The development of an integrated computer based system for knee joint related clinical diagnosis, pre-surgical planning and post-operative monitoring

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**THE DEVELOPMENT OF AN INTEGRATED
COMPUTER BASED SYSTEM FOR KNEE
JOINT RELATED CLINICAL DIAGNOSIS,
PRE-SURGICAL PLANNING AND POST-
OPERATIVE MONITORING**

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SCHOOL OF CHEMICAL & BIOMEDICAL ENGINEERING

2010

COMPUTER BASED SYSTEM FOR KNEE JOINT RELATED CLINICAL DIAGNOSIS

HO J.H.

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**The Development of an Integrated Computer
Based System for Knee Joint Related Clinical
Diagnosis, Pre-Surgical Planning and Post-
Operative Monitoring**

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SUMMARY

Knee joint is the largest joint within the human body and is most prone to injuries. This thesis presents the works that were carried out as part of a major research to develop an integrated system for knee joint related clinical diagnosis, pre-surgical planning and post-operative monitoring. The research is divided into three phases. Phase one involves in the creation of image segmentation modules for specific tissues at the joint, while phase two focuses on reconstruction of three-dimensional models from segmented images. Phase three dwells in the development of clinical based application modules.

This project focuses on phase one of the development of the proposed integrated system. The specific aims of the project are to develop semi-automated segmentation techniques for anterior cruciate ligament (ACL) and menisci of the knee joint in magnetic resonance (MR) images, because these two tissues are most prone to damages when a knee joint is injured. Achieving these aims will set the foundation for future developments of this integrated system. The first presented work is the profile studies of knee joint related MR images. This study revealed a reproducible landmark in the vertical intensity profile which can aid computer based systems in locating the menisci automatically in MR images. In the second and third works, methodologies to the innovated semi-automated segmentation programs of ACL and meniscus are presented respectively. Both programs relied on morphological operations to locate the anatomical structures and active contour to perform the segmentation. Proton density weighted isotropic MR images were acquired and used to test the programs developed. Validation studies were conducted and the methodologies developed were proven to be feasible in achieving the segmentation tasks.

In the last portion of this thesis, some future works are proposed for phases two and three as an ongoing effort to develop the integrated system.

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

With the world population becoming more affluent as education level increases globally, people have become more health conscious and are actively engage in sports to maintain a healthy body. Unfortunately, incorrect practices of sports often lead to undesirable orthopaedic-related injuries that may require, in worst case scenarios, surgical correction procedures or artificial joint implantations for recovery.

Among the numerous physiological joints residing within humans, knee joint is the largest joint and typically most vulnerable to injuries [1-2]. A study by Ingram et al [3] reported approximately 60 % of the yearly estimate of 2.5 million adolescents who visit the emergency departments due to sports-related injuries [3-4] are diagnosed as knee joint related injuries [3, 5]. Bollen [6] conducted a survey and revealed that among the various form of knee joint related injuries, ligament injuries accounted the most. This is shown in Figure 1.1. In a NIH (National Institute of Health) consensus on total knee replacement (TKR) published in 2003 by U.S. Department of Health and Human Services, it noted there are about 300,000 TKR surgeries performed annually in United States [7].

Figure 1.1: Various types of knee joint related injuries (*left*) and the typical incidence of different ligament injuries at the knee joint (*right*) [6].

Recent advancement in clinical imaging modalities has allowed clinicians to efficiently acquire large clinical image database with great ease and at high image

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quality. This effectively enables clinicians to make accurate diagnosis regarding the severity of such injuries, disease progressions and assessment of treatment responses. This advancement also causes many clinicians to abandon the information limited specific tissue analysis in favour of the more informative whole organ diagnosis which was considered impossible in the past.

However, relative to this advancement, the developments in automated tissue segmentation systems are still lagging behind. With the ease of acquiring a large volume of images per imaging session, this leads to a large amount of clinical image database available per patient. Due to the limitations in current tissue segmentation systems, radiologists/radiographers have to rely on tedious and time-consuming manual segmentations [8] to provide reasonable and reliable segmentations of the tissue in question for clinicians to make sounded treatment decisions. In addition, the existing systems only provide qualitative analysis with little or no quantitative information to complement such analysis.

In this thesis, the presented studies were conducted with aim to formulate a viable integrated clinical imaging processing system that provides semi-automated segmentations of various tissues within a knee joint. The preliminary motivation is to supply clinicians with a system that greatly shortens the time required to perform tissue segmentations coupled with better accuracy and reproducibility. The final goal is to create an integrated system that provides necessary information which facilitates clinical diagnosis, pre-surgical planning and post-operative monitoring. The main idea, in particular, is to provide quantitative information to complement the existing qualitative analysis made available by clinical imaging modalities.

1.2 OBJECTIVES

In recent years, magnetic resonance imaging (MRI) has garnered wide acceptance from clinicians as the most preferred clinical imaging modality. This is due to its numerous advantages over other clinical imaging modalities that are currently available. Among these advantages, its ability to provide non-invasive image acquisition of soft tissues and the use of a non-ionising source [9-10] are the two driving factors that pivoted many clinicians' opinions toward the adoption of MRI.

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Thus, MRI is fast becoming a primary imaging modality of choice for diagnosis purposes. Two different forms of MRI scanners are shown in Figure 1.2.

Figure 1.2: Siemens Magnetom Verio 3T MRI [11] scanner is a close system (left) while Siemens Rhapsody 1T MRI [12] scanner is an open system (right).

The research presented in this thesis is in line with a grander objective to develop an integrated system that provides necessary information to facilitate knee joint related clinical diagnosis, pre-surgical planning and post-operative monitoring. Since MRI is widely recognised by orthopaedic surgeons and radiologists/radiographers as the best imaging modality for knee joint related diagnosis, the proposed system is designed to complement it.

The development of this proposed system is divided into three phases. The first phase involves in the creation of several sub-modules in which each will perform semi-automated segmentation of a specific tissue of interest. The motivation in creating these sub-modules is to assist the radiologists/radiographers in overcoming the limitations faced while carrying out manual segmentations. The aim is to simplify the current segmentation process in practice so as to reduce the time involved while producing accurate and reproducible segmentation results.

In phase two, the sub-modules created are involved in segmenting the MR images which are acquired for this research. The two-dimensional (2D) masks produced from these segmentations will facilitate in the development of a module that utilises a series of such masks to reconstruct a three-dimensional (3D) object of the tissue of interest. The motivation in developing this module is to provide orthopaedic surgeons with a

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realistic panoramic view of the tissue of interest. The aim is to create a feasible means which directly translate a series of 2D images into a reconstructed 3D object that will truly depict the actual appearance and conditions of the tissue in view and as close to the physical realm as possible.

For the final phase, a set of modules will be innovated with capabilities to provide information that are necessary to facilitate in clinical diagnosis, pre-surgical planning and post-operative monitoring. Some of these modules may carry out measurements using the reconstructed 3D object of the tissue of interest to produce data required for surgical/implantation procedures. Other modules may possess abilities such as making a comparison between the 3D reconstructed objects of a tissue before and after a surgical operation to provide information for surgeons to assess the recovery outcome. The motivation in creating these application based modules is to assist clinicians in making sounded treatment decisions by providing useful data. The long term goal is to create an integrated system that serves as a single platform from which clinicians can rely on when making decisions during injury/pathological diagnosis, pre-surgical planning and post-operative monitoring. A summary of the objectives for each phase is tabulated in Table 1.1 while Figure 1.3 illustrates the flow process of proposed integrated system for knee joint related clinical diagnosis, pre-surgical planning and post-operative monitoring.

Table 1.1: Summarised objectives at each phase of the proposed research.

Phases	Objectives
One	Develop semi-automated segmentation modules in which each specialises in segmenting a particular tissue at the knee joint.
Two	Create a module which possesses the capability of translating a series of 2D segmentation masks directly into a reconstructed 3D object of the tissue of interest.
Three	Design a series of application based modules that provide measurement data necessary for clinical diagnosis, pre-surgical planning and post-operative monitoring.
Main Goal	To improvise an integrated system that supplies necessary diagnosis data for knee joint related clinical diagnosis, pre-surgical planning and post-operative monitoring purposes.

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Figure 1.3: Flow process of proposed integrated system for knee joint related pre-surgical planning and post-operative monitoring.

Projects presented in this thesis will focus on phase one of the development of the proposed integrated system. The specific aims of these projects were to develop semi-automated segmentation techniques of anterior cruciate ligament (ACL) and menisci of the knee joint in magnetic resonance (MR) images, because these two structures are most prone to damages when a knee joint is injured. Achieving these aims will set the foundation for future developments of this integrated system.

CHAPTER 2: THEORETICAL REVIEWS

2.1 CLINICAL ANATOMY

2.1.1 Knee Joint

Knee joint is the largest joint residing within human [1] and it facilitates the ease of movement from one place to another. In addition, it can withstand up to 24 times the bodyweight of a human [13] but is also most vulnerable to injuries [2]. Figures 2.1 and 2.2 depict the architectural construct of knee joint.

The knee joint is a modified hinge joint that allows flexion–extension motions and rotation [1, 14]. At the joint, three bones: patella, tibia and femur are directly connected with one another [1]. The attachments between these bones are facilitated by the following ligaments: anterior and posterior cruciate ligaments, capsular ligament, ligamentum patellae, medial and lateral collateral ligaments, and oblique popliteal ligament.

Figure 2.1: Anterior superficial (left) and posterior deep (right) views of knee joint [1].

The bony structures of patellar, tibia and femur contribute to the stability of knee joint while the ligaments, capsule and muscles provide the necessary static and dynamic

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restrains its motions [14]. In fact, the knee joint is a very complex joint of the human body. It actually consists of three joints within a single synovial cavity [1]. Both lateral and medial femorotibial joints are responsible for the actual load-bearing and mobility while patellofemoral joint provides stability to the knee through its role in the extensor mechanism [14].

Figure 2.2: Sagittal section (*left*) and anterior deep view (*right*) views of knee joint [1].

2.1.2 Cartilage

Cartilage is an avascular, aneural and alympatic tissue which resides on the surface of articulating bones at the joints [15-17]. It plays the primary role of lubricating the articulating surface of bones and improves their resistance against the wearing experienced during motions [15, 18-19]. Thus, it is one of the crucial components that dictate the proper functionality of knee joint.

The cartilage is a composition of chondrocytes and a supportive matrix containing proteoglycans, water and collagen-fibril network [15-16, 18, 20-21]. The typical thickness of cartilage in human varies within a range of 2 to 4 mm, while its histology comprises the following four layers [15-16, 18-19, 22] shown in Figure 2.3: -

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- Tangential layer (also known as superficial layer)

This is the superficial layer of cartilage where collagen fibrils run parallel to the articular surface of cartilage. The presence of collagen fibrils is the highest within this layer while proteoglycan content is the lowest.

- Transitional layer (also known as intermediate layer)

This accounts for a thickness ranging between 40 % and 60 % of the cartilage and tends to be isotropic.

- Radial layer (also known as deep layer)

Water content is low within this region but the proteoglycan content is high. This layer accounts for 30 % of the cartilage thickness and the collagen fibrils are the thickest within this region.

- Ossified cartilage layer

This layer is separated from the radial layer by a “tidemark”. It rests on the underlying cortex of the bone and anchors the cartilage to it. The cartilage within this region is calcified.

Majority of the collagen fibrils residing within cartilage are type II collagen [15-16] which cross-linked with one another to setup the fundamental matrix framework of cartilage. This provides cartilage with resistance against tensile forces. Within the spaces of this matrix reside both the proteoglycans and chondrocytes. Proteoglycans are negatively charged macromolecules, responsible for the entrapment of water within cartilage [15-16, 18]. This water entrapment ability provides cartilage with resistance against compressive forces while assisting it in undergoing reversible deformations under loading conditions [15, 18, 20]. Both collagen fibrils and proteoglycans are synthesized by chondrocytes, which are cells responsible for the homeostasis (i.e. repair and maintenance) of cartilage [15-16, 18]. Since cartilage is avascular, the chondrocytes within it rely on the diffusion of synovial fluid, which is entrapped within the synovial membrane encapsulation of knee joint, for nourishment [15-16]. In addition, nutrients are also supplied to chondrocytes by diffusion from blood vessels that course through the calcified cartilage layer near the bone.

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Figure 2.3: Schematic diagram [23] (left) and polarised microscopy image [24] (right) of cartilage.

2.1.3 Anterior and Posterior Cruciate Ligaments

Both anterior and posterior cruciate ligaments (ACL and PCL respectively) are bands of dense connective tissue that course from femur to tibia. The attachment of ACL at tibia is wider than its attachment at femur while the converse is true for PCL. ACL primarily restrains the anterior drawer translation of tibia relative to femur while playing the secondary role of constraining internal rotation, varus, valgus, and hyperextension [14, 25]. In contrast, PCL plays the main role of limiting the posterior drawer translation of tibia while acting as secondary constrain to both varus-valgus and external rotations [14, 26].

Both ACL and PCL are composed of a few interspersed cells and a supportive matrix that consists of water, collagen-fibril network, glycosaminoglicans (GAGs), glycol-conjugates, and elastic components [25]. Due to the presence of GAGs, this gives rise to the water entrapment capability of ligaments which enables them to undergo reversible deformations under loading conditions. Majority of the collagen fibrils residing within these ligaments are type I collagen and can be classified into two categories. The first category refers to the large inhomogeneous fibrils which have variable diameters and are secreted by fibroblasts. They play the specialised role of

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resisting high tensile stresses experienced by the ligaments [25]. The second category refers to the small homogeneous fibrils that possess a uniform diameter. They are synthesized by fibro-chondroblasts and are responsible for the three-dimensional organisation of ligaments [25].

