2D/3D biometric and biomedical image matching using line constraints

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**NANYANG
TECHNOLOGICAL
UNIVERSITY**

**2D/3D BIOMETRIC AND BIOMEDICAL IMAGE
MATCHING USING LINE CONSTRAINTS**

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SCHOOL OF COMPUTER ENGINEERING

2013

2D/3D BIOMETRIC AND BIOMEDICAL IMAGE MATCHING USING LINE CONSTRAINTS

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University

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Abstract

The work reported in this thesis is a research on 2D and 3D biometric and biomedical image registration, which is of current interest. Three body parts (palmprint, hand veins, and brain surfaces) identification/ registration have been investigated in this research. The three parts are selected from three categories (outer surface, beneath the skin, and internal organ). The goal of the research is to develop 2D/3D algorithms for robust and effective matching in palmprint/vein identification systems or surface registration.

Biometrics is the study of measurable biological characteristics of identifying a person using their physical or behavioral characteristics. Personal identification and verification based on two-dimensional (2D) biometrics features have attracted more and more attention in today's society. Among the biometrics features, palmprint/hand vein have high potential to become major ones.

The tradeoff between discriminative power and user friendliness is a big challenge to today's palmprint/hand vein identification systems. During the extraction process of palmprint/hand vein, there will always be a problem of distorted or broken lines which causes difficulty in the matching process. Moreover, most palmprint/vein matching systems principally rely on perfect alignment, which is a challenging job in image preprocessing. Researchers used special image acquisition devices to restrict the movement and positioning of the

hand during the acquisition process in order to improve the image quality to solve rotation and translation problem. However, the lack of mobility consequently results in the restrictive application of palmprint/vein authentication system. Motivated by the above difficulties, we are interested in developing a rotation/translation invariant algorithm capable of solving the broken line problem as well.

In this work, we propose a novel 2D approach for palmprint/hand vein matching. The lines are retrieved as primitives and presented as line segments. A set of pair-wise angle relationships among lines are extracted to present the local structure of line pattern. Pair-wise angle relationships are simple, invariant to translation and rotation, robust to end-point erosion and segment error, and sufficient for discrimination. In order to keep positional information as well, dynamic region division technique is proposed.

The algorithm has been applied to three different databases including a benchmark palmprint database, a vein pattern database, and a mobile phone palm print database and achieved 100%, 87.5%, 83.5% accuracy respectively. Besides using lower quality images, experiments have also been concluded to test the sensitivity of the algorithm when the palm print images have been modified or distorted. The results of the experiment show a high 97% match when palm print images have been skewed to 10 degrees. The matching experiment has shown encouraging results, which implicate that line segments can provide sufficient information for palmprint and hand vein recognition. Moreover, an interesting application, fortune telling has been investigated and been proved to be useful.

After getting promising results in matching 2D biometrics images captured from surface of human body, we extend our research to some part inside human

body. The brain stem and vestibular system are two of the key organs in the balance control system. Significant anomalies of the balance function, proprioception and oculomotor reflexes have been reported, and morphological difference has been found in the vestibular system. However, there is no reported work on studying the morphological alterations in brain stems in the Adolescent Idiopathic Scoliosis (AIS) subjects in an objective and quantitative way. Motivated by this, we developed mathematical models, which facilitate the morphometry of brainstem surfaces in AIS and normal controls.

In 3D surface registration, we present a rigorous algorithm to register brainstem surfaces for the disease analysis of Adolescent Idiopathic Scoliosis. The basic idea is to extract four consistent features, which describe the global geometry of the brainstem, to guide the surface registration. Using the Ricci Flow method, brainstem surfaces are parameterized conformally onto quadrilaterally-faced hexahedron, which naturally induces the feature landmark-matching brainstem registration. Our registration algorithm can guarantee the exact landmark correspondence between brainstem surfaces. A shape energy can then be defined to measure the local shape variations between different brainstem surfaces.

We have tested our algorithms on 30 real brainstem surfaces extracted from MRIs of 15 normal subjects and 15 AIS patients. Experimental results show the efficacy of the proposed algorithm to register brainstem surfaces, which matches landmark features consistently. The computed registration can be used for the morphometry of brainstems. It has high potential to apply our proposed 3D surface registration to biomedicine applications.

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Chapter 1 Introduction

1.1 Motivations

Human body is a very complex system. People will naturally think of medical sciences when we mention human body. In our research, we investigate different parts of human body from a computer vision's point of view. We selected three parts from outer surface, beneath the skin, and internal organ respectively to explore the way to enhance security system and promote health.

Personal identification and verification are playing a more and more important role in the society [1, 2]. Traditional authentication method, such as password and smart card, often cannot meet today's security requirements, as they can be easily forgotten, lost or stolen [3, 4]. Today, a person's identity is recognizable with high confidence using biometrics-based personal identification which appeared as a new solution to these problems[5], [6]. Among all the variable biometric technologies, automatic palmprint/hand vein verification is an important complement to biometric authentication [7-9]. Therefore, we chose palmprint as outer surface feature and vein as the representative of beneath skin feature.

A palmprint is mainly composed of lines and ridges. Researchers are working on palmprint matching systems based on texture features and line features. Veins are blood vessels that carry blood towards the heart. The modern vein matching systems extract point feature and line features from the vein

pattern captured on the finger, front and back of palm [9-11].

In palmprint/vein identification systems, the matching accuracy is highly dependent on the quality of images captured. However during the extraction process of palmprint/hand vein, there will always be a problem of distorted, or broken lines which causes difficulty in the matching process. Moreover, most palmprint/vein matching system principally relies on perfect alignment, which is a challenging job in image preprocessing. In order to solve the alignment problem, some special image acquisition devices are developed[12]. They utilize pegs to restrict the movement and positioning of the hand during the acquisition process in order to improve the image quality to solve rotation, scaling and translation (RST) problem, and to ensure that the fingers are properly separated[7, 13, 14]. However, the lack of mobility consequently results in the restrictive application of palmprint/vein authentication system. Motivated by the above difficulties, we are interested in developing a RT invariant algorithm capable of solving the broken line problem as well.

Adolescent idiopathic scoliosis (AIS) is a three-dimensional structural deformity of the spine that occurs during adolescence, and the prevalence is about 4% of the adolescent population worldwide. Due to the lack of generally accepted scientific theory on the etiology of AIS, the treatment and prognosis of AIS are limited [15]. Many experiments and evidences point toward the nervous regulation of the postural balance in the idiopathic scoliosis patients. The brainstem and vestibular system are two key organs in the balance control system. Significant anomalies of the balance function, proprioception and oculomotor reflexes have been reported[16], and morphological difference has been found in the vestibular system[17]. However, there is no reported work on studying the

morphological alterations in brain stems in the AIS subjects in an objective and quantitative way. Motivated by this, we are interested in developing mathematical models which facilitate the morphometry of brainstem surfaces in AIS and normal controls. Therefore, we chose brainstem surface as the internal organ to investigate.

1.2 The Proposed Approach

In 2D world, cognitive psychological studies indicated that human recognizes line drawing as quickly and almost as accurately as gray-level pictures [18]. Line pattern are highly effective for shape representation. With the advantages of simpler representation, low storage demand and consistency in detection, line is one promising primitive feature for shape matching involving large database. In this work, we propose an algorithm capable of solving the broken line problem and distortion by introducing pairwise relative angle with dynamic image partition. Only long lines are adopted as primitives to construct local structures to reduce time complexity, at the same time, abstract most of the essential data. The inherent structural relationship between a pair of primitives will then be extracted for representation. The proposed algorithm generates histograms based on subdivided region to represent positional information. The final similarity between two images is achieved using Hausdorff distance [19] while the similarity of histograms is calculated using the L2-Norm. The idea to use pairwise relative angle is new to palmprint/vein matching. Furthermore, dynamic region division can maintain positional information to reinforce the algorithm. The combination highly improves the matching accuracy and enables this palmprint/vein identification system to be rotational and translational

invariant, at the same time, noise tolerant.

In 3D surface registration, we present a rigorous algorithm to register brainstem surfaces for the disease analysis of Adolescent Idiopathic Scoliosis. The basic idea is to extract four consistent features, which describe the global geometry of the brainstem, to guide the surface registration. Using the Ricci Flow method, brainstem surfaces are parameterized conformally onto quadrilaterally-faced hexahedron, which naturally induces the feature landmark-matching brainstem registration. Our registration algorithm can guarantee the exact landmark correspondence between brainstem surfaces. A shape energy can then be defined to measure the local shape variations between different brainstem surfaces.

1.3 Contributions

The primary contributions of the thesis are as follows.

1. The thesis proposes to use lines as primitives for representing palmprint and hand vein images. The angles between lines are computed and a relative angle histogram is built for the description of structure of line pattern. To further take the position of lines into consideration, a concept of subset division is introduced and incorporated into the construction of histogram. The proposed histogram representation reflects the inherent structure of line pattern of the images. It is rotation/translation invariant. Moreover, it can overcome the broken line problem that often exists in palmprint/hand vein identification systems. A matching algorithm based on the histogram is then presented, which can achieve high accuracy and robustness.
2. A palmprint/hand vein matching system is developed. The system consists

of image acquisition, image processing and image matching. In particular, the mechanisms for vein pattern acquisition are investigated. A medium-sized database containing far-infrared and near-infrared hand vein pattern images is constructed to provide a benchmark for research purpose. Various image processing algorithms are integrated, which generate lines for the proposed histogram based matching. Experiments are conducted on various databases to demonstrate the developed system.

3. A new 3D surface registration algorithm is proposed for matching brainstem surfaces for the disease analysis of Adolescent Idiopathic Scoliosis. Four salient features that describe the global geometry of the brainstem surface are extracted. The discrete Ricci Flow method is used to parameterize the brainstem surface onto a quadrilateral faced hexahedron based on the extracted features. Surface registration between brainstems is then achieved through the parameterization. The proposed algorithm can guarantee the exact salient feature correspondence.

1.4 Thesis Organization

The rest of this thesis is organized as follows: background of Palmprint and Vein recognition, and 3D surface registration are reviewed in Chapter 2. The system structure is presented in Chapter 3. Chapter 4 introduces 2D line feature extraction, the generation of hierarchical matching structure and varied Hausdorff distance algorithms based on line segments. The proposed vein pattern acquisition mechanisms are described in Chapter 5. Chapter 6 compares and discusses the experiment results for system evaluation. An interesting application,

fortune telling is investigated in Chapter 7. Registration of 3D brainstem surfaces is discussed in Chapter 8. Conclusion and future work are given in Chapter 9.

Chapter 2 Related Work

2.1 Biometrics-based Personal Identification

In this information era, more and more business activities are computerized. E-Commerce applications such as e-banking, building access demand fast, real time and accurate personal identification. Traditional token based method such as a physical key, ID card or knowledge based method, such as a password is time-consuming and inefficient. They can be lost, stolen, or forgotten. To overcome the shortcomings of the traditional methods and meet today's security requirements; Biometrics-based personal identification is emerging as a powerful means for recognizing a person's identity. It plays an important role in today's society.

Biometric identification contains methods of uniquely identifying humans based on one or more intrinsic physical or behavioral characteristics [6]. Physiological characteristics include fingerprint [20-22], face[23], iris[24], DNA[25] and palmprint. Voice[26, 27], gait[28] are examples of behavioral traits. Commercial advancements for biometric devices began in the 1970s when the Identimat was installed as part of an employee attendance time clock at system Shearson Hamill, a Wall Street investment firm [29]. At the same time, fingerprint based identification system is widely used in law enforcement by FBI and by the US government departments. Improvements in hardware such as faster processing power and greater memory capacity made biometrics more

viable. Iris, face, voice, palmprint and DNA technologies have joined biometric family since 1990s.

In general, there are four stages in biometric identification system: 1) Data acquisition, 2) Image preprocessing 3) Feature extraction and 4) Feature matching.

1) Data acquisition - Biometric data (image) is obtained from an input device.

2) Image preprocessing – Enhancement of the image is performed in this stage, including segmentation, noise reduction, and rotation and translation normalization.

3) Feature extraction – the features defined possess the stable and unique properties of low intra-class difference and high inter-class difference. These features are used to create a master template which is stored in the system database.

4) Feature matching – A matching score is obtained by matching the identification template against the master templates. If the score is less than a given threshold, the user is authenticated.

Fingerprint's technique is mature and DNA provides best accuracy, however, the collection and storage of fingerprint profiles and DNA samples in the field of forensic science for nonviolent crimes is highly controversial [30, 31]. This motivates us to develop automatic palmprint/hand vein verification scheme to let them become important complement to biometric authentication techniques.

2.1.1 *Palmprint Recognition*

In this section, palmprint based biometric identification system is studied. The following subsection will discuss the history of palmprint study, the application of palmprint recognition and the features of palmprin.

