback utilizing real-time intra-operative tissue models was introduced. Instead of using empirical tissue model parameters, the tissue model in this method represented the properties of investigated soft tissue. This model presented stiffness similar to the tested silicone block and the applied methodology could be easily extended to real organs' palpation. A validation test of the concept was conducted by evaluating the performance of the tumour localization on a soft tissue phantom containing buried stiff nodules. Analyzing the evaluation tests, one can see that deformable tissue models and real-time tissue deformation could be generated. Participants were able to notice the stiffness differences at the locations of embedded hard inclusions using the proposed haptic palpation method. The proposed method and manual palpation had no significant difference, concerning the nodule identification result and the time needed for nodule seeking. Thus, it is proven that the tissue models which were generated based on indentation data on soft tissue can be used to convey haptic information for tumour identification in a virtual environment.

A low-cost haptic simulation method of rigid tool-soft tissue interaction was proposed and validated in this chapter. The proposed method requires no expensive haptic devices and this is what distinguishes it from other current work on rigid tool / soft tissue interaction haptic simulations. The role of visualization of tissue surface deformation and pseudo-haptic feedback in tumour identification were investigated by examining the nodule detection performance of the recruited human participants when palpating on virtual soft tissue with stiffness distribution information conveyed by different feedback modalities, including visual feedback of tissue surface deformation only, pseudo-haptic feedback only, and the combination of the two feedbacks. 2D and 3D pseudo-haptic feedback methods were proposed to express haptic perception through visual display. The combination of pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation performed the best at nodule detection *Se*, *Sp*, *ACC* and consumed time. The test results prove that the pseudo-haptic feedback can be used to convey haptic information in rigid tool / soft tissue interaction in virtual environments; the visualization of tissue surface deformation and pseudo-haptic feedback both play important roles in tumour identification. It provides guidelines for the further development of palpation simulators without using expensive haptic devices that both the visualization of tissue surface deformation and pseudo-haptic feedback should be provided.

Five input devices, including a computer mouse, a 3-DOF motion tracking device (PHANToM Omni), a force-sensitive 2D surface (touchpad), a tablet computer with an S-pen, and a tablet computer with a bare finger, were tested applying this method. Analyzing the evaluation tests, one can see that participants were able to notice the stiffness differences at the locations of embedded hard inclusions using all these input devices. Using the mouse speed changing strategy had no significant difference compared to using other auxiliary strategies in the nodule detection *Se* and *PPV* of tangent force simulation tests. Similarly, using the tangent force simulation and the normal force simulation had no significant difference in the nodule detection *Se* and *PPV*, and using this force-sensitive 2D surface – touchpad input device had no significant difference from using a 3-DOF motion tracking input device. Applying direct touch interaction simulation by using tablet computers instead of other input devices improved the hard inclusions detection performance regarding *Se*, *PPV*, and

consumed time. Applying direct touch immersive illusion using tablet and S-pen had a better *Se* even compared to manual detection.

The proposed pseudo-haptic soft tissue stiffness simulation technique is an effective and low-cost alternative to conventional haptic devices and impresses with its performance in the detection of hard inclusions which rivals detection done via hand / soft object interaction. Potential applications include remote medical palpation. Using patient-specific tissue models with archived stiffness distribution information (acquired for instance via the rolling/sliding indentation method) and pseudo-haptic soft object stiffness simulation, a surgeon could examine a patient without actual skin-to-skin contact. In addition, with the video gaming community always in the look for more realistic experiences, our proposed technique is sure to find many applications in gaming too.

Furthermore, a low-cost combined pseudo-haptic and force feedback method to enhance the perception of haptic feedback was conceived, implemented and tested in identification of hard inclusions inside a soft object. Compared to pseudo-haptic or force feedback only, the proposed combined feedback technique enabled participants to detect faster hard nodules in soft tissue. The performance of combining both pseudo-haptic and force feedback techniques was comparable with the gold standard manual interaction. The survey showed that participants using the pseudo-haptic feedback combined with force feedback method experienced an enhanced palpation perception. The proposed combined method which has been evaluated to successfully augment haptic perception can find future applications in medical palpation simulators.

Chapter 5 A Novel Multi-Fingered Palpation Method

The control complexity and high cost of tactile actuators limits their application in palpation simulation. Thus, single-point force feedback is more common currently, although it offers significantly reduced haptic information. Multi-fingered palpation is more common than single-fingered palpation in real practice of tumour localization and is considered more useful than the latter when attempting to detect differences in stiffness in the examined tissue. To find a balance between the control complexity and the efficiency of tactile information rendering, this chapter proposes multi-fingered haptic feedback systems for palpation simulation. Two methods of multi-fingered palpation were designed as part of this PhD study: (1) pseudo-haptic feedback and (2) stiffness feedback actuators. Both are evaluated and compared with the performance of single-fingered palpation.

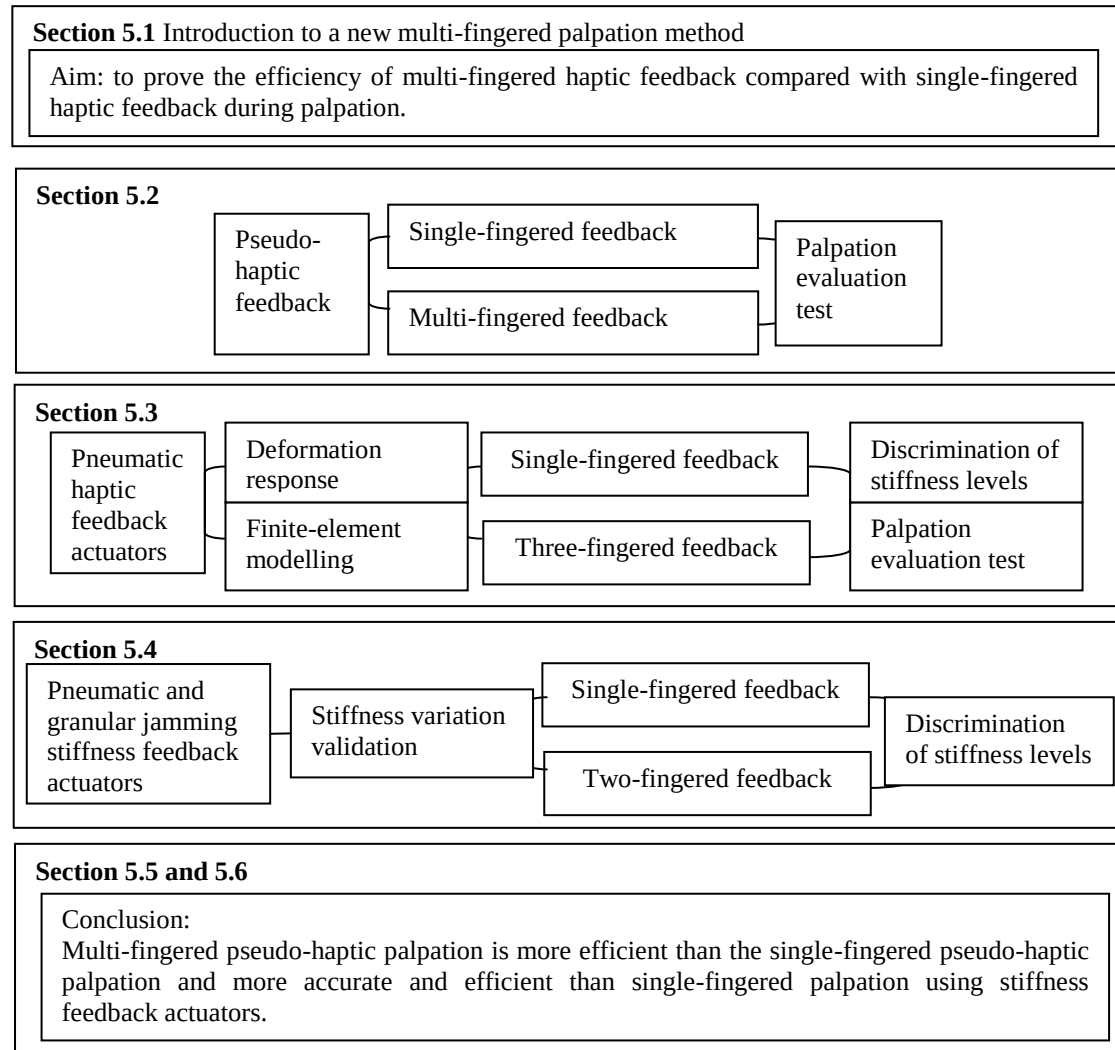


Figure 5-1 Structure of Chapter 5.

5.1. Introduction to a novel multi-fingered palpation method

Tactile actuators, which provide the user with tactile feedback as experienced during palpation, have been introduced for tumour identification in MIS, as for instance described in [198]. Currently, tactile actuators can be divided into two main types: actuators utilising movable components and actuators utilising materials with variable stiffness. Providing distributed pressure (tactile information) to one finger during palpation has been conducted in [91], [122], [199]. However, its current application is limited by the complexity and high cost of the required tactile actuators.

Multi-fingered palpation is more common than single-fingered palpation in real practice and is considered more useful than single-fingered palpation when attempting to detect differences in stiffness in the examined tissue [17]. While multi-fingered haptic feedback conveys more haptic information than single-point force feedback, the actuator elements in this multi-fingered palpation haptic system are much reduced compared to tactile haptic methods as, for example, described in [91], [122]. Tactile feedback, single-point force feedback, and multi-fingered feedback are shown in Figure 5-2. There are some reports about multi-fingered palpation simulation [16], [72], [96], [97] as previously reviewed in Chapter 2. Nevertheless, the prices of those devices are relatively high.

This chapter presents the creation and validation of two multi-fingered palpation methods: (1) pseudo-haptic feedback and (2) stiffness actuators. Figure 5-3 illustrates how the proposed stiffness actuators can be used in RMIS and MIS environments as well as medical training environments. Tissue stiffness information can be captured by the force and position sensors attached to the surgical tool at the slave side of the robot. At the master side, stiffness actuators are added to the control console to provide stiffness feedback to the fingers of the surgeon. The proposed methods also have potential to be used in palpation simulators for medical training to provide a more intuitive haptic feedback than conventional single-point force feedback palpation simulators.

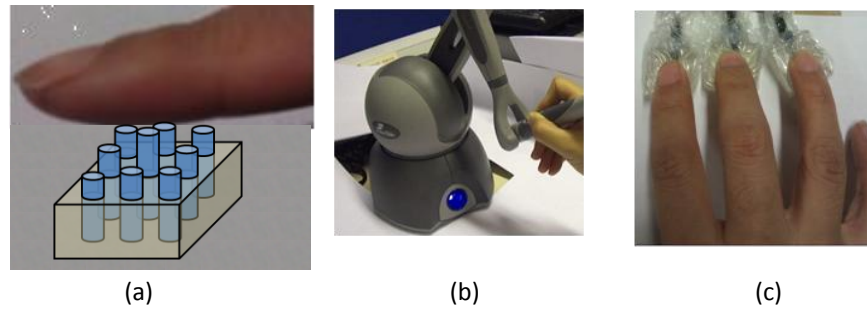


Figure 5-2 Tactile feedback, shown in (a); single-point force feedback, shown in (b); multi-fingered haptic feedback, shown in (c).

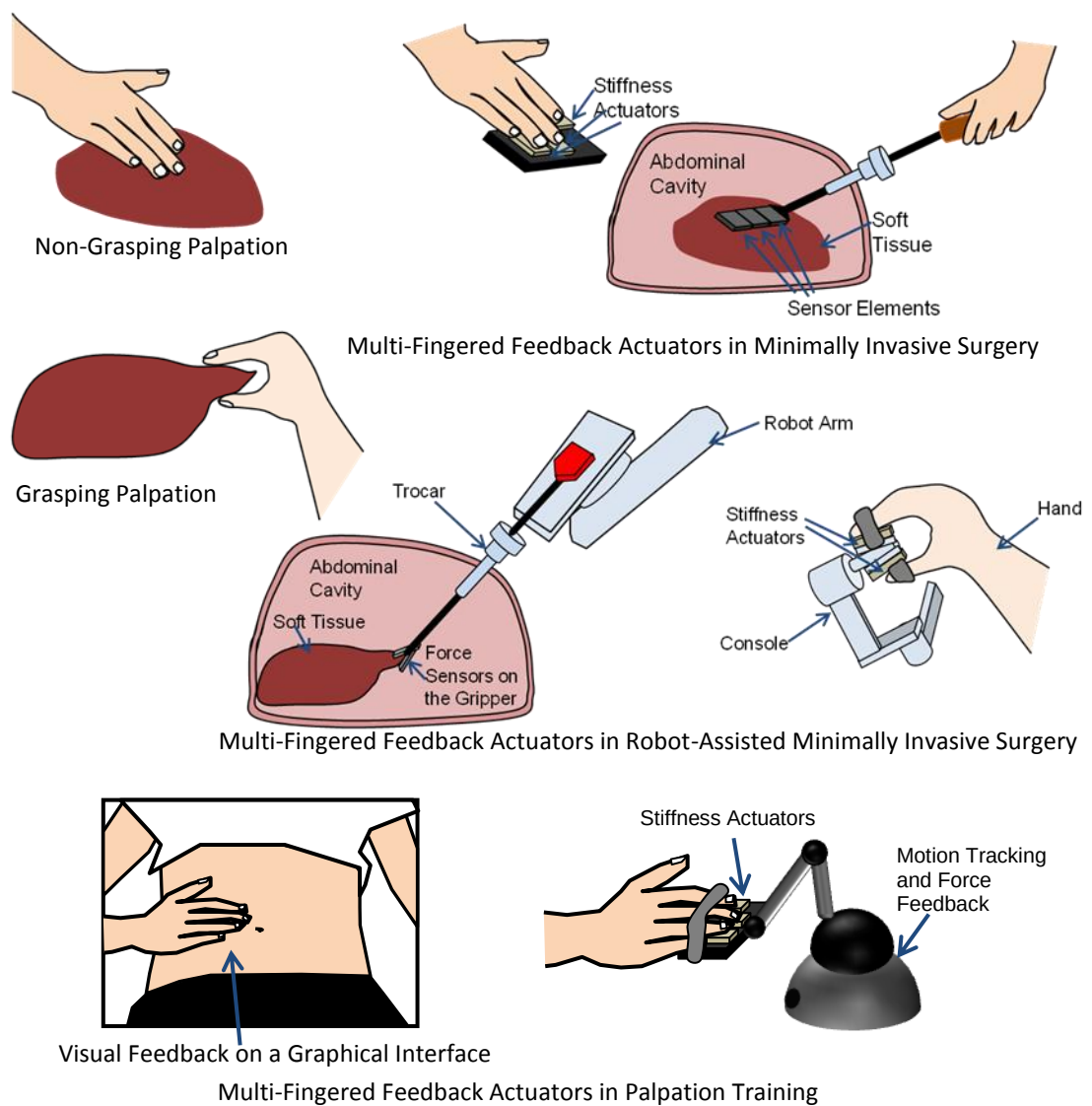


Figure 5-3 Schematic diagram of the applications of the proposed multi-fingered palpation in conventional MIS, RMIS, and medical training contexts.

This chapter makes the following contributions:

1. Multi-fingered palpation is simulated using pseudo-haptic feedback and the efficiency advantage of multi-fingered palpation over single-fingered palpation is proven in a user study;
2. Two multi-fingered systems using pneumatic actuators or pneumatic and granular jamming actuators that allow a user to carry out palpation of soft tissue experiencing haptic sensations at multiple fingers are created. The feasibility of this system is proven in evaluation studies.