These fibrils form the basic matrix framework of a ligament which is a mixture of both helical and planar, non-linear networks that are densely arranged and running parallel along the longitudinal axis of ligament. Fibrils located near its surface are organised in a helical wave pattern. Those situated centrally within the ligament are either straight or undulated in a planar wave pattern [25]. Hence, these fibrils present a regular sinusoidal-like pattern when superimposed onto a two-dimensional plane. The purposes of this wave and non-linear pattern of fibrils are respectively defined as “crimping” and “recruitment” [25]. Crimping occurs when the load applied to a ligament is small which induces the sinusoidal fibrils to undergo slight longitudinal elongation (i.e. straightening of fibrils) without damaging the fibrils. This mechanism acts as a buffer to lower the incidence of ligament damages while providing a means to control tension. In addition, it serves to absorb any shocks experienced along the ligament length. When the load imposed is large, crimping eventually leads to recruitment in which an increasing number of fibrils becomes load-bearing and a gradual increase in tissue stiffness is experienced (i.e. straighten fibrils are now stretched). Thus, both crimping and recruitment give rise to the non-linear load-elongation curve of a ligament [25]. Beyond recruitment, fibrils are fully stretched and may eventually lead to snapping of fibrils that leads to a torn ligament.

Although ACL is a single band of connective tissue, it undergoes non-isometric length changes during flexion-extension motions [14, 25]. ACL is widely regarded as a composition of two functional bundles. They are namely the anteromedial bundle (AMB) and posterolateral bundle (PLB) [14, 25]. During flexion, AMB will lengthen while PLB shortens. This is shown in Figure 2.4. When AMB lengthens during flexion, it becomes taut and spirals around PLB which slackens as it shortens. Thus, both bundles are no longer parallel with each other when the knee joint is in a flexed position [14, 25] as illustrated in Figure 2.4.

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Figure 2.4: AA' denotes AMB being lengthen while BB' being shorten during flexion [14] (*left*). AMB spirals around PLB during flexion [25] (*right*).

Similarly, being a single band of connective tissue, PCL also undergoes non-isometric length changes during flexion-extension motions [14, 26]. In addition, it is also widely considered as a composition of two functional bundles. They are namely the anterolateral bundle (ALB) and posteromedial bundle (PMB). ALB is lax in extension but becomes taut during flexion while the opposite is true for PMB [14, 26]. Figure 2.5 displays both ALB and PMB of PCL and take note of its non-isometric length changes during flexion-extension motion.

Figure 2.5: ALB and PMB of PCL [25] (*left*). AA' represents AMB being lengthen while BB' being shorten during flexion [14] (*right*).

In general, both ACL and PCL are separated from one another when the knee joint is in extension but they wrap around each other during flexion [14]. Although both ligaments are intra-articularly located within the knee joint, they are covered by a fold of synovial membrane and are thus considered extra-synovial [14].

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2.1.4 Menisci

Two menisci namely: medial and lateral menisci are located at the knee joint between tibia and femur [1, 13-14]. These are important structures necessary to compensate the incongruent articulation between both bones. This is because tibia has a flat articulating joint surface while femur has a curved surface [13]. The absence of both menisci will give rise to a small contact area between the two articulating bones, as seen in Figure 2.6, which leads to undesirable cartilage damages and bone remodelling under normal loading conditions [13]. Thus, the menisci serve to increase joint congruency and play a primarily role in both load transmission and shock absorption [13-14]. This ensures even pressure distribution across the cartilage and underlying bones to reduce the joint pressure experienced under loading conditions. In addition, other functions of menisci include joint stability, lubrication, and providing proprioceptive feedback and cartilage nutrition [13-14].

Figure 2.6: Influence of menisci on the pressure distribution pattern on tibia [27].

The menisci at knee joint are fibrocartilaginous disks. These are functional extensions from tibia and their surfaces conform to both femoral and tibial articulating surface contours [13-14]. Because each meniscus possesses a thick convex outer edge that recedes to the thin concave inner edge, this gives rise to its triangular cross-section

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[13]. In addition, the anterior horn of each meniscus is typically narrower than its posterior horn. These meniscal horns are attached to the tibia via the meniscal insertion ligaments, which are also known as coronary ligaments [13-14]. Figure 2.7 illustrates the arrangement of both menisci on tibia.

Figure 2.7: Proximal view of both menisci on tibia [28].

With reference to Figure 2.7, the medial meniscus has a crescent conformation while lateral meniscus is almost circular. Hence, the lateral meniscus occupies a larger tibial surface area than medial meniscus [13-14]. In general, the entire length of the convex outer edge of the medial meniscus is connected to the joint capsule. At its midpoint, the capsule coagulates to form the deep medial collateral ligament that firmly connects the medial meniscus to tibia and femur [13-14]. In contrast, the convex outer edge of lateral meniscus is loosely bounded to the joint capsule and does not attach to the lateral collateral ligament [13-14]. Hence, the medial meniscus is more restricted from motion and this accounts for its higher injury incidences as compared to lateral meniscus[13]. Figure 2.8 shows the average meniscal translation across the tibial plateau during knee flexion and that the anterior horns are more mobile than posterior horns [29].

In general, each meniscus is composed of a few interspersed cells and a supportive matrix containing both water and a collagen-fibril network with a small proportion of hexosamine, elastin and other non-collagenous proteins [13]. Unlike cartilage, the majority of collagen fibrils residing within meniscus is type I collagen. In addition, the proteoglycan content is much lesser than that in cartilage [13]. However, the

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meniscus is still capable of performing reversible deformations under loading conditions. On the surface of meniscus, the collagen fibrils are oriented randomly and mesh-like but are parallel to the surface. This arrangement facilitates the gliding between femur and tibia. However, the fibrils beyond the surface are organised in uniform circumferential pattern that conforms to the shape of respective menisci. The motion of these circumferential fibrils is restricted by periodic tie fibrils that spread radially from the convex outer edge to the free concave inner edge [13, 30-31]. Figure 2.9 displays a schematic of collagen fibrils arrangement in meniscus.

Figure 2.8: Mean meniscal excursion along tibial plateau [29].

Figure 2.9: Schematic of collagen fibrils arrangement in meniscus [31].

2.2 CLINICAL IMAGING

2.2.1 Magnetic Resonance Imaging

X-ray radiography is currently the prime imaging modality employed for the non-invasive diagnosis of knee joint damages [18, 32]. Unfortunately, the information

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presented by it is restricted to the osseous (i.e. bone) morphology and does not provide a direct visualisation of other tissues which are important to the functional integrity of knee joint [17, 32]. These tissues include: articular cartilage, synovium, menisci, and ligaments. In addition, the information from X-ray radiography does not reveal the distribution pattern of tissue degradation throughout the joint [33].

There are other non-invasive imaging modalities available that can visualise those tissues which X-ray radiography is incapable of. These imaging modalities include: arthrography, computed tomography (CT), CT arthrography, and ultrasonography [22]. However, these are not widely used due to their respective shortcomings.

In recent years, improvements in magnetic resonance imaging (MRI) have made it a common choice by many clinicians as an alternative for the diagnosis of knee joint damages. Unlike the previous imaging modalities mentioned, MRI is the only modality that allows a direct non-invasive evaluation of soft tissues without contrast agents [19, 32]. Contrast agents are only used when there is a need to improve the contrast appearance of the tissue of interest in magnetic resonance (MR) images.

In general, the image acquired by MRI machine is actually a display of radio-frequency (RF) signal intensities that are emitted by magnetised tissues during the imaging process [34]. Elements with odd mass number have a net spin characteristic as seen in Figure 2.10. Hence, charged nuclei with such characteristic produce a magnetic moment which allows them to interact with external magnetic field as illustrated in Figure 2.10. These nuclei are commonly referred to as spins. In reality, hydrogen is the only magnetic nuclei in the human body that has adequate concentration to produce good MR images. Thus, MRI is widely regarded as proton imaging.

The principle of MRI can be explained by assuming the tissue of interest as a container filled with water as seen in Figure 2.11. Since water constantly undergoes the repeated cycles of disassembling from H_2O to both H^+ and OH^- and reassembling back to the former in less than a second, it is rational to assume that all three of these components are present at any time. When an external magnetic field B_0 is applied,

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the protons will align under its influence to yield a net magnetisation vector M_0 in the same direction. Thus, the tissue is said to be magnetised. Although each individual proton precesses about the external axis (i.e. B_0) at the same frequency, they are out of phase with one another. Hence, M_0 does not precess [34].

Figure 2.10: Magnetic and non-magnetic nuclei [34] (left). RF pulse can influence the interaction of magnetic nuclei with magnetic field [34] (right).

Figure 2.11: Protons align under B_0 influence and a net magnetisation is produced [35].

When a RF pulse is applied in the x-direction as displayed in Figure 2.12, it introduces a new magnetic field B_1 and causes a new precession frequency to arise. Thus, there are now two magnetic fields present. B_0 is the stronger magnetic field (e.g. 1.5 Tesla) while B_1 being the weaker one (e.g. 50 mTesla) [34]. Since the latter is much weaker than the former, the precession frequency of protons about the axis of B_1 is much slower. If the frequency of an applied RF pulse matches the precession frequency of protons under B_0 influence, then a resonance occurs. However, no resonance will occur if this condition is unmet. At resonance, the RF energy is absorbed by M_0 . With reference to the coordinate system in Figure 2.12, this causes M_0 to spiral downwards from its initial direction to the xy-plane where it becomes M_{xy} . Thus, a transverse magnetisation is yielded and this process is known as excitation. Note that M_{xy} continues to rotate on the xy-plane and about the z-axis.

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After the application of this RF pulse, transverse relaxation occurs. During this relaxation, M_{xy} undergoes random de-phasing on the xy-plane as illustrated in Figure 2.13. Through this unique property, T2-weighted contrast images can be acquired during MRI. Figure 2.14 plots the relationship between transverse relaxation and the contrast of a typical T2-weighted image. Note that the contrast of a T2-weighted image darkens as transverse relaxation progresses with time.

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While transverse relaxation is taking place, longitudinal relaxation also occurs concurrently. This leads to the regeneration of longitudinal magnetisation as M_{xy} decays and eventually restoring M_0 . This process is depicted in Figure 2.15. The occurrence of longitudinal magnetisation allows the acquisition of T1-weighted contrast images. The contrast of such images brightens as the longitudinal relaxation proceeds with time. Figure 2.16 illustrates this relationship.

Figure 2.15: Longitudinal relaxation regenerates as transverse relaxation diminishes [35].

Figure 2.16: Relationship between longitudinal relaxation and contrast of T1 image [34].

Base on the above paragraphs, MRI can acquire three different types of images. In addition to both T1 and T2 weighted images mentioned previously, proton density (PD) weighted images are the third image type attainable by MRI. The image intensity of PD-weighted images is determined by the proton concentration present within the tissue of interest. High proton concentration will lead to high image signal intensity. Although the image intensity of T1-weighted images is influence by longitudinal relaxation, it is also magnetic field and tissue dependent [34]. Note that a high magnetic field will lead to a higher T1 signal intensity as a result of slower longitudinal relaxation. Similar to T1-weighted images, the image intensity of T2-

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weighted images is not solely affected by transverse relaxation. Instead, it is also dependent on the random microscopic motions [34]. Table 2.1 lists the typical characteristics of all three types of MR images obtainable by MRI while Figure 2.17 shows the relationship between these images.

Table 2.1: Typical characteristics of all three types of MR images.

	Intensity of PD-weighted images	Intensity of T1-weighted images	Intensity of T2-weighted images
Fat	High	High	Low
Fluid	Low	Low	High

Figure 2.17: Relationship all three types of MR images [34].

Unlike X-ray radiography which yields two-dimensional (2D) planar images, MRI machine acquires a volume of image slices. Each image slice is actually a thin volumetric slice as illustrated in Figure 2.18. In addition, an MR image is composed of voxels (i.e. 3D cubes), which contribute to the image resolution, but an X-ray image is made up of pixels (i.e. 2D planar squares). In order for the MRI machine to acquire images related to the tissue of interest, selectivity is necessary. This selectivity is achieved through the implementation of a magnetic field gradient with both phase and frequency encodings as briefly depicted in Figure 2.19. The magnetic field

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gradient is used to enable image slice selection while the encodings facilitate the pinpointing of a particular location within an image.

Figure 2.18: Spatial characteristics of MR images [34].

Figure 2.19: A simplified illustration on the image selectivity implementation in MRI.

2.2.2 Typical Knee Joint Related Magnetic Resonance Images

Although magnetic resonance imaging (MRI) provides accurate depictions on the states of knee joint, there is a consensus among clinicians and researchers that the acquired magnetic resonance (MR) images are not exact representations of knee joint. Instead, they only provide a close approximation of the actual structure. This is proven in a study by Mandelbaum et al [10] which attempted to establish the

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anatomical correlations between multi-planar cadaveric cryosections and corresponding multi-planar MR images as part of a boarder study to investigate the viability of MRI in evaluating traumatic knee injuries. Figures 2.20 to 2.25 shows the correlated images extracted from this study. Note that the images were acquired using a 0.3 Tesla MRI machine (Fonar Beta 300 unit).

Figure 2.20: Sagittal medial cadaveric cryosection (*left*) and corresponding MR image (*right*) showing medial meniscus [10].

Figure 2.21: Sagittal intercondylar notch cadaveric cryosection (*left*) and corresponding MR image (*right*) showing posterior cruciate ligament [10].

Figure 2.22: Sagittal medial cadaveric cryosection (*left*) and corresponding MR image (*right*) showing anterior cruciate ligament [10].

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Figure 2.23: Sagittal lateral cadaveric cryosection (*left*) and corresponding MR image (*right*) showing lateral meniscus [10].

Figure 2.24: Axial cadaveric cryosection (*left*) and corresponding MR image (*right*) showing patellofemoral articulation [10].

Figure 2.25: Coronal cadaveric cryosection (*left*) and corresponding MR image (*right*) of knee joint [10].