The history of the study of the palmprint is ancient. Palmistry [32, 33] can trace its roots back to India in Astrology, Chinese Yijing and Roma fortune tellers. China was the first country to use palmprints for forensic applications. In the Tang Dynasty, palmprints were applied to business contracts.

Personal identification is the major application for palmprint. Apart from the rich features introduced above, no two palmprints are completely identical, it is unique. This is one advantage of palmprint. Compared to fingerprint identification, it provides a larger surface area such that more features can be extracted. And features of palm are more stable than a fingerprint.

Another application of palmprint is fortune-telling. As the names of the principle lines imply, the life line is related to the life of a person, the heart line is related to the emotions, and the head line is related to the intellect of a person. The study of the patterns of the three principle lines is supposed to tell a person's thoughts and feelings.

Palm is defined as the inner surface of the hand between wrist and finger. A palmprint is defined as the skin patterns of a palm. As shown in Figure 2.1, it consists of principal lines, wrinkles (secondary line) and ridges. There are rich and useful features in a palmprint. Some kinds of features are as follows:

1) Geometry features: According to the palm's shape, we can extract the corresponding geometry features, such as width, length, and area, which can be easily detected.

2) Principal-line Features: Both location and form of principal lines in a palmprint are very important physiological characteristics to identify an individual, because they vary little from time to time.

3) Wrinkle features: In a palmprint, there are many wrinkles, which are different from the principal lines in that they are thinner and more irregular, so more detailed features can be obtained.

4) Delta-point features: A delta point is defined as the center of a delta-like region in the palmprint. It is known that there always are some delta points located in the finger-root region and the outside region. This makes it possible to acquire these features and establish their stability and uniqueness.

5) Minutiae features: A palmprint is basically composed of ridges; hence the minutiae can be used to extract stable and unique features.

Figure 2.1: Palmprint image.

Palm size and shape, which are geometrical features, can be faked easily by

making a model of a hand. Moreover, the shapes of hands can vary significantly over time due to the wearing of rings, the finger nails, or the pregnancy of women. So, geometrical features cannot be used as main features to differentiate impostors from genuine ones. Ridges and singular points are used in fingerprint matching system and the techniques are well-established[8, 34]. However, based on current researches, ridges and singular points can only be extracted from ink-palm images. Ridges and singular points are marked out in the sample ink-palm image shown in Figure 2.1.

The ink-palm images are not applicable for frequently-used applications[7]. So most palmprint related works focus on the palmprint images captured by camera which are shown in Figure 2.2. Lines and texture are the most stable and clearly observable features of the palmprint image captured by a normal digital camera.

Figure 2.2: Samples of features on palm captured by normal camera.

Extracting palmprint line is based on the palmprint structural features while extracting texture features is on statistical features [35].

To extract structural information, like principal lines and creases, from the

palm for recognition, it is natural to represent the feature of palmprint using line segments. Many researchers have worked on palmprint matching using line features and it is still an area worthy of investigation. In [36], the Euclidean distance between the endpoints of two line segments, the difference of angle of inclination and intercepts are used to determine the similarity between two line segments according to three thresholds. The method is simple in concept. However, besides the thresholds determination issue, perfect alignment is required. Duta and Jain [37] extracted a set of feature points along the prominent palm lines together with the associated line orientations. The feature points/orientation from model image and input image are matched using point matching technique. In the study, noise can affect the discriminant power because the feature point connectivity is not extracted, i.e., points on one line may match to points on multiple lines instead of one.

The statistics-based approach transforms palmprint features into other transformation domains for representation. The works that appear in the literature include eigenpalm[35, 38, 39], fisherpalms[40, 41], Gabor filters[42-44], Fourier Transforms[45, 46], and local texture energy[47]. Among statistics-based approaches, the features are extracted, represented, and compared based on the whole palmprint. The main limitations of these approaches are that perfect alignment is required and the whole palm image is needed.

Principal lines and wrinkles are even more appealing than the palm texture for human vision.

2.1.2 Vein Recognition

In 1991, a system that scanned the back of a clenched fist to determine vein structure for verifying user identity was first reported by MacGregor and Welford. Cambridge Consultants Ltd., in collaboration with the British Technology Group (BTG), also studied the vein pattern concept with the aim of developing a commercial system which they called Veincheck[48], and it was first presented at a seminar in September 1993. Though this product did not achieve much commercial success, the concept of using vein patterns as a biometric measure attracted an increasing amount of research interest. Three characteristics of vein patterns are the major sources that drive the development of the vein pattern biometrics, namely, uniqueness, stability, and tolerance to forgery.

Anatomically, aside from growth, accidental injury, and surgical intervention, a person's vascular patterns are distinct from person to person. It is believed even identical twins have different vascular network structures (and hence different vein patterns). The shapes of vein patterns are also very stable. A person's pattern of blood vessels is "hardwired" into the body at birth, and remains relatively unaffected by aging, except for predictable growth as with fingerprints[49].

Unlike other biometric systems (such as face recognition systems) that can be easily defeated by intentional disguise, the blood vessels are hidden underneath the skin and are generally invisible to the human eye and other simple visual inspection systems, thus making vein patterns are much harder for intruders to copy. In addition, although it is possible to restructure the patterns

of superficial blood flow by surgery, this attempt faces very high risks of damaging the surrounding tissues and body nerve systems. Therefore, compared to other biometrics features, vein patterns have much stronger immunity from forgery[50].

Whilst its high tolerance to forgery is intuitive, the uniqueness and stability of vein patterns has never been proven in a strict scientific sense. Recently, several institutes and companies have carried out research into vein pattern biometric technology.

Data Preparation

There are two major concerns about data preparation. The first is the object of interest, and the second is the acquisition mechanism. Typically, for vein pattern biometrics, the object of interest is selected to be a part of human body that is considered less intrusive. The face, the hand, and the finger are considered most acceptable by the public.

Equinox Corporation (<http://www.equinoxsensors.com/>), a New York head- quartered company, constructed a thermal image database for the face. This Face Thermogram technology utilizes the vein patterns in the human face as the biometric feature. The vein pattern image is captured using a thermal camera that records the temperature information of the face, and hence is also referred to as a Face Thermogram. These temperature values of a face thermogram are affected by changes in ambient temperature and some physiological conditions such as sinus problems, inflammation etc. However, when the objective is identification only, the temperature data itself is not used directly. Instead, the thermal data is analyzed to yield the anatomical structure

information of the vein, which is constant with regardless of the medical condition variables.

Compared to the face thermogram[51], acquiring vein patterns in the hand is considered less invasive and easier to use by many people. There are several research groups and companies investigated the biometrics based on hand vein patterns. A research team in the Australian Institute of Security and Applied Technology and a Korean research team both acquire the vein patterns in the back of the hand[52]. Fujitsu Laboratories came up with a product that detects the vein pattern in the palm side of the hand. All these works use the active infrared imaging technique to acquire the images[53]. However, the details of the acquisition setups are not revealed in any public publications. Meanwhile, there are no publicly available databases for hand vein patterns.

Miura et. al. investigated the vein patterns in a finger[54]. They irradiate an infrared light beam and let it pass through the finger, and a camera captures the IR lights and forms an image which contains the vein patterns in the finger.

Though varieties of techniques have been attempted to acquire vein patterns images from various parts of human body, there lacks of detailed design setup information on the data acquisition. In addition, there is no analysis specifically addressing the factors (both internal and external) that affect the data acquisition process and the subsequent impacts on the image quality. Last but not least, for hand vein patterns, to the best of our knowledge, there is no database available to the public research community, and thus limiting the research activities from further investigating the potential of the vein pattern biometrics.

Processing of the Vein Patterns Images

Most of the current works do not provide sufficient preprocessing to the vein pattern images. The selection of region of interests (ROI) is relatively ambiguous. The analysis of the performance and effect of these preprocessing efforts are not reported clearly in their works.

Features Used for Verification

There are two main types of features that have been used as the vein pattern signature. Cross and Smith stored the vein patterns using the medial axis representation as the feature[55]. A library template was constructed from several independently acquired signatures by continuously taking the union of the original template with the next signature that has been translated to have the highest correlation with the original template. Then matching was performed in a two-fold manner: a signature to be verified was matched against the dilated library template (forward match) using constrained sequential correlation, and then the library template was matched against the dilated testing signature (reverse match). The final matching decision was made based on whether both the forward and reverse match percentages were high. Cross examines a data set with 20 individuals, and claimed the features and algorithm used achieved around 5% FRR and 0% of FAR.

Lin & Fan attempted a second approach by extracting the “Feature Points of Vein Patterns” (FPVP)[56], which essentially are the residues after applying a modified watershed transformation to the vein pattern images. Experiments were carried out on their database containing images from 32 participants, and it

was reported that the features and algorithm achieved 2:3% FRR and 2:3% of FAR.

Fujitsu Lab claimed that their systems achieve relatively high level of accuracy (the FRR is 1% whilst FAR is 0:5%), however, their technologies and features used are not revealed in any publication form accessible to the public.

Research Issues of Vein Pattern Biometrics

There are four major research issues remaining unsolved for the vein pattern biometrics.

1. Uniqueness Validation. The uniqueness of vein patterns cannot be proved in a strict scientific sense; however, it is important to study its uniqueness in a statistical significance manner. It is necessary to assess its discriminating power in a computational measure in order for the vein patterns to qualify as another biometrics. In addition, so far, there is no research addressing the issue of genetic relationship for vein patterns. It is valuable to find out this genetic relationship of vein patterns by measuring their correlation distances, even though the vein patterns might yield a low level of similarity.

2. Standard Vein Pattern Image Database. The lack of a standard vein pattern image database to the public research community is a problem which prevents any research works from bench-marking the performance of their methods or algorithms.

3. Optimum Data Acquisition and Processing Techniques. It has been shown that several data acquisition techniques have been applied to acquire vein pattern images. However, there is only little information on the data acquisition

system design, and there is scant analysis on the factors that affect the image quality. The data quality plays a critical role in any biometric systems, therefore, finding an optimum data acquisition technique is an important issue for vein pattern biometrics. Meanwhile, additional processing techniques are required to increase image quality for better system performance.

4. Optimum Feature Sets. Like other biometric technologies, identifying an optimum feature set is a key and usually difficult problem. Though several feature types have been investigated to represent the vein patterns. There is plenty of room to find more optimum features so as to improve the matching accuracy as well as to encode the vein patterns in a more efficient manner. Hence, this research is targeting to tackle all these challenges currently faced by vein pattern biometric technology.

2.2 2-D Shape Representation

Object shape features are very powerful when used in similarity retrieval since shape is usually strongly linked to object functionality and identity. Human can recognize characteristic objects solely from their shapes. A shape representation is a language for describing shape or some aspects of shape. It includes a set of shape descriptors, and a mapping between shape descriptors and shapes.

In MPEG-7, shape descriptors are required to meet the following general criteria [57]: 1) good retrieval accuracy, 2) small memory requirement, 3) general applications, 4) low computational complexity, 5) no drastic performance degradation with increasing database, and 6) hierarchical coarse to fine representation structure. Two popular descriptors are defined in the MPEG-7

standard for 2D objects retrieval: the *contour-based shape descriptors* [58] and the *region-based shape descriptors* [57].

Shape descriptors may be classified by different criteria: 1) *global* methods [57-59] and *local* methods [60-70] according to whether the shape is represented as a whole or represented by local shape features. 2) *contour-based* methods [58, 61, 62, 71-73] and *region-based* methods [57, 74-78] according to whether shape features are extracted from the outline contour / boundary or the distribution of all pixels within outline contour / boundary. 3) *Transform domain* methods [67, 79-83] and *space domain* methods [66, 84, 85] according to whether the shape features are derived from the transformed domain or spatial domain.

Since a local structure based method is proposed in this work, the shape descriptors will be reviewed with respect to the global / local methods in this chapter.

2.2.1 Global Methods

Global methods represent the shape as a whole and do not divided the shape into sub-parts. Usually, a feature vector is derived from the whole object to describe the shape and the similarity measure is a metric distance between the acquired feature vectors.

Contour-based methods

Contour shape techniques only exploit shape boundary information. They extract shape features from the outline contour / boundary of the object. Curvature scale space is one common method adopted by MPEG-7.

➤ Simple shape descriptors

A few simple descriptors are used widely, such as area, perimeter, circularity,

eccentricity, elongation, rectangularity, major axis orientation, convexity, ratio of principle axis, circular variance, and elliptic variance [86, 87].

Area = the number of pixels in the shape.

Perimeter = the number of pixels in the boundary of shape.

Circularity = $perimeter^2 / area$, it describes the compactness of a shape. The most compact shape is a circle (4π). All other shapes have compactness larger than 4π .

Eccentricity = length of major axis / length of minor axis,

Rectangularity = area of object / area of bounding box. It is the extent to which a shape fits a rectangular. It is 1 for a rectangular and can approach 0 in the limit.