5.2. Multi-fingered palpation using pseudo-haptic feedback

Palpation on tissue model using pseudo-haptic feedback with a single indenter avatar has already been presented in Chapter 4. Here, a multi-fingered palpation simulation using pseudo-haptic feedback with three indenter avatars is introduced and evaluated to prove the hypothesis that multi-fingered palpation is more efficient than single-fingered palpation.

5.2.1. Algorithm of multi-fingered pseudo-haptic feedback

Three spheres were used to represent three fingers in this simulation. Hence, during exploration a wider area can be covered instead of only one spot. During operation, these three spheres, whose centre was set to follow the input motion, were aligned in a triangular-shape. The same input force was applied to all the three spheres while they translated the height in the z-direction independently from each other according to the stiffness value of the nearest vertex on the surface. In this way, users were able to explore stiffness properties of three neighbouring areas simultaneously as if using three fingers to palpate. The same pseudo-haptic algorithm as described in Chapter 4 was used here. The average value was applied when the vertex had overlapped height values (see Figure 5-4 (a)). When the deformations at the three points were different, one could easily compare the stiffness values (see Figure 5-4 (b) and (c)). In order to prevent the S-pen or the finger of the user from obstructing the view, the indenter avatars were set to be apart from the interaction point at a 15 mm distance (see Figure 5-5 (b), (c) and (d)).

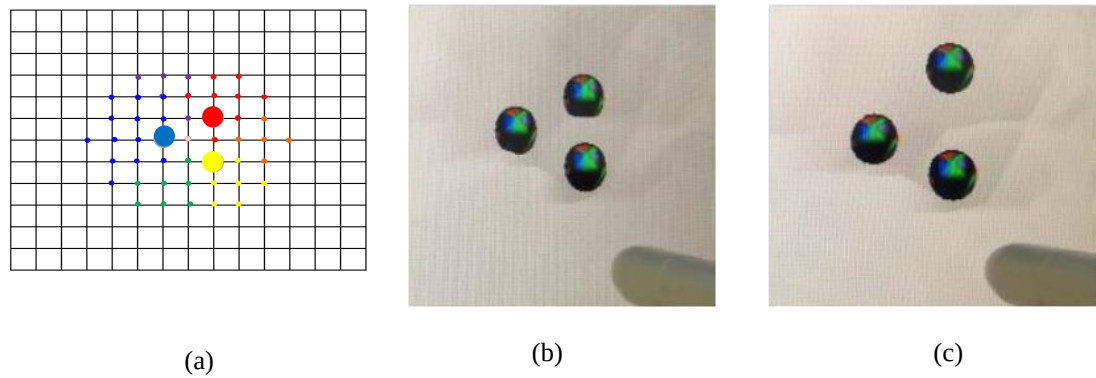


Figure 5-4 (a): the locations of the three indenter avatars and the overlapped affected vertices; (b): the three indenter avatars are at the same height representing no abnormalities; (c): the three indenter avatars are at different heights representing possible tissue abnormalities.

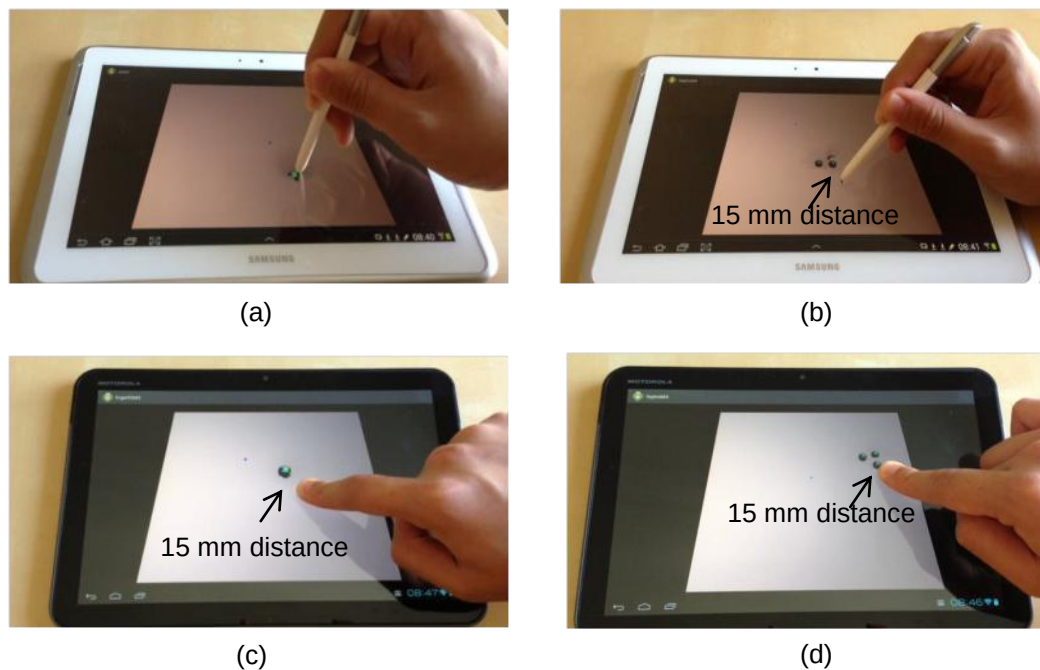


Figure 5-5 Pseudo-haptic palpation: (a): single-fingered palpation using a tablet and an S-pen; (b): multi-fingered palpation using a tablet and an S-pen; (c): single-fingered palpation using a tablet and a bare finger of the user; (d): multi-fingered palpation using a tablet and a bare finger of the user.

5.2.2. Evaluation test protocol of multi-fingered pseudo-haptic feedback

In order to validate the proposed multi-fingered palpation using pseudo-haptic feedback, four evaluation tests were conducted: 1) single-fingered pseudo-haptic palpation using a tablet and S-pen as input devices, 2) multi-fingered pseudo-haptic palpation using a tablet and S-pen as input devices, 3) single-fingered pseudo-haptic palpation using a table and a bare finger of the user as input devices, 4) multi-fingered pseudo-haptic palpation using a table and a bare finger of the user as input devices. Twenty participants, who had normal or corrected vision, participated in this empirical study. All of the participants were right-handed, had engineering background and no palpation experience (see Table 5-1). Firstly, participants were asked to do a practice run with known tumour locations. Then, they were asked to manipulate the input device to "palpate" the virtual soft object and observe the change of the ratio between the indenter avatar displacement distance and their input. When they found hard inclusions, they reported the locations. The researchers recorded the nodule detection rates and the time consumed. The order of tests was pseudo-random. For all those tests, the same stiffness distribution was used, but the orientation of the soft object was different from test to test. So the participants would not know the nodules' locations from the earlier tests.

Table 5-1 Overview of demographics and experience of multi-fingered palpation using pseudo-haptic feedback

Item	Detail
<i>Age range</i>	20-30
<i>Gender</i>	♀: 7; ♂: 13
<i>Handedness</i>	R: 20; L: 0
<i>Palpation experience</i>	0
<i>Engineering background</i>	20
<i>VR simulator</i>	0

5.2.3. Result of multi-fingered pseudo-haptic feedback

Figure 5-6 and Figure 5-7 present the nodule detection sensitivity Se (see equation (3.4)). The list of Se sorted from largest to smallest was as follows: single-fingered pseudo-haptic palpation using a tablet and an S-pen as input devices (91.67%, 95% confidential interval: 82.0 – 96.4%), multi-fingered pseudo-haptic palpation using a table and a bare finger of the user as input devices (90%, 95% confidential interval: 79.9 – 95.3%), multi-fingered pseudo-haptic palpation using a tablet and an S-pen as input devices (88.3%, 95% confidential interval: 77.8 – 94.2%), single-fingered pseudo-haptic palpation using a table and a bare finger of the user as input devices (85%, 95% confidential interval: 73.9 – 91.9%). The Se values were compared in pairs using the method described in Section 3.3. Table 5-2 shows the test result. There was no significant difference on the performance of nodule detection Se between the single-fingered pseudo-haptic palpation and multi-fingered pseudo-haptic palpation using neither a tablet and an S-pen as input devices nor a tablet and a bare finger of the user as input devices. Figure 5-8 presents the consumed time for nodule detection. Consumed time was (41.65 s, SD = 19.1) for multi-fingered pseudo-haptic palpation using a tablet and an S-pen as input devices, (41.75 s, SD = 12.7) for multi-fingered pseudo-haptic palpation using a table and a bare finger of the user as input devices, (61.75 s, SD = 25.1) for single-fingered pseudo-haptic palpation using a tablet and an S-pen as input devices, (61.8 s, SD = 23.6) for single-fingered pseudo-haptic palpation using a table and a bare finger of the user as input devices. Wilcoxon signed-rank test (see equation (3.7)) was used to compare the time consumed in pairs. The results are presented in Table 5-3. The results show that the multi-fingered pseudo-haptic palpation either using an S-pen or a bare finger consumed less time than single-fingered pseudo-haptic palpation. They also reveal that the multi-fingered pseudo-haptic palpation is more time-efficient than the single-fingered pseudo-haptic palpation.

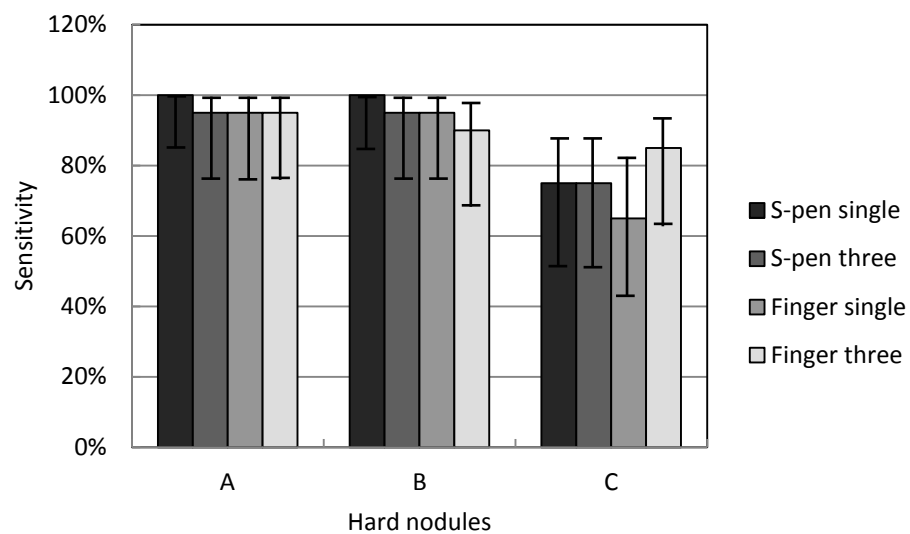


Figure 5-6 Nodule detection sensitivities for nodule A, B, and C with Wilson score intervals at a 95% confidence level of single-fingered palpation and multi-fingered palpation using pseudo-haptic feedback.

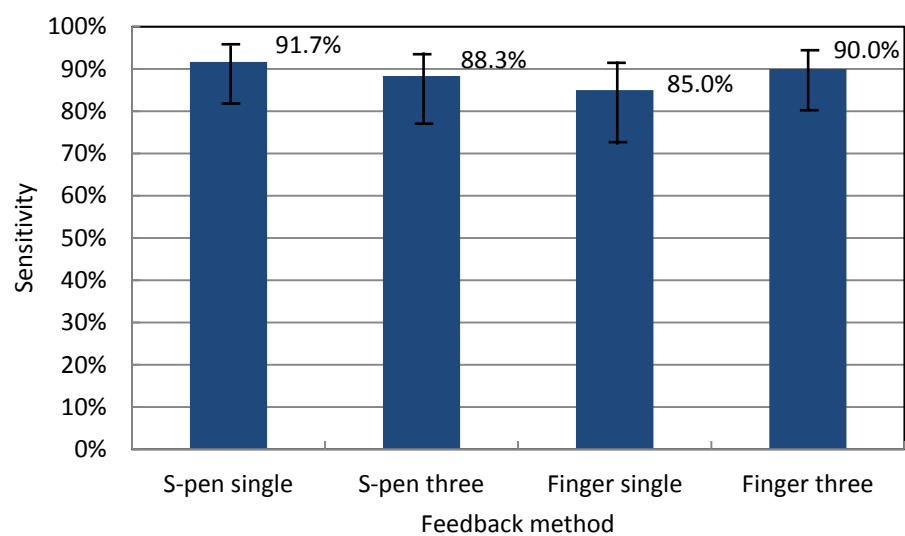


Figure 5-7 Overall nodule detection sensitivities with Wilson score intervals at a 95% confidence level of single-fingered palpation and multi-fingered palpation using pseudo-haptic feedback.

Table 5-2 Comparison of sensitivity of single-fingered palpation and multi-fingered palpation using pseudo-haptic feedback

Item	Combined interval (CI)	Probability difference (Δp)	Significance
<i>Single-fingered tablet + S-pen & multi-fingered tablet + S-pen</i>	0.114	0.034	$CI > \Delta p$, No
<i>Single-fingered tablet + bare finger & multi-fingered tablet + bare finger</i>	0.123	0.050	$CI > \Delta p$, No

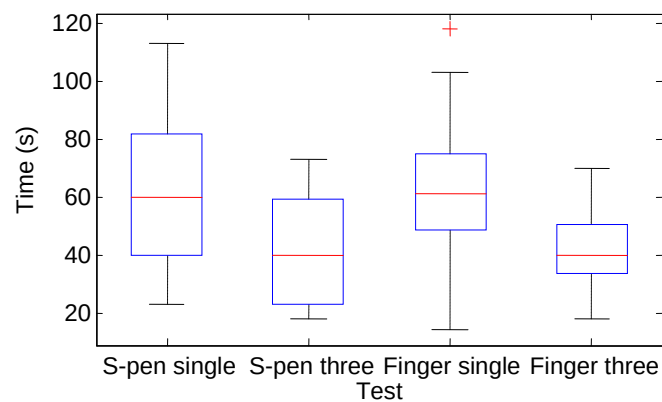


Figure 5-8 Consumed time of single-fingered palpation and multi-fingered palpation using pseudo-haptic feedback.

Table 5-3 Wilcoxon signed-rank tests for consumed time of single-fingered palpation and multi-fingered palpation using pseudo-haptic feedback.

Item	n_r	W	$W_{critical}$	Significance
<i>Single-fingered tablet + S-pen & multi-fingered tablet + S-pen</i>	18	3	47	$W < W_{critical}$, Yes
<i>Single-fingered tablet + bare finger & multi-fingered tablet + bare finger</i>	20	25	52	$W < W_{critical}$, Yes

5.3. Multi-fingered palpation using novel pneumatic actuators

5.3.1. Design of the novel pneumatic actuator

A pneumatic actuator, which was designed as part of this PhD study, was used to convey soft tissue stiffness information. This actuator contained a deformable surface, a non-deformable substrate with a cylindrical hole, air tubing and a pressure-controllable air supply. Figure 5-9 shows the proposed pneumatic haptic feedback actuator, which consists of four main parts – a soft silicone layer, a silicone rubber film (SILEX Ltd., HT6240, 0.25 mm thick, tensile strength 11 N/mm², elongation at break 440%, tear strength 24 N/mm [200]), a PDMS substrate (GE RTV615) with a cylindrical cavity (4 mm in diameter), and air tubing. When it is in use, air can be injected into the cavity of the PDMS substrate and cause the silicone rubber film to inflate. A finger of the user is in contact with the surface of the actuator and the actuator creates a stress change on the user's fingertip and gives an impression of the indentation when palpating a soft organ. The upper soft silicone layer (RTV6166 A : B = 1 : 2, thickness: 3 mm) was used to simulate the touch impression of soft tissue and limit the deformation of the silicone rubber film. The silicone rubber film and the substrate were bonded with translucent silicone rubber adhesive E41. The air tubing was connected to the PDMS substrate by using RTV108 clear silicone rubber adhesive sealant. The PDMS substrate was constructed using 3D prototyped moulds fabricated using a 3D rapid prototype machine (ProJetTM HD 3000 Plus), which has a minimum layer resolution of 16 µm (see Figure 5-10).