Using an MRI machine with higher magnetic field strength will provide better MR images than those displayed in Figures 2.20 to 2.25. This is because an increase in magnetic field strength will lead to higher signal-to-noise ratio which improves both image resolution and acquisition speed [36-40]. In addition, thinner image slice and better fat suppression are also achievable. However, these advantages are accompanied with disadvantages that include greater radio-frequency power deposition [37-38] and more pronounce artefacts caused by both *in-vivo* metallic

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implants and chemical shift [34, 36-37, 40]. Other alterations such as an increase in T1 relaxation time coupled with a decrease in T2 relaxation time must also be considered as they may affect the tissue contrast [36-37, 40]. Figure 2.26 illustrates the detrimental influence of chemical shift effect at higher magnetic field strength.

Figure 2.26: Pronounce chemical shift effect seen in MR image of an ankle acquired at 3 Tesla (*left*) than that obtained at 1.5 Tesla (*right*) [37].

2.2.3 Knee Joint Diagnosis Using Magnetic Resonance Imaging

It is now widely accepted that the diagnosis of knee joint damages should be performed on the basis of a whole joint organ evaluation rather than focusing on the tissue of interest (i.e. damaged tissue) alone. This is because specific structural abnormalities will not arise in isolation but are often influenced by the complex inter-relationship between the *in-vivo* biochemical environment and biomechanical construct [41-42]. Hence, the information gathered can provide important insights necessary for knee joint reconstruction to achieve both structural and functional integrities. The followings explain how various knee damages are diagnosed using magnetic resonance imaging (MRI): -

- **Synovitis and effusions**

Synovitis refers to inflammation that involves the entire synovium while effusion only occurs at a localised region. Synovitis is a secondary event in osteoarthritis (OA) and its incidence increases with OA severity [18, 42]. Although synovitis is best detected using intravenous paramagnetic-enhancing agent gadolinium with T1-weighted spin echo or SPGR (i.e. spoiled gradient recalled) sequences [18, 42], optimised non-gadolinium MRI sequences may

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also be used for such purposes. These optimised sequences include [42] fast spin echo (FSE) with fat saturation, proton density (PD) weighted and T2-weighted spin echo. Non-gadolinium MRI sequences are the most preferred choice by clinicians because the use of gadolinium has implications on patients, MRI scanning duration and selection of MRI sequences [42]. Figure 2.27 shows the diagnosis of synovitis using T1-weighted spin echo with gadolinium contrast agent. Severity of synovitis is determined either by quantifying the volume or analysing the signal intensity characteristic. Unlike synovitis, joint effusion is identified using either fat-suppressed PD-weighted or T2-weighted FSE sequences [42]. Its severity is quantified by the effusion volume [42].

Figure 2.27: Synovitis diagnosis using T1-weighted spin echo with gadolinium agent [42].

- Subchondral bone

Abnormalities of subchondral bone are usually associated with pain and progression of OA [18, 42]. Its most common abnormality is bone marrow edema [18, 42]. This appears as poorly defined regions with intermediate to high intensity appearance on fat-suppressed T2-weighted or STIR (i.e. short TI inversion recovery) images [18, 42]. Figure 2.28 depicts an MR image of bone marrow edema. Other abnormalities of subchondral bone include bone marrow necrosis (i.e. cell death), fibrosis and abnormal trabeculae remodelling [42]. The severity of subchondral bone abnormalities and experienced pain correspond to the load applied at the joint [42]; and the severity is usually quantified base on joint surface, incongruity and curvature.

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Figure 2.28: MR image of bone marrow edema as delineated by a white arrow [42].

▪ Menisci

MRI has been considered the best imaging modality for menisci evaluation [42] and is capable of detecting tears in both medial and lateral menisci. The diagnosis of menisci is commonly conducted in sagittal plane, using PD-weighted FSE sequences [42]. Most grading systems used to denote meniscal damages are based on the signal intensity distribution relative to the articulating surface of meniscus [42]. This is illustrated in Figure 2.29. Meniscal damages are common in OA [18, 42] and sports-related injuries. Such damages often contribute to abnormal joint movements, radiographic joint space narrowing, wear and tear of cartilage, meniscal subluxation (i.e. partial dislocation), and mal-alignment of knee joint [18, 42]. Studies have revealed that the medial meniscus is more prone to damages [13-14, 18] while the pain experienced by OA patients with meniscal damages is no greater than patients without such damages [42].

Figure 2.29: A meniscal tear at posterior horn as depicted by a white arrow [42].

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▪ Ligaments

Studies have revealed that in severe cases of OA progression, ligaments tend to get rupture as a result of joint laxity and mal-alignment [42]. In most cases, anterior cruciate ligament (ACL) appears to be most prone to ruptures [42] and this is common in sports-related injuries. The evaluations of knee joint ligaments in MRI are typically performed using PD-weighted and T2-weighted FSE or turbo spin echo sequences [38, 42]. Both ACL and posterior cruciate ligament (PCL) are best examined on sagittal plane while collateral ligaments on coronal (i.e. frontal) plane [42]. Figure 2.30 shows a torn collateral ligament. Currently, there are a few published MRI scoring methods regarding ligament evaluation in OA knees [42]. Most of these methods rely on signal intensities, bulk continuity (i.e. any discontinuity which signifies a torn ligament) and thickness to determine the status of ligament damage.

Figure 2.30: Collateral ligament tear as illustrated by a white arrow [42].

▪ Osteophytes

The presence of osteophytes is common in OA and is a contributing factor to radiographic joint space narrowing, subchondral sclerosis (i.e. thickening or hardening), mal-alignment of joint, and pain [18, 42]. MRI is very suitable for osteophyte detection due to its multiplanar imaging capability and absence of bone superimposition [18, 42]. The grading system used to grade the severity of osteophyte presence is based upon the number of site and size of osteophyte present [42]. The appearance of an osteophyte in MR image is displayed in Figure 2.31.

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Figure 2.31: Presence of an osteophyte is outlined by a white arrow [42].

A summary regarding the aforementioned details on the preferred MRI sequences and imaging planes for knee joint related diagnosis can be found in Table 2.2.

Table 2.2: A summary regarding preferred MRI sequences and imaging planes for knee joint related diagnosis.

Tissue/Symptom of Interest	Preferred Imaging Plane	MRI Sequence
Synovitis	-	- Gadolinium Enhanced: T1-weighted spin echo or SPGR sequences - Non-Gadolinium Enhanced: PD-weighted, T2-weighted spin echo and FSE with fat saturation sequences
Effusions	-	Fat suppressed PD-weighted or T2-weighted FSE sequences
Subchondral Bone	-	Fat suppressed T1-weighted or STIR sequences
Menisci	Sagittal plane	PD-Weighted FSE Sequences
Ligaments	- Cruciate ligaments: Sagittal Plane - Collateral ligaments: Coronal Plane	- PD-weighted sequences - T2-weighted FSE or Turbo Spin Echo sequences
Osteophytes	-	PD-weighted sequences
Cartilage	Sagittal plane	PD-weighted sequences

2.3 DIGITAL IMAGE PROCESSING

2.3.1 Various Image Segmentation Approaches

In general, there are numerous approaches available to carry out clinical image segmentations. These approaches are broadly classified [43-44] in Figure 2.32. Each approach consists of multiple techniques. Due to the extensiveness of this list of approaches, only a brief introduction to each approach will be given in the following paragraphs. In order to fully appreciate these approaches, the readers are encouraged to refer to the following reviews and works: [43-59].

Figure 2.32: Classification of various segmentation techniques available.

Among the approaches shown in Figure 2.32, thresholding approaches are considered the simplest to implement. Such approaches attempt to segment the desired feature by performing a binary partitioning on the intensities of an image [43-44, 47, 55]. In practice, thresholding approaches are commonly deployed to pre-process images before the actual segmentation is performed. An example is the morphological operations described in Section 2.3.2. In contrast to the thresholding approaches, region growing approaches extract a desired feature base on the connectivity of pixels and their fulfilment of some pre-defined criteria which are common among them. These criteria may be intensities of pixels, edges within the image and etc [43]. An example of region growing approaches is the split-and-merge algorithm.

With reference to Figure 2.32, both classifiers and clustering approaches are specified as two different categories. In fact, they are actually pattern recognition techniques. The only difference between both categories is that the supervised pattern recognition

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techniques are labelled under classifiers while clustering approaches comprise those unsupervised techniques. The former utilises training data, which are pre-manually segmented images, as references to segment the images automatically but the latter relied none. Instead, unsupervised techniques constantly switch between image segmentation and property characterisation of each class during the extraction of desired features to make up for the absence of training data [43]. A typical example of unsupervised techniques is the *K*-means algorithm while that of supervised techniques is the Bayes classifier. If the readers are interested to understand more on pattern recognition techniques, they are recommended to refer to the reviews by Clarke et al [53], Bezdek et al [54] and Duda et al [59].

Unlike the other categories listed in Figure 2.32, Markov random field (MRF) modelling is not a segmentation method. Instead, it is a statistical model deployed in segmentation methods [43] and is often incorporated within unsupervised pattern recognition techniques. MRFs model the spatial interactions between neighbouring pixels and such local correlations supply a mechanism for modelling various image properties [43]. The artificial neural networks (ANNs) on the other hand are parallel networks of processing nodes which imitate biological learning [43]. Each node within an ANN performs the essential basic computations. Learning is achieved through adjustment of weights allocated to the connections between nodes [43]. ANNs are frequently used with pattern recognition techniques to perform image segmentations. Readers should refer to the book by Duda et al [59] for more information on ANNs.

In recent years, deformable models have become a popular choice in carrying out image segmentations. Such models can either be closed parametric surfaces or curves that varied their surfaces or shapes under the manipulation of internal and external forces to outline the region boundaries of desired features. Closed parametric curves are commonly known as “active contours” or “snakes”. Such curves are usually employed to perform two-dimensional segmentations but can also be used in three-dimensional (3D) segmentations as well. In contrast, the closed parametric surfaces are used for 3D segmentations and are frequently referred to as “active surfaces” or “balloons”. In comparison, the closed parametric surfaces are more computational

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intensive than the closed parametric curves. For more information on deformable models, the readers are urged to see the following reviews and works: [50-51, 60-62]

Recently, atlas-guided approaches have also gained wide interests from researchers for clinical image segmentation purposes. Such approaches are used only when a template (i.e. standard atlas) is available for reference. In a general sense, atlas-guided approaches and classifiers are alike but the former are utilised in spatial domain rather than in feature space [43]. These approaches often treat segmentation as a registration problem.

In response to the different approaches described in previous paragraphs, it is important to highlight that not every approaches are suitable for a particular situation. Some approaches may be suitable for a particular condition while others may be more appropriate for other situations. In most cases, multiple approaches are coupled together to achieve the best possible segmentation result attainable to solve the problems encountered.

2.3.2 Morphological Operations

Morphological operations are a set of techniques typically deployed during the pre- or post-processing stages of digital image processing. They utilise pre-defined shapes commonly referred to as structuring elements to process images base on their geometrical properties such as shape and connectivity. The shape of a structuring element can be of an arbitrary or any standard geometrical shape resembling square, disk or etc.

In a morphological operation, the corresponding pixel is compared with its neighbourhood within the input image to determine the value of each pixel in an output image. The success of such operation heavily relies on the selected structuring element. In general, morphological operations can be used to extract features of desired shapes, remove undesirable features and manipulate the morphologies of features. Although they can be applied to both greyscale and binary images, the discussions in following paragraphs are confined to the latter.

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In short, all morphological operations are various combinations of erosion and dilation. Both erosion and dilation are fundamental to morphological operations [57]. The erosion of an object A by a structuring element B is represented by [57-58]: -

$$A \ominus B = \{z | (B)_z \cap A^c = \emptyset\} \quad (1)$$

This expression indicates that the erosion of A by B is a set of points z in which the translation of B by z will lead to a null if the entire structuring element at z is not contained within A . Hence, this process is often used to shrink or thin objects in binary images while removing features smaller than the structuring element [57]. Figure 2.33 illustrates the erosion process and its outcome.

Figure 2.33: Erosion of A by either square (top) or elongated (bottom) structuring element B [57].

In contrast to erosion, dilation operates in an opposite manner. Thus, it is used to expand or thicken objects in binary images [57]. In dilation, the structuring element B is reflected about its origin and subsequently translated by z . It dilates an object as long as the origin of resultant structuring element intersects object A without regard to whether the entire structuring element is contained within A . Dilation is denoted by the expression below [57-58] and Figure 2.34 depicts the dilation operation and its result.

$$A \oplus B = \{z | (\hat{B})_z \cap A \neq \emptyset\} \quad (2)$$

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Figure 2.34: Dilation of A by either square (top) or elongated (bottom) structuring element B [57].

Depending on how erosion and dilation are applied relative to one another within a sequence and how many times they are applied, the resultant image will differ. When erosion is first applied followed by dilation, thin protrusions of an object and narrow isthmuses between objects can be eliminated [57]. In addition, the contour of an object can be smoothened in this manner as well. This particular combination of erosion and dilation is known as opening. Figure 2.35 shows the opening process.

Figure 2.35: Opening process showing the object (top) undergoing erosion (centre) followed by dilation (bottom) through the application of a disk structuring element [57].

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Unlike opening, closing involves the deployment of dilation and subsequently followed by erosion. Closing is used to fuse narrow breaks and long thin gulfs between objects, remove small holes within objects, and fill gaps along the contours of objects [57]. Although closing is an opposite of opening, it smoothen the contour of an object similarly. The expressions for opening and closing [57-58] are respectively defined below while the closing process is shown in Figure 2.36.

$$A \circ B = (A \ominus B) \oplus B \quad (3)$$

$$A \bullet B = (A \oplus B) \ominus B \quad (4)$$

Figure 2.36: Closing process showing the object (top) undergoing dilation (centre) followed by erosion (bottom) through the application of a disk structuring element [57].