Elongation = the ratio of the height and width of a rotated minimal bounding box. That is, rotate a rectangle so that it is the smallest fit rectangle of the shape, and compare its height with width.

These descriptors are simple and can only recognize shapes with big differences; hence, they are usually used to filter false hits or discriminate shapes by working with other shape descriptors. They are not suitable to be standalone shape descriptors.

➤ Shape Context

Shape context matching [62] is an improvement to traditional Hausdorff distance based method. It extracts a global feature, called shape context, for each corresponding point. The matching between corresponding points is then the matching between the context features. To extract the shape context at a point p , the vectors of p to all the other boundary points are found. The length r and orientation θ of the vectors are quantized to create a histogram map which is

used to represent the point p . The histogram of each point is flattened and concatenated to form the context of the shape. To make the histogram more sensitive to positions of nearby points than to those of points farther away, these vectors are put into log-polar space. The matching of two shapes is done by matching two context maps of the shapes, which is a matrix-based matching. It minimizes the total cost of matching between one context matrix and all the permutations of another context matrix. In order to reduce the matching overhead, it samples the boundary at a number of points and uses the shortest augmenting path algorithm for the matrix matching.

➤ Wavelet descriptor (WD)

Wavelet descriptor has the advantage over Fourier descriptor (FD) in that it is of multi-resolution in both spatial space and spectral space, but the increase of spatial resolution will certainly sacrifice frequency resolution. In [82], wavelet coefficients of the few low frequencies are used to represent shape. Since the similarity measurement is the all level shift matching of all the zero-crossing points of the wavelet approximation of the shape, the number of matching for similarity measurement is large and dependent on the complexity of the shape. The complicated matching scheme makes it impractical for online shape retrieval. Apart from the matching complexity, the dyadic wavelets used can rarely associate the feature segments on the shape boundary.

Region-based methods

Region-based methods take into account of all the pixels within a shape region to obtain the shape representation. Moments are commonly used to describe shapes.

➤ Moments based methods

The standard 2-D moment, $m(u, v)$ of an image function $f(x, y)$ is defined as

$$m(u, v) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) x_u^u y_v^v dx dy \quad (1)$$

The use of moments for shape description was initiated by Hu [88]. He proved that moment-based shape description is information-preserving. Using nonlinear combinations of lower order moments, a set of moment invariants is derived. The moment invariants have the desirable properties of being invariant under translation, scaling and rotation. The main problem with moment invariants is that only a few invariants derived from lower order moments is not sufficient to accurately describe a shape. Higher order invariants are difficult to derive.

➤ Morphological methods

Mathematical morphology has evolved as a useful tool for various image processing. It is suitable for shape-related processing since morphological operations are directly related to the object shape. There are a number of shape description approaches using mathematical morphology based on the global shape, such as the shape description method based on the area of morphologically processed images [89] or morphological covariance [90]. Loui [91] used the geometrical correlation function, which is based on morphological covariance, to represent 2D shape. This method has rotation and translation invariance. As with most scalar transform methods, morphological method based on global shape is not robust to describe occluded objects.

➤ Fourier descriptor (FD)

The standard 2-D Fourier transforms $F(m, n)$ of an image function

$f(x, y)$ is

$$F(m, n) = \sum_{x=0}^{X-1} \sum_{y=0}^{Y-1} f(x, y) \exp(-j2\pi)(\frac{mx}{X} + \frac{ny}{Y}) \quad (2)$$

2-D Fourier transform is independent of translation and rotation. It can overcome the problem of noise sensitivity and shape variations by analyzing shape in spectral domain. The Fourier descriptors are proper for the analysis and synthesis of the closed planar curves. Ezer and Anarim [92] applied Fourier descriptors to the problem of classification of 2-D images of airplanes. In this method, for every test sample, a series of Fourier descriptors is calculated to represent the shapes. Because of its intensive computation, this algorithm is slow.

2.2.2 Local Methods

Local methods break the shape into sub-parts, called *primitives*, using a particular criterion.

Contour-based methods

In contour-based methods, the shape boundary is broken down into segments. The following are commonly used methods of boundary decomposition.

➤ Chain coding

Chain coding method was introduced in 1961 by Freeman [93], which describes an object by a sequence of unit-size line segments with a given orientation. In implementation, a planar curve is superimposed with a grid, the boundary points are approximated to the nearest grid point. From a selected starting point, the planar curve is traced on the boundary of a shape. At each boundary point, a choice of only four or eight directions can be considered to look for the next boundary point. Then the direction at each point on the curve

can be coded by only two or three bits. In this approach, an arbitrary curve is represented by a sequence of small vectors of unit length and a limited set of possible directions. Chain coding technique can provide significant data reduction. The disadvantage of this code is that it is sensitive to noise as the errors are cumulative. In addition, if the chain code is used for matching, it has to be independent of the choice of the first boundary pixel in the sequence. One possibility for normalizing the chain code is to find the pixel in the border sequence which results in the minimum integer number and that pixel is then used as the starting pixel. Alternatively, the boundary can be represented by the differences in the successive directions in the chain code instead of representing the boundary by relative directions. This can be computed by subtracting each element of the chain code from the previous one and taking the result. After these operations, a rotationally invariant chain code is obtained by a cyclic permutation which produces the smallest number. Chain code derived in this way is not scale invariant. The chain code usually has high dimensions and is sensitive to noise. It is often used as an input to a higher level analysis, such as polygon approximation, finding boundary curvature.

➤ Polygon Approximation

Approximation of a closed planar curve by a sequence of straight line segments is known as polygonal approximation. The polygon vertices are used as primitives. The feature for each primitive can be expressed as internal angle, the distance from the next vertex, or its coordinates. Any curve can be approximated by a polygon by certain criteria such as minimizing the maximum error between the data points and the fitted lines or requiring the approximated curve to retain the overall shape of the original curve. Polygonal approximation can not only

satisfactorily code a shape, but also significantly reduce the amount of processing data for further application. It can represent occluding contour due to dependence on only local properties. To make use of its advantages, a number of work use polygonal approximation to describe shapes. Hu and Yan [94] developed a polygonal approximation method of digital curves based on the principles of perceptual organization. This method is independent of the starting point and searching directions, and is rotation and translation invariant. Hosur and Ma [95] approximated a shape contour by a polygon with minimal number of vertices for given allowable approximation error and initial vertex. This method provides a low computational complexity and simple implementation. However, in polygonal approximation, sequential and iterative methods are commonly used. Sequential techniques have the drawbacks of missing some important features such as sharp corners and spikes, while the performance of iterative techniques is sensitive to the setting of the starting points for partitioning curves. On the other hand, some polygonal approximation methods are somewhat sensitive to non-consistent results of polygonal approximation.

➤ Shape decomposition

In shape decomposition techniques, a shape is represented as a combination of components. The idea is to represent complex shapes in terms of simple components. Pavlidis [96] stated the global shape decomposition as: “*Among the boundary points find sets of points which are closely related. Such sets maybe used to assign labels to corresponding parts of the object.*” In [97], the curvature zero-crossing points from a Gaussian smoothed boundary are used to obtain primitives, called tokens. The matching efficiency depends on the number of tokens for each shape, and on the scale used in the smoothing stage. The method

depends on the continuous and identified boundary of the shape. We propose here to use lines as primitives to construct consistent local structure.

➤ Shape invariants

Shape invariants represent shapes based on primitives, which attempt to represent properties of the shape which remain unchanged under appropriate transformations.

Common invariants include (1) geometric invariants such as cross-ratio, length ratio, distance ratio, angle, area, triangle, invariants from coplanar points [64, 98-100]; (2) algebraic invariants such as determinant, eigenvalues, trace [101, 102]; (3) differential invariants such as curvature, torsion and Gaussian curvature [61, 97]. Geometric invariants and algebraic invariants are suitable in situations where boundaries can be represented by straight lines or algebraic curves. Typical applications of them are for man-made object recognition. If object boundaries cannot be represented by lines or algebraic curves, differential invariants can be formed. Differential invariants are local in nature and large in number.

Region-based methods

Region-based methods decompose the shape region into parts which are then used for shape representation and description.

➤ Medial axis transforms (MAT)

The methods are first represented by Blum's medial axis transform [103]. It converts a full figure boundary into a skeleton or stick figure drawing, which is defined as a connected set of medial lines along the limbs of figure. The medial axis is the locus of centers of maximal disks that fit within the shape. The basic idea of the skeleton is eliminating redundant information while retaining only the

topological information concerning the structure of the object that can help with recognition. The skeleton can then be decomposed into segments and represented as a graph according to certain criteria. The matching between shapes becomes a graph matching. The computation of the medial axis is a rather challenging problem. Medial axis is highly sensitive to boundary noise and variations. Preprocessing the contour of the shape and finding its polygonal approximation has been suggested as a way of overcoming these problems. But, as has been pointed out by Pavlidis [96], obtaining such polygonal approximation have to be quite sufficient in itself for shape description.

In this section, shape representation techniques have been reviewed. They are classified as global methods and local methods. Under each class, the methods are divided into contour-based and region-based methods. Among the reviewed techniques, only Fourier and Wavelet descriptors work in transform domain.

Global features are usually easy to compute and robust against noise and shape distortions. Local methods are complicated requiring sophisticated implementations; however, they are more suitable than global methods while alignment is not perfect and image quality is not very good.

Contour-based approaches are more popular than region-based ones in literature. It might be because the shape contour carries so much shape information that one can discriminate shapes mainly by the contour features. However, compared with region-based method, contour based methods are generally sensitive to noise and variation because only a part of shape information is used. Moreover, the shape contour is not always available, and, in some applications, shape content is too important to be overlooked. On the contrary, region-based

methods are more robust since all the shape information is available. However, they might be not efficient on similarity based retrieval [104].

The transform domain methods are computationally intensive. Many of them rely on either the entire contour or the whole shape region, and the distortion of an isolated region of the shape will result in changes to every feature. This disadvantage makes them lack of accuracy in the presences of noise or under occlusion. The spatial domain methods are relative computationally inexpensive and perceptually meaningful.

2.2.3 Hausdorff Distance

Hausdorff distance (HD) is one of the commonly used measures for shape matching and has been widely investigated. It measures two images' dissimilarity without explicit point correspondence [105]. It is a distance defined between two sets of points. It is defined as the “*maximum distance of a set to the nearest point in the other set*” as

$$hd(A, B) = \max_{a \in A} \min_{b \in B} \|a - b\| \quad (3)$$

where a and b are points from sets A and B respectively, and $\|\cdot\|$ is any norm, e.g. Euclidean distance.

The following will discuss the detailed steps in obtaining the Hausdorff Distance for the above formal equation. For the two sets of points $A = A_1, \dots, A_m$ and $B = B_1, \dots, B_n$, There are two steps to calculate the $h(A, B)$. The first step is to calculate the minimum distance for all points in set A to set B . In the following figure, the distance between a particular point A_i and all points in set B is the

shortest Euclidian distance $D(A_i, B_i)$. A shortest distance for all points in Set A to Set B can be calculated in similar way.

Figure 2.3: Minimum Euclidian Distance

Next step to obtain the $h(A, B)$ is shown below which is to obtain a maximum of the minimum distance calculated in first step. Suppose $D(A_1, B_1)$, $D(A_2, B_2)$, $D(A_3, B_3)$ are the respective shortest distance between point A_1 , A_2 , A_3 to points in Set B . Among the 3 distances, $HD(A, B)$ is defined as $\max(D(A_1, B_1), D(A_2, B_2), D(A_3, B_3))$. The calculation of Hausdorff distance between points can be applied to images. Each line in the image is equivalent to each point in the set.

Figure 2.4: Maximum of Minimal Distance

It should be noted that Hausdorff Distance is *oriented* (we could say *asymmetric* as well), which means that most of the times $hd(A, B)$ is not equal to $hd(B, A)$. A more general definition of Hausdorff Distance would be:

$$HD(A, B) = \max(hd(A, B), hd(B, A)) \quad (4)$$

it computes the directed Hausdorff Distance from A to B .

Unlike most shape comparison methods that build a one-to-one correspondence between a model and a test image, HD can be calculated without explicit point correspondence. HD has therefore been employed to explore the matching similarity between palmprints/hand veins in our research.

2.3 3-D Mapping Between Two Surfaces

Surface registration, which aims to find a meaningful 1-1 correspondence between different surfaces, has been studied extensively by different groups. Conformal surface registration is commonly used, which gives a parameterization minimizing the angular distortions. An advantage of this approach is that they preserve local geometry very well. However, it cannot map landmark features, such as sulcal landmarks on brain surfaces, consistently. Landmark-based diffeomorphisms are often used to compute, or adjust, cortical surface parameterizations[106, 107]. For example, Glaunes et al. [106]proposed to generate large deformation diffeomorphisms of the sphere onto itself, given the displacements of a finite set of template landmarks. Leow et al. proposed a level-set based approach to match different types of features, including points and 2D or 3D curves represented as implicit functions. These methods provide good registrations when the corresponding landmark points on the surfaces can be labeled in advance. On surfaces without well-defined landmarks, some authors have proposed driving features into correspondence based on shape information. Lyttelton et al.[108] computed surface parameterizations that match surface curvature. Fischl et al.[109] improved the alignment of cortical folding

patterns by minimizing the mean squared difference between the average convexity across a set of subjects and that of the individual. Lord et al.[110] matched surfaces by minimizing the deviation from isometry.