Figure 5-11 shows the block diagram of the control of the proposed pneumatic haptic feedback actuator. Data from the tactile sensor elements can be divided into three groups, whose average values can be used as the input of the system. The calculation of the three channels of air pressure values relates to the tactile sensing input (e.g. from a tele-manipulator). In the following evaluation studies, predefined stiffness levels or premeasured tissue stiffness were used instead of the tactile sensing input. Two NI DAQ cards (USB-6211) were used as analogue signal generators for the pressure regulators (ITV0010, SMC). Pneumatic supply was provided by a

compressor (Compact 106, Fiac Air-Compressors). The pressure output from the air compressor was set to be 1500 kPa. The pressure regulators reduced the air pressure and inflated each of the actuators with proportional pressures to the analogue signals ranging from 0 to 100 kPa.

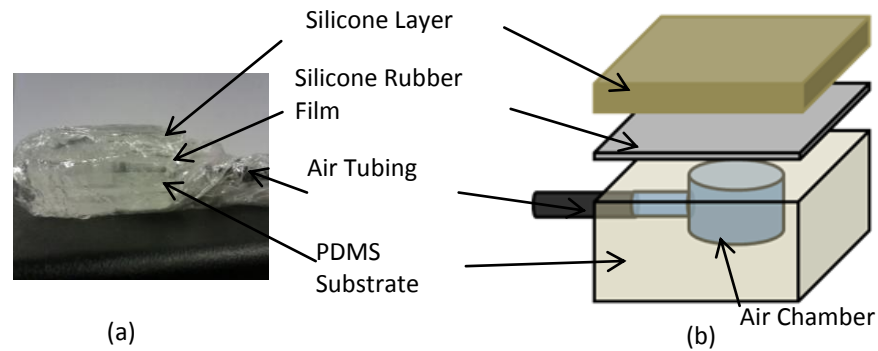


Figure 5-9 A pneumatic haptic feedback actuator, shown in (a); schematic diagram of the components, shown in (b).

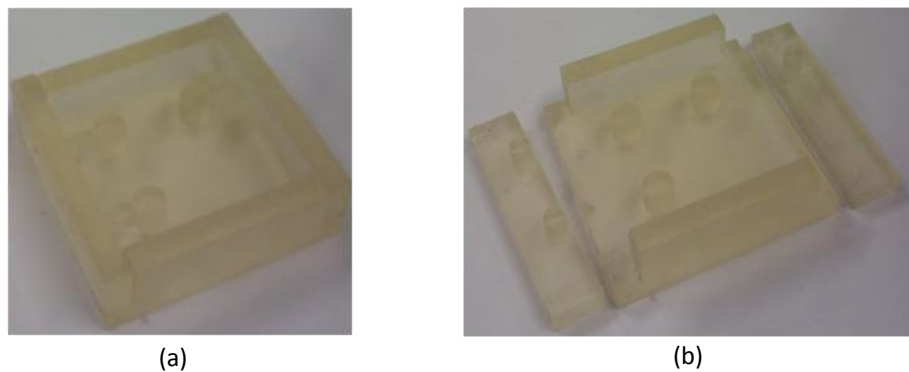


Figure 5-10 3D prototyped parting mould for PDMS substrate: assembled is shown in (a); parted is shown in (b).

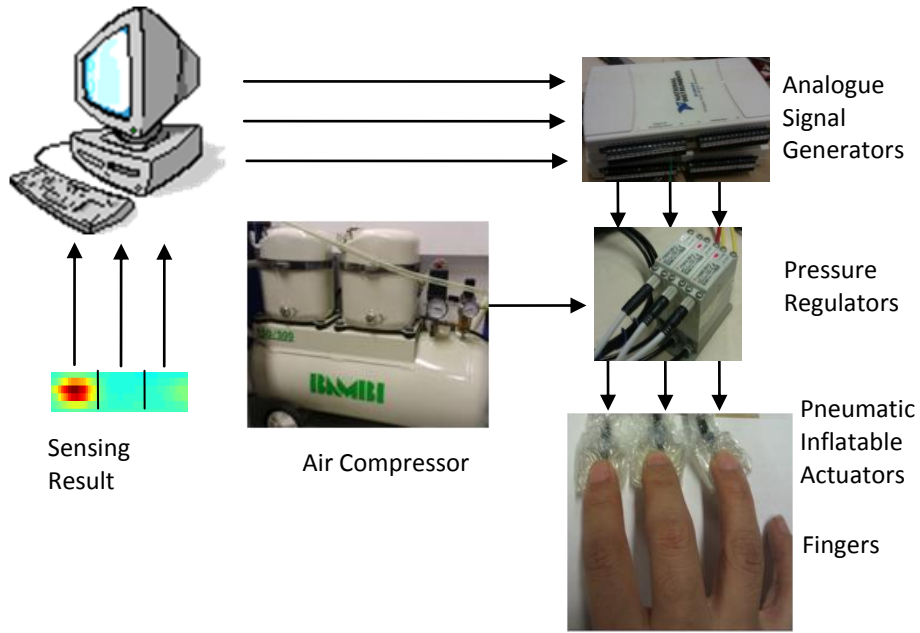


Figure 5-11 Multi-fingered palpation system.

5.3.2. Deformation response of the actuators

The deflection response of the actuators was examined under different inflation pressures ranging from 0 kPa to 100kPa when the top soft silicone layer had not been mounted on. The deflection of the actuators was measured by using a digital sliding calliper (Resolution: 0.01 mm, accuracy ± 0.02 mm). Tests were repeated five times. Figure 5-12 (a) and (b) shows a non-activated and an activated pneumatic haptic feedback actuator, respectively.



Figure 5-12 (a): Non-activated pneumatic haptic feedback actuator; (b): activated pneumatic haptic feedback actuator without the top silicone layer.

Figure 5-13 shows the experiment set-up for measuring the deformation response of the actuator. The calliper was first zeroed at the actuator surface with no inflation. The trammel was then raised so that it would not influence the deformation of the actuator. The trammel was lowered until it contacted the actuator surface after the actuator was

inflated. Figure 5-14 and Table 5-4 show the test results of actuator deformation (ξ). The accuracy of the linear trend lines are indicated by the correlation coefficients, confirming the linear relationship between the vertical actuator deformation and the inflation pressure.

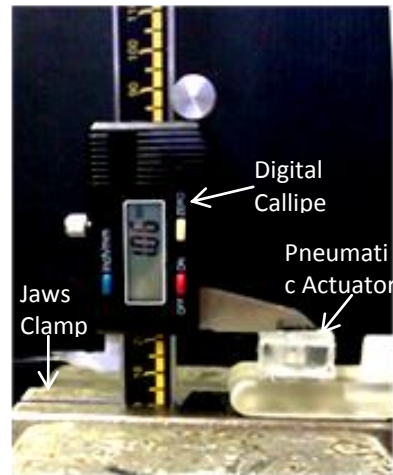


Figure 5-13 Experiment set-up for the deformation response of the actuator.

Table 5-4 Pneumatic haptic feedback actuators deformation regression

Status	Equation	R-squared value
<i>Inflation</i>	$y = 0.0428x - 0.3032$	0.9834
<i>Deflation</i>	$y = 0.0475x - 0.1333$	0.9725
<i>All</i>	$y = 0.0458x - 0.2098$	0.9563

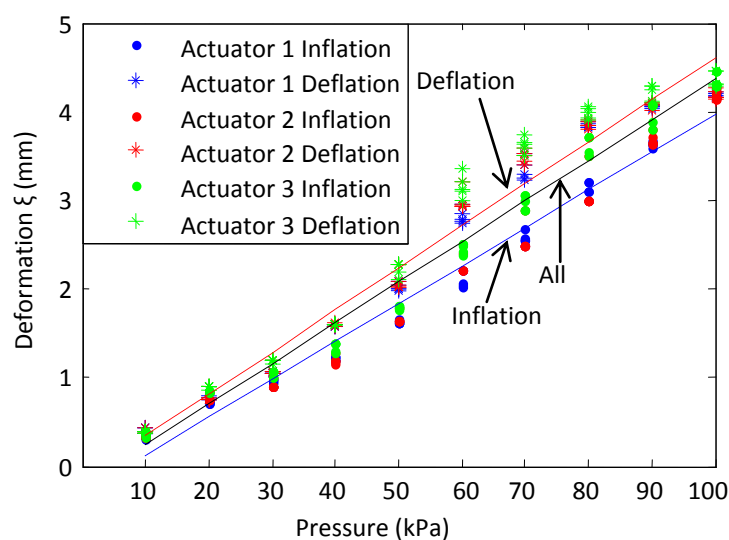


Figure 5-14 Pneumatic haptic feedback actuators deformation (ξ) testing results, across five trials.

5.3.3. Finite-element modelling of the proposed pneumatic actuator

According to the design, the perception of stiffness comes from the air pressure inside the pneumatic actuator. The stress on the fingertip caused by the inflation of the actuator gives an impression of the indentation when palpating a soft organ. To validate this concept, the stress of the fingertip caused by palpation was compared with the stress caused by the actuator using FE modelling.

The anatomical structures of fingertips can be mimicked by using continuum models, which can predict the stress / strain distributions of the fingertip during finger / soft tissue or finger / actuator interaction. This method has been used to investigate the mechanics of tactile sense [201], [202], predict the responses of mechanoreceptors in fingertip to edges, bars, and gratings [203], and explore the responses of the fingertip to static and dynamic compressions [204] and vibrations [205], [206]. The contact interactions between the human fingertip and soft tissues or tactile actuators have seldom been analyzed.

5.3.3.1. Finite-element models

The stress distribution of the fingertip during fingertip / tissue interaction was analyzed using a multi-layered 2D FE model, as shown in Figure 5-15. The fingertip, which was representative of the index finger of a male subject, was assumed to have a height of 12 mm and a width of 16 mm [207]. The skin was assumed to be 0.8 mm thick [205]. The cross section of the fingertip was obtained with reference to fingertip anatomy images [208]. The nail and bone were considered as linearly elastic. The cross section of the bone was assumed to be elliptical. The Young's moduli of the nail and bone were assumed to be 170.0 MPa and 17.0 GPa, respectively [209]. The Poisson's ratio was set to be 0.30. The densities of bone, nail, skin, and soft tissue were considered to be 2.7, 2.0, 1.0, and 1.0 [205]. The elastic deformation behaviour of the finger skin and subcutaneous soft tissue was assumed to be hyperelastic. The Ogden model was used to describe the elastic behaviour of the tissue:

$$U = \sum_{i=1}^N \left[\frac{2\mu_i}{\alpha_i^2} (\bar{\lambda}_1^{\alpha_i} + \bar{\lambda}_2^{\alpha_i} + \bar{\lambda}_3^{\alpha_i} - 3) + \frac{1}{D_i} (J - 1)^{2i} \right], \quad (5.1)$$

where $J = \lambda_1 \lambda_2 \lambda_3$ is the volume ratio, $\bar{\lambda}_i = J^{-1/3} \lambda_i$ with λ_i ($i = 1, 2, 3$) is the principal stretch ratios, N is the number of terms used in the strain energy function, and α_i , D_i , and μ_i are the material parameters, whose values used here are shown in Table 5-5.

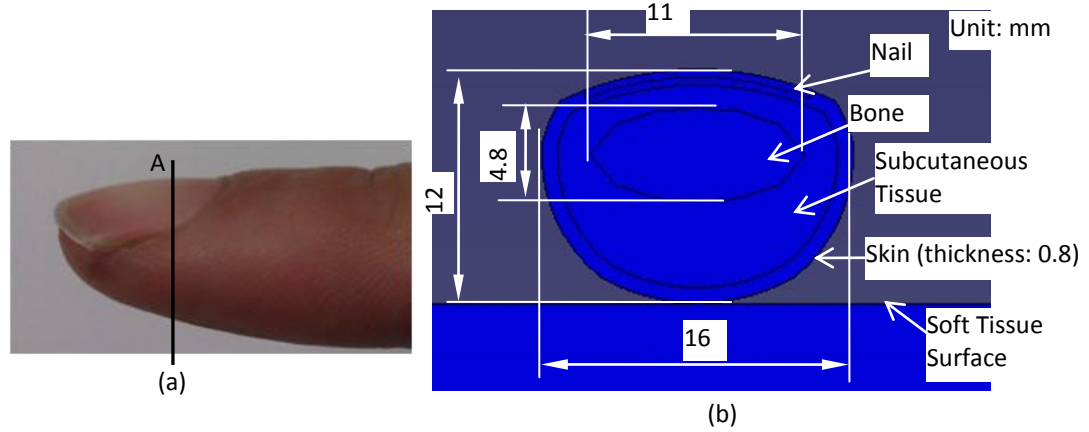


Figure 5-15 FE model of a fingertip cross section in contact with a soft tissue surface: the fingertip model is a cross section of a fingertip, shown in (a), and is composed of skin, subcutaneous tissue, nail, and bone; the nail and bone are assumed to be linearly elastic, shown in (b); the soft tissue, subcutaneous tissue, and the skin are assumed to be nonlinearly elastic.

The cross section of the simulated soft tissue sample was $100 \text{ mm} \times 30 \text{ mm}$. The cross section of the simulated tumour was circular (10 mm in diameter). The density was 1000 kg/m^3 . The elastic deformation behaviour of the soft tissue and tumour inside was also assumed to be hyperelastic. The Arruda-Boyce strain energy function was used to describe the hyperelastic behaviour of the tissue:

$$U = \mu \sum_{i=1}^5 \frac{C_i}{\lambda_m^{2i-2}} (I_1^i + 3^i) + \frac{1}{D} \left(\frac{J_{el}^2 - 1}{2} - \ln J_{el} \right), \quad (5.2)$$

where $C_1 = \frac{1}{2}$, $C_2 = \frac{1}{20}$, $C_3 = \frac{11}{1050}$, $C_4 = \frac{19}{7000}$, $C_5 = \frac{519}{673750}$; U is the strain energy; λ_m

is locking stretch, $I_1 = (\lambda_1^2 + \lambda_2^2 + \lambda_3^2)^{\frac{1}{2}}$; μ is shear modulus; J_{el} is the elastic volume ratio; D is a temperature dependent material parameter related to the bulk modulus. For fully incompressible materials $J_{el} = 1$, thus the second term of equation is zero. In the model, the chain stretch is represented in terms of the principal stretches λ_1 , λ_2 , and λ_3 as [210]:

$$\tau_{chain} = \frac{1}{\sqrt{3}} (\lambda_1^2 + \lambda_2^2 + \lambda_3^2)^{\frac{1}{2}}, \quad (5.3)$$

Under a uniaxial compression λ along the direction of λ_1 , the principal stretches follows: $\lambda_1 = \lambda$, $\lambda_2 = \lambda_3$. Since the tissue is assumed as incompressible, it holds: $\lambda_1 \lambda_2 \lambda_3 = 1$. Thus, $\lambda_2^2 = \lambda_3^2 = \frac{1}{\lambda}$, and the chain stretch can be expressed as:

$$\tau_{chain} = \sqrt{\frac{1}{3} \left[\lambda^2 + \frac{2}{\lambda} \right]}. \quad (5.4)$$

The locking stretch, τ_m , is equal to the chain stretch τ_{chain} at which the stress starts to dramatically increase as λ increases. Material parameters are shown in Table 5-5.