When closing is deployed immediately after the application of an opening, a morphological operation commonly referred as morphological filtering will result. Morphological filtering is an effective operation frequently used to remove salt-and-pepper noises while preserving the overall appearances of objects that are present in a binary image. A good example that displays the strength of morphological filtering in the removal of salt-and-pepper noise is illustrated in Figure 2.37.

Figure 2.37: Morphological filtering applied on an image that contains undesirable salt-and-pepper noises (*left*) by applying opening (*centre*) first followed by closing (*right*) [57].

2.3.3 Active Contour

Active contour is an elastic, continuous curve generated by the computer on a two-dimensional plane [51, 61-62]. It can evolve base on several parameters to delineate the boundary of a desired object [51, 60-61, 63-65]. Active contour is widely known as snake and is represented by the following expression [51, 60-66]: -

$$E_{total}(X, Y) = E_{int}(X, Y) + E_{ext}(X, Y) \quad (5)$$

The first term in Equation 5 denotes the internal energy that ensures the smoothness of active contour [8, 60, 63, 66] while mitigating any undesirable jaggedness caused by the presence of noise [63]. The second term in this equation represents the external energy that guides the active contour towards the object of interest in the image [8, 66]. Both terms are expressed in Equations 6 and 7 respectively [50-51, 60-66]. Increasing the value of α will make the active contour more elastic while increasing that of β will induce the active contour to develop more curves.

$$E_{int}(X, Y) = \frac{1}{2} \int_0^1 \alpha \left[\left| \frac{dX}{ds} \right|^2 + \left| \frac{dY}{ds} \right|^2 \right] + \beta \left[\left| \frac{d^2X}{ds^2} \right|^2 + \left| \frac{d^2Y}{ds^2} \right|^2 \right] ds \quad (6)$$

$$E_{ext}(X, Y) = - \int_0^1 f(X(s), Y(s)) ds \quad (7)$$

In general, the segmentation of desired object in an image is achieved by minimising the energy of Equation 5. This causes the curve to propagate towards points of maxima while maintaining its smoothness [66]. Thus, a classical active contour

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operates like an edge detector and it relies on the image gradient to terminate the evolving curve along the boundary of a desired object [8, 50, 66].

In order for an active contour to delineate an object of interest in the image, it must be initially positioned near the object boundary [8]. This is known as snake initialisation [63]. The active contour will then undergo a phase known as snake evolution [63] in which it moves across the object. This phase is an iterative computation process that seeks the minimum energy of Equation 5 [60, 63]. The external energy term in this equation will push the active contour towards the object boundary while the internal energy term ensures the curve smoothness is maintained. Once the active contour ceases to change, the snake evolution will terminate. Figure 2.38 displays the steps carried out by an active contour to segment an object of interest.

Figure 2.38: Segmentation of circular object begins with snake initialisation (*left*), followed by snake evolution (*centre*) and finally the segmentation is achieved (*right*) [63].

In short, different types of active contour can be implemented through modifications made to Equation 5. Some of the widely implemented active contours for segmentation purposes include gradient vector flow (GVF) active contours, vector field convolution active contours and active contours without edges. Due to the extensiveness of different types of active contour available, the readers are encouraged to refer to the following reviews and works to fully appreciate them: [51, 60-66].

2.4 RELATED STUDIES

2.4.1 Profile Studies of Knee Joint Related MR Images

The intensity profile studies of knee joint related magnetic resonance (MR) images are useful because they can provide valuable information. One such purpose of these

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studies is to develop a meniscus segmentation program that utilised the information from the intensity profiles to locate the meniscus automatically within the image itself prior to segmentation.

The idea to locate the meniscus automatically in a MR image was first introduced in a paper by Sasaki et al [67] in 1999. This was also the first paper that touched on the topic regarding computer-based meniscus segmentation. In this paper, the authors made use of the fact that the cartilage possessed higher intensity levels relative to that of menisci as the key to locate the latter automatically in T1-weighted 3D spoiled gradient (SPGR) images. Although the methodology employed to locate the meniscus automatically did not involve the use of any intensity profiles, the source from which the information was derived to demarcate it did somehow resembles an intensity profile. This is shown in Figures 2.39a) and b).

Figure 2.39a): A model of the candidate region [67] (left) and how a unit is defined within this region [67] (right).

Figure 2.39b): The fuzzy logic scheme used in deciding the membership of a unit, within the candidate region, as either unit A or B [67].

In 2008, an article by Ramakrishna et al [68] showed evidence that it was indeed viable to locate the meniscus automatically within a MR image of a knee joint through

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the use of an intensity profile of the image itself. Although this concept was proven in the article to be applicable on both proton density (PD) and T1-weighted MR images, only the intensity profile along the vertical axis of these images were used for this task. Unfortunately, the article did not elaborate much on the unique characteristics seen in these intensity profiles nor did it mention anything on whether the intensity profile along the horizontal axis of these images can also be used. Figure 2.40 shows the scheme which was used in this article to pinpoint the location of meniscus.

Figure 2.40: Intensity profile along the vertical axis of a T1 MR image (*left*) and the scheme used to pinpoint the location of meniscus on the same image through this information (*right*).

A year later, Köse et al [69] published a study on a computer-based meniscus segmentation program which his team had developed. In this study, two methods were introduced to locate the meniscus automatically in fat-suppressed T2-weighted images. They were namely: histogram based location method and segmentation based location method. In summary, their difference was only on the source from which the information was derived to locate the meniscus automatically. For the former, it essentially utilised only the information from the intensity histograms of the image itself to locate the meniscus while the latter relied on the intensity histograms of segmented knee bones in the same image to perform similar purpose. In a strict sense, both methods involved the intensity profiles to locate the meniscus automatically. From the comments made by the authors in the study, they had indicated that a landmark did exist in the intensity profile along the vertical axis of knee joint related MR images; and it provided good reliability in locating the meniscus automatically. However, they had noted that no such landmark could be found in the intensity profile along the horizontal axis of these images. The intensity profiles acquired through both methods are shown in Figures 2.41a) and b) respectively.

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Figure 2.41a): Intensity histograms of both fat suppressed T2-weighted [69] (left) and its corresponding normalised MR images [69] (right).

Figure 2.41b): Intensity histograms of segmented knee bones [69].

Although the two latter studies did show that it is viable to utilise the intensity profiles to locate the meniscus automatically, they did not provide a thorough perspective on how the landmark will alter within an image set. In addition, they did not show whether its existence would persist when the menisci were absent.

In view of these issues, the intensity profile studies presented in this thesis were carried out to address them. The results from the studies showed that the prominence of this landmark does vary within an image set and its presence persisted even when

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the menisci were absent. The supporting evidences and analysis to such findings can be found in Section 4.1.

2.4.2 Meniscus Segmentation Programs

To date, there are only five published papers on devising computer-based meniscus segmentation programs [67-71]. Although the methodologies and techniques involved in each of these papers differ, the programs were designed with a similar aim to provide automated meniscus segmentation on magnetic resonance (MR) images. The first paper that touched on such innovation was by Sasaki et al [67] in 1999. His team had developed a meniscus segmentation program which employed fuzzy rule base approach. The program was structured into two stages and it took advantage of the cartilage's bright intensity appearance in T1-weighted 3D spoiled gradient (SPGR) MR images to facilitate its operations. Note that this program was only applicable for MR images that were acquired on coronal plane and through T1-weighted 3D SPGR sequence.

In its first stage of operation, the program automatically extracted the region of interest (ROI) that was located between the tibia and femur while bordered by cartilages. This extraction was done through the fuzzy if-then rules formulated by the pre-defined threshold values that corresponded to cartilage, bone, fat, and menisci respectively. Upon ROI extraction, another set of fuzzy if-then rules were used in the second stage of operation to segment the menisci from the extracted ROI. For this set of fuzzy if-then rules, the decision on whether a pixel within the ROI belonged to one of the menisci was determined base on the pixel's distance from the centre of ROI. Hence, a pixel with shorter distance from the ROI centre would likely be deemed as a member of menisci. In general, this program is categorised as a semi-automated meniscus segmentation program. This is because user's interaction was necessary in specifying the threshold values that denote cartilage, bone, fat, and menisci respectively.

In 2007, Ramakrishna et al [70] presented a meniscus segmentation program which operated through three stages. They were the ROI selection followed by thresholding and finally ending off with morphological processing. The program was developed to

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operate on both proton density (PD) and T1-weighted MR images which were acquired on sagittal plane.

In a strict sense, this program did not qualify as “automated”. This is because the ROI selection procedure relied on user’s intervention to pre-define the size and location of a rectangular mask which was used to extract the ROI that encompassed the meniscus. Hence, the program was deemed as a semi-automated meniscus segmentation program due to this interaction from the user. In addition to this, user’s intervention was also involved in calibrating the thresholding parameters which were used to threshold the ROI into binary format. A limitation of this program was that it could only detect meniscal horns but not meniscus that appeared as a single feature. This was because the segmentation performed by the program’s morphological processing operations relied on pattern matching between the features within ROI and a database of pre-defined triangular masks to extract the meniscus.

In 2008, Ramakrishna et al presented an improved version of their program [68]. Unlike the initial program which only detects normal meniscus, this improved version can detect and evaluate damaged meniscus as well. In addition, the ROI selection procedure was fully automated without necessary user’s intervention. The improvement made to the ROI selection procedure relied on the vertical intensity profile of MR image to locate the meniscus. Even with vast improvements made to the program, its inability to detect the meniscus when it appeared as a single feature still remained.

Coincidentally in 2008, another paper on the development of a computer-based meniscus segmentation program was published by Boniatis et al [71]. This program was reported to be applicable on T1-weighted MR images. In summary, the program utilised a database of pre-defined masks to extract the meniscal horns. The actual meniscus segmentation was later accomplished with the use of region growing algorithm. Once the meniscal horns were segmented, texture analysis was deployed to categorise the meniscal horns as either normal or degenerated. Unfortunately, the paper did not elaborate much on the methodology employed to segment the meniscal horns. Instead, it mainly focused on how texture analysis was involved in categorising

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the normal and degenerated menisci. Base on the presented data in this paper, it is safe to comment that this program can only segment meniscal horns. Hence, the program will fail to operate properly when the menisci appeared as a single region feature.

The last study on the development of a computer-based meniscus segmentation program was published by Köse et al [69] in 2009 and it was developed to work on fat-suppressed T1-weighted MR images that were acquired in sagittal plane. The program proposed in this study utilised the segmentation based location method to automatically extract the ROI that encompassed the meniscus. This method relied on the textural properties of bones to segment both femur and tibia. The intensity profiles of these segmented bones were used to automatically extract the ROI that encompassed the menisci. Once the ROI was extracted, thresholding was applied to binarise it. Together, a set of pre-defined triangular masks was used with template matching technique to segment the meniscal horns from the binarised ROI. The degree of meniscus tear was then evaluated by calculating the number of bright pixels present within the segmented meniscal horns. Because the meniscus were segmented by template matching the features in ROI with pre-defined triangular masks, this program could only segment meniscal horns.

Base on the aforementioned paragraphs in this section, it was thus possible to conclude that the current programs available for meniscus segmentation were mainly semi-automated and can only segment meniscal horns but not meniscus that appeared as a single region feature. In addition, the proposed methodologies heavily relied on thresholding for pre-processing purposes and on pattern matching for segmentation task.

In contrast to these observations, the semi-automated meniscus segmentation program proposed in this thesis overcomes the limitations of existing programs. Through the use of morphological operations and active contour for respective pre-processing and segmentation purposes, the proposed program is not only able to segment the meniscal horns but also capable of segmenting meniscus that appeared as a single region feature. Hence, the segmentations produced by this proposed program are closer representations of the menisci in reality as shown in Section 4.3.

CHAPTER 3: EXPERIMENTAL PROCEDURES

3.1 IMAGE ACQUISITIONS AND MANUAL SEGMENTATIONS

For the studies presented in this thesis, a population of four volunteers ranging in ages from 30 to 35 years (average age: 33 years) with no previous history of knee traumas were involved. Four sets of isotropic proton density (PD) weighted images of knee joints on sagittal plane were acquired using a Siemens Magnetom Verio 3T MRI scanner (as shown in Figure 1.1) with a lower extremity knee coil. Each set corresponded to either the right or left knee of a volunteer and consisted 192 images. The images were acquired according to the following parameters: spin echo (SE) imaging sequence with echo time (TE) of 38 ms, repetition time (TR) of 1300 ms, field of view 150 cm x 150 cm, matrix size 320 x 320, slice thickness 0.5 mm. It is important to state here that among the four acquired sets of magnetic resonance (MR) images, only Set 1 has a matrix size of 520 x 520. All image acquisitions were performed by the Department of Diagnostic Radiology at Singapore General Hospital (SGH).

The MR images were acquired as PD-weighted images because the visualisation of both menisci and ligaments were best achievable with PD-weighted MR sequences. This was mentioned in Section 2.2.3. Since each set of MR images were obtained as an isotropic volume, the isotropic characteristic allowed the images within a set to be reconstructed and viewed from a different plane perspective (i.e. either coronal or axial plane) even though they were imaged on a sagittal plane. In order to attain the best image resolution, a slice thickness of 0.5 mm per MR image was yielded. With reference to Section 2.2.1, a MRI scanner tends to acquire a volume of images and each MR image is actually a thin volumetric slice that contributes to this volume. When the slice thickness of each MR image is reduced, the amount of images within this volume increases and this leads to improved image resolution. To-date the thinnest slice thickness attainable is 0.5 mm and this is only achievable with a 3 Telsa MRI scanner.

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The MR images acquired at SGH were assessed by a radiologist who is experienced in musculoskeletal MR imaging. All knee joints displayed in the images were deemed anatomically normal with no abnormalities found. Manual segmentations of ACL and menisci were carried out on all four sets of images using a custom-built program that was written in MATLAB. The segmented results were evaluated by the radiologist to ensure the ACLs and menisci were correctly traced.