There is a large body of literature in computing mapping between two surfaces. Li et al. [111] proposed a variational framework to compute the bijective map between two surfaces of the same topology. Taking two closed genus- g surface as input, their method first computes the homology basis and cuts each model into a topological disk (i.e., a $4g$ -gon). Then their method generates a harmonic map between the two topological disks. Such a map is bijective, however, it usually has very large angle distortion. To improve the mapping quality, their method iteratively minimizes the stretching energy under Riemannian uniformization metric. Li et al. proved that their variational method is guaranteed to converge. Furthermore, for genus-1 model, the computed map is an extremal quasi-conformal map, which minimizes the maximal angle distortion. He et al. [112] developed a method to automatically convert a genus-0 3D model into a spherical triangular B-splines. Taking advantage of the high order continuity of the spherical splines, all differential properties, such as principal curvatures and their derivatives, can be computed accurately. They applied the spherical splines to model human brain surfaces and observed advantages of using the continuous model compared to the conventional triangle meshes. Li et al. [113] presented an automatic, topology-based method to compute the mapping between two surfaces with negative Euler characteristics. The key idea is to conduct pants decomposition on both surfaces to segment them into consistent sets of pants patches (a pants patch is intuitively defined as a genus-0 surface with three boundaries), then composes global mapping between two surfaces by

using harmonic maps of corresponding patches. Li et al. [114] tackled the non-rigid shape matching problem by a non-linear optimization, which simultaneously solves for correspondences between points on source and target, confidence weights that measure the reliability of each correspondence and identify non-overlapping areas, and a local deformation that brings the source into alignment with the target. This method is fully automatic and works pretty well for 3D models obtained from structured light-based scanners, which can be modeled as height functions. However, it requires that the target surface is parameterized, thus, it cannot apply to general 3D models with non-trivial topology. Recently, Chang and Zwicker [115] presented a global registration algorithm for articulated model reconstruction. This algorithm is able to align multiple range scans simultaneously to reconstruct a full 3D model from the geometry of these scans. The key idea is to model the object's motion in terms of a reduced deformable model and then solve for joints and skinning weights. Therefore, this algorithm is limited to articulated models only. In this dissertation, we investigate the constrained mapping between two brainstem surfaces. Our technique is different than the aforementioned techniques in that our method produces the constrained mapping, i.e., the mapping with exact landmark correspondence, while the existing techniques [111-115] do not allow the constraints.

2.4 Summary

This chapter first presents an overview of 2D shape description, several current biometric systems, and 3D surface matching. In our work, we extract contour-based local information for palm/ hand vein matching. We use lines as

primitives to construct consistent local structure. Hausdorff distance has been employed to explore matching similarity in our research.

In order to perform shape analysis effectively, meaningful one-to-one correspondences between different brainstems must be obtained. In this work, we introduce an algorithm to automatically register brainstem surfaces based on the discrete Ricci flow method.

Chapter 3 System Description

3.1 2D Image Matching System

In real-time palm print or hand vein matching systems, the images are obtained and transmitted to the computer instantaneously, and then matched with a set of previously captured model images. Figure 3.1 shows the flow chart of the system. We take the processing of palmprints as an example, as the palmprint matching and hand vein matching follow the same process.

Figure 3.1: Flow chart of the matching system.

In this identification system, only long lines are selected as primitives. Executing the identification algorithm based on the entire set of line segments

including short line segments on a palmprint will take longer time than using only those long lines. Long lines are capable of abstracting most of the essential data of the palmprint. Therefore for this identification algorithm, length is the measurement to select reference lines, and half of the total lines are used to generate histograms required for matching. The detailed matching method using pairwise relative angle based Hausdorff distance will be described in Chapter 4.

The access to visual database to retrieve desirable images has two main components: storage and retrieval. In the storage process, images are processed to extract features which describe their contents. The extracted features are then represented, organized, and stored in the database. In the retrieval process, the system analyzes a query and extracts the appropriate feature vector and then a search process is performed. The search process is carried out by computing the “similarity” between the query and the candidate images stored in the database. Images with higher similarity rank higher. The retrieved images are presented to the user in descending order according to their similarity to the query.

3.1.1 2D Image Preprocessing

The preprocessing module includes Region of Interest (ROI) extraction, edge detection, image thresholding, line thinning, contour tracing, and polygonal approximation. The image preprocessing module operates on the input images and extracts useful information that is needed by other processing modules. This is the first stage of the prototype system. The flowchart is illustrated in Figure 3.2.

Figure 3.2: Flowchart of the image pre-processing module.

Region Of Interest (ROI) Extraction

After image acquisition, the raw input is passed to the verification stages to perform various image processing operations. Normally, the raw image consists of palm, fingers, wrist, and a substantial amount of background area. For the verification process, only the inner area of the palm is of interest. The system needs to trim away those unwanted portions of the raw image to reduce the amount of computation required in the subsequent stages. Another problem with the raw input image is that the location and orientation of the

palm is not fixed.

ROI extraction involves placing all the palm prints in the database under the same coordinate system and orientation such that the proper expected area of each palm print can be extracted for use in accurate feature extraction and matching, greatly improves the efficiency and correctness of the identification system.

The output of palm print segmentation is a sub image, known as the Region of Interest (ROI) or central part sub-image of the palm print, which is cut out from the original input image. This sub image represents the inner area of the palm, where most of the palm print features are within this area. Those methods can be further classified into two different classes: square-based ROI extraction and inscribed circle-based ROI extraction. As the circle-based approach consumes a significantly higher amount of computation resources, based on this experimental outset, we will only focus on square-based ROI extraction approach throughout this research.

The basic idea of square-based ROI extraction technique as demonstrated in Figure 3.3 is to determine key gaps-between-fingers point on a palm print, thereafter two selected key points are lined up to form the y-axis, subsequently, a second line, which is the x-axis is drawn perpendicular to the y-axis through the middle point to form the origin. Finally, a square with a fixed size, ROI, is extracted under this coordinate system. All the pixels within this ROI are retained for further processing whereas the area outside the window is ignored and discarded. The essential rule in this extraction process is that the portion of

the image extracted should be available in all palm prints from the database and there are sufficient palm print features for extraction and comparison. Moreover, the extraction should be RST invariant and gesture difference tolerant.

Figure 3.3: Basic idea of square-based segmentation technique.

All ROI extraction techniques principally rely on the determination of the key gaps-between-fingers to draw up the coordinate system through the use of boundary tracking algorithm. Thus this imposes a limitation in that for a palm print image to be properly segmented, the fingers in the image need to be sufficiently separated in order for the boundary tracing to work, and thus the key points are determined accurately.

Such requirement led to the development of image acquisition devices [12], which are shown in Figure 3.4[13], Figure 3.5[14] and Figure 3.6[7], that utilizes pegs to restrict the movement and positioning of the hand during the acquisition process in order to improve the image quality, to solve RST problem, and to ensure that the fingers are properly separated.

Figure 3.4: Palm image acquisition device with pegs.

Figure 3.5: Palm image acquisition device with pegs and fixed ROI location.

PolyU-Online-Palm print is a benchmark palm print database for research purpose. In the database, all the palm images are captured by a specially designed device as shown in Figure 3.6. The distance from palm to camera, pegs between fingers, and the board between middle and ring fingers are fixed. A lot of researchers use this benchmark database and the device constraint ROI extraction process based on this database is shown in Figure 3.6.

Figure 3.6: Patent Palm image acquisition device designed by D. Zhang et al[7].

Figure 3.7: ROI extraction process based on database PolyU-Online-Palm print.

For these images captures by special devices with special structure to limit the finger position, we make use of the design of the device to extract ROI easily. However, such devices are normally fixed to a site, and too bulky to move around for usage. This lack of mobility consequently results in the restrictive applications of palm print authentication system. So it motivates us to capture a database without any position constraint. In this research, mobile palm print images are captured using embedded cameras with different resolutions from two different mobile phones. During the image capturing process, no fixed pegs were used to restrict the movement, rotation and stretching of the hands.

An improved ROI extraction technique that is robust enough to overcome this reliance of a standard image acquisition device is implemented. Thus, we are able to make use of the ubiquitous digital cameras and embedded cameras in mobile phones to perform the image capturing process, which in turn, will widen the scope of applications for palm print-based systems.

The improved square-based ROI extraction technique is shown in Figure 3.8.

Figure 3.8: ROI extraction process based on mobile palmprint database.

Each image contained in ROI has subtle features and thus each palm print has thin and delicate lines which are vulnerable to noise. A minor noise pixel may cause a line in the image to be broken or affect the feature matching later. The image matching will be based on the comparison of the line segments that are found within the rectangular sub image that is crop and clip by the previous Image Processing stage. The approach for the line extraction involves edge detection, image thresholding, line thinning, contour tracing and polygonal approximation.

Edge Detection

Edges of intensity images are usually used as important features in image processing[116]. Cognitive psychological studies indicated that human beings recognize line drawings as quickly and almost as accurately as gray-level pictures. These results imply that edge images of objects could be used for object recognition and achieve similar accuracy as gray-level images. The edge detection process is to detect pixel discontinuities of image intensity. In edge detection, the word “lines” refers to curvilinear image event in which the intensity surface forms a roof, a valley or a ridge with a narrow width [117]. Palm curves, which consist of principal lines and wrinkles, are stable and essential traits to describe structure features for palmprint-based identification. The widths of the palm curves are relatively narrow so as to be “lines”. Instances of thin lines in an image occur frequently enough that it is useful to have a separate mechanism for detecting them while edges are by far the most common type of discontinuity in an image. Extended from edge detector, convolution based technique which produces an image description of the thin lines in an input image

is commonly used. Heath et al.[118] had investigated the performance of different edge detectors and claimed “No one single edge detector was best overall; for any given image it is difficult to predict which edge detector will be best”. Since line detection is extended from edge detection, same conclusion can be got.

In this thesis, the proposed method does not rely on any specific edge detector. Any edge detector can be used, and the implementation from Nevatia and Babu [119] is adopted in this study.

Image Thresholding

In the resulting image of applying line detection masks, the value of each pixel represents the strength of response to the convolution. Image thresholding is required to convert the 8-bit image into a binary image, with white representing pixels on the lines, and black otherwise.

The amount of extracted lines depends on the threshold value. With a high threshold, only those pixels with strong response to line detection will survive, so the number of extracted lines will be small. With a low threshold, more lines can be extracted, since the weaker ones are also included. Palmprint matching is based on comparison between the line segments of two images, it is desired that the same amount of lines appear in both images being compared; otherwise the matching result may not be accurate.

The images captured in different lighting environments have different strength of responses to the line detection masks. Hence, using a fixed threshold[7, 35, 120], or using a percentage of the strongest response value as threshold [121] does not guarantee that the same amount of lines are extracted in

the different images. This can be tackled by calculating the threshold value based on a percentage of normalized image area. The normalized image area is consistent for all images. One example is shown in Figure 3.9. If the threshold is too high, e.g., above 10%, too much noise will be introduced. However, if the threshold is too low as 2%, some useful information is missing. Experimentally, 5% is the optimal threshold. Using this approach, the number of surviving pixels is always 5% of the total number of image pixels. In this palmprint matching system, since the size of the rectangular sub image is normalized, the number of resulting foreground pixels after thresholding will always be the same.

Figure 3.9: Example of image thresholding

(a) Original image; (b) After line detection; (c) Threshold=2%; (d) Threshold=5%; (e) Threshold=10%; (f) Threshold=20%

Figure 3.10 shows two sample results of thresholding. The two sample images are the palmprint of the same person, but captured under different brightness. The amounts of extracted line pixels from both samples are same, i.e., 5% of the normalized image area.

Figure 3.10: Thresholding Palmprint Lines.

Line Thinning

Thinning is the operation to remove selected pixels from a binary image so that all lines in the image are reduced to single pixel width. There are several methods for thinning operation. In this project, a morphological thinning algorithm [117] is employed. In this algorithm, a set of eight structuring elements are defined (see Figure 3.11).

Figure 3.11: Structuring Elements for Thinning Operation.

The thinned image is calculated by translating the origin of the structuring

element to each possible pixel position in the original image, and comparing the pixel pattern of the structuring element with the underlying part of the image. At each position, if the pixel patterns match, the image pixel underneath the origin of the structuring element is set as background, in other words, a redundant foreground pixel is removed. If the pixel pattern of the structuring element does not match with the image, the corresponding pixel remains unchanged.