The membrane was considered to be linearly elastic. The ASTM D 2240 hardness of the membrane was 40 Durometer, Shore A [200]. The relationship between the Young's modulus and the ASTM D 2240 hardness is described as [211]:

$$\log(E) = 0.0235S - 0.6403, \quad (5.5)$$

$$S = \begin{cases} S_A, 20 < S_A < 80 \\ S_D + 50, 30 < S_D < 85 \end{cases}, \quad (5.6)$$

where E is the Young's modulus in MPa, S_A is the ASTM D2240 type A hardness, and S_D is the ASTM D2240 type D hardness. Thus, E of the membrane was calculated to be 1.994 MPa. The silicone layer was considered as hyperelastic. Arruda-Boyce strain energy function was used to describe the elastic behaviour of the silicone layer (see Table 5-5).

5.3.3.2. Palpation finite-element simulation

Using the proposed FE models of the fingertip and the soft tissue sample, the behaviour of indentation on the soft tissue with and without tumour embedded was modelled. The indentation depth increased from 0 to 7 mm. Thus, a downward displacement of 7 mm was applied to the finger bone. Figure 5-16, Figure 5-17 and Figure 5-18 show the simulation results of palpation on a soft tissue. The highest stress was 7.967 kPa at interaction centre when the indentation depth was 7 mm when there was a tumour embedded while the highest stress was 4.990 kPa when there was no tumour embedded. When there was a hard nodule underneath, the stress was concentrated to the contact point on top of the hard nodule. The stress distribution on

the fingertip was more even when palpating on a soft tissue without any hard nodule embedded than with a hard nodule embedded.

Table 5-5 Models and parameters used to describe elastic deformation behaviours of human fingertip, soft tissue with tumour embedded, and the pneumatic actuator

Item	Model	Parameters	Density (kg/m ³)
Bone	Linear elastic model	$E = 17 \text{ GPa}$, $\nu = 0.3$ [209].	2700 [205]
Nail	Linear elastic model	$E = 170 \text{ MPa}$, $\nu = 0.3$ [209].	2000 [205]
Finger tissue	Ogden model	$\alpha_i = -4.4894$, $D_i = 0.0$, $\mu_i = 1.934 \times 10^{-2} \text{ MPa}$ [205].	1000 [205]
Skin	Ogden model	$\alpha_i = -10.898$, $D_i = 0.0$, $\mu_i = 1.8428 \times 10^{-3} \text{ MPa}$ [205].	1000 [205]
Healthy soft tissue	Arrude-Boyce model	$\mu = 1.850 \text{ kPa}$, $\tau_m = 1.05$ [48].	850 [48]
Tumour tissue	Arrude-Boyce model	$\mu = 73.4 \text{ kPa}$, $\tau_m = 1.01$ [48].	1000 [48]
Silicone rubber membrane	Linear elastic model	$E = 1.994 \text{ MPa}$, $\nu = 0.49$.	970 [212]
Silicone layer	Arrude-Boyce model	μ is 4.98 kPa ; τ_m is 1.05 [48].	980 [48]

The interaction between the fingertip and the pneumatic actuator was simulated using the proposed FE models of the fingertip, the silicone rubber membrane, and the silicone layer (see Figure 5-19, Figure 5-20 and Figure 5-21). The air pressure was simulated by a distributed load which was increased from 0 to 100 kPa. At the same time, a downward displacement of 1 mm was applied to the finger bone to simulate the pressing behaviour of the finger. Figure 5-21 illustrates the change of the highest interaction stress at the interaction centre when different air pressure was applied to the pneumatic actuator. There was a linear relationship between the interaction stress and the applied air pressure. Using the curve fitting equation, an air pressure of 11.750 kPa, which should be applied to the pneumatic actuator, was calculated to convey the similar highest stress at the fingertip as 7.967 kPa in the simulation result of palpating on a soft tissue when there was a hard nodule embedded inside. The simulation results are shown in Figure 5-22. Similar to palpating on soft tissue without any hard nodule

embedded, the stress distribution on the fingertip was even when palpating on the inactivated actuator. Although the slope of the stress distribution for the interaction between the fingertip and the activated pneumatic actuator changed slightly at the air chamber edge, the stress was concentrated to the contact point on top of the air bump, which was similar as palpating on soft tissue with a hard nodule embedded inside. Figure 5-23 presents difference of the change of interaction stress at the interaction centre between palpating on a soft tissue and palpating on the pneumatic actuator. When using activated actuator to simulate the situation of tumour embedded, the correlation R-squared value was 0.9969 while the value was 0.9998 when using inactivated actuator to simulate the situation of no tumour embedded.

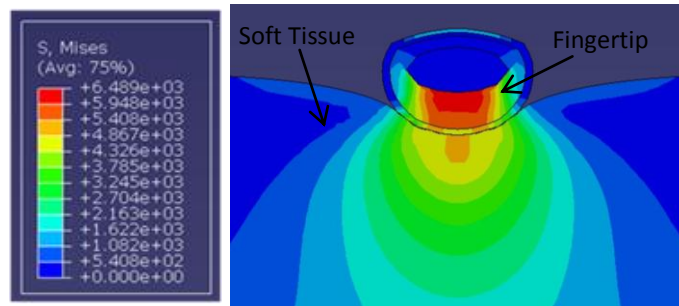


Figure 5-16 Stress distribution for palpation on a soft tissue without any hard nodule embedded at 7 mm indentation depth.

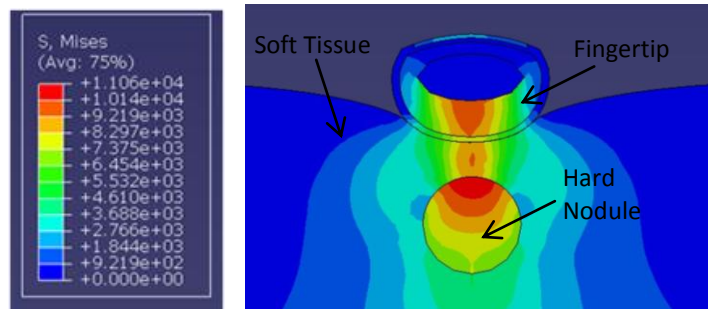


Figure 5-17 Stress distribution for palpation on a soft tissue with a hard nodule embedded at 7 mm indentation depth.

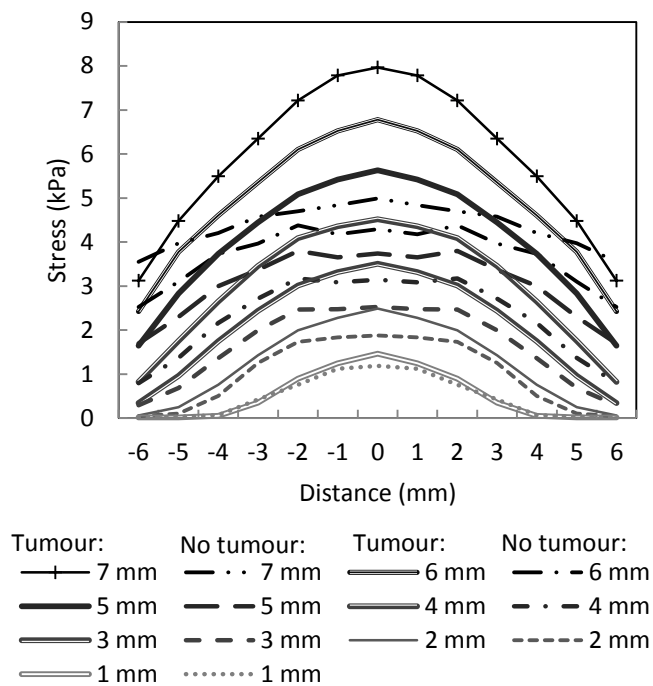


Figure 5-18 The stress distribution of the fingertip when palpating on the soft tissue with and without a hard nodule embedded.

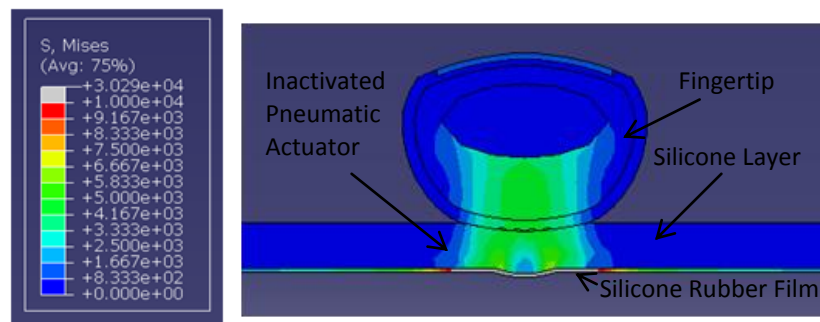


Figure 5-19 Stress distribution for the interaction between the fingertip and the inactivated pneumatic actuator.

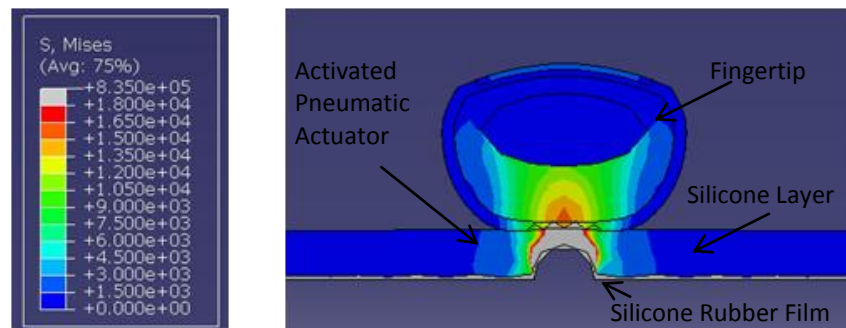


Figure 5-20 The stress distribution for the interaction between the fingertip and the activated pneumatic actuator at 100 kPa air pressure.

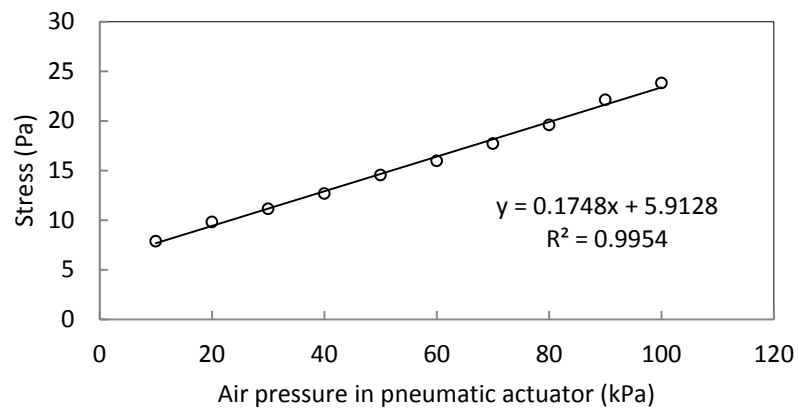


Figure 5-21 The change of interaction stress at the interaction centre when different air pressure is applied to the pneumatic actuator.

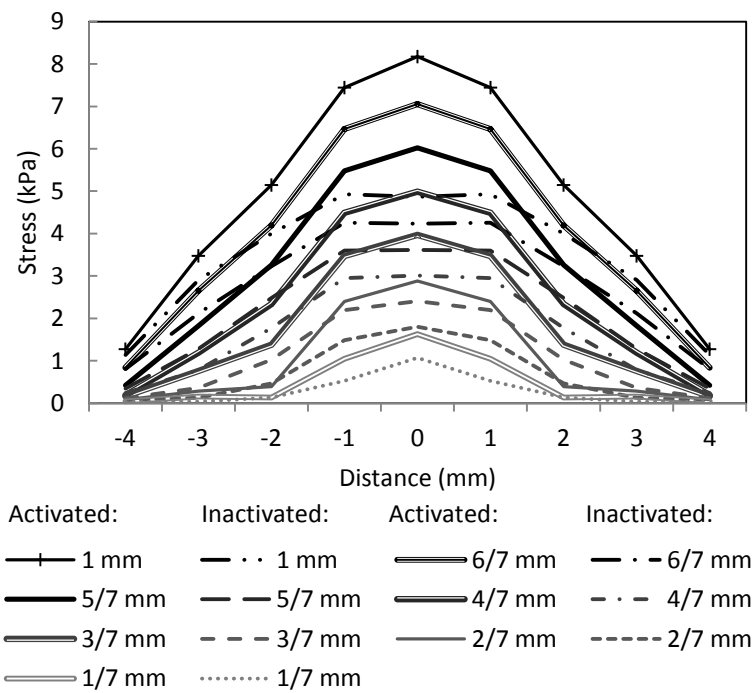


Figure 5-22 The stress distribution of the fingertip when palpating on the inactivated and activated pneumatic actuator.

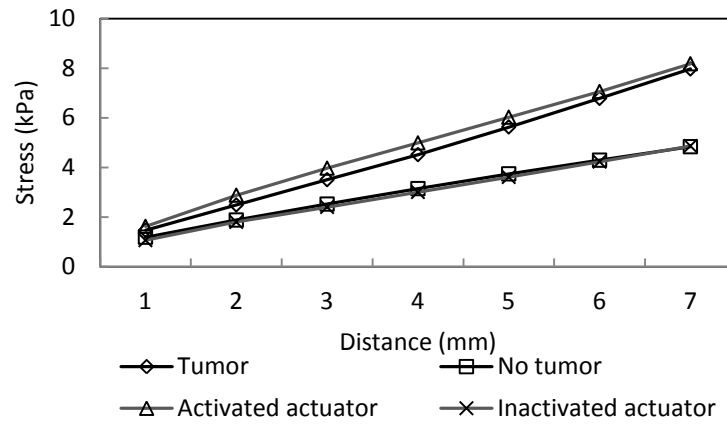


Figure 5-23 The comparison of the change of interaction stress at the interaction centre between soft tissue palpation and palpation with pneumatic actuator.

5.3.4. User study of multi-fingered palpation using the proposed pneumatic actuators

5.3.4.1. Discrimination of stiffness levels

A comparison study between a single-point feedback and the proposed multi-fingered feedback is helpful to demonstrate the advantages of the proposed method. Thus, a user study of discrimination of stiffness levels was conducted involving single-fingered feedback and three-fingered feedback. Three levels of air pressure were involved – 0, 10, 30 kPa. When the air pressure was higher at the actuator underneath one finger, a “tumour” was considered to be present; when the air pressure was higher at the actuators underneath two adjacent fingers, a “tumour” was considered to be present as well; when the air pressure levels were equal at the three actuators underneath all the three fingers, no “tumour” was present. Fourteen types of combination of air pressure levels at the three actuators were used. During the single-fingered feedback experiment, the participants perceived three pressure values of stiffness in order, while during the three-fingered feedback experiment they perceived the three values simultaneously. They were asked to report whether there was a tumour and where the location of the tumour was. During the test a stopwatch was used in order to measure the time required by the participant to acquire the stiffness information of each trial. The instrument allowed a precision of the time measurement of ± 1 s.

Twelve participants were involved in the trials: 4 women and 8 men. The demographics of the involved participants are presented in Table 5-6. All the tests were performed pseudo-randomly by each participant.