3.2 PROFILE STUDIES OF KNEE JOINT RELATED MR IMAGES

Profile studies of knee joint related magnetic resonance (MR) images were conducted to facilitate the development of proposed semi-automated meniscus segmentation program. These studies were performed either to devise a viable technique or identify possible landmarks for which the proposed program can use to locate the meniscus automatically. The details on how these studies assisted in the development of this proposed program is elaborated in Section 3.4.

From the four image sets available, profile plots of MR images that contained the presence of menisci were plotted. Two profile plots of each image were created and they were namely: horizontal and vertical profiles. Since the pixels in each image were arranged in rows and columns, the horizontal profile of an image was plotted by summing the intensities of every pixel within a column. Thus, the horizontal axis denotes the columns while the vertical axis marks the cumulative intensity of each column. The same is true for the corresponding vertical profile except that the cumulative intensity of each row was represented by the horizontal axis and the rows were designated by the vertical axis. For clarification purpose, Figure 3.1 illustrates the horizontal and vertical profiles of a binary image that contains an arbitrary feature.

Once the profiles were plotted, they were analysed. In order to present a systematic qualitative analysis of these profiles, each image set was partitioned into six regions relative to the menisci presence as depicted in Figure 3.2. **These partitioning were carried out manually and via visual inspections.** Cross-examination of profiles belonging to different image sets of corresponding region was conducted to discover any similar characteristics available in these images that are not detectable by mere visual inspection of these images. It is important to state here that Regions A to F of

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Figure 3.2 are labelled accordingly from the medial to lateral meniscus. Regions A and F represent those images in which a meniscus appeared as a single feature on the sagittal plane. Regions B and E denote those images in which the meniscus was seen as two separate features that corresponded respectively to its anterior and posterior horns on the sagittal plane. Regions C and D signify images in which the meniscal insertions on the sagittal plane were viewable.

Figure 3.1: Horizontal and vertical profiles of a binary image containing an arbitrary feature.

Figure 3.2: Partitioned regions relative to menisci [72].

3.3 PROPOSED SYSTEMS

3.3.1 Semi-Automated Anterior Cruciate Ligament Segmentation Program

The proposed semi-automated anterior cruciate ligament (ACL) segmentation program was implemented using MATLAB and according to the methodology illustrated in Figure 3.3. Morphological operations were heavily deployed for pre-processing purposes to remove the large amount of undesirable features present. Active contour was utilised to carry out the actual segmentation of ACL after the pre-processing stages. A summary of this program flow is described in the following paragraphs.

At the launch of the program, the user is prompted to specify the number of images available in the image set and the range of images in which the ACL is present. Only images with the presence of ACL are read and duplicated. The first duplicated image will undergo a pre-processing procedure that comprises Steps 3 to 6 of Figure 3.3. During this process, gamma transformation is first applied onto the duplicated image to amplify the differences of intensity values among the low intensity features present in this image. This is to improve the contrast of ACL relative to its surrounding tissues since it tends to appear as a homogenous low intensity feature in MR images [73-75]. Thresholding is subsequently performed using Otsu's method [57] to convert the resultant image into a binary format.

By employing both femur and tibia as references, a predefined bone mask and a cropping mask as displayed in Figure 3.4 are used together with morphological operations to extract the region of interest (ROI) within the binary image. This predefined bone mask is created through the manual segmentation of an unrelated knee joint MR image and the dimensions of the cropping mask are specified based on this bone mask as shown in Figure 3.5. Both masks are created prior to the application of this program.

When the predefined bone mask is applied onto the binary image by a multiplicative operation, the resultant output will often contain not only the features related to both tibia and femur but also other features as well. This is because the segmented tibia and

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femur of the bone mask are typically larger than those seen in the binary image. The program will perceive such output as undesirable. Hence, it will erode the size of both segmented tibia and femur in the predefined bone mask through morphological operations before applying this modified mask onto the binary image again. If the output is again undesirable, this process of eroding the modified bone mask and applying the resultant onto the binary image will continue until the output only contains two features in which one will correspond to the tibia and the other is related to the femur.

Once this condition is met, a horizontal intensity profile (as displayed in Figure 3.5) of the output is plotted. The location of the peak within this profile will determine the location of the cropping window (i.e. the white box) in the cropping mask illustrated in Figure 3.4. The cropping mask is then applied onto the binary image via a multiplicative operation to extract the ROI. Thus, only features surrounding the ACL now remain in the image.

In order to improve the segmentation accuracy, ACL localization is carried out through Steps 7 to 11 as illustrated in Figure 3.3. This involves the application of additional morphological operations to further remove the undesirable features present in the ROI. Line structuring elements at 45° and 60° are used with morphological filtering process for this purpose.

Prior knowledge via visual observations of ACL appearance in MR images of knee joints in extended posture has proved that its appearance is not strictly linear at 45° . This is depicted in Figure 3.6. Hence, the use of line structuring elements at various angles were experimented but only those at 45° and 60° are able to remove large amount of undesirable features while preserving the overall structure of ACL in the ROI. Any line structuring elements with a variance of $\pm 5^\circ$ from such angles will still produce satisfactory results but a variance beyond this will fail to preserve the overall ACL structure.

The use of these structuring elements is considered feasible since MR images of knee joints are typically acquired in an extended posture. This is because the involvement

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of a lower extremity knee coil during the imaging process restricts the knee joints from being in a flexed position.

Steps:

Figure 3.3: Process flow of proposed semi-automated ACL segmentation program [76].

Connected component labelling is subsequently applied to label the remaining features as separate regions. Since ACL is probably the longest feature within the

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resultant image, a diagonal profile at 135° is used to locate it while the other remaining features are removed with ease due to the prior labelling. An illustration of the diagonal profile is displayed in Figure 3.6.

Figure 3.4: Predefined bone mask (*left*) and cropping mask (*right*) created through manual segmentation of an unrelated knee joint MR image [76].

Figure 3.5: Dimensions of cropping mask specified base on predefined bone mask (*top*) and intensity profile of predefined bone mask (*bottom*) [76].

Finally in Steps 12 to 13, the achieved image is used as an initialization mask for the application of an active contour on its corresponding original image. The principle of this active contour is based on a paper by Chan and Vese [66], which is a modification of the original snake by Kass et al. [60]. This active contour is ideal for the present study since it does not rely on edge information and can detect objects whose boundaries are not necessarily defined by gradient. Hence, these characteristics ensure that a good ACL segmentation is obtainable. This active contour, which is used to segment the ACL, was implemented by Shawn Lankton of Georgia Institute of Technology [77].

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Figure 3.6: Non-linearity of ACL (left) and diagonal profile of ACL (right) [76].

The resultant images at various steps of Figure 3.3 are shown in Figure 3.7. For the remaining images in the image set with ACL presence, they undergo the same processes independently as described in prior paragraphs.

Figure 3.7: Resultant images at respective stages of proposed semi-automatic ACL segmentation program [76].

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3.3.2 Semi-Automated Meniscus Segmentation Program

MATLAB was used to implement the proposed semi-automated meniscus segmentation program and in accordance to the process flow outlined in Figures 3.8a) and b). Similar to the proposed semi-automated ACL segmentation program, both morphological operations and active contours were involved for the same purposes. However, logical operations were added in the implementation of this proposed program. A description related to the program flow is detailed in the following paragraphs.

At the commencement of program, the user is prompted to input the number of images available in the image set and the range of images that possesses the presence of lateral and medial menisci. Only images with the presence of menisci are read and duplicated. The duplicated images will undergo a morphological close operation at Step 3 in Figure 3.8a) where a disk structuring element will translate across the images. As it translates, the structuring element averages the intensity values of those pixels contained within the region covered by it. Thus, this process leads to images with patches of homogeneous intensity and such images are deemed here as “mosaic images”.

The rationale behind this process is to homogenise the intensity value of menisci to ensure that the menisci will appear as homogeneous low intensity features observed in many studies [10, 68-71, 78-80]. This is also done to segregate the menisci from surrounding tissues and to demarcate them from the thick borders of bones caused by the chemical shift effect at high magnetic field strength [34, 36-37]. In order to accomplish this, the structuring element must be smaller than the menisci and resembles the shape of meniscal horns. Since the typical appearance of meniscal horns in MR images is either triangular or circular shaped, a disk structuring element is chosen for this task. This structuring element has to be smaller than the meniscal horns to provide selectivity as a larger structuring element will lead to undesirable mergers of menisci with other unwanted features during the intensity averaging process.

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Steps:

Figure 3.8a): Process flow of proposed semi-automated meniscus segmentation program.

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Steps:

Figure 3.8b): Process flow of proposed semi-automated meniscus segmentation program.

At Steps 4 and 5, a pre-specified threshold intensity value converts all mosaic images into binary images. The removal of undesirable large features in these images is subsequently accomplished by logical operations. Once this is completed, the resultant images are duplicated and the duplicates are summed together to obtain a cumulative image (i.e. the intensity value is an accumulation of all images summed together).

Subsequently, the user is prompted by the program to specify a threshold intensity percentile value. This value is used in Step 6 to binarise the cumulative image. A vertical profile of this image is plotted and examined by the program to determine which row along the vertical axis of the image contains the presence of menisci. From this row, two rows that are located 20 rows above and below it are taken as the parameters to crop the top and bottom of the cumulative image.

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After the vertical cropping, a horizontal profile of the cropped image is plotted and examined by the program. Two parameters which correspond to columns that mark the beginning of anterior meniscal horn and the end of its posterior horn along horizontal axis of the cropped image are recorded. These are used subsequently to crop the left and right of the cropped image. A depiction regarding the parameter acquisition procedures for both vertical and horizontal cropping are shown in Figure 3.9.

Figure 3.9: Procedures involved in acquiring parameters for both vertical and horizontal cropping of processed images.

It is important to note that the vertical cropping must be carried out first and then followed by horizontal cropping. This is because the profile studies mentioned in

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Section 3.2 indicate that it is possible to locate the menisci by relying on the landmarks which only appear in the vertical profile. By first performing a vertical cropping of the image, a huge amount of undesirable features will be removed. Hence, the subsequent application of horizontal cropping helps to narrow the downstream segmentation processes to the small region surrounding the menisci. This rationale is illustrated in Figure 3.10.

Figure 3.10: Steps involved in cropping processed images to narrow the area over which segmentation will be carried out.

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Before proceeding to Step 7, the cropped image is displayed to the user for decision making. In this case, the primary task of the user is to determine if the image is the best representation that only displays features corresponding to the menisci. If not the user can repeat Step 6 with newly specified threshold intensity percentile values until he/she is satisfied with the outcome.

Once the program proceeds to Steps 7 and 8, the parameters that are involved in the cropping of cumulative image are used to crop the processed images of Step 4. Eventually, these images are again duplicated and undergo Steps 9 to 12. The routines in Steps 9 to 12 are similar to those explained for Steps 5 to 8, but there are three exceptions. The first exception is that the combined image in Step 10 is now thresholded by a pre-determined threshold intensity percentile value. Secondly, a more stringent condition is applied for the vertical cropping. Two rows that are located 15 rows above and below the row which contains the menisci are used as the vertical cropping parameters. This is to enhance the removal of undesirable remnant features that are not removed in the initial vertical cropping. Lastly, the parameters acquired in Step 11 are used to crop the processed images of Step 8.

In Step 13, each processed image of Step 12 undergoes a morphological manipulation process which eliminates any unwanted features positioned between the meniscal horns. During this, the features are shrunk to single pixel features and two markers from left and right edges of the image will sweep inwards to detect the meniscal horns. In this routine, it is assumed that the first features detected during the sweeping of both markers correspond to the meniscal horns. Hence, the markers will highlight these columns as positive and convert all other columns to an intensity value of 0. Figure 3.11 provides a clear depiction of this morphological manipulation process.

Finally in Step 14, the features in the processed images are dilated by a disk structuring element that has a radius of five pixels. These resultant images are served as initialisation masks for the application of an active contour on their corresponding original images. The same active contour by Shawn Lankton from Georgia Institute of Technology is deployed for this purpose [77]. Figure 3.12 displays the resultants at various steps of Figures 3.8a) and b) as described in prior paragraphs.

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Figure 3.11: Processes involved in removing features between meniscal horns.

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Figure 3.12: Resultant images at respective stages of proposed semi-automatic meniscus segmentation program.

3.4 VALIDATIONS

3.4.1 Sensitivity and Specificity

In digital image processing, sensitivity and specificity are the typical validation parameters use to gauge the performance of binary classifications [81]. Since the

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segmentation results from the manual segmentations and proposed programs were binary images, these parameters were involved in validating the performance of proposed programs. In this case, the manually segmented images were used as ground truths for the validation purpose.

The expressions for both sensitivity and specificity are shown in Equations 8 and 9 respectively [81-82]. From these expressions, it is evident that sensitivity gauges the relative amount of actual positives correctly classified while specificity yields the ratio of actual negatives correctly labelled.

$$\text{Sensitivity} = \frac{\text{Number of True Positives}}{\text{Number of True Positives} + \text{Number of False Negatives}} \quad (8)$$

$$\text{Specificity} = \frac{\text{Number of True Negatives}}{\text{Number of True Negatives} + \text{Number of False Positives}} \quad (9)$$

If a low sensitivity is achieved, this will denote an under-segmentation situation. In other words, this implies that the proposed programs failed to identify those pixels that constitute part of the region of interest (ROI). If a low specificity is yielded, then it will signify an over-segmentation situation. This indicates that the proposed programs have incorrectly identified those pixels which are not part of the ROI.