After thinning by structuring element $B1$, the same process is repeated with $B2$, using the previous output as new input. The process is executed eight times, until all structuring elements are applied. This finishes one cycle of the thinning operation. The operation of each cycle can be expressed as:

$$A \otimes [4] = (((((A \otimes B1) \otimes B2) \dots) \otimes B8).$$

where A is the input image, B is the set of structuring elements.

The entire operation is repeated until it causes no further changes. The final output is the image containing the hand's boundary of single pixel thickness. The thinned edge image makes the analysis of boundary information much easier, which helps to extract the feature points more efficiently. The sample of thinned edge is shown in Figure 3.12.

Figure 3.12: Display of extracted edges.

Contour Tracing

Contour is traced by traversing the edge map generated by edge detection and thinning. Contour stores sequential lists of pixel locations which are represented by integer coordinates. Given a sequence of integer coordinate points $p_1(x_1, y_1), p_2(x_2, y_2), \dots, p_i(x_i, y_i), p_{i+1}(x_{i+1}, y_{i+1}), \dots, p_n(x_n, y_n)$, where p_i is connected to p_{i+1} , $1 \leq i \leq n$, we have $|x_i - x_{i+1}|$ and $|y_i - y_{i+1}|$ both less than or equal to one but not both equal to zero. The quality of the resulting contours may affect the polygonal approximation; therefore, correct contour extraction is important.

Polygonal Approximation

Polygonal Approximation is accomplished by Dynamic two-strip algorithm (Dyn 2S) [122], which fits the curve with lines. Dyn 2S is a curve fitting method using feature points. The whole procedure has two stages. In the first stage, important properties of the data points are derived. Two strips are fitted to the left and right sides of each point on the curve respectively and the points inside each strip are approximated as the left or right straight line. The best fitted strips are derived by adjusting the width of the strip and rotate it up or down dynamically using the starting point as the pivot. Longer and narrower strips are preferred. In the second stage, a subset of the most representational points is selected based on the local maxima of point merits.

Figure 3.13: Illustration of the dynamic two-strip algorithm [123].

One example is illustrated in Figure 3.13 where the minimum and maximum strip widths can be easily pre-selected as 1 and $0.1 \times D$ pixels, where 1 is considered small enough while D is the length of the image diagonal. Let P_0 be the current point to be processed, L_i ($i = 1, 2, \dots, 6$) be points on P_0 's left side and R_j ($j = 1, 2, 3$) be points on P_0 's right side. An initial strip of minimal width would first extend from P_0 to encompass as many points as possible to its left side (i.e. the dashed-line box). Its width is then increased and its orientation is adjusted to include as many points as possible, until the maximum strip width is reached (i.e. the left solid-line box). The measure of fit (i.e. elongate value) is recorded for each strip as a function of strip width but only the strip with the largest elongate value is marked and used. The same procedure is applied on the other side of the feature point. There are advantages using strips to extract local features. First, digitization noise can be tolerated because the strip has width and it can enclose points that can be approximated as a straight line. Then the support region of one feature point can be reflected honestly by the strips.

After fitting all the contours by polygons, the gray scale image is reduced to its Line Edge Map (LEM) [124], one example is shown in Figure 3.14. The computation complexity is greatly reduced if line primitives is extracted from

LEM instead of gray image.

Figure 3.14: Display of Line Edge Map.

The techniques used in image pre-processing have been described in this chapter. Their visual effects are illustrated by several examples. The effectiveness of the image preprocessing is crucial to the other processes which build on top of the result. The proposed system will collapse if most edges cannot be detected. Furthermore, the preprocessing is application independent, and one can always find a suitable edge detector to meet special requirements. Otherwise, if no edge detector is able to work well, it might mean even human cannot do it due to the poor quality of the image. This is reasonable for the proposed system to fail on such image.

3.1.2 2D Line Feature Extraction

The *primitive extraction* module extracts primitives from the LEM. Primitives are the simplest / elementary sub patterns decomposed from a complex pattern, and used to represent the complex pattern in terms of their interrelationships.

In this work, the line primitives extracted in this stage are used to

construct the local structures.

Local Structure Construction: The *local structure construction* is to build the local structure by means of image primitives. The local structure is a relative high level structure, which can highlight the salient structure in one object. It is constructed by one reference primitive and several neighbor primitives selected around the reference. In this work, 50% of the longest primitives will be selected as a reference primitive. The module is highly dependent on shape representation, since it dominates the extraction of the salient and consistent local features which is crucial to the efficiency and effectiveness of image description. The details are discussed in Chapter 4.

3.1.3 2D Image Matching

The *image matching* module is the one after the line feature extraction module. It is used to fast identify similar models from the image database by searching the pre-built matching structure. Image retrieval is performed by firstly nominating suitable candidates from intersection of the input local structures to the coarse matching created through FT. This is then followed by a relative angle histogram hausdorff distance to determine the best candidates. Ranking is carried out by computing the similarity between the query and the candidates. The top ranking ones will be selected. Finally, the retrieved images are presented to the user in descending order according to their similarity to the query. The details are discussed in Chapter 4.

3.2 3-D Surface Registration

Our proposed algorithms are based on conformal geometry and Ricci flow.

In this section, we give a brief overview of the basic mathematical theories. Given two Riemann surfaces M and N , a map $f:M \rightarrow N$ is called *conformal* if it preserves the first fundamental form up to a scaling factor. Mathematically, this means that: $f^*(ds_N^2) = \lambda(x_1, x_2) ds_M^2$, where ds_M^2 and ds_N^2 are the first fundamental forms on M and N respectively. The scaling factor λ is called the *conformal factor*. An immediate consequence is that every conformal map preserves angles. With the angle-preserving property, a conformal map can effectively preserve the local geometry of the surface structure. This is the reason why conformal maps are commonly used for surface registration.

Ricci flow is a widely used method for conformal parameterization, which conformally deforms the Riemannian metric of a surface by its Gaussian curvature, such that the curvature evolves according to a heat diffusion process.

Ricci flow is given by the following heat diffusion PDE: $\frac{dg(t)}{dt} = 2(\bar{K} - K)g(t)$,

which deforms the metric g in the following way: at each point p , the metric g is locally scaled to a new metric $\tilde{g}$ such that the scaling factor is proportional to the curvature at p . This deformation is conformal, as the angles measured by g are equal to that measured by $\tilde{g}$. After the deformation, the new metric $\tilde{g}$ induces a new curvature, which in turns keeps deforming the metric. The final metric $g(\infty)$ is conformal to the original one $g(0)$ and the induced Gaussian curvature is equal to the prescribed target curvature $\bar{K}$. The discrete Ricci flow on triangle meshes can be computed by deforming the circle packing metric. Chow and Luo [125] proved that the discrete Ricci flow is the negative gradient flow of the so-called discrete Ricci energy, and the metric inducing $\bar{K}$ is the

minimizer of the energy. As the Hessian matrix of the discrete Ricci energy can be computed analytically, one can minimize the discrete Ricci energy by Newton method which has second order convergence rate [126]. Landmark extraction procedure is shown in Figure 3.15. The details are discussed in Chapter 8.

Figure 3.15: Landmark extraction. (A) and (B) show the computed ridge and valley lines respectively. The two strongest ridge and valley lines are chosen as landmarks, as shown in (C). (D) shows the four consistent features extracted on brainstems of a normal and an AIS subject.

3.3 Summary

In this chapter, we give a general introduction to the proposed system. The system is divided into three modules according to the functionalities. Details of 2D Image Preprocessing has been described in this Chapter. Description of techniques in 2D line feature extraction, 2D image matching module, and 3D surface registration will be described in detail in the following chapters.

Chapter 4 2D Line Feature Extraction and Matching

In many recognition problems involving complex patterns, it is more appropriate to adopt a hierarchical perspective to view a pattern as being composed of simple sub-patterns which are themselves built from yet simpler sub-patterns. The simplest / elementary sub patterns to be recognized are called *primitives* and the given complex pattern is represented in terms of the interrelationships between these primitives [127].

In this work, the proposed shape primitives are lines. Lines are adopted as primitives due to their good properties: 1) efficient representation; 2) low storage demanding; 3) ease of being detected. Cognitive psychological studies [18] indicated that human recognizes line drawings as quickly and almost as accurately as gray-level pictures. Line patterns are highly effective for shape representation [64]. This observation motivates us to develop a rotation, translational invariant, at the same time, noise tolerant matching scheme for the palm lines captured by a normal digital camera and hand vein lines captured by a CCD camera with IR filter.

Shape representation is important for image retrieval. Many good approaches have been proposed [57, 58, 61, 62, 70]. However, there is a lack of effective approach to tackle imperfect alignment and images without good quality or with some distortion. A local structure based method is proposed to cope with the difficulties since local method is more suitable for such problems

than global method. Psychology studies [128, 129] indicated that a shape can be viewed as a hierarchical structure, which is formed around one or several centers. Salient structures can capture the essential information of the object [130]. Therefore, local structures of the proposed method are constructed by grouping several primitives around one reference primitives from an object. The local structure is salient and can be extracted consistently.

The inherent structural relationship in one structure will be extracted to build unique, robust, and invariant representation. The proposed algorithm generates pair-wise angle difference histograms based on dynamically divided region to represent positional information. The similarity of histograms is calculated using L2-Norm. The final similarity between two images is achieved using Hausdorff distance. The above techniques will be discussed in details in this chapter. Experiments had been conducted on a palmprint database collected by the Hong Kong Polytechnic University, mobile phone palmprint database collected by ourselves, distorted image database generated by skewing images in PolyU database, and hand vein database collected by ourselves.

4.1 Pairwise Relative Angle Algorithm

The inherent structural relationships of the local structures can be extracted for compact and numerical representation. The extracted numbers will be used for coarse and fine retrieval later. Pair-wise geometric relationships are employed to represent the local structure, i.e. one local structure is represented as a set of pair-wise geometric attributes between the reference and neighbors.

Palmprint/hand vein identification usually has difficulty in achieving 100% matching accuracy using line feature due to some factors such as poor quality of

palmprints/hand vein captured due to environments and background lighting, and alignment of input palmprints/hand vein. At the same time, hand vein NIR imaging faces the problem of corruption from the skin features such as hair, cuts, and external marks. Poor quality issue will increase the occurrence of broken and missing lines which is a known problem to palmprint/hand vein matching system. In order to tackle above problems, the geometric relationships should be simple, invariant to translation / scaling / rotation, relatively robust to fragmentation / end-point-erosion, and sufficient for discrimination. Motivation for using pairwise relative angle is the ability to solve or minimize broken line problem.

Let the length and orientation of line be represented as $|l_m|$ and θ_m . The relative angle between the lines l_m and l_n becomes $\phi_{mn} = (\theta_m - \theta_n)$ as shown in Figure 4.1.

Figure 4.1: Pairwise geometric attributes from line l_m to l_n .

The broken line issue is illustrated in Figure 4.2. However, the pairwise relative angles remain the same with $\phi_{mn} = \phi_{mn'} = \phi_{mo} = \phi_{mp} = \phi_{mq}$. Based on this observation, we can build a feature representation of pairwise relative angle that tolerates the broken line problem.

Figure 4.2: Pairwise geometric attributes from line l_m to the fragmented lines.

In Figure 4.2, The direction of l_n can be reversed. Hence, ϕ_{mn} will be negative. In general, ϕ_{mn} can have two different values with a difference of 180° .

To simplify computation and let ϕ_{mn} have a unique value, we simplify that

$0 \leq \theta_m, \theta_n < 180^\circ$ and ϕ_{mn} is computed as

$$\phi_{mn} = (\theta_m - \theta_n + 180^\circ) \bmod 180^\circ. \quad (1)$$

4.2 Relative Angle Histogram

Local structure of a line l_m in image I is represented as a set of pair-wise relative angles between l_m and all other lines l_n in I . The bin-incrementing process of the relative angle histogram h_m with respect to l_m can be described as follows:

$$\left\{ \begin{array}{ll} h_m(\beta) = h_m(\beta) + |l_n| & \text{if } n \in [1, N] \text{ and } \phi_{mn} = \beta \text{ and } n \neq m \\ h_m(\beta) & \text{otherwise} \end{array} \right\} \quad (2)$$

where N is the total number of lines in I and $h_m(\beta)$ with $0 \leq \beta < 180^\circ$ captures one signature of a palmprint with respect to l_m . Each line is represented by a histogram. We take two images captured from same subject as example to

demonstrate the process in Figure 4.3.

Figure 4.3 Global relative angle histogram generation.

In order to measure the pattern similarity between a line l_q from query image Q and a line l_t from template image T in database, L2-Norm is used to compute the difference between two histograms h_q and h_t . It is shown as follows:

$$d_{qt} = \sqrt{\sum_{\beta=0}^{B-1} (h_q(\beta) - h_t(\beta))^2} \quad (3)$$

where B is the total number of bins in Histogram. Currently, B is set to 180.