Table 5-6 Overview of demographics and experience of the participants of experiments of discrimination of stiffness levels using pneumatic actuators

Item	Detail
<i>Age range</i>	23-36
<i>Average age</i>	28.7
<i>Gender</i>	♀: 4; ♂: 8
<i>Handedness</i>	R: 12; L: 0
<i>Palpation experience</i>	0
<i>Engineering background</i>	12

Figure 5-24 presents the sensitivities Se , specificities Sp , positive predictive values PPV , and accuracies ACC with Wilson score intervals (see equation (3.5)) at a 95% confidence level of the stiffness levels discrimination tests using the proposed pneumatic actuators. The Se , which relates to the test's ability to identify positive results, was defined in equation (3.4). The Sp , which is the measure of the test's ability to identify negative results, was defined in equation (4.19). The PPV , or precision rate, was defined in equation (4.16). The ACC was defined in equation (4.20). The sample size was 504 (3 values $\times$ 14 trails $\times$ 12 participants). From Figure 5-24 one can see that three-fingered feedback had higher values in Se , Sp , PPV and ACC . There was no overlap of Se and PPV intervals between the single-fingered feedback and the three-fingered feedback, in other words, the differences were significant. The differences of Sp and ACC between the single-fingered feedback and the three-fingered feedback were also significant. These were examined using the same method as described in Section 3.3. The combined interval (CI) of Sp was 0.026 while the probability difference (Δp) was 0.027, $\Delta p > CI$; the combined interval (CI) of ACC was 0.027 while the probability difference (Δp) was 0.035, $\Delta p > CI$.

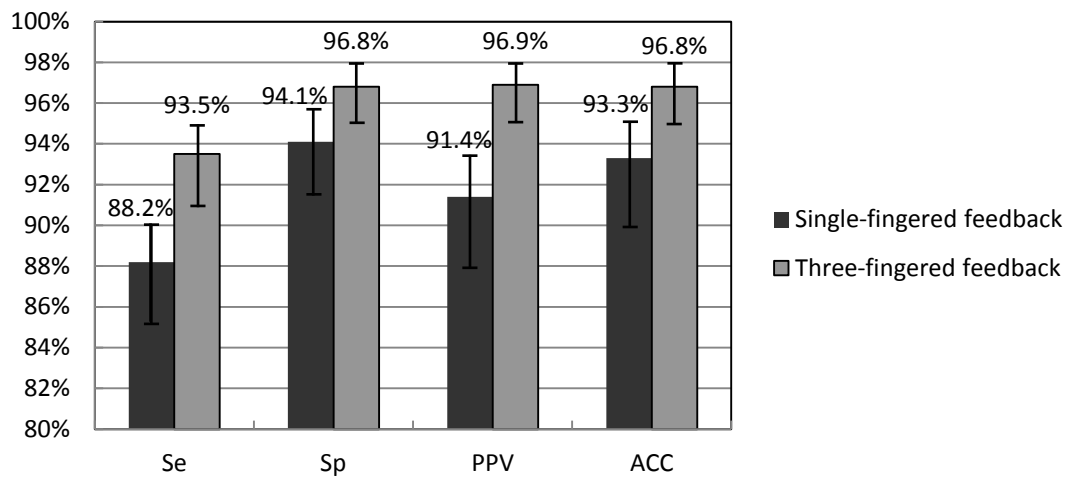


Figure 5-24 The sensitivities, specificities, positive predictive values, and accuracies of stiffness levels discrimination with Wilson score intervals at a 95% confidence level of single-fingered feedback and three-fingered feedback using pneumatic actuators.

Figure 5-25 presents the consumed time during the discrimination tests of stiffness levels. Since the sample size was 168 (14 trails $\times$ 12 participants), it was considered as normally distributed and a student t-test was performed to compare the consumed time during the tests. The three-fingered feedback test consumed significantly less time than the single-fingered feedback test since p -value was 7.42×10^{-32} .

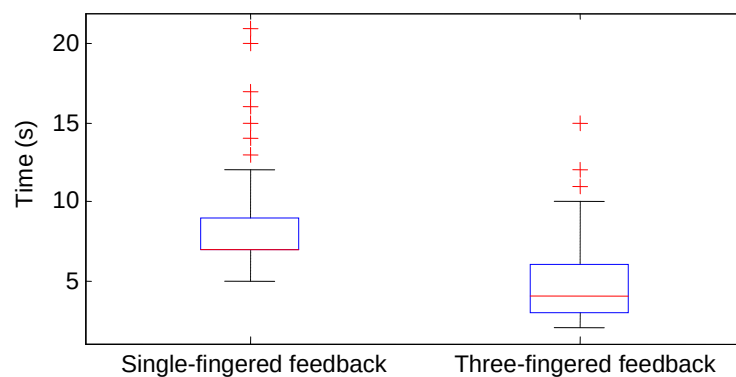


Figure 5-25 The consumed time during the tests of stiffness levels discrimination of single-fingered feedback and three-fingered feedback using pneumatic actuators.

5.3.4.2. Palpation performance of tumour detection

To further prove the efficiency of the proposed actuator and multi-fingered palpation method for tumour detection in palpation simulation, a user study on palpation using a premeasured stiffness distribution map was conducted. The stiffness distribution map is shown in Figure 5-26 and the experimental set-up is shown in Figure 5-27. A pressure-sensitive touchpad (Wacom BAMBOO Pen & Touch) was used as a position and normal force input device. Both the graphical feedback of the interaction point on the tissue surface through computer graphics and the mechanical feedback via the pneumatic haptic feedback actuators were provided. The graphical interface and the computation of the reaction force were realized in a VC++ programme while the analogue signal values were sent to the NI DAQ cards (USB-6211) via a Labview programme. UDP communication was used between the two programmes. The coordinates of the touchpad surface were linearly mapped to the soft object surface. Three spheres displayed on the graphical interface were used to represent three fingers. During operation, these three spheres were aligned in a right angled triangular-shape, whose vertex at the right angle was set to follow the motion of the pen. The output forces via the pneumatic actuators to the three fingers translated independently from each other according to the applied palpation force on the touchpad and the stiffness value of a closest vertex on the surface. In this way, users were able to explore three neighbouring properties at the same time. Nine subjects were involved in this study. None of them had any palpation experience. The demographics of the involved participants are presented in Table 5-7. All participants could feel the simulated stiffness differences. The measured stiffness distribution came from a silicone phantom soft tissue embedded with artificial tumours A, B, C (see Figure 5-26), which were plastic cubes with thickness of 4 mm, 12 mm and 8 mm. The detection sensitivities Se of simulated tumour A, B, C were 66.7%, 100%, and 88.9%, respectively. There was a positive correlation between the nodule detection sensitivities and nodule sizes.

Table 5-7 Overview of demographics and experience of the participants of experiments of palpation user study using pneumatic actuators

Item	Detail
<i>Age range</i>	23-43
<i>Average age</i>	29.1
<i>Gender</i>	♀: 2; ♂: 7
<i>Handedness</i>	R: 9; L: 0
<i>Palpation experience</i>	0
<i>Engineering background</i>	9

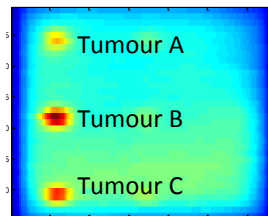


Figure 5-26 Measured stiffness distribution.

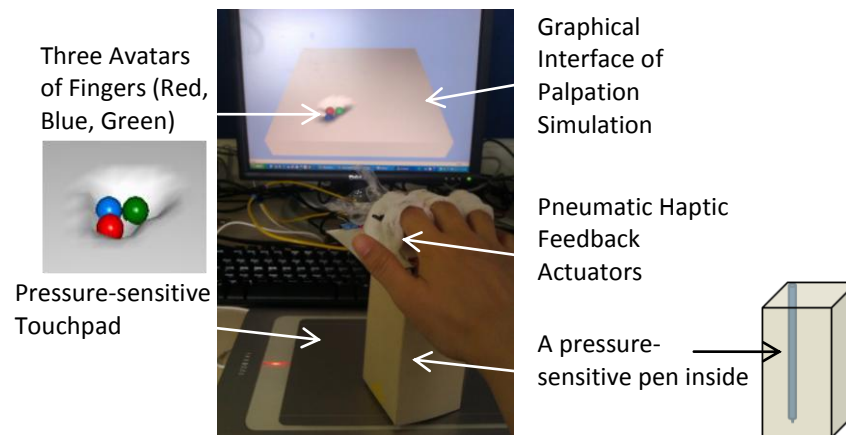


Figure 5-27 Experimental set-up for evaluation test.

5.4. Multi-fingered palpation using novel pneumatic and granular jamming actuators

5.4.1. Design of the novel pneumatic and granular jamming actuator

Stiffness control technologies can be divided into material stiffening and structural stiffening. The viscosity of ER (Electro-rheological) fluid can be controlled by being subjected to an electric field. Similarly, the rheological properties of MR (Magneto-rheological) fluid change when applying an external magnetic field. Khaled et al. [22] described a tactile actuator array using ER fluid. Liu et al. [127] described a single MR fluid-based tactile element. Variations in the magnetic field effect instant changes to the sensed surface profile. However, the controllability of these two methods is relatively low. It is difficult to tune stiffness. Moreover, the yielding strengths of ER fluid and MR fluid are only about 0–5 kPa (5,000 V/mm at 2–15 mA/cm²) and 0–100 kPa (239 kA/m magnetic field) [213].

In Section 5.3, the tissue stiffness information was conveyed by using the proposed pneumatic actuators to change the stress on the user's fingertip. In this section, the tissue stiffness is simulated directly by using granular jamming. To the best knowledge of the author, this is the first time this approach has been proposed and studied. The physical phenomenon of granular jamming is a structural stiffening method for stiffness variation. Jamming is a phenomenon where a type of phase change of the granular matter occurs due to external stimuli [214]. Jamming can be induced by increasing density when a flexible membrane containing granular matter, e.g. coffee or rice, is vacuumed. The density can be controlled by regulating the vacuum level; thus it is possible to make particles act like a liquid, solid, or something in between. Jamming has been used for haptic feedback [215] and has been already used in several robotic devices even in the medical field [216]–[220]. Other researchers have shown that ground coffee is the ideal granule type for jamming [217]. In this PhD study, granular jamming was chosen for stiffness control. Coffee was used inside the granular jamming chamber as the granular material and latex was used as the containing membrane. For the specific application of palpation, the main

drawback of using granular jamming is that the particles will tend to adapt to the shape of the indenter (the finger in this case) as happens in the universal gripper [216]. This drawback was addressed by adding a pneumatic chamber under the granular jamming chamber. The pneumatic chamber made sure that the coffee returned to a flat shape and kept in contact with the fingertip when it was jammed. Placing an air cushion below the granular jamming chamber prevented it from changing shape by absorbing the applied indentation force on the actuator. Moreover, when the applied contact force was released, the pneumatic chamber bounced back, which caused the coffee powder to loosen up in the granular jamming chamber. The proposed pneumatic and granular jamming actuator is shown in Figure 5-28. The granular jamming chamber was made by filling 5 g of coffee powder (Lavazza, Aualita Rossa, medium roasting) in a latex membrane (average thickness: 0.07 mm), which provides a relevant change in the elastic modulus during compression and has low hysteresis [221]. When the granular jamming chamber is activated (see Figure 5-28 (d)), the size of the chamber is reduced compared to the loose status as shown in Figure 5-28 (c). The particles will tend to adapt to the shape of the indenter (the finger in this case) the achieved behaviour is comparable to that of the universal gripper where this phenomenon is exploited for gripping materials of different shapes [216]. In the envisaged use of the granular jamming based stiffening chamber, it is not desirable to have a permanent deformation of the granules when the finger is pressed against them. In order to avoid the permanent deformation, a pressurized pneumatic chamber was added below the granular jamming chamber. The pneumatic air chamber was made by pouring silicone liquid (Ecoflex™ 0050 – Smooth on Inc.) in a printed mould using a 3D rapid prototype machine (ProJet™ HD 3000 Plus), which has a minimum layer resolution of 16 µm. A rigid substrate was used to restrict the deformation of the pneumatic chamber except for the top surface.

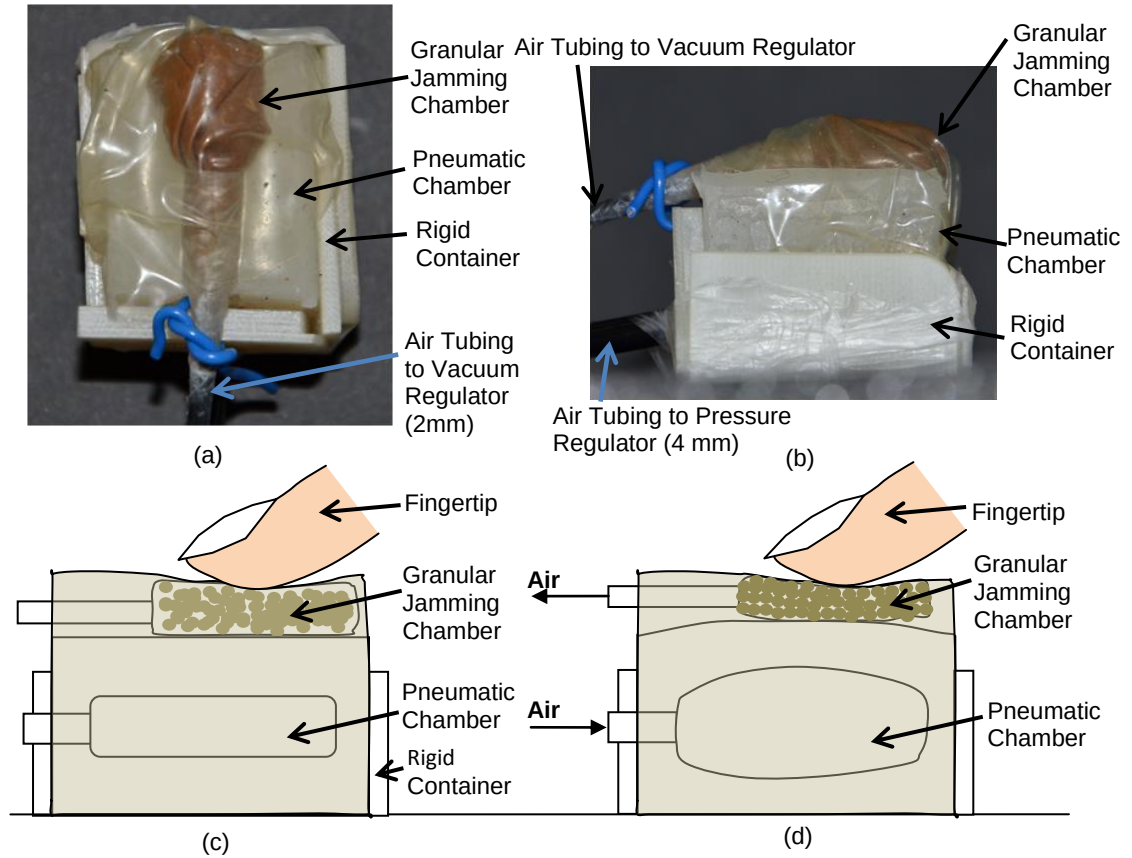


Figure 5-28 (a) Top and (b) side view of a prototype of pneumatic and granular jamming actuator, and a profile view of the (c) inactivated and (d) activated actuator.