3.4.2 Dice Coefficients

In addition to the parameters mentioned in Section 3.4.2, Dice coefficient is also involved in the validation process. It measures the degree of similarity between corresponding results produced by the proposed programs and those manually segmented. A high value of Dice coefficient means high similarity. In general, a value of 1 would indicate perfect similarity while a value of 0 would denote no similarity. The expression of this coefficient is shown in Equation 10 [81].

$$\text{Dice Coefficient} = \frac{2 (\text{True Positives})}{(\text{True Positives} + \text{False Positives}) + (\text{True Positives} + \text{False Negatives})} \quad (10)$$

Chapter 4: Results and Discussions

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 PROFILE STUDIES

The profile studies were conducted to facilitate the development of proposed semi-automated meniscus segmentation program. These studies were intended to devise a technique for which the proposed program could utilise to automatically locate the menisci within an image.

Although each of the four acquired sets of isotropic magnetic resonance (MR) images comprised 192 images, the menisci did not appear in every image. Approximately 52 ~ 57 % of the images in each set contained the menisci presence. In total, 418 images from all four image sets were involved in the profile studies. The profile studies were conducted with reference to the manually partitioned regions mentioned in Section 3.2. Figures 4.1 to 4.6 show the inter-comparisons of vertical profiles at various partitioned regions.

Figure 4.1: Inter-comparison of vertical profiles in Region A.

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Figure 4.2: Inter-comparison of vertical profiles in Region B.

Figure 4.3: Inter-comparison of vertical profiles in Region C.

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Figure 4.4: Inter-comparison of vertical profiles in Region D.

Figure 4.5: Inter-comparison of vertical profiles in Region E.

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Figure 4.6: Inter-comparison of vertical profiles in Region F.

From the vertical profiles, it was observed that a landmark which corresponded to the menisci presence along the vertical axis of MR images existed. This landmark appeared as a sudden dip in the vertical profile plots and could be in two typical forms as illustrated in Figure 4.7.

Figure 4.7: Typical forms of the landmark that corresponds to the menisci presence in the vertical profiles of knee joint related MR images.

A plot describing the probability of observing this landmark in the vertical profiles of all four sets of images involved is shown in Figure 4.8. The averaged data from the vertical profile studies were calculated in terms of probability and are tabulated in Table 4.1. In this table, each value pertains to the average probability of observing the subject of interest in a particular region was obtained by averaging the respective probabilities of such observation from all four sets of images.

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Presence of Landmark in Vertical Profile

Figure 4.8: Probability of observing the landmark in the vertical profiles of involved image sets over the partitioned regions.

Table 4.1: Averaged data of vertical profile studies tabulated as probabilities.

	Partitioned Regions of Menisci					
	A	B	C	D	E	F
Presence of landmark associated with meniscus	0.893	1	0.637	0.578	1	0.906
Presence of other valleys that look similar to landmark but not associated to menisci	0.132	0.225	0	0.309	0.133	0.300
Presence of landmark associated with menisci but differ from described shapes	0	0	0.214	0	0	0

Using the same images involved in the vertical profile studies, the horizontal profile studies were conducted in similar fashion. However, no distinctive landmarks associated with the presence of menisci could be observed in the horizontal profiles. This is evident from Figures 4.8 to 4.13 which show the inter-comparisons of horizontal profiles at various partitioned regions.

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Figure 4.8: Inter-comparison of horizontal profiles in Region A.

Figure 4.9: Inter-comparison of horizontal profiles in Region B.

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Figure 4.10: Inter-comparison of horizontal profiles in Region C.

Figure 4.11: Inter-comparison of horizontal profiles in Region D.

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Figure 4.12: Inter-comparison of horizontal profiles in Region E.

Figure 4.13: Inter-comparison of horizontal profiles in Region F.

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Base on the profile studies performed, the results suggest that the landmark observed in the vertical profiles can probably be used to assist the proposed semi-automated meniscus segmentation program in locating the menisci automatically. According to the data plotted in Figure 4.8, the existence of this landmark is observable at all partitioned regions. In general, this landmark arises because the menisci appear as homogenous low intensity features in MR images [10, 68-71, 78-80]. When a vertical profile is plotted, the rows along the vertical axis that contain the menisci presence tend to have the lowest cumulative intensity values. Thus, this contributes to the sudden dip in the plotted vertical profile and gives rise to the distinctive shapes as described in Figure 4.7.

Although this landmark presence diminishes greatly in Regions C and D relative to the other regions, the reliability of using it to locate the menisci is considered acceptable. This is because on average the lowest mean probability of observing the landmark is approximately 0.578 as listed in Table 4.1. Note that it is unsurprising to observe such poor presence of the landmark at Regions C and D since both regions correspond to the meniscal insertions. These insertions are often obscured in MR images as they are very small noticeable features and are likely masked by chemical shift effect at high magnetic field strength.

At regions B and E, the mean probability of observing the landmark is 1 as shown in Table 4.1. This denotes that they are the best regions to locate the menisci with high reliability. Regions B and E consist of MR images in which the middle portion of the menisci is always prominently displayed. This is because the cross-sectional thickness of a meniscus varies gradually and uniformly in Regions B and E unlike other regions. Since the menisci are always prominently displayed in these regions, this explains why they have the highest mean probability of observing the landmark.

To date, there are only five studies on meniscus segmentation [67-71]. However, only two papers [68-69] have used such profile analysis to assist in the meniscus segmentation.

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4.2 Semi-Automated Anterior Cruciate Ligament Segmentation Program

Each of the four acquired sets of isotropic MR images comprised 192 images. However, as tabulated in Table 4.2, the number of images with the presence of anterior cruciate ligament (ACL) varied in each set and was dependent on the volunteers' body size. Thus, the numbers stated in Table 4.2 denote the amount of images from each set that had underwent the segmentation performed by the proposed semi-automated ACL segmentation program.

Table 4.2: Number of images with ACL presence within an image set [76].

	Set 1	Set 2	Set 3	Set 4
Number of images within an image set which contains the presence of ACL	28	21	26	36

A total of 111 images were segmented and Figure 4.14 displays the representative segmentation results of an image from each set. The proposed program was run on a computer with the following specs: Windows Vista 32-bit operating system, 3 GB RAMs, Intel Core 2 Quad 2.5 GHz. It took 10 mins to segment a set of 192 MR images in contrast to the 45 mins spent when segmentation was done manually. In addition, similar segmentation results were attained from repeated segmentations of the same images by the program. This was unachievable when manual segmentation was carried out.

Figure 4.14: Representative segmentation results featuring (A) Set 1, image 98; (B) Set 2, image 89; (C) Set 3, image 89; (D) Set 4, image 89 [76].

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The proposed program relied on a series of morphological operations to locate and extract the ACL related features during the pre-processing stages, while active contour utilised these features to carry out the actual ACL segmentation. The term “ACL related features” here refers to the voxels that compose the ACL displayed in a MR image. Base on Figure 3.3, Steps 3 to 11 are referred to as the pre-processing stages while the actual ACL segmentation is accomplished in Step 12.

Table 4.3 shows the performance of these morphological operations (i.e. Steps 3 to 11 of Figure 3.3) in the extraction of ACL related features. Each data in Table 4.3 is a ratio in which the denominator is the total number of images within an image set that is involved in the ACL segmentation. The numerator of this ratio is the number of these images which contained at least one voxel that belongs to the ACL after undergoing the morphological operations, but before the active contour is applied. For example, 28 images of Image Set 1 were involved in the ACL segmentation. Among these images, only 23 images contained at least one voxel that belonged to the ACL after undergoing the morphological operations. Hence, the successfulness of the proposed program in locating and extracting ACL related features from Image Set 1 is approximately 82.1 %.

Table 4.3: Performance measure of the pre-processing stage of proposed semi-automated ACL segmentation program.

	Set 1	Set 2	Set 3	Set 4
Successfulness in locating and extracting ACL related features	0.821	0.857	0.730	0.425
Average:	0.708 $\pm$ 0.196			

With reference to Table 4.3, the results indicated that the morphological operations implemented in a series of combination (i.e. Steps 3 to 11 of Figure 3.3) had performed well with average extraction successfulness at 70.8 % $\pm$ 19.6 %. Among the four image sets involved in this evaluation, the extraction of ACL related features fared the worst for Image Set 4. In this particular image set, intensity values of the voxels representing ACL were very inhomogeneous. This led to a poor contrast between the ACL and its surrounding tissues. This problem was further enhanced by

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the thin anatomical thickness of the ACL in this set relative to those seen in other image sets as evident in Figure 4.14. Since morphological operations heavily depended on intensity values to operate successfully, the poorly defined ACL in Image Set 4 greatly hampered the extraction of its related features. This affected the segmentation produced by the active contour at the downstream of the proposed program as illustrated in Table 4.4.

The parameters involved in validating the overall performance of the proposed program are tabulated in Table 4.4. The results revealed that the proposed program had an overall sensitivity of $43.3 \% \pm 14.0 \%$ while its overall specificity was $99.4 \% \pm 0.3 \%$. When the segmented images from the proposed program were compared with those manually segmented, the overall Dice coefficient achieved was 0.381 ± 0.091 . This denotes that average similarity between the segmented images of both manual segmentation and proposed program was 38.1% .

Table 4.4: Performance measures of proposed semi-automated ACL segmentation program [76].

	Set 1	Set 2	Set 3	Set 4	Average
Sensitivity	0.430	0.614	0.416	0.270	0.433 ± 0.410
Specificity	0.998	0.992	0.991	0.996	0.994 ± 0.003
Dice Coefficient	0.472	0.413	0.385	0.256	0.381 ± 0.091

When the values in Table 4.3 were compared with those of sensitivity and Dice coefficient in Table 4.4, it was noted that the program performed well in locating and extracting the ACL related features during the pre-processing stages. However, the ACL segmentation accomplished by the active contour at the downstream of the program was not satisfactory as evident by the low values of both sensitivity and Dice coefficient. One reason to such low values was that the active contour tended to include the posterior cruciate ligament (PCL) during segmentation when both ligaments appeared in the same image. In some cases, the active contour would include part of the tissue boundary of the bones nearest to ACL due to intensity similarity as a result of chemical shift effect. Most often, the active contour would only segment the ACL partially because of the intensity inhomogeneity among the

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voxels defining the ACL in the images. Hence, these denoted that the optimisation of active contour may be required and the introduction of some image pre-processing techniques to manipulate the image intensity was necessary.

In Figure 4.15, trend plots were plotted to show how the degree of similarity varied between the corresponding segmented images obtained from both manual segmentation and the proposed program. Although the parameters validating the performance of proposed program illustrated it as having low sensitivity and Dice coefficient value, the plots from Figure 4.15 had evidently showed the program's potentiality in ACL segmentation. This is because the achievable Dice coefficients in these plots were high for images located in the middle region with average value at approximately 0.6; while this varied drastically near the beginning and end of the plots. Such observation was unsurprising since the presence of ACL begun to emerge in images located at the beginning of these plots while fading in those situated near the end. Thus, the appearance of ACL in images within the middle region would be marked by a prominent area of approximate homogeneous low intensity with good contrast relative to its surrounding as opposed to those images not within this region.

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Figure 4.15: Trend lines showing variations in the degree of similarity between corresponding results obtained by manual segmentation and proposed program [76].

Based on the validation data acquired and observations made, the operation of this proposed program heavily relied on the intensity values of the voxels that represented ACL in magnetic resonance (MR) images. Good segmentation results can be achievable when the ACL in MR images is represented by a prominent area of homogeneous intensity value and the intensity values of the surrounding tissues differ greatly from this.

4.3 Semi-Automated Meniscus Segmentation Program

Since the menisci did not appear in every image within an image set, the same images partitioned into Regions A to F in the profile studies mentioned in Section 4.1 were used to validate the performance of proposed program. Table 4.5 shows a breakdown on the number of images from each image set that were involved in the validation. In total, 418 images were segmented by the proposed program which was operated on the same computer that was involved in the validation described in Section 4.2. The program took approximately 20 mins to segment a set of 192 MR images in contrast to the 105 mins spent when segmentation was conducted manually. In addition, the repeated segmentations of the same images yielded similar results. This was unachievable when segmentation was done manually.

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Table 4.5: Number of images with menisci presence within an image set.

	Set 1	Set 2	Set 3	Set 4
Number of images within an image set which contains the presence of menisci	99	109	108	102

The proposed semi-automated meniscus segmentation program relied on a series of morphological and logical operations to locate and extract the meniscal related features during the pre-processing stages. These features were utilised by the active contour at the downstream of the program to accomplish the actual segmentation. The term “meniscal related features” here refers to the voxels that compose the meniscus displayed in a MR image. Base on Figures 3.8a) and b), Steps 3 to 13 are referred to as the pre-processing stages while the actual meniscus segmentation is accomplished in Step 14.

Table 4.6 depicts the performance of these morphological and logical operations during the pre-processing stages (i.e. Steps 3 to 13 of Figures 3.8a) and b)) for the extraction of meniscal related features. The data in this table is calculated in the same manner as that explained for Table 4.3. Each data in Table 4.6 is a ratio in which the denominator is the total number of images within an image set that is involved in the meniscus segmentation. The numerator of this ratio is the number of these images which contained at least one voxel that belongs to the meniscus after undergoing the pre-processing stages, but before the active contour is applied.

Table 4.6: Performance measure of the pre-processing stage of proposed semi-automated meniscus segmentation program.

	Set 1	Set 2	Set 3	Set 4
Successfulness in locating and extracting meniscal related features	0.914	0.866	0.620	0.843
Average:	0.811 ± 0.130			

With reference to Table 4.6, the results indicated that the morphological and logical operations applied in a series of combination (i.e. Steps 3 to 13 of Figures 3.8a) and b)) had performed well with average extraction successfulness at 81.1 % ± 13.0 %. A

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breakdown showing the performance of the pre-processing stages (i.e. Steps 3 to 13 of Figures 3.8a) and b)) at each region of an image set is shown in Table 4.7. Similar to Table 4.6, each data in Table 4.7 is a ratio but the denominator is now the total number of images belonging to a particular region within an image set that is involved in the meniscus segmentation. Likewise, the numerator of this ratio is now the number of these images in that particular region which contained at least one voxel that belongs to the meniscus after undergoing the pre-processing stages, but before the active contour is applied.