Figure 4.4: L2-Norm is used to compute the difference between two histograms.

4.3 Position Information-subset Partition

In the whole image based pairwise relative angle histogram scheme

described in section 4.2, all the lines in the same image contribute to the reference line histogram regardless of their locations. It achieves palmprint representation with rotational and translational invariant capability. However, it also introduces a possible matching error, that is, incorrect matching between two different palmprints due to the lack of position information. Figure 4.5 serves as a good illustration for this possible problem.

As shown in Figure 4.5, two lines, l_1 and l_2 are in two different image patterns, A and B. These two lines are visually different by analysing their relative structures with neighbours. However, the whole image based pairwise relative angle histograms generated for both lines are exactly the same.

Figure 4.5: Different images with similar overall angle relationship.

Therefore depending solely on the histograms based on whole image is insufficient. Position information also need be considered. In order to maintain

the advantage to handle broken line issue and produce accurate identification result as well, dynamic image partition is introduced to solve the above potential errors.

Figure 4.6 demonstrates the working scheme of dynamic image partition. We divide a sliding window into sub regions evenly as shown in Figure 4.6(a). We overlap the sliding window onto the image with the middle line of the sliding window superpose the reference line, which is in yellow, in our image as shown in Figure 4.6(b).

Figure 4.6 working scheme of dynamic image partition.

Figure 4.7 (a)(b) shows the procedure of image partition. In Figure 4.7 (a)(b), reference lines l_1 and l_2 are highlighted as examples. A palmprint is divided into a few regions with equal width by a series of lines parallel to the reference line in sliding window. Those regions in left hand side are labeled in sequence from nearest to furthest as R1(1st region), R3(3rd region), and so on. The regions in right hand side follow the same way to be labeled as R2(2nd region), R4(4th region), and so on.

Figure 4.7: Solution to problem in Figure 4.5 by introducing dynamic image partition.

The histogram based on lines in γ^{th} region, $h_{m\gamma}(\beta)$, is generated similarly to equation (3). The only difference is that only l_n that located within γ^{th} region will contribute to it.

The distance between the query line, l_q , and template line, l_t , is improved

from equation (3) to (4) as follows:

$$d_{qt} = \frac{1}{v} \sum_{\gamma=1}^{v-1} \sqrt{\sum_{\beta=0}^{B-1} (h_{q\gamma}(\beta) - h_{t\gamma}(\beta))^2} \quad (4)$$

Where v is the total number of regions divided.

Number of regions v in sliding window shown in Figure 4.6 is a major factor in this dynamic image partition algorithm. It has the relation with width and height of the images, ω , that $v \times \omega$ is the diagonal of the image as shown in Figure 4.8. In this research, the image size is 160×160 . So, the diagonal of the image $= \sqrt{(\text{width of the image})^2 + (\text{height of the image})^2} = 240$ and $\omega = 240 / v$.

If ω is too large, it becomes a single image, however, if ω is too small, the tolerance to distortion is too low. To determine the number of subsets and subset width, trial and error or even exhaustive experiments repeated with different values countless times until all the combinations are all tried. From there, the most efficient number of subsets and subset width can be determined. In this research, the number of subsets is 8 and the width of the subset is 30 pixels.

Figure 4.8 Relation between number of regions in sliding window and the diagonal of the image.

After introducing image partition in Figure 4.7, two lines in Figure 4.5 can

be differentiated clearly since the pairwise matching based on regions are significantly different. Therefore after image partition is introduced, previous problem of incorrect matching can be solved.

Figure 4.9 shows the subset partition on our palmprint LEM.

Figure 4.9: Subset Division on Palmprint LEM.

The output of the subset division phase is histogram file. The system will generate one histogram for each subset and a complete histogram for the whole image. In each histogram, there will be 180 bins corresponds to 180 degrees in pairwise relative angle. The length of the bin represents the length of the line which has the same pairwise angle with the reference line. Figure 4.10 shows the process to generate subset histograms.

Original image	LEM	Longest line as reference line	Sample histograms generated in sub regions			

Figure 4.10 The process to generate histogram.

4.4 Solution to Distortion-subset Combination

While capturing in different time, same line of same person might have slightly different orientation in different images due to possible distortion. It will affect region labeling during image partition if the line is a horizontal line or approximate to horizontal line, so as to affect the matching result. Figure 4.11 demonstrates one possible distortion.

Figure 4.11: Distortion issues. (a) one reference line; (b) same line rotates 5° clockwise in another image.

From Figure 4.11 we can see that due to minor distortion, the labelling of the regions become opposite sequence as shown in the figure. It might cause match error. In order to be robust to distortion, the two symmetrical regions are grouped into one region, which is shown in Figure 4.12 and Figure 4.13. The regions with same shade are grouped together. E.g, R5 and R6 in (a) are grouped into its new region R3', the rule applies to (b) as well. Distortion problem can solved with least effort in this way.

Figure 4.12: Improved region division.

Figure 4.13: Sample of combined histogram, R1 is no longer useful.

4.5 Relative Angle Histogram Hausdorff Distance

Hausdorff distance (HD) is one of the commonly used measures for shape matching and has been widely investigated [8][20]. It is a distance defined between two sets of points. It is defined as the “*maximum distance of a set to the*

nearest point in the other set” as

$$hd(A, B) = \max_{a \in A} \min_{b \in B} \|a - b\| \quad (5)$$

where a and b are points from sets A and B respectively, and $\|\cdot\|$ is any norm, e.g. Euclidean distance. It should be noted that Hausdorff Distance is *oriented* (we could say *asymmetric* as well), which means that most of the times $hd(A, B)$ is not equal to $hd(B, A)$. A more general definition of Hausdorff Distance would be:

$$HD(A, B) = \max(hd(A, B), hd(B, A)) \quad (6)$$

Unlike most shape comparison methods that build a one-to-one correspondence between a model and a test image, HD can be calculated without explicit point correspondence. HD has therefore been employed to explore the matching similarity between palmprints. As show in eq. 7, the distance from one line segment l_q in query image Q , to the template image, T , is the distance from l_q to the best matched line segment in image T .

$$d(l_q, T) = \min_{t \in N_T} \{d_{qt}\} \quad (7)$$

where N_T is the collection of top 50% longest lines in image T . d_{qt} is computed using Eq(4) .

The distance between two images Q and T becomes

$$hd(Q, T) = \frac{1}{\sum_{l_q \in N_q} |l_q|} \sum_{l_q \in N_q} \{d(l_q, T) \cdot |l_q|\} \quad (8)$$

where N_q is the collection of top 50% longest lines in image Q .

The final Hausdorff distance between two images are defined in eq. 9 as.

$$HD(Q, T) = \max\{hd(Q, T), \quad hd(T, Q)\} \quad (9)$$

4.6 Hierarchical Matching Structure Generation

When the number of images in database is large, the price for brute force matching between the test and model images is high. To cut down CPU time, one can do coarse matching in order to narrow down the searching scope. In this section, the work related to coarse level matching has been reviewed.

The Fourier Transform[131] is an important image processing tool which is used to decompose an image into its sine and cosine components. It transforms one function into another, which is called the frequency domain representation or Fourier. The original function is in its spatial domain or time domain equivalent. In this new domain image, each point represents a particular frequency contained in the spatial domain image. By representing the significant transform coefficients obtained, system time and space complexity will be reduced.

Discrete Fourier Transform

Since the computers only deal with discrete signals, the continuous Fourier Transform will be ignored; only the Discrete Fourier Transform will be discussed in the following sub-section.

Figure 4.14 shows the process of Discrete Fourier Transform. In the time domain, $x[j]$ consists of N points. In the frequency domain, DFT produces two signals, the real part, $Re\{X[j]\}$ and the imaginary part, $Im\{X[j]\}$. Each of these frequency domain signals are $(N/2 + 1)$ points long. The real component of the output is used for matching process. The imaginary part is used for inverse transformation.

Figure 4.14: Discrete Fourier Transform.

Fourier Transform is quite mature technique. So the details of it will not be discussed in this work. We have investigated a few FFTs and decided to adopt Mixed-Radix FFT in this system. The biggest advantage of Mixed-Radix is its ability to perform FFT transform on arbitrary sized data. The size of the data in our system is 180, which is not power-of-2 size input data. FFT is applied to histogram files, the first N value from the sets of real number, instead of using all 180 values are used, this method reduced time and space requirement.

Table 4-1 shows that by using different N real values from Fourier Transform, the matching algorithm has achieved high identification rate at the same time reduce the time a lot. N=10 is good enough considering the trade off between the accuracy and time complexity.

Table 4-1: Fourier Transform using First N Coefficients

Number of Coeffs	Top 1	Top 3	Top 10	Top 15
First 10	0.76	0.81	0.93	1
First 20	0.76	0.81	0.93	1
All values (180)	0.78	0.86	0.94	1

In Table 4-1, TOP 1 matching ratio means the accuracy of the genuine model match the input as first matched image; TOP 3 matching ratio means the genuine model is among the first 3 matched images match the input. Top 10 means the genuine model ranks among top 10 matched images. Top 15 means the genuine model ranks among top 15 matched images. The above concept will apply to all the result discussion in this work. From Table 4-1 we can see, the matching ratios are 76%, 81%, 93%, and 100% respectively if first 10 real values from Fourier Transform are used as feature data for matching. We can reduce time complexity by using this coarse level matching as first filter.

4.7 Summary

The work related to shape description has been reviewed in this chapter. A local structure based shape representation method is proposed. A set of invariant pair-wise geometric attributes are proposed to capture the inherent local structural information accurately and achieve the desired robustness under adverse conditions. Mixed-Radix FFT is employed for coarse matching. Relative angle histogram is used for fine matching.

Chapter 5 Vein Pattern Acquisition Mechanisms

The data quality for any biometric application is vital. It is therefore critical to find an optimum solution for acquiring vein pattern images. This chapter studies the principles of Far- and Near- Infrared imaging techniques to assess their capability of acquiring vein pattern images. It also presents the designs of the image acquisition system setup, as well as the data collection procedures. Further analysis was performed to evaluate the image data quality and the factors affecting the data quality.

5.1 General Medical Practices

As the vein patterns formed by superficial blood vessels lie underneath the skin surface, the invisibility of veins to any traditional visual inspection system makes the successful image acquisition of the vein patterns a technical challenge. As the quality of the images plays a key role in all the subsequent processing stages of the vein pattern biometric systems, the image acquisition is critical for the systems. In many medical practices, X-ray and ultrasonic scanning are used to obtain vascular images.

The X-ray film or image of the blood vessels is commonly called an angiogram[132]. As blood has the same radiodensity as the surrounding tissues, a radiocontrast agent (which absorbs X-rays) is added to the blood to make

angiography visualization possible. Figure 5.1 shows examples of coronary angiograms[132] and an X-ray machine¹.

Figure 5.1: (a) Examples of coronary angiograms showing coronary artery[132];
(b)X-ray machine¹.

X-ray method can produce good quality images of blood vessels, it is an invasive technique as it requires injection of agents into the blood vessels. In addition, excessive doses of X-ray radiation is dangerous.

Another well-known technique is by ultrasonic scanning, also called ultrasound imaging or sonography. It involves exposing part of the body to high-frequency sound waves to produce pictures of the inside of the body. Because ultrasound images are captured in real-time, they can show blood flowing through blood vessels. Ultrasound exams do not use ionizing radiation (x-ray), however, it requires user to apply clear gel to the area of the body to be studied so as to help the transducer make secure contact with the body and

¹ <http://www.rayur.com/chest-x-ray-definition-machine-indications-and-complication.html>

eliminate air pockets between the transducer and the skin. Figure 5.2 shows an ultrasound image of a fetus in its mother's womb and the way to capture the image.

(a)

(b)

Figure 5.2: An Example of ultrasound image². (a) A fetus in its mother's womb;
(b) An ultrasonic examination.

Ultrasonic imaging is less dangerous but requires the application of a gel to the surface of the skin and the images take several seconds to acquire.

Such constraints are not acceptable for general purpose biometric applications in the real-world, and hence X-ray and ultrasonic scanning methods are more commonly used in the medical practices instead. Obtaining the vein pattern images in a non-invasive manner is the key challenge in a vein pattern biometric system.

² <http://en.wikipedia.org/wiki/Ultrasound>

5.2 Non-Intrusive Vein Pattern Acquisition

Human eyes can only detect visible light that occupies a very narrow band (approx. 400 - 700 nm wavelength) of the entire electromagnetic spectrum, as shown in Figure 5.3.

Figure 5.3: Electromagnetic spectrum with light highlighted.³

However, generally speaking, there is much more information contained in other bands of light in the electromagnetic spectrum reflected/emitted by the objects of interest. Imaging objects within different spectral regions involves different physical principles, which requires special imaging devices, and results in images with significantly different properties. Applications like remote sensing use special multi-spectral or hyper-spectral imaging instruments to obtain images in a wide spread of bands within the electromagnetic spectrum.