Figure 5-29 (a) shows the block diagram of the control of the pneumatic haptic feedback actuators. According to the tactile sensing input (e.g. from the tele-manipulator), the air pressure values of the corresponding two channels can be calculated. In our evaluation study, predefined stiffness levels were used instead of the tactile sensor input. Pneumatic supply was provided by a compressor (BAMBI 150/500 air compressor) with an output of 1500 kPa. Three NI DAQ cards (USB-6211) were used as analogue signal generators for the electronic pressure regulators and vacuum regulators. The pressure regulators (SMC ITV0010) reduced the air pressure and inflated each of the actuators with proportional pressures ranging from 0 to 100 kPa. A Mastercool 90066-2V-220 pump and vacuum regulators (ITV0090, SMC) were used to extract air from each of the actuators with proportional pressures ranging from -1 to -100 kPa. A piece of non-woven fabric was used at the air tubing tip in the granular jamming chamber to prevent coffee powder to enter into the tubing

and a filter (ZFC050-04B, SMC) was used to further prevent particles to enter into the pump. A haptic device with two actuators was fabricated and integrated in the structure as depicted in Figure 5-29 (b) to produce a two-fingered palpation system. Such structure provided a compact assembly of the two interfaces and limited the expansion of the silicone, during the air inflation, in all directions with the exception of the top surface, where the granular jamming chamber was placed.

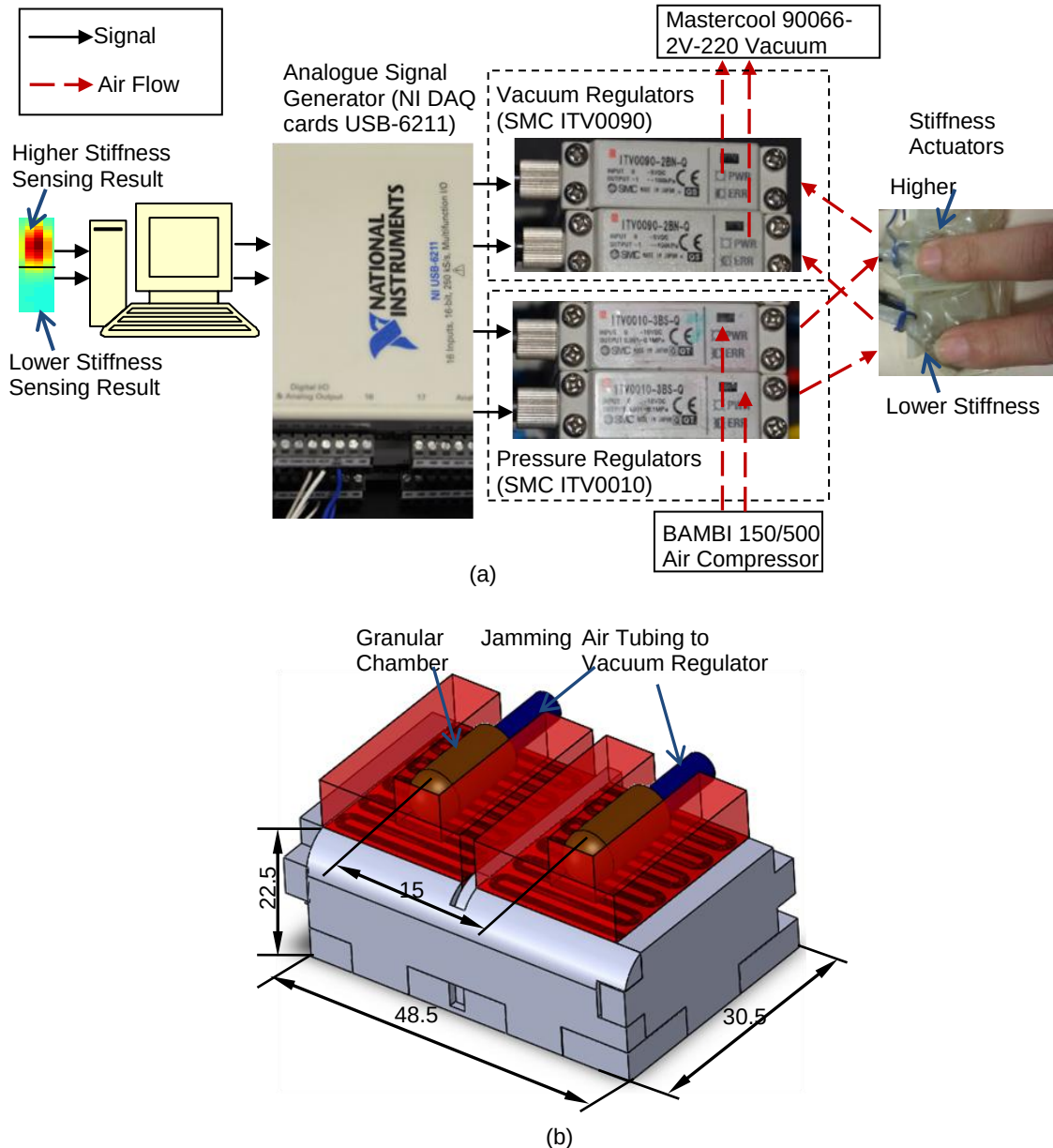


Figure 5-29 Schematic diagrams of (a) the multi-fingered palpation system and (b) CAD model showing assembly of the two finger palpation system (units: mm).

5.4.2. Structure enhancement validation

According to the previous study of pneumatic actuator described in the last section, the application of air pressure caused a hemispherical deformation of the silicone rubber membrane. To even the surface deformation of the pneumatic chamber it is proposed to embed a cotton thread in the silicone layer. To validate this idea, a comparison study was conducted using a 3D finite element model, as shown in Figure 5-30. The material properties used in this FE model are shown in Table 5-8. At the controlled trial, the material of the thread was replaced by the silicone material. In the simulation, a uniform distributed load (100 kPa) was applied on the inner surface of the air chamber. The other five surfaces of the chamber were fixed by an encastre boundary condition.

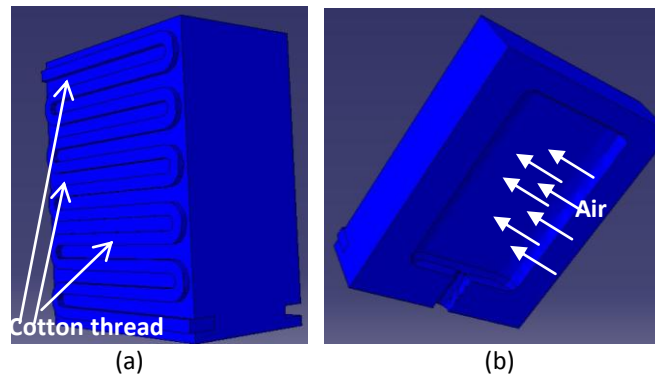


Figure 5-30 3D model of a silicone air chamber: (a) integral structure; (b) semi-section.

Table 5-8 Material properties used in the finite element model

Properties	Cotton thread	Silicone
<i>Mass density (tonne/mm³)</i>	1.54×10^{-9} [222]	1.07×10^{-9} [223]
<i>Young's Modulus (MPa)</i>	8200 [222]	Null
<i>Hyperelasticity</i>	Null	Uniaxial test data
<i>Poisson's ratio</i>	0.5	0.4

The inflation behaviour of the silicone chamber was modelled using the proposed FE models of the cotton thread and the silicone chamber. The simulation result was shown in Figure 5-31. The maximum deformation of the air chamber with the cotton thread was smaller (5.96 times) than without the cotton thread. The deformation of the

actuator surface when the cotton thread was used distributed more evenly than when there was no structure enhancement.

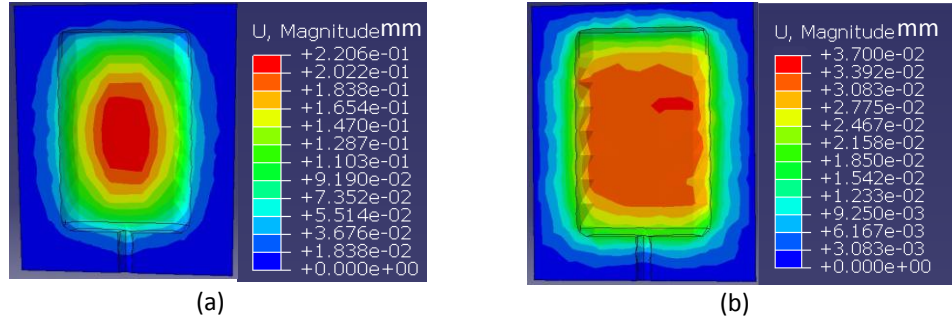


Figure 5-31 Deformation result: (a) without structure enhancement; (b) with structure enhancement.

Another type of condition was modelled, namely a deformable fingertip contacting the surface when the actuator was activated. The fingertip, representative of the index finger of a male subject, was assumed to have a height of 18 mm and a width of 20 mm [206]. The cross section of the fingertip was obtained with reference to fingertip anatomy images [208]. The cross section of the bone was assumed to be elliptical. Figure 5-32 shows the fingertip in shaded and wireframe render model. The nail and bone were considered as linearly elastic. The Young's moduli of the bone and nail were assumed to be 17.0 GPa and 170.0 MPa [209]. The Poisson's ratio was assumed to be 0.30. The densities of bone, nail, inner skin, outer skin and soft tissue were considered to be 2.7, 2.0, 1.0, 1.0, and 1.0 [205]. The elastic deformation behaviours of the subcutaneous soft tissue and inner skin were simulated using the polynomial model which was defined as:

$$U = \sum_{i+j=1}^N C_{ij} (\bar{I}_1 - 3)^i (\bar{I}_2 - 3)^j + \sum_{i=1}^N \frac{1}{D_i} (J - 1)^{2i}, \quad (5.7)$$

where $\bar{I}_1$ and $\bar{I}_2$ are the two deviatoric strain invariants; N , C_{ij} , D_i are the material parameters; J is the elastic volume ratio. The material parameters are listed in Table 5-9.

Figure 5-33 shows the simulation result when a deformable fingertip is in contact with the actuator surface. Similarly to when there was no fingertip in contact with the actuator surface, the deformation of the actuator surface when the cotton thread was used distributes more evenly than when there was no structure enhancement. The

maximum deformation of the air chamber with the cotton thread was smaller (4.74 times) than without the cotton thread. The fingertips reduce the deformation magnitude of the actuator surface slightly, from 0.221 mm to 0.220 mm and from 0.037 mm to 0.035 mm.

Table 5-9 Elastic parameters for the soft tissues of the fingertip [206]

Item	C10 (MPa)	C01 (MPa)	C11 (MPa)	C20 (MPa)	C02 (MPa)	D1 (MPa ⁻¹)
<i>Inner skin</i>	2.34E-3	5.42E-3	-0.262	0.239	7.47E-2	13.3
<i>Tissue</i>	5.97E-4	1.34E-3	-6.55E-2	5.96E-2	1.87E-2	53.3

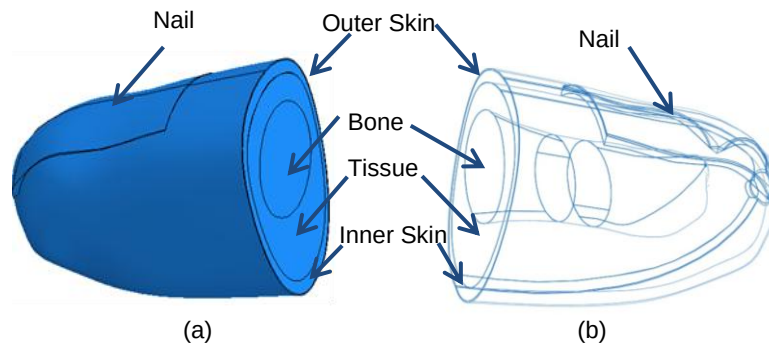


Figure 5-32 Fingertip model: shaded (shown in (a)) and wireframe (shown in (b)) render model.

To validate whether this design also works if a rigid indenter is used, e.g. in the stiffness variation validation test described in the next section, a rigid fingertip was modelled. The results show that the maximum deformation of the air chamber with the cotton thread was smaller than without the cotton thread (see Figure 5-34). The deformation magnitude was reduced by 2.80 times when the rigid finger was used. Therefore, the cotton thread can be used in the actuators for the following validation tests both when contacting with a rigid indenter and with human fingers.

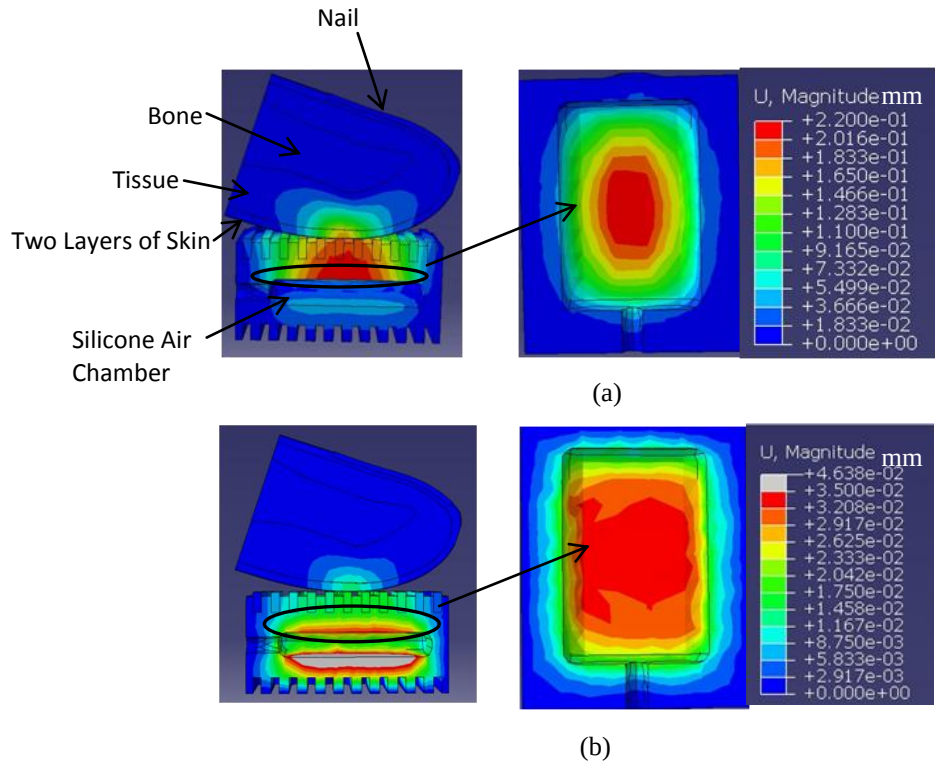


Figure 5-33 Deformation result: (a) deformable finger and actuator with no structure enhancement; (b) deformable finger and actuator with structure enhancement.