Table 4.7: A breakdown showing the performance of the pre-processing stage at each region of an image set.

	Region A	Region B	Region C	Region D	Region E	Region F
Set 1	1	1	0.840	0.687	0.875	1
Set 2	1	0.833	0.823	0.843	0.857	1
Set 3	0.923	0.500	0.500	0.500	0.500	0.941
Set 4	1	1	0.816	0.700	0.724	0.941
Average	0.980 ± 0.038	0.833 ± 0.235	0.745 ± 0.163	0.682 ± 0.140	0.739 ± 0.173	0.970 ± 0.033

Table 4.8 tabulates the parameters involved in the evaluation of the program's overall performance. The results showed that the program was able to achieve an overall sensitivity at $62.0 \% \pm 13.5 \%$ while the overall specificity was $99.8 \% \pm 0.02 \%$. A comparison between the corresponding segmented images produced by the proposed program and the manually segmented images revealed that the overall Dice coefficient yielded was at 0.577 ± 0.066 . This indicates that the average similarity between the corresponding segmented images of both manual segmentation and proposed program was 57.7% . Figure 4.16 displays the representative segmentation results from each image set produced by the program.

Among the four image sets involved in the validation, the segmentation performed by the proposed program on Image Set 3 yielded the worst performance with a poor Dice coefficient at 48.8% as evident from Table 4.8. Inspections conducted on the

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segmented images of this particular set had revealed that the proposed program segment the anterior meniscal horns incorrectly. Apparently, the pre-processing procedures implemented prior to the application of active contour did not extract the anterior meniscal horns successfully and this explained why the performance measure for Image Set 3 was lower than the rest in Table 4.6. Since the active contour relied on the mask to carry out the segmentation correctly, this missing feature had caused the poor segmentation to occur. Figure 4.17 displays one such example.

Table 4.8: Performance measures of proposed semi-automated meniscus segmentation program.

	Set 1	Set 2	Set 3	Set 4	Average
Sensitivity	0.748	0.680	0.433	0.620	0.620 ± 0.135
Specificity	0.998	0.998	0.998	0.998	0.998 ± 0.0002
Dice Coefficient	0.626	0.631	0.488	0.562	0.577 ± 0.066

Figure 4.16: Representative segmentation results featuring (A) Set 1, image 50; (B) Set 2, image 140; (C) Set 3, image 158; (D) Set 4, image 120.

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Figure 4.17: Mask with missing meniscal anterior horn (*left*) led to incorrect segmentation produced by the active contour (*right*).

When the data in Table 4.6 were compared with those of sensitivity and Dice coefficient in Table 4.8, it was noted the program performed well in locating and extracting the meniscal related features during the pre-processing stages. However, the segmentation accomplished by the active contour at the downstream of the program achieved marginal values for both sensitivity and Dice coefficient. This was because the active contour often included the cartilage as the menisci were being segmented. This was due to their close proximity and intensity similarity. This issue worsened when the presence of chemical shift effect over-exaggerated the cartilage thickness. In worst case scenario, the menisci might even be obscured by the cartilage.

The breakdowns showing the average sensitivity and Dice coefficient at each region of each image set are tabulated in Tables 4.9 and 4.10 respectively. In Figures 4.18a) and b), trend lines are plotted to illustrate the variations in the degree of similarity between the corresponding segmented images yielded from both manual segmentation and the proposed program.

Table 4.9: A breakdown showing the average sensitivity at each region of an image set.

	Region A	Region B	Region C	Region D	Region E	Region F
Set 1	0.750	0.825	0.693	0.608	0.812	0.724
Set 2	0.778	0.653	0.559	0.809	0.722	0.700
Set 3	0.408	0.425	0.497	0.399	0.431	0.380
Set 4	0.514	0.457	0.658	0.637	0.651	0.663
Average	0.613 ± 0.180	0.590 ± 0.186	0.602 ± 0.090	0.613 ± 0.168	0.654 ± 0.162	0.617 ± 0.160

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Table 4.10: A breakdown showing the average Dice coefficient at each region of an image set.

	Region A	Region B	Region C	Region D	Region E	Region F
Set 1	0.735	0.784	0.461	0.506	0.583	0.682
Set 2	0.832	0.731	0.521	0.517	0.659	0.798
Set 3	0.540	0.545	0.585	0.327	0.419	0.474
Set 4	0.666	0.603	0.518	0.405	0.475	0.747
Average	0.693	0.665	0.521	0.439	0.534	0.675
	± 0.122	± 0.110	± 0.050	± 0.089	± 0.107	± 0.142

From both Figures 4.18a) and b) and Table 4.10, the results indicate that the proposed program operated with promising performance. Good segmentation was easily achievable when segmentation was performed on the medial meniscus, which was represented by Regions A to C, with average Dice coefficient at 0.626. In contrast, the segmentation performance decreased when segmentation was conducted on the lateral meniscus, which was denoted by Regions D to F. The average Dice coefficient attainable for this segmentation was 0.549. The rationale to why a higher average Dice coefficient was achievable for the segmentation of medial meniscus was due to its consistent shape variation and larger cross-sectional size in magnetic resonance (MR) images. Unlike the medial meniscus, the shape and cross-sectional size of lateral meniscus tended to vary drastically in MR images.

With reference to Table 4.10, it was also noted that the segmentations at Regions C and D appeared poorer than the other regions. This is clearly evident from the plots seen in Figure 4.19. Both Regions C and D, as mentioned in Section 3.2, represented the images in which only the meniscal insertions were present. The below average Dice coefficient values at these regions were caused by the miniature size of meniscal insertions and their tendency of being obscured by the chemical shift effect which prevented the proposed program from carrying out the segmentations successfully. Similarly, these factors also lead to subjective manual segmentations by the experts in most cases.

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Figure 4.18a): Trend lines showing variations in the degree of similarity between corresponding results obtained by manual segmentation and proposed program.

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Figure 4.18b): Trend lines showing variations in the degree of similarity between corresponding results obtained by manual segmentation and proposed program.

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Figure 4.19: Plots showing the average Dice coefficients at each region of the image sets.

When segmentation was conducted without including the meniscal insertions (i.e. Regions C and D), the performance of proposed program improved. This improvement is notable when the corresponding data tabulated in both Tables 4.6, 4.8, 4.11 and 4.12 are compared. On average, the successfulness in locating and extracting the meniscal related features improved by 4.6 % while the Dice coefficient and sensitivity enhanced by 4.8 % and 0.85 % respectively. Since the Dice coefficient measures the similarity between the corresponding segmentations produced by manual segmentation and the proposed program, this improvement is considered significant over the small increase in sensitivity.

Table 4.11: Improvements in performance of the pre-processing stage of proposed meniscus segmentation program when the meniscal insertion regions C and D are not included.

	Set 1	Set 2	Set 3	Set 4
Successfulness in locating and capturing meniscal related features	0.969	0.898	0.696	0.865
Average	0.857 ± 0.115			

According to the examinations made on the segmented images yielded by the proposed program, it was concluded that the chemical shift effect would most likely be the prime detrimental cause which affected the performance of proposed program. In general, the chemical shift effect becomes pronounce at high magnetic field

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strength and it tends to exaggerate the boundaries thickness between tissues displayed in both T1- and density (PD) weighted MR images. In most cases, this artefact will cause the cartilage and menisci to merge since they possess similar low intensity values in such images. Consequently, the proposed program was incapable of segregating them correctly as its operations heavily relied on the image intensity values. Thus, a possible solution to this issue is to acquire MR images using either fat-suppressed T1-weighted or PD-weighted sequences. In these fat suppressed sequences, the cartilage is displayed with bright intensity values while the menisci remain as low intensity features. This provides a better distinguish between the cartilage and menisci, and will help assist the proposed program in producing better meniscus segmentation. An example showing the difference in appearance between PD-weighted and fat-suppressed T1-weighted images of a knee joint is displayed in Figure 4.20.

Table 4.12: Improvements in the performance measures of proposed semi-automated meniscus segmentation program when the meniscal insertion regions C and D are not included.

	Set 1	Set 2	Set 3	Set 4	Average
Sensitivity	0.785	0.716	0.412	0.602	0.629 ± 0.162
Specificity	0.998	0.998	0.998	0.998	0.998 ± 0.0001
Dice Coefficient	0.703	0.725	0.478	0.593	0.625 ± 0.113

Figure 4.20: Difference in appearance between PD [68] (left) and fat suppressed T1 [69] (right) images of a knee joint.

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5.1 SUMMARIES

5.1.1 Profile Studies

The profile studies presented in this thesis were conducted to assist in developing the proposed semi-automated meniscus segmentation program. The intention was to utilise the observations discovered in the studies to formulate a valid methodology in detecting the meniscus automatically.

From the results detailed in Section 4.1, they do agree to the comments made by Köse et al [69] as mentioned in Section 2.4.1. Firstly, a landmark does exist in the intensity profile along the vertical axis of knee joint related magnetic resonance (MR) images but none is present in the intensity profile along the horizontal axis of the same image. Secondly, the observed landmark does indeed provide a reliable mean of locating the meniscus automatically in MR images. However, the observations made during the profile studies presented in Section 4.1 also revealed that the landmark is not unique to menisci alone.

In other words, the prominence of this landmark does vary among the images within an image set but it is present even when the menisci are absent. The landmark existed apparently due to the tissue boundaries between the cartilage, bones and menisci; and not because of the menisci even though its presence does contribute to the prominence of this landmark. This is evident from Figure 5.1 in which the landmark still existed even when the menisci are not present.

Nonetheless, this landmark is still a reliable feature for locating the menisci automatically as proven by Ramakrishna et al [68], Köse et al [69] and in this thesis. Thus, the discoveries from the profile studies were incorporated into the development process of the semi-automated meniscus segmentation program which was proposed in this thesis.

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Figure 5.1: Comparison between MR images without (*top*) and with (*bottom*) presence of menisci.

5.1.2 Semi-Automated Anterior Cruciate Ligament Segmentation Program

There are currently no published works regarding the development of computer-based anterior cruciate ligament (ACL) segmentation programs, even though most of the knee joint surgery relates to ACL reconstruction. Thus, one of the works presented in this thesis was on developing a semi-automated meniscus segmentation program. The motivation was to provide radiologists/radiographers with a program that provides reliable and reproducible semi-automated ACL segmentation of MR images while reducing the time spent on such purpose.

A description of the proposed program's methodology is detailed in Section 3.3.1. In short, this program relied on both morphological operations and active contour to carry out the segmentation while taking advantage of the unique shape and orientation of ACL in MR images. Based on the validations presented in Section 4.2, the program performed well in the extraction of ACL related features with an average successfulness at 0.708 ± 0.196 prior to the ACL segmentation. From an overall perspective, the program was able to achieve an average Dice coefficient of $0.381 \pm$

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0.091 with average sensitivity and specificity at 0.433 ± 0.140 and 0.994 ± 0.003 respectively. In addition, the time spent on ACL segmentation was reduced from 0.24 secs to just 0.06 secs per image. Although from a first glance of these data showed that the program did not achieve satisfactory performance, the program did prove that the methodology proposed is feasible. This is evident from Figure 4.15.

From Figure 4.15, the plots showed that the proposed program has the potential to achieve very good segmentation result with the highest achievable Dice Coefficient at approximately 0.839. Although the plots showed that the achievable Dice Coefficients largely range between 0.400 and 0.600, the coefficients tend to vary drastically near the beginning and end of the plots. This is unavoidable because the presence of ACL begins to emerge in images located at the beginning of these plots while fading in those situated near the end. As a result, the ACL appearance in these images is represented by a weakly defined area of poor intensity homogeneity that causes the proposed program to produce poor ACL segmentations. Unlike these images, the ACL appearance in the images located within the middle portion of the plots is a well defined area of homogenous intensity. This explains why the variation of achievable Dice Coefficients is gradual in the middle portion of these plots. Base on this information from Figure 4.15, an immediate future work on improving the proposed program is to explore possible imaging or image processing techniques to manipulate the image intensity such that ACL is represented by a well defined area of homogenous intensity in images which its presence begins to appear or fade away.

Another main issue leading to the program's poor performance was its tendency to include the posterior cruciate ligament (PCL) during the ACL segmentation. This occurred frequently when the ACL and PCL appeared together in the same image. The source to this undesirable segmentation was due to the close proximity between ACL and PCL coupled with their similarity in image intensity values. In some cases, the segmentation would also include part of the tissue boundary of the bones at the knee joint nearest to either ACL or PCL. This outcome was a result of the chemical shift effect which thickened the tissue boundary that possessed similar image intensity values to that of ACL and PCL. Most often, the ACL was only partially segmented

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because of the intensity inhomogeneity present within it. Some of the undesirable segmentations mentioned above are shown in Figure 5.2.

With regard to the undesirable ACL segmentations obtained by the proposed program, some possible solutions are raised. One of these solutions is to optimise the time response (TR) and time echo (TE) of the magnetic resonance imaging sequence involved in acquiring the images. The rationale to this is to minimise the chemical shift effect seen in the images since such artefact becomes pronounce at high magnetic field strength. A second solution is to carry out intensity inhomogeneity correction to counter the intensity inhomogeneity of ACL appearance in MR images. This will help improve the probability of acquiring good and reasonable ACL segmentation. Unfortunately, the problem related to the incursion of PCL during ACL segmentation is the toughest obstacle to overcome. This is because the similarity in image intensity values between ACL and PCL made it difficult for the program to segregate them correctly due to the heavy implementation of morphological operations within the program. Thus, investigations into other image processing technique should be carried out to address this problem.