³ <http://en.wikipedia.org/wiki/Light>

For human vein patterns beneath the skin, their visibility under normal visible light conditions is fairly low, which prevents the visual inspection system from forming images containing clear structures of the patterns. An ideal solution is to inspect the entire electromagnetic spectrum to determine the optimum imaging spectral range. Nevertheless, this attempt requires very expensive and usually specially-manufactured instruments and devices. Since the vein pattern images in this research is targeting for general biometric applications, it is more reasonable to consider the existing imaging techniques used in other applications, which generally have lower cost. Infrared imaging is a well-established no-contact imaging technique and considered more acceptable to most people.

In the entire electromagnetic spectrum, Infrared refers to a specific region with wavelength typically spanning from 750 nm to 1000 μm . This region is commonly further divided into four sub-bands: 1. Near Infrared (750 – 2000 nm); 2. Middle Infrared (2 μm – 6 μm); 3. Far Infrared (6 μm – 14 μm); 4. Extreme Infrared (14 μm – 1000 μm) [133]. Due to the constraint of the equipment, this research mainly focuses on vein imaging using two sub-bands of the infrared spectrum: Far-Infrared (FIR) and Near-Infrared (NIR).

5.2.1 Far-Infrared Image Formation

Almost all black body objects emit radiation when they are heated. The Far-Infrared (FIR) imaging technology forms an image passively using the infrared radiation emitted by the human body.

Principles of Imaging

To determine the IR radiation range for the human body, it is firstly assumed that the human body is a black body and the temperature is 37°C. More typically, a human body emits infrared radiation with wavelength in the range of 3–14 μm . These infrared waves radiate into the atmosphere and are attenuated according to the infrared transmittance spectrum of the atmosphere, and at the ranges of 3–5 μm and 8–14 μm , the radiant emittance of infrared spectrum possesses the highest transmittance rate. Therefore, a thermal camera with detector sensitivity in the range of either 3–5 μm or 8–14 μm , is capable of capturing the radiated IR waves within these ranges, and based on the energy of the IR radiation. An image can be further generated by converting the temperature value to the corresponding pixel intensity value, which visually shows the heat distribution of the human body part. The correlation between temperature value and pixel intensity is shown in Figure 5.4.

Figure 5.4 Thermogram of a snake held by a human⁴.

It has been noted by researchers [56] that human superficial veins generally have higher temperature than the surrounding tissues. Therefore, via thermal

⁴ <http://en.wikipedia.org/wiki/Thermography>

imaging, the images containing the heat distribution of body parts can clearly display the structure of the desired vein patterns, as can be seen in Figure 3.5. The advantage for FIR imaging is that it forms images using the infrared radiation emitted from the objects. No external lighting is required. Therefore it does not suffer from illumination problems like many other imaging techniques.

System Setup and Image Acquisition

In this research, an NEC Thermo Tracer TS7302 was used as the FIR image acquisition device. It operates in the spectral range of 8–14 μm , and has a temperature resolution of 0.08°C and spatial resolution of 320(H) x 240(V) pixels. The camera was mounted on a copy-stand and adjusted to a height of approximately 30cm above the base of the copy-stand. A workstation is connected to the camera to receive and process the image data. The overall system setup is shown in Figure 5.5.

(a) NEC

(b) Overview of the System Setup

Thermotracer

Figure 5.5: Far Infrared Vein Pattern Image Acquisition System Setup.

During the FIR image acquisition, the subject placed one hand on the base of the copystand with the back of the hand facing upwards so that the FIR camera can capture the temperature profile of the back of the hand and transfer

it to the workstation. On the workstation, the thermo analyzer software converts the temperature data into 256 level gray-scale images for analysis in the subsequent stages.

Far-Infrared Vein Image Quality Analysis

Figure 5.6, Figure 5.7(a) and Figure 5.7(b) show some sample vein pattern images captured using this FIR imaging method. From Figure 5.6, it can be seen that the major vascular network in the back of the hand is successfully captured. However, for the palm side (Figure 5.7(a)) and the wrist area (Figure 5.7(b)), there is no meaningful information of the vein patterns contained in the image.

Figure 5.6: FIR images of the back of four different hands taken in a normal office environment.

(a) FIR image for palm

(b) FIR image for wrist

Figure 5.7: Far-Infrared images of the palm and wrist taken in a normal office environment.

The images of four different hands shown in Figure 5.6 were captured in a normal office environment, where the ambient temperature and humidity were constant and the ambient temperature was at least 10 degrees centigrade less than the human body temperature. Figure 5.8 shows another set of images captured in a tropical outdoor environment (30 – 34°C and > 80% humidity). It can be seen that the ambient temperature and humidity have a negative impact on the image quality, and the vein patterns in these images are now not easily visually distinguishable. In addition, perspiration on the skin surface will also affects the image quality. Figure 5.9 shows the images of the same hand at two different time instances. Far-Infrared imaging technology is very sensitive to external conditions.

Overall, most of the FIR images obtained have low levels of contrast, which makes it difficult to separate the veins from the background. Also, due to heat radiation, the tissue near the blood vessels has similar temperature (and hence similar gray level in the image) as the vein. This makes it difficult to locate the exact position of the vein. In addition, as the Far-Infrared imaging can only capture the major vein patterns, the information contained in these patterns is limited, which will reduce its uniqueness and thus will prevent it from being used as the only biometric in a large scale person identification task.

Figure 5.8: FIR images of the back of the hands in an outdoor environment, where veins are not clearly visually discernible.

Figure 5.9: Far-Infrared image of the same hand taken a few weeks apart.

5.2.2 Near-Infrared Image Formation

Principle of Imaging

Two special attributes of infrared radiation and human veins lead to another method of vein pattern imaging: (i) The incident infrared light can penetrate into the biological tissue of the hand to a depth of approximately 3mm, and (ii) The reduced hemoglobin in venous blood absorbs more of the incident infrared radiation than the surrounding tissue [55]. Therefore, by shining an infrared light beam at the desired body part, a CCD camera with an attached IR filter can be used to capture an image of veins near to body surface. The vein patterns near the skin surface appear darker than the surrounding parts and are easily discernible.

System Setup and Data Acquisition Process

In our study, we used two LED array lamps to shine infrared light onto the hand from both sides. The infrared light emitted by the LED lamps peaks at a wavelength of 850nm. In order to form an image with this reflected infrared light from the hand, we need to use a camera whose spectral response also

peaks at a wavelength of around 850nm. A Hitachi KP-F2A infrared CCD camera was selected for this purpose. The system setup is shown in Figure 5.10. Similar to the far-infrared imaging, participants were required to place their hand at the center of the base of the copy-stand. At first, they placed their hand with the back of the hand facing up at the camera. Three images were then taken of the vein patterns in the back of the hand. Then the participant flipped the hand over with palm side facing up, and three more images were taken of the vein patterns in the palm. Finally, the participant moved the wrist to the center of the board, and another three images were taken of the veins in the wrist area on the underside of the hand.

Figure 5.10: The near-infrared imaging system used to capture images.

Near-Infrared Vein Image Quality Analysis

Figure 5.11 and Figure 5.12 show vein pattern images captured by the NIR camera for the three parts of the hand: the back of the hand; the palm; and the wrist. By inspection, it can be seen from Figure 5.12 (a), that the NIR imaging technique can capture the major vein patterns in the back of the hand as effectively as the FIR imaging technique. More importantly, as shown in Figure 5.11, the NIR camera is capable of capturing images of the small veins lying near the skin surface in the palm and wrist areas. Unlike the image of the back of the hand, where only major veins are visible, the vein pattern in the palm is far more complex and contains much more information than the one in the back of the hand. This is important because it significantly increases the potential discrimination power of the vein pattern biometrics when the size of the user group is large.

The NIR imaging technique is more tolerant to the external environment and the subject's medical condition and environmental situation. In our study, the quality of the image does not change significantly for both air-conditioned and outdoor environment. Also, the colour of the skin does not affect the visibility of the vein patterns in the image. In our study, it is clear that the white skinned Caucasian and the tan skinned Indian, both have vein patterns that are all clearly visually distinguishable in the images.

However, NIR imaging of vein patterns suffers from the common illumination problem. It can be seen from Figure 5.12(a) that the centre of the image is brighter than the border areas due to uneven illumination. Another disadvantage of NIR imaging is that marks and defects on the skin surface are also visible in the image, which occasionally will corrupt the structure of the vein patterns and lead to problems when it comes to the later image processing

and pattern recognition stages. Figure 5.12(b) shows confusion in the NIR images caused by hairs on the back of the hand. Also, in Figure 5.11(a), the usual creases on the palm of the hand are difficult to distinguish from the vein patterns. Whilst human beings are capable of distinguishing these defects from the vein patterns in the image with a high degree of accuracy, it is a challenging, and as yet unresolved, task to remove these defects using automatic processing.

(a) NIR image of palm

b) NIR image of the wrist

Figure 5.11: Typical NIR images for the palm and wrist.

(a) NIR image of back of a hand (b) NIR image of the back of a hand with hair

Figure 5.12: Typical NIR images of the back of the hand.

5.2.3 A Comparison between Far- and Near-Infrared Imaging

It can be seen easily from Sections 5.2.1 and 5.2.2 that the principles between FIR and NIR image formation are totally different. This leads to

different imaging devices and system setup, and consequently results in different image properties.

Whilst both imaging techniques are capable of capturing major veins in the hand, FIR imaging is less sensitive to the finer detailed structures formed by small veins. This prevents the FIR imaging from acquiring images in the palm or wrist areas, where the vein structure is more complex and richly textured. In addition, compared to NIR imaging, the FIR images are very sensitive to the external environment, changes of ambient temperature and humidity can easily degrade the visibility of the vein structure in the image. However, FIR imaging is based on the IR radiation from the human body, which makes it immune to illumination problems commonly faced by many other imaging applications.

For NIR imaging, it is capable of capturing the finer details of vein structures; therefore, it outperforms the FIR imaging when the vein patterns in the palm or wrist areas are the objects of interest. NIR imaging is more tolerant to the change of external environment, nevertheless, NIR imaging suffers from the disadvantage of the marks and defects on the skin surface being visible in the image, which in some occasion, will corrupt the structure of the patterns.

Table 5-1 shows a general comparison between Far- and Near- Infrared imaging techniques in the application of hand vein pattern image formation.

Table 5-1: A Comparison of FIR and NIR Imaging of Hand Vein Patterns

	Details Captured	Tolerance to Ext. Conditions	Tolerance to Skin Features	Tolerance to Illumination	Costs
FIR	Moderate	Low	High	High	High
NIR	High	High	Moderate	Moderate	Low

5.3 The Infrared Hand Vein Pattern Database

To the best of our knowledge, there was no hand vein pattern database available to the public research community. Therefore, it was necessary to construct a database for preliminary investigation of the vein pattern biometrics. In April 2006, we, research group of FORSE Lab, NTU, initiated an infrared hand vein pattern image data collection event that lasted for one week's time. A relatively medium-sized database containing both Far-infrared and Near-infrared vein pattern images was obtained. We set up two data acquisition stations in a public venue, and invited volunteers (both female and male) from the public to participate in our data collection exercise. The participants were of various racial groups, representing the racial mix in Singapore. They were mainly Chinese, Indian, and Caucasian but included other ethnic groups from Asia. The age group of those participants was between 18 to 60 years, and their occupations ranged from university students, professors, and technicians to manual workers such as cleaning ladies and electricians.

The database of Far-infrared vein pattern images currently has 47 distinct subjects. Each subject provided 3 images of the vein patterns in the back of their hands, which overall, resulted in a total of 141 Far-infrared images obtained from 47 participants in the database. The images are in 256 level gray-scale of size 320 x 240 pixels and are stored in Bitmap (bmp) format.

For the Near-infrared vein pattern images, we have currently collected images from 200 subjects. The database contains 600 NIR images for the back of the hand (3 images per subject). The NIR images are also in gray-scale of size 644×492 pixels, and they are stored as Tagged Image File Format (tiff).

The reason why the FIR database is much smaller than the NIR database is because the failure rate for acquiring the FIR images containing visually discernible vein patterns is high. During our data collection process, only around 30% of subjects produced images with good quality. On the contrary, NIR imaging has around 90% of successful rate. It might require the user to capture multiple images until it is recognisable when the system is used in real-world application. It makes NIR images not suitable for real security system at this moment.

5.4 Vein Matching

The process of image pre-processing, line feature extraction, and image matching is same as that of palmprint. The process has been described in details in Chapter 3 and Chapter 4. Some samples of intermediate results will be used to demonstrate the flow in following figures.

Figure 5.13: ROI extraction.

Figure 5.14: LEM generation.

Figure 5.15: Sample histograms generated.

5.5 Summary

This chapter investigates imaging technologies for acquiring hand vein patterns for biometric purposes. General medical practises such as X-ray angiogram and Ultrasonic scanning are found to be invasive and difficult to use. Two other major imaging methods were then studied: Far-Infrared (FIR) imaging and Near-Infrared (NIR) imaging. It was observed that both imaging techniques are capable of producing the vein pattern images effectively, though the two techniques use different physical phenomena and exhibit differences in image quality and features.

It was further observed that far-infrared imaging can capture the large veins in the back of the hand, it is not sufficiently discriminative to capture vein images in the palm and wrist. FIR imaging is sensitive to ambient temperature and humidity conditions and also the temperature variation of the human body. The temperature difference at the surface of skin near a vein is only of the order of 0.2°C warmer than the surrounding tissue. The ability to detect this temperature difference is close to the capability of the FIR sensors and the temperature across the hand surface may vary by several degrees centigrade making it impossible to accurately detect all veins in one image. Each image will result in flaring or "white-out" of some parts of the image, as can be seen in Figure 5.7. FIR imaging is difficult and the fact that only 30% subjects imaged resulted in images which could be used for biometric comparison illustrates the difficulty in obtaining good FIR images of veins near the surface of the skin.

Near-infrared imaging was observed to perform better than FIR imaging by producing good quality images when capturing vein patterns in the back of the

hand, palm, and the wrist. It is more tolerant to the changes in the ambient environmental and body temperature conditions. However, NIR imaging faces the problem of corruption from the skin features such as hair, cuts, external marks and palm prints. FIR does not suffer from this problem as the images are not affected by visible light.

Two infrared hand vein pattern image databases were constructed with the aim of providing bench marking data for vein pattern biometrics research activities. This database is used throughout the course of the work, and particular interests are paid to the NIR vein pattern images in the back of the hand based on the following reasons:

1. The difficulties in getting FIR images with satisfied quality makes FIR become inapplicable in real life usage.
2. The cost of NIR acquisition is lower than that of FIR acquisition.
3. NIR imaging suffers from the disadvantage of the marks and defects on the skin surface being visible in the image, which might corrupt the structure of the patterns. It is not suitable for real security system. However, it can be used to test how robust our algorithm is in identifying images with poor quality.

Chapter 6 Matching of 2D Biometrics Images

In this chapter, system performance evaluation for 2D Biometrics images matching is carried out. The proposed system has been employed in retrieving palmprint and hand vein images. Impressive results have been obtained.

6.1 Input Data

The system performance is evaluated in the retrieval of palmprint database¹ downloaded from internet, the mobile palmprint database², and vein images database³.

Palmprint database downloaded from internet

The PolyU Palmprint Database was provided by Biometric Research Centre, The Hong Kong Polytechnic University. The database contains 600 palmprint images from 100 individuals (6 images for each person). The images were collected using a special palmprint capture device shown in Figure 6.1 [7]. The subjects mainly consisted of volunteers from the students and staffs at the Hong Kong Polytechnic University with a wide range of age distribution and different genders.

¹ PolyU Palmprint Database, <http://www.comp.polyu.edu.hk/~biometrics/>

² Palmprint Image Database captured by Forensics and Security Laboratory, Nanyang Technological University, Singapore.

³ Infrared Hand Vein Pattern Image Database captured by Forensics and Security Laboratory, Nanyang Technological University, Singapore.

Figure 6.1: Patent Palm image acquisition device designed by D. Zhang et al [7].

NTU Mobile palmprint database

Singapore emerged second in The Nielsen Company's survey of 52 countries as the country with the highest ownership and usages of media technology, there are many mobile users in Singapore [134]. This form an interest in testing the effectiveness of the image matching using the lower quality image captured from the mobile phone. Mobile phone camera has been evolving significantly and most mobile phone now has at least a 2 megapixel camera [135]. Although mobile phone camera capture lower quantity image compared to camera, it is still able to capture most of the lines feature of the palm print image. So, besides using a general purpose camera or scanner to capture the palm print image, mobile phones have been used for this experiment to investigate the effectiveness of the image matching using lower quantity images.

The mobile palmprint database contains 200 colour images corresponding to 100 different palms in BMP image format. The images were collected using

different mobile phones. The subjects mainly consisted of volunteers in Singapore with a wide range of age distribution and different genders.

Figure 6.2: Mobile phones used to capture palms for mobile palmprint database.

NTU Vein images database

To the best of our knowledge, there is currently no hand vein pattern database available to the public research community. Therefore, it was necessary to construct a database for preliminary investigation of the vein pattern biometrics. In April 2006, we, research group of FORSE Lab, NTU, initiated an infrared hand vein pattern image data collection event that lasted for one week's time. A relatively medium-sized database containing both Far-infrared and Near-infrared vein pattern images was obtained. We set up two data acquisition stations in a public venue, and invited volunteers (both female and male) from the public to participate in our data collection exercise. The participants were of various racial groups, representing the racial mix in Singapore. They were mainly Chinese, Indian, and Caucasian but included other ethnic groups from Asia. The age group of those participants was between 18 to 60 years, and their occupations ranged from university students,

professors, and technicians to manual workers such as cleaning ladies and electricians.

For the Near-infrared vein pattern images, we have currently collected images from 200 subjects. The database contains 600 NIR images for the back of the hand (3 images per subject). The NIR images are also in gray-scale of size 644×492 pixels, and they are stored as Tagged Image File Format (tiff).

Figure 6.3 shows several sample images from this database,

Figure 6.3: NIR images of the back of three different hands taken in a normal office environment.

Distorted palmprint database

Besides the matching of normal images in the above palmprint and vein databases, a series of distortion experiments were carried out using the PolyU Palmprint Database.

500 test palmprint images were generated from the 100 models. The 500 test images can be grouped into 5 sets, each one has 100 images. Skewing the original images for 5, 10, 20, 30, and 40 degrees horizontally respectively produced the five sets of images. Examples of the inputs are given in Figure 6.4.

Figure 6.4: Samples of model images and test images in our experiment.

6.2 Test Methodology

An identification system examines whether the user is one of enrolled candidates. The palm image of unknown user is presented to the system and the system will match the user with all the enrolled candidates in the database, thus the match is 1-to-many based. The experiments were carried out by first inputting an example image and then outputting the retrieved results. For the images captured from each subject, one image is randomly chosen as the model image. Another one among the rest images is chosen to be the input image. The input images are matched to all the model images and the model images are ranked according to the distance between the input image and model image. The model image with smaller distance is more similar to the input image.

Software specification:

The following is a list of system requirements for developing this project:

- Windows OS (XP or Windows 7)
- Microsoft Visual C++ 6.0 (for palmprint identification system)
- Microsoft Visual Studio 2008 (for fortune-telling system)

Hardware specification:

The following system hardware specifications were used to obtain the results in the report:

Laptop:

- Windows 7 64 bit Operating System
- Intel(R) Core(TM) i5 CPU
- 4 Gigabyte RAM

Desktop:

- Windows 7 32 bit Operating System
- Intel(R) Core(TM) 2 Quad CPU Q9400 @2.66GHz 2.67GHz
- 4 Gigabyte RAM

6.3 Experiment Results

6.3.1 Experiment 1: Palmprint Retrieval

The PolyU Palmprint Database was provided by Biometric Research Centre, The Hong Kong Polytechnic University. The database contains 600 palmprint images from 100 individuals (6 images for each person). The images were collected using a special palmprint capture device. The subjects mainly consisted

of volunteers from the students and staffs at the Hong Kong Polytechnic University with a wide range of age distribution and different genders.

The matching result shows in Figure 6.5.

Figure 6.5: Matching result of polyU Database

The matching accuracy can reach as high as Top 1 match. The reason is that the quality of the images in this database is very good.

6.3.2 Experiment 2: Mobile Palmprint Matching

Instead of using a general purpose camera or scanner to capture the palm print image, mobile phones have been used for this experiment to investigate the effectiveness of the image matching using lower quantity images. Mobile phone camera has been evolving significantly and most mobile phone now has at least a 2 megapixel camera. Although mobile phone camera capture lower quantity image compared to camera, it is still able to capture most of the lines feature of the palm print image. Singapore emerged second in The Nelson Company's survey of 53 countries as the country with the highest ownership and usages of media technology, there are many mobile users in Singapore. This form an interest in testing the effectiveness of the image matching using the lower quality

image captured from the mobile phone.

To determine the different parameters to be applied to perform image matching for the whole mobile phone database, a sample of 100 mobile images will be used. The parameter ratio which determines the percentage threshold of the pixels area that will be used for matching will be configured different to obtain the best value. The ratio 0.07, 0.08, 0.09 and 0.10 will be used for comparison.

Figure 6.6: Different accuracy of Identification for different ratio parameter.

From the figure, the parameter ratio 0.08 will produce the best top 1 % accuracy match compared to the other ratio parameter. Although the ratio 0.09 has the best accuracy for the top 3% instead of ratio 0.08, the top 1 percentage match will be more important as that determines the very first match of the Test image to the Model image.

Determining the best parameter is important as it affects the overall image accuracy results. From the previous experiment of using ratio 0.07 which results in 78% accuracy match, changing the ratio to 0.08 results in an increase of 8% to 86% accuracy match. This parameter is important because the matching accuracy

may be reduced due to the size of the database. This ratio value of 0.08 will be used as the ratio parameter when performing image matching for the whole mobile database. The matching results show in Figure 6.7.

Figure 6.7: Matching result of mobile palmprint database.

Figure 6.8: Accuracy of the Identification rate for 100 and 200 images.

Using the best parameter, the accuracy of the top 1% for 200 mobile print images will be 83.5%. The Figure 6.8 shows the drop in accuracy of

Identification rate as the number of images increased. The image matching algorithm is still able to provide good matching accuracy as an increase of image size from 100 to 200 results in only 2.5% drop in accuracy. The results are promising for the image captured by mobile phones with free hand position and illumination conditions.

6.3.3 Experiment 3: Vein Matching

For the Near-infrared vein pattern images, we have currently collected images from 200 subjects. The database contains 600 NIR images for the back of the hand (3 images per subject). The NIR images are also in gray-scale of size 644×492 pixels, and they are stored as Tagged Image File Format (tiff).

The following results is the Identification results of using 2 sets of 50 vein images as Model and Test data to derive the optimal Averaging Mask and ratio based on the accuracy of the Identification result.

Figure 6.9: Identification result for vein images for different ratio and masking for 50 images.

The ratio parameter is the threshold by percentage of area of each pixel after applying the averaging mask. To obtain the best accuracy of Vein line for identification for the Vein database, different number of the ratio and average masking is used.

Based on the 50 samples Model and Test images, the best accuracy obtained from Identification is 94% with ratio 0.1 and an average masking of 6.

These two parameters are then used to perform identification for the whole NTU Vein Database which contains 200 images. The results of the NTU Vein Database are as follow.

Figure 6.10: Matching result of NIR hand vein database.

Although the identification result was not fully satisfied, Experiments showed encouraging results. This result indicates the line features in the vein patterns can be used as a feature set in personal verification applications. The experiments have shown the high achievability of using the Palmprint Identification System for hand vein identification.

6.3.4 Experiment 4: Distortion Experiment

To investigate the sensitivity of the Biometric Identification System to the various degrees of image distortion, 500 test palmprint images are generated from the 100 models. The 500 test images can be grouped into 5 sets. We Skew the original images for 5, 10, 20, 30, and 40 degrees horizontally respectively produced the five sets of images. The trend of the drop of identification rate with respect to the increasing degree of skewed images is shown in Figure 6.11.

Figure 6.11: Matching result of distorted palmprint image database.

Although the palm print image has been skewed, all the important geometry and minutiae features have not been removed or modified by distortions. This enables the accuracy of the image matching to be almost similar to the original matching of the palm print image. As seen from the previous figure, the accuracy for image matching for skewing 5 degree is almost 100% for all the top 1, 3 and 10 matches. The accuracy for the image matching when skewing increased to 10 degree skewing also maintain a high level of identification rate when is above 90% for all 3 different top matches. However, from 20 degree onwards, the

accuracy rate drops by almost half each time the degree of skewing increased by 10. By 40 degree, the result for the top 1 matching is only 1%. Normal 3D to 2D distortion should not exceed 10 degree. So our method can tackle the normal distortion well.

The results of experiments show that the quality of the image is the major factor causes inaccurate retrieval.

6.4 Discussion and Comparison

6.4.1 Discussion

From above experimental results, the proposed system, has fulfilled all the objectives.

1. A proposed system is capable to tackle the need of “personal verification in unconstraint way”.
2. The proposed system can demonstrate the discriminative power of hand vein patterns in biometric applications. The work reported in this thesis shows that the vein pattern (in the back of the hand in our work) can provide strong discriminating power for personal verification purpose and it has a very high potential to become another major biometrics.
3. The proposed system can prove the accuracy of image matching when using lower quality images taken by