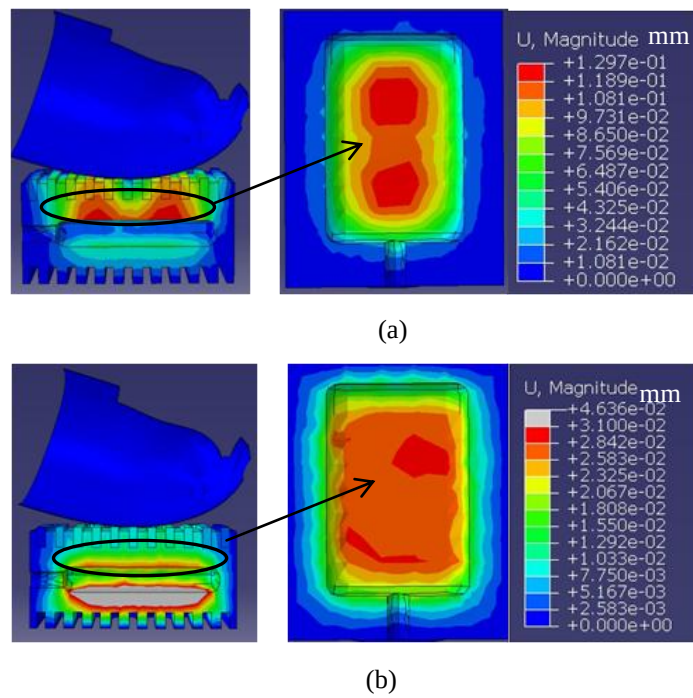


Figure 5-34 Deformation result: (a) rigid finger and actuator with no structure enhancement; (b) rigid finger and actuator with structure enhancement.

5.4.3. Stiffness variation validation

In order to validate the performance of the stiffness variation using the proposed pneumatic and granular jamming actuator, an experiment was set up as shown in Figure 5-35. A rigid indenter was used to conduct the indentation test and the normal reaction force and indentation depth information was recorded. A pneumatic and granular jamming actuator was fixed at one side of a guide rail. An ATI Nano 17 F/T sensor (SI-12-0.12, resolution 0.003 N with 16-bit data acquisition card), which was attached to a hemispherical indenter for force measurement, was fixed to the sliding block on the guide rail. A Maxon EC-30 motor powered linear module controlled the indentation depth. A Labview program was used to control the motor position and record the indentation depth, air pressure, vacuum level, and force data.

Tests were conducted with 3 mm indentation depth and using different combinations of pressure inside the chamber and vacuum level in the granular jamming based stiffening chamber. A maximum pressure of 20 kPa was chosen in order to maintain a small amount of deformation of the air chamber surface. The maximum vacuum pressure was -100 kPa. The indentation speed was set at a very low 0.1 mm/s in order to neglect possible dynamical effects. Each test was repeated 8 times.

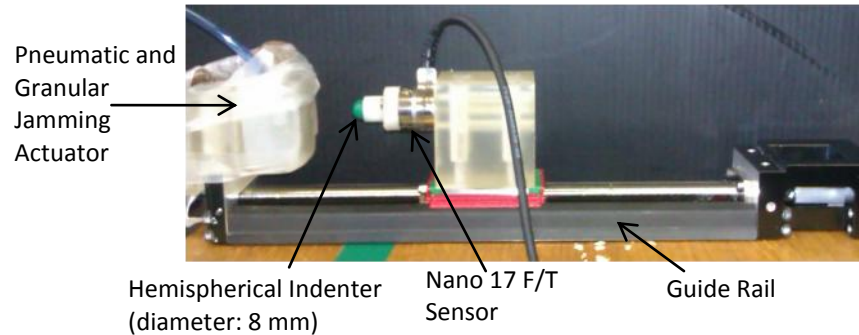


Figure 5-35 Experiment setup of stiffness variation validation.

Figure 5-36 (a) presents the reaction force from the actuator during the indentation tests when only the pneumatic chamber was activated and the granular jamming chamber was present but not vacuumed. From this figure it is evident that an increase in the pressure level increased the stiffness of the actuator, but it would be very difficult to discriminate the stiffness levels since the curves corresponding to pressures greater than 0 kPa almost overlapped. In addition, as evident from Figure

5-36 (a), the silicone behaviour was dominant. Figure 5-36 (b) shows the reaction force from the actuator during the indentation tests when three levels of air pressure (0 kPa, 15 kPa, and 20 kPa) and three levels of vacuum pressure (0 kPa, -30 kPa, and -100 kPa) were applied. We can observe that as expected when the granular jamming chamber was activated, higher vacuum pressures produced steeper slopes of the stress-strain curves. The actuator had an almost linear response with the exception of the very first tract when both the two chambers were not activated and the hyperelasticity of the silicone material was dominant. The inflation of air in the pneumatic chamber affected mainly the slope of the curves and tended to increase the distance between the curves corresponding to the different vacuum levels. The maximum reached force, however, did not increase considerably since the air cushion absorbed part of the load and thus avoided permanent deformation of the variable stiffness chamber. From the test results shown in Figure 5-36 (a) and (b), one can see that the stiffness variation was amplified by the inflation of air.

Figure 5-36 (c) depicts the stiffness variation calculated using Hook's law on the curves of Figure 5-36 (b). One of the main advantages of the proposed combination of air pressure and granular jamming, as evident from Figure 5-36 (c) is that the pressurized actuator presented a more linear change in stiffness at the different vacuum levels. In contrast, the change in stiffness was more abrupt when no air pressure was applied. When the air pressure was 20 kPa, the relationship between vacuum pressure and stiffness was more linear and the hysteresis was lower than when the other two air pressure levels were applied. The hysteresis was computed as the area between the loading and the unloading cycles. As shown in Figure 5-36 (d) hysteresis decreased considerably (up to 65%) when the air chamber was inflated. This data confirmed that the permanent deformation of the granular jamming chamber was considerably reduced. Therefore, 20 kPa air pressure was applied in the following user study.

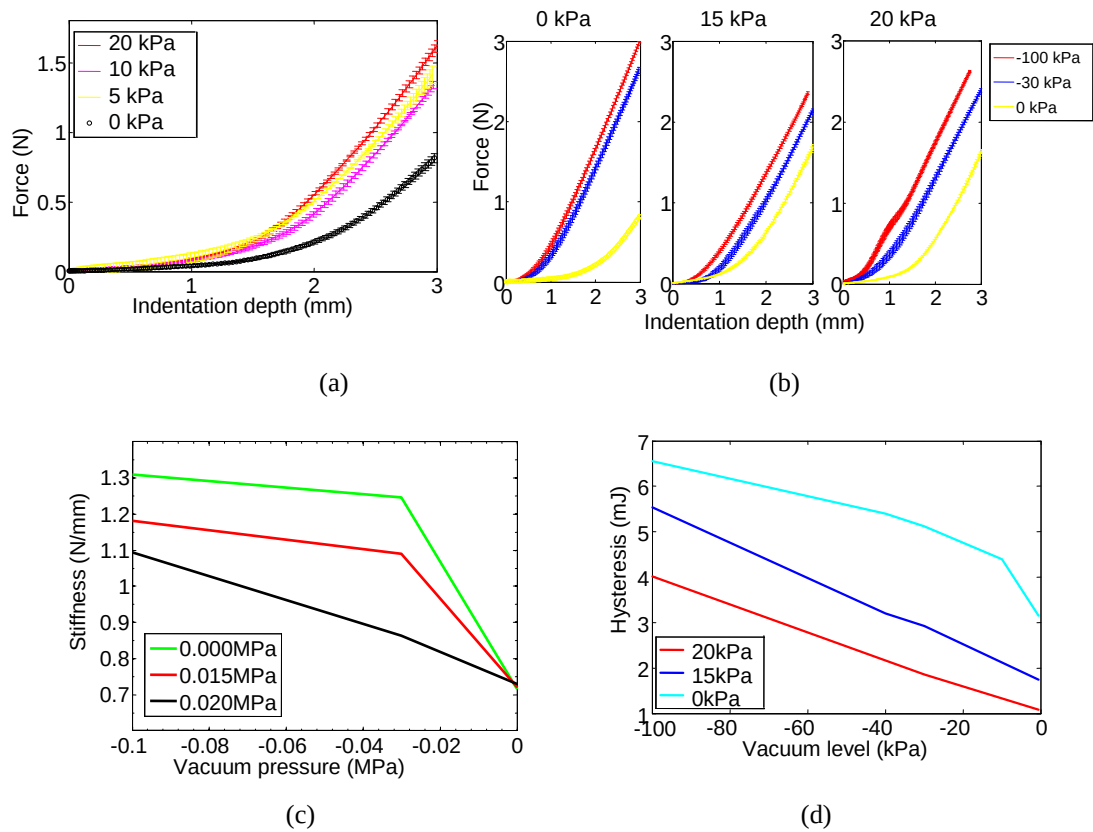


Figure 5-36 Indentation result with error bar shown when only the pneumatic chamber in the actuator is activated, shown in (a); indentation result with error bar shown when both the pneumatic chamber and granular jamming chamber in the actuator are activated, shown in (b); stiffness variation when both the pneumatic chamber and granular jamming chamber in the actuator are activated, shown in (c); hysteresis when both the pneumatic chamber and granular jamming chamber in the actuator are activated, shown in (d).

5.4.4. User study of multi-fingered palpation using the proposed pneumatic and granular jamming actuators

A user study of stiffness discrimination was conducted to validate the ability of tissue stiffness interpretation of the proposed pneumatic and granular jamming actuators. Two types of feedback were investigated, namely single-fingered feedback and two-fingered feedback. Three levels of vacuum were involved, that is 0, -10, -100 kPa. When the stiffness level was higher at the actuator underneath one finger, a “tumour” was considered present; when the stiffness levels were equal at the two actuators

underneath both fingers, no “tumour” was considered present. Eight types of combination of stiffness levels were used. During the single-fingered palpation, the participants were asked to perceive two levels of stiffness one after the other, while during two-fingered palpation the two levels of stiffness were fed back simultaneously to them. During the test a stopwatch was used in order to measure the time required by the participant to explore the surface of each trial. The instrument allowed a time measurement precision of ± 1 s. Twelve participants were involved in the trials: 4 women and 8 men. The demographics of the involved participants are presented in Table 5-6. All the tests were performed pseudo randomly by each participant.

Figure 5-37 presents the sensitivities Se , specificities Sp , positive predictive values PPV , and accuracies ACC with Wilson score intervals (see equation (3.5)) at a 95% confidence level of the stiffness levels discrimination tests by using single-fingered feedback and two-fingered feedback through the proposed pneumatic and granular jamming actuators. The Se , which relates to the method's ability to identify positive results, was defined in equation (3.4). The Sp , which is the measure of the method's ability to identify negative results, was defined in equation (4.19). The PPV , or precision rate, was defined in equation (4.16). The ACC was defined in equation (4.20). The sample size was 192 (2 values $\times$ 8 trails $\times$ 12 participants). From Figure 5-37 one can see that two-fingered feedback had higher values in Se , Sp , PPV and ACC . However, the difference significance examination method described in Section 3.3 (see Table 5-10) shows that the differences were not significant.

Figure 5-38 presents the consumed time during the tests of stiffness levels discrimination. Since the sample size was 96 (8 trails $\times$ 12 participants), it was considered as normally distributed and a student t-test was performed to compare the consumed time during the tests. The two-fingered feedback test consumed significantly less time than the single-fingered feedback test since p -value was 2.60×10^{-14} .

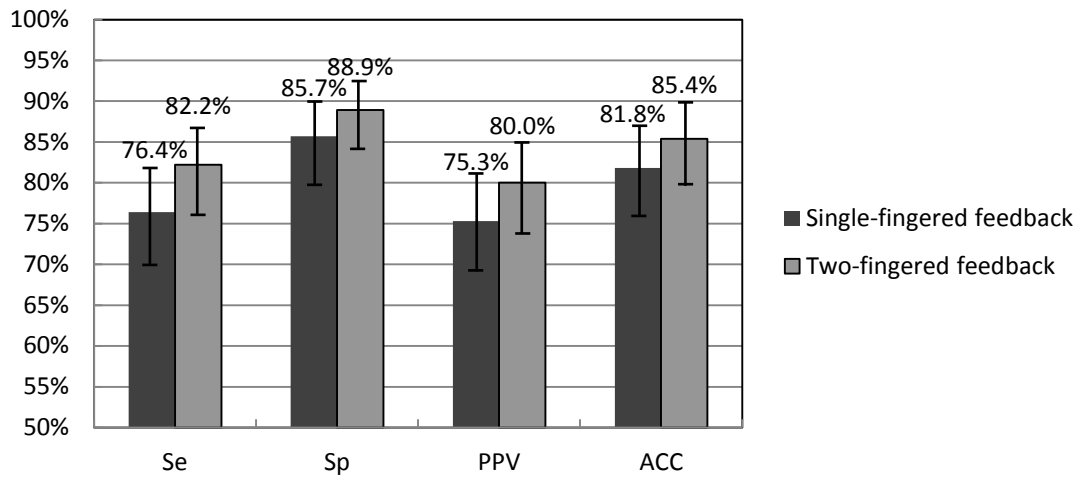


Figure 5-37 The sensitivities, specificities, positive predictive values, and accuracies of stiffness levels discrimination with Wilson score intervals at a 95% confidence level of single-fingered feedback and two-fingered feedback using pneumatic and granular jamming actuators.

Table 5-10 Comparison of sensitivity, specificity, and accuracy in stiffness levels discrimination tests of single-fingered feedback and two-fingered feedback using pneumatic and granular jamming actuators

Item	Combined interval (CI)	Probability difference (Δp)	Significance
<i>Se</i>	0.081	0.058	$CI > \Delta p$, No
<i>Sp</i>	0.067	0.032	$CI > \Delta p$, No
<i>PPV</i>	0.083	0.047	$CI > \Delta p$, No
<i>ACC</i>	0.074	0.036	$CI > \Delta p$, No

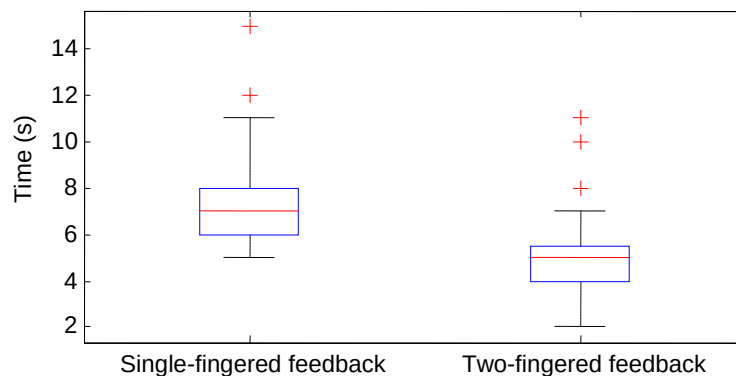


Figure 5-38 The consumed time during the tests of stiffness levels discrimination of single-fingered feedback and two-fingered feedback using pneumatic and granular jamming actuators.

5.5. Discussion

5.5.1. Pneumatic actuators

While high correlation R-squared values (inflation: 0.9834, deflation: 0.9725) in Section 5.3.2 indicate the consistency in performance among those three pneumatic actuators, there were some differences on mid- to high-range of the deflections between the different finger actuators, which can be overcome by a standardized manufacturing process. Although there was a high R-squared value (0.9563) for all actuators during inflation and deflation, some hysteresis can be observed between inflation and deflation (see Figure 5-14). Hysteresis compensation would be necessary.

During the deformation response of the actuators, visual determination of the contact between the calliper trammel and the inflated silicone rubber film on the actuator may have added some error despite the digital sliding calliper being accurate enough for the measurement. In fact, the average standard deviation at each measurement point was quite low (2.82%). Therefore, the visual determination of the contact between the calliper trammel and the inflated silicone rubber film did not add large error to the data.

In Figure 5-22, there was a noticeable change of the slope of the stress distribution for the interaction between the fingertip and the activated pneumatic actuator at the air chamber edge. The diameter of the cylindrical cavity of the air chamber inside the actuator may have influenced the stress distribution on the fingertip when the actuator was activated. Further study is needed.