In conclusion, the results in Section 4.2 illustrate that the methodology implemented in the program is feasible for ACL segmentation even though its performance is not satisfactory. Hence, optimisations are necessary to enhance the program's performance.

Figure 5.2: Undesirable segmentation that included the PCL and part of the bone tissue boundaries (left), and incomplete ACL segmentation (right).

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5.1.3 Semi-Automated Meniscus Segmentation Program

In response to the available programs mentioned in Section 2.4.2, a proposed program was presented in this thesis to perform similar task while addressing some of the mentioned limitations faced by these programs. The motivation was to provide radiologists/radiographers with a program that provides much realistic meniscus segmentation (i.e. Regions A to F of Figure 3.2) rather than just restricting the segmentation to meniscal horns only (i.e. Regions B and E).

The methodology of this proposed program is described in Section 3.3.2. In short, this program relied on both morphological and logical operations for pre-processing purposes while segmentation was accomplished by active contour. The program was developed to operate on PD-weighted magnetic resonance (MR) image volumes which were acquired on sagittal plane. Unlike those programs mentioned in Section 2.4.2, this program relied on the information within the MR image volume to segment the meniscus. In other words, it cannot correctly segment the meniscus if the MR images are inputted into the program separately or if the inputted MR image set contains images belonging to different patients and knees. Hence, the proposed program is said to provide a volumetric segmentation through two-dimensional (2D) means. The deformable three-dimensional (3D) surface models were not considered because their implementation necessitated the involvement of more parameters than the active contours. This would undesirably increase both the computing resources required and the time spent to complete a given segmentation task.

According to the validations illustrated in Section 4.3, the proposed program performed well in the extraction of meniscus related features with an average successfulness at 0.811 ± 0.130 prior to the meniscus segmentation. From an overall perspective, the program achieved an average Dice coefficient of 0.577 ± 0.066 with average sensitivity and specificity at 0.620 ± 0.135 and 0.998 ± 0.0002 respectively. In addition, the time spent on meniscus segmentation was reduced from 0.54 secs to just 0.10 secs per image.

Base on Figures 4.18 and 4.19, the plots showed that the proposed program has the potential to achieve very good segmentation result with the highest achievable Dice

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Coefficient at approximately 0.926. Although the plots showed that the achievable Dice Coefficients largely range between 0.600 and 0.800, the coefficients tend to diminish and vary greatly when segmentation was carried out on images displaying meniscal insertions (i.e. Regions C and D). When the segmentation of meniscal insertions was excluded, the average successfulness in the extraction of meniscus related features improved to 0.857 ± 0.115 . Likewise, the average achievable Dice Coefficient, sensitivity, and specificity improved to 0.625 ± 0.113 , 0.629 ± 0.162 and 0.998 ± 0.0001 respectively. These improvements were largely because the meniscal insertions were too small and were obscured by chemical shift effect which leads to frequent unsuccessful segmentation. In practice, most radiologists/radiographers relied on past experiences to manually segment the meniscal insertions. Thus, such segmentations are often termed as “subjective”.

Two solutions are suggested to counter this issue caused by chemical shift effect. One is to optimise the MR sequence used to acquire the PD-weighted MR images and second is to modify the program to make it applicable on either fat-suppressed T1-weighted or PD-weighted MR images. In the latter solution, the fat-suppressed images tend to have a better contrast delineating the meniscus from cartilage and the presence of chemical shift effect is not noticeable. Thus, it is speculated that successful meniscal insertions segmentation is achievable on such MR images. An example showing the difficulty in discerning the presence of meniscal horns as a result of chemical shift effect is depicted in Figure 5.3.

In conclusion, further optimisations are required to improve the program's performance. However, the promising data in Section 4.3 have showed that the methodology implemented is indeed viable for meniscus segmentation.

A fair comparison on the performances between the proposed program and the publications presented in Section 2.4.2 is difficult. This is primarily because among the five presented publications, only the work by Sasaki et al. [67] focused on the segmentation of normal meniscus while the rest [68-71] centred on the segmentation of meniscus with meniscal tears (i.e. injured meniscus). Since the proposed semi-automated meniscus segmentation program presented in this thesis is designed to

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segment only normal meniscus, hence no objective comparison can be made between it and the presented publications in Section 2.4.2. Secondly, Sasaki et al. [67] only presented their methodology on the segmentation of normal meniscus but did not provide any performance measures to validate the performance of their methodology. Hence, there are no means to compare the performance of their methodology to the proposed program presented in this thesis. However, it is reasonable to comment that the proposed program is superior to those works [67-71] presented in Section 2.4.2. This is because as mentioned in the Section 2.4.2 the methodologies employed by those works were designed in mind to segment only meniscal horns (i.e. Regions B and E), unlike the proposed program which can segment the entire meniscus (i.e. Regions A to F). This is due to the use of an active contour for the segmentation purpose which provides the proposed program with the necessary flexibility in carrying out the meniscus segmentation.

Figure 5.3: Original MR image (left) in which the meniscal insertions were correctly segmented by manual segmentation (centre) and incorrectly segmented by the proposed program (right).

5.2 FUTURE WORKS

Since there are multiple tissues at the knee joint, it is deemed too exhaustive to create every module to cater for the specific diagnosis of different tissues at the joint. Thus, the initial development of the integrated system for knee joint related clinical diagnosis, pre-surgical planning and post-operative monitoring was confined to the anterior cruciate ligament (ACL) and menisci. This is because both tissues are most prone to damages. Although this thesis is centred on phase one of the development of this integrated system, this portion of the thesis will propose some possible future works which can be carried out in phase two and three. These proposed works were crafted in support of the ongoing effort in the development of this integrated system.

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For phase two of the research as mentioned in Section 1.2, the focus will be on the three-dimensional (3D) model reconstructions of ACL and meniscus. In this case, the segmentation masks acquired from both manual segmentations and the proposed programs will be used to reconstruct these models. Various 3D modelling techniques can be explored for this purpose. Some of these may include marching cube, finite element modelling (FEM) and etc. The motivation behind this portion of the research is to conceive a methodology which will allow the 3D model of a tissue to be reconstructed directly from a volume of two-dimensional (2D) segmentation masks. The aim is to supply clinicians with models that closely resemble the actual *in-vivo* tissues which are being examined and thus providing a more realistic view on the conditions of these tissues. In addition, these models may be used in pre-surgical planning, post-operative monitoring and clinical simulation studies. An example of a reconstructed 3D model of knee joint is displayed in Figure 5.4.

In phase three of the research, the focus is on the development of a series of application based modules that provide measurement data necessary for clinical diagnosis, pre-surgical planning and post-operative monitoring. One of these modules which can be developed is the ACL functionality analysis module. At present, a patient with ACL issues must undergo a series of examinations as illustrated in Figure 5.5 before any decision is made by a clinician to carry out the necessary surgical treatment. This is time consuming and the numerous visits before administering the surgical treatment may delay the right timing opportunity to operate on the knee. Thus, the motivation in creating this ACL functionality analysis module is to hasten this process by providing useful quantitative data to support the treatment decision.

With regard to Figure 5.5, it is mandatory for patients with suspected ACL damages to undergo a physical examination followed by X-ray imaging. The idea behind physical examination is to determine the functionality of knee joint while X-ray imaging is performed to provide visual confirmation of suspected damages. In general, magnetic resonance imaging (MRI) is always reserved as the final diagnosis procedure before a surgical treatment is carried out. This is due to the higher cost associated with MRI which most clinicians at public hospitals do not wish to burden their patients with, unless it is confirmed that a surgical treatment is necessary to

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rectify the functionality of ACL. Figures 5.6 to 5.8 show some of the common physical examinations performed by a physiotherapist to assess the integrity of ACL.

Figure 5.4: A reconstructed 3D model of knee joint [83].

Figure 5.5: Typical number of visits leading up to ACL reconstruction surgery.

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Figure 5.6: A schematic of Lachman test which is used to test for anterior instability [84].

The Lachman test shown in Figure 5.6 is used to test for both ACL laxity and rupture. In this test, an anterior force is applied at the proximal tibia while the patient is laid supine (i.e. laying on his/her back) with the injured knee flexed at 30° [84]. The anterior translation by the tibia and the location of endpoint are then evaluated. The anterior drawer test illustrated in Figure 5.7 is also used for same purpose with similar evaluations made. In this case, the setup is exactly similar to that of Lachman test but with the injured knee now flexed at 90° [84]. The pivot-shift test displayed in Figure 5.8 differs from the two former tests mentioned. It is used to test for antero-lateral knee instability and is conducted in two stages. In this test, the patient is laid supine with the injured leg extended. If the ACL is completely ruptured, an anterior tibial subluxation will occur as seen in (A) of Figure 5.8. This subluxation will abruptly reduce when the knee is flexed to an angle between 30° and 40° as shown in (B) of Figure 5.8 [84]. In general, all three of these tests are performed during the physical examination by a physiotherapist while the pivot-shift test is often used as a gauge to determine if a surgical treatment is necessary [84].

Figure 5.7: A schematic of anterior drawer test which is used to test for anterior instability [84].

Figure 5.8: A schematic of pivot-shift test which is used to test for anterior instability [84].

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The aim in developing the ACL functionality analysis module is to remove visits 4 and 5 of Figure 5.6. Hence, there is two parts to this proposed module. One is by introducing a new technique to image the injured knee using an open coil MRI scanner and the other is to implement a methodology to acquire the required evaluation data. For part one of this work, it is proposed that two volumes of MR images are required. The first volume of MR images shall be acquired when the patient is laid supine during the imaging session as seen in Figure 2.19. The second volume of MR images is to be acquired in the posture depicted in Figure 5.9.

With reference to Figure 5.9, the injured knee is flexed at a desired angle with the help of a customised support. During the imaging process, the patient will be asked to exert a downward force at the femur in an attempt to straighten the leg without applying any strength to the tibia. In response to this, an equal and opposite upward reaction force will result. Hence, depending on the angle at the inclined roof of the customised support, this action will replicate either the Lachman or anterior drawer test during the imaging process. Thus, the first volume of MR images features the images taken when the injured knee is fully extended at anatomical zero position while the second volume resembles those acquired during a physical examination by a physiotherapist.

Legend: -

Red: Force exerted by patient.

Blue: Reactive force in response to exerted force.

Green: Customised support with possible inclined roof.

Figure 5.9: A schematic to replicate either the Lachman or anterior drawer test during MRI.

With both volumes of MR images yielded, a methodology to perform quantitative assessment on the severity of ACL damages can be proposed. One of these proposed schemes is shown in Figure 5.10. Base on this figure, three prominent landmarks on the femur can be identified. The first landmark is selected at the start of the curvature (i.e. the left red dot on femur displayed in Figure 5.10), the second is found at the

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terminal of the curvature (i.e. the right red dot on femur displayed in Figure 5.10) while the last is located at the point where this curvature is most concave (i.e. the centre red dot on femur displayed in Figure 5.10). A horizontal line is then drawn between the first and second landmark, and a vertical line is extended from this line at the location where the third landmark is located. Similarly, two landmarks can be found at the tibia. One is located at the beginning of tibial plateau while the other is found at the end of this plateau. A horizontal line is drawn between the two landmarks and a vertical line is extended from the midpoint of this line.

Figure 5.10: A proposed scheme to measure the severity of ACL rupture.

From each of the image volumes acquired, the scheme shown in Figure 5.10 is applied only to the image in which the ACL appears superimposed onto the posterior cruciate ligament (PCL). The selected images are then overlaid for the measurement to be taken as illustrated in Figure 5.11. From the measurement, a large anterior translation of tibia relative to femur will signify a badly ruptured ACL. In order to provide a more quantitative meaning to the measurement yielded, it is proposed that a scale that grades the severity of ACL damage can be formulated to gauge this measurement.

Since an open coil MRI scanner is employed for the imaging purposes, it is natural that both the contrast and resolution of acquired images will be inferior to that yielded by a closed coil MRI scanner. However, it is believed that the quality of such images will not compromise the performance of the program module which is developed to evaluate the tibial translation mentioned in prior paragraphs.

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Figure 5.11: The procedure to measure ACL damage.

Hence, the development of this ACL functionality analysis module provides a new window to functionality imaging and this is believed to provide the following advantages: -

- Reduces the number of visits to the clinician,
- Increases the number of patients a clinician can cater to,
- Cost savings due to lesser clinical consultations,
- Enhances treatment decisions and surgical planning, and
- Hasten the entire treatment process to achieve optimal recovery outcome.

5.3 CONTRIBUTIONS TO-DATE

In addition to the works presented in this thesis proposal, there are also many other works that were carried out concurrently but are not mentioned here. Below is a complete list of works that has been accomplished to-date: -

- Created a semi-automated anterior cruciate ligament segmentation program,
- Innovated a program module which can automatically plot the intensity profiles at a particular location within an image,
- Conducted intensity profile studies on knee joint related magnetic resonance (MR) images,
- Developed a semi-automated meniscus segmentation program,
- Investigated the presence of magic angle effect in ligaments,
- Experimented different intensity correction techniques and random artefacts removal methods on MR images,

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- Improved a program module that can manipulate the background of MR images to a desired intensity value,
- Customised a program module that is capable of plotting and extracting contours automatically base on the intensity of features displayed in MR images,
- Investigated various forms of line and edge detectors and their efficiencies, and
- Assisted in the development of an interactive system for the measurement of cervical and lumbar spine segmental motion from digital radiographs.

5.4 PUBLICATIONS TO-DATE

Below is a list of publications that has either been submitted to or published by the respective journals or conferences: -

- Ho J.H., et al., *Anterior Cruciate Ligament Segmentation: Using Morphological Operations with Active Contour*. 4th International Conference on Bioinformatics and Biomedical Engineering (iCBBE 2010).
- Ho J.H, et al., *Meniscus Segmentation: Using Morphological Operations with Active Contour*. (under preparation)

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APPENDIX