The system's response time is another aspect that needs further study. The selected pressure regulator can operate with a response time as low as 50 ms. In this palpation experiment, the UDP communication between the VC++ graphical programme and the Labview analogue signal generation programme slowed down the system. An integration of the software would be needed to avoid this issue.

5.5.2. Pneumatic and granular jamming actuators

Both sets of FEM simulation results (when a rigid fingertip and deformable fingertip was in contact with the surface of pneumatic and granular jamming actuator described

in Section 5.4) have confirmed that the cotton thread can strengthen the silicone surface of the actuator. As expected, the rigid fingertip restricted the deformation more than the deformable fingertip when no cotton thread was embedded. Compared to the original structure, the enhanced structure reduced the deformation magnitude of the actuator surface. The difference was larger when the deformable finger was used than when the rigid finger was used.

When the same vacuum pressure is applied to different actuators the size consistency of the granular jamming chambers affects stiffness consistency. In this study, the granular jamming chambers described in Section 5.4 were hand-made and hand-picked to achieve the size consistency. The difficulty of making granular jamming chamber with the same dimension can be overcome by a standardized fabrication process.

As observed during the stiffness variation tests, the pneumatic and granular jamming actuators described in Section 5.4 had an almost linear response except when the actuator was not activated. When the actuator was not activated, it presented the hyperelasticity of the silicone material during the indentation tests. The inflation of air in the pneumatic chamber amplified the stiffness variation by affecting the slope of the curves and tended to increase the distance between the curves corresponding to the different vacuum levels. Part of the indentation load was absorbed by the air cushion and thus permanent deformation of the variable stiffness chamber was avoided.

Some hysteresis can be observed between the stress-strain curves of loading and unloading especially when the vacuum was higher than -60 kPa (see Figure 5-36 (d)). By introducing the air chamber under the granular jamming chamber, hysteresis decreased considerably (up to 65%) when the air chamber was inflated. This data confirmed that the permanent deformation of the granular jamming chamber was considerably reduced. To further diminish hysteresis, hysteresis compensation would be necessary in the future studies.

Although the two-fingered feedback produced higher values in Se , Sp , PPV and ACC than single-fingered feedback, the differences between the two were not significant. In other words, the advantage of two-fingered feedback on stiffness levels discrimination

was not significant. The two-fingered feedback test consumed significantly less time than the single-fingered feedback test. Therefore, the user study results of discrimination of stiffness levels revealed that the two-fingered feedback was more time-efficient to convey tissue stiffness information to the user.

5.6. Conclusion

This chapter validated multi-fingered palpation methods: (1) pseudo-haptic feedback and (2) stiffness feedback actuators and compared them with the performance of single-fingered palpation. The hypothesis that multi-fingered palpation should be more efficient than single-fingered palpation was proven to be true.

First, a multi-fingered palpation method using pseudo-haptic feedback was introduced. In order to validate the multi-fingered palpation using pseudo-haptic feedback, four tests were conducted: single-fingered and multi-fingered pseudo-haptic palpations using a tablet and an S-pen as input device, single-fingered and multi-fingered pseudo-haptic palpations using a table and a bare finger of the user as input device. The user study results showed no significant difference on the performance of nodule detection among the four methods of input and feedback. The multi-fingered pseudo-haptic palpation either using an S-pen or a bare finger of the user consumed less time than single-fingered pseudo-haptic palpation. The user study revealed that the multi-fingered pseudo-haptic palpation was more time-efficient than the single-fingered pseudo-haptic palpation.

A multi-fingered pneumatic actuator system that allowed a user to carry out palpation of soft tissue experiencing haptic sensations at multiple fingers was proposed. The tissue stiffness information was conveyed by using the proposed pneumatic actuators to change the stress on the user's fingertip as experienced during palpation. This principle was proven by examining the deflection response of the actuators, analyzing the contact stress using finite element analysis, and evaluating the performance of discrimination of stiffness levels and tumour localization in user studies. The experimental results proved that the stress changing on fingertips during palpation could be recreated by using the proposed pneumatic multi-fingered haptic feedback method. The three-fingered feedback using the proposed pneumatic actuators was

more accurate and efficient on discrimination of stiffness levels than single-fingered feedback.

Finally, a novel pneumatic and granular jamming actuator was proposed to simulate tissue stiffness directly. This principle was proven by examining the stiffness variation of the actuators and evaluating the performance of discrimination of stiffness levels in a user study. The experimental results proved that the stiffness of the actuator could be controlled to simulate tissue stiffness; the introduction of pneumatic chamber to granular jamming could amplify the stiffness variation and reduce hysteresis of the actuator; the two-fingered feedback using the proposed pneumatic and granular jamming actuators was more time-efficient on discrimination of stiffness levels than single-fingered feedback.

The proposed pneumatic actuators as well as pneumatic and granular jamming actuators provide solutions for multi-fingered palpation haptics. The accuracy and time-efficiency advantages of using multi-fingered palpation over single-fingered have been proven. With real-time tactile sensing data, the application of these actuators can be extended from simulated haptics to intra-operative palpation haptics. Those proposed methods of multi-fingered haptic feedback can also be adopted for other applications where sensory substitution is required, including VR-based games and general robotic manipulation.

Chapter 6 Conclusions

This chapter concludes with an overview of the research presented in this thesis on the topic of haptic palpation in medical training and RMIS. A summary of the salient contributions of this research is presented and suggestions for future research are proposed.

6.1. Summary

The aim of the thesis was to research the performance of different feedback modalities of soft tissue stiffness information and the combination of those modalities for palpation training and mimicking the function of palpation in RMIS. Visual stiffness feedback, force feedback, pseudo-haptic feedback, and multi-fingered haptic feedback were investigated for tumour identification using tissue computer models based on indentation tests.

RMIS provides many advantages compared to conventional open surgery such as small incisions via Trocar ports and, thus, less operative trauma for the patient. However, it does not enable the direct hand / soft tissue interaction inside the patient's body for tumour localization. This puts constraints on the identification of tumours and their boundaries in RMIS. The state-of-the-art in intra-operative tumour localization in RMIS was reviewed in Chapter 2 in order to identify the limitations of existing systems and future research directions. The reviewed intra-operative methods were divided into several categories including force-based sensing, tactile-based sensing, and medical imaging techniques, which have already been in use or have the potential to be used for mimicking the function of intra-operative hand / soft tissue interaction. The limitations and challenges of the current state-of-the-art were addressed and discussed. Overall, no robust and fast intra-operative solution has been proposed and most existing methods are still in a laboratory stage and have not been tested *in-vivo* as yet. In order to improve user experience and create a technique that comes as close as possible to manual palpation, this thesis proposed the use of multi-

fingered actuators and the combination of different feedback modalities, including pseudo-haptic and real haptic feedback, graphical and haptic displays.

In Chapter 3, a real-time visual stiffness feedback method for RMIS was proposed and validated in an experimental tele-manipulation environment. The usefulness of three feedback modes (visual stiffness feedback, force feedback, and the combination of the two) for tissue stiffness examination was evaluated using tumour identification performance as an evaluation indicator. The experiment results showed that 1) stiffness maps could be successfully generated, 2) subjects could localize hard nodules inside the artificial tissue using all feedback modes, 3) the proposed tele-manipulator was time-efficient for tumour identification with an average time for all trials of 107.6 s, 4) there was no significant difference among methods concerning nodule detection sensitivities and the time consumed for tumour seeking, and 5) the limit of the indentation depth was beneficial for preventing tissue damage and reducing the requirements of the haptic feedback device stiffness. In the circumstances that direct force feedback is not achievable, for instance, when haptic feedback device is difficult to be integrated in the surgical tele-operator, visual stiffness feedback can be used to provide tissue property information for surgeons as long as the indentation depth is controlled to keep the palpation force maintained in a safe range.

In Chapter 4, an intra-operative haptic tissue model generation and pseudo-haptic feedback method was presented that is capable of representing tissue stiffness distribution of the examined soft tissue to avoid the control issues of direct force feedback and can give users a direct impression of reaction force value during palpation. The proposed pseudo-haptic method eliminates the need for expensive haptic devices. Tangent reaction force of sliding behaviour and normal reaction force of indentation behaviour during palpation were firstly simulated separately using a 2-DOF input device (i.e. a computer mouse) and then were compared using the evaluation indicator of tumour identification performance. To provide a realistic tumour identification experience, a geometrical soft tissue deformation computation method was proposed to provide tissue deformation visual feedback during haptic palpation. Different from the popular mass-spring models where indenters are

simplified to small points, the influence of the indenter diameter on tissue deformation was considered. The roles of visualization of tissue surface deformation and pseudo-haptic feedback in tumour identification were investigated. Moreover, a pseudo-haptic feedback method with 3D haptic information was proposed and validated to be applied in soft tissue stiffness simulation using different input devices: a 3-DOF motion tracking input device and force-sensitive 2D haptic surface input devices. Furthermore, the combination of force feedback and pseudo-haptic feedback was proposed and experimentally examined to improve on what can be achieved in the haptic feedback system for tumour identification.

Analyzing the evaluation tests, one can see that participants were able to notice the stiffness differences among different tissue areas using all these input devices and feedback methods. There was no significant difference in nodule detection sensitivity between the tangent force simulation and the normal force simulation. Pseudo-haptic tissue stiffness simulation and visualization of tissue surface deformation performed the best on nodule detection sensitivity, specificity, accuracy and consumed time when they were combined rather than when they were used separately. The use of the force-sensitive 2D surface - touchpad input device and a 3-DOF motion tracking input device produced nearly the same results. Applying direct touch interaction simulation by using tablet computers improved the performance of hard inclusions detection while applying direct touch immersive illusion using tablet and S-pen even had a better result than the manual detection. Compared to sole pseudo-haptic or force feedback, the proposed combined feedback technique enabled participants to detect faster hard nodules in the soft tissue. The survey showed that participants using the pseudo-haptic feedback combined with force feedback method experienced an enhanced palpation perception.

Therefore, it can be safely concluded that the pseudo-haptic feedback can be used to convey haptic information in rigid tool / soft tissue or hand / soft tissue interaction in virtual environments. Both visualization of tissue surface deformation and pseudo-haptic feedback play important roles in tumour identification. Direct touch immersive illusion can achieve a hard nodule detection result as well as manual palpation while combination of the pseudo-haptic and force feedback for haptic perception of the

interaction between a rigid tool and a soft object has benefits over sole pseudo-haptic or force feedback.

In Chapter 5, multi-fingered palpation using pseudo-haptic feedback and stiffness actuators were evaluated and compared with the performance of single-fingered palpation. Multi-fingered palpation was simulated using pseudo-haptic feedback and the efficiency advantage of multi-fingered palpation over single-fingered palpation was proven in a user study. A multi-fingered system using pneumatic or pneumatic and granular jamming actuators that allows the user to carry out palpation on soft tissue experiencing haptic sensations at multiple fingers was created. The feasibility of this system was proven by examining the deflection response of the actuators, analyzing the contact stress using finite element analysis, and evaluating the performance of discrimination of stiffness levels and localization of embedded tumours in user studies. The experimental results proved that 1) the contact stress on fingertip during palpation can be recreated by using the proposed pneumatic actuator, 2) the stiffness of the proposed pneumatic and granular jamming actuator can be controlled to simulate tissue stiffness, 3) the introduction of pneumatic chamber to granular jamming can amplify the stiffness variation and reduce hysteresis of the actuator, and 4) the multi-fingered feedback using the proposed actuators is more accurate and efficient on soft tissue stiffness information transmission than single-fingered feedback. With real-time tactile sensing data, the application of these actuators can be extended from simulated haptics to intra-operative palpation haptics.

The research results provide potential solutions for tissue stiffness feedback and tumour identification in medical training and RMIS. The application areas of the research results would also be extended to general rigid tool-soft object interaction in virtual reality environments, like in video games.

6.2. Achievements

This thesis has achieved the following:

- Novel visual feedback methods of soft tissue stiffness information
 - The creation of a novel efficient real-time visual tissue stiffness feedback method (colour stiffness map) using sliding indentation,

which performed as well as force feedback in an experimental tele-manipulation environment using tumour identification performance as an evaluation indicator.

- The creation of a geometrical soft tissue deformation computation method to provide real-time visual feedback of tissue deformation during haptic palpation.
- The creation of pseudo-haptic feedback methods for soft tissue stiffness simulation using a strategy of cursor speed modification and other auxiliary feedback strategies, including a mouse cursor size changing strategy, a flashing cursor strategy, and a shaking background strategy.
- Multi-fingered haptic feedback interfaces
 - The design of a novel pneumatic haptic actuator which simulates soft tissue stiffness by changing the pressure of an air balloon and recreates the stress distribution on the fingertips as experienced during palpation.
 - The design of a novel stiffness feedback actuator using combined granular jamming and pneumatic air balloon to realize stiffness variation; for the first time, granular jamming has been applied to haptic feedback.
 - The creation and evaluation of a multi-fingered palpation feedback method using the proposed novel stiffness actuators to provide a better balance between the control complexity and the efficiency of tactile information rendering than using tactile feedback devices or single-point force feedback devices.
- Hybrid feedback methods
 - The introduction and validation of force feedback and pseudo-haptic feedback combination to further improve on what can be achieved in a haptic feedback system for tumour identification.
 - The examination of the roles of the visualization of tissue surface deformation and cursor speed modification in tumour identification.
 - The creation and evaluation of a combination of the multi-fingered palpation concept with the pseudo-haptic tissue stiffness feedback.

6.3. Future projects suggestion

Future research based on this thesis includes the following topics:

6.3.1. *In-vivo* experimental study

The proposed methods have been tested on a range of silicone phantom organs. In order to further prove the feasibility of the proposed methods, *in-vivo* experimental study in realistic surgical environments is needed. The Kinect depth sensor needs to be replaced by a miniaturized sensor to acquire the shape and contour information of the soft tissue for 3D reconstruction. From the 3D reconstruction result of the tissue surface, a surgical robot with a miniaturized rolling / sliding indentation probe needs to be programmed to scan the soft tissue to acquire the information of tissue stiffness distribution and form a patient-specific virtual tissue model. Learning algorithms such as artificial neural networks ANN [224], [225] and radial basis functions RBF [197], [226] can be introduced for data-driven soft tissue modelling.

6.3.2. Conveying surface texture or shape and stiffness information of soft tissue using pseudo-haptic feedback

Pseudo-haptic feedback was used to convey shape information like holes and bumps [181] in the past. Here, it was applied to convey tissue stiffness information. It was proven that direct touch immersive illusion using tablet computer and pseudo-haptic feedback could achieve a hard inclusion identification result as well as using manual interaction. It would be interesting to convey texture or shape and stiffness information of soft tissue simultaneously. Thus, the user can explore a virtual organ model with an uneven surface to acquire both contour and stiffness information.

6.3.3. Combination of force feedback and multi-fingered stiffness feedback

In real palpation, both force and tactile feedback are involved. It was proven that a better result can be achieved by combining force and tactile feedback [91]. In this thesis, multi-fingered stiffness feedback was proven to be more efficient than single-fingered stiffness feedback. It would also be interesting to combine force feedback and multi-fingered stiffness feedback. Moreover, further improvements can be made

to the proposed multi-fingered feedback actuators, such as standardized fabrication process and hysteresis compensation. Experiments on different dimensions of the air chamber and different thickness of the silicone rubber film in the pneumatic actuator are needed to further optimize the actuator.

6.3.4. Vibration feedback and other feedback methods

Vibration is a popular feedback method for cell phones and tablet computers. It would be interesting to convey stiffness information of soft tissue using vibration and other feedback methods.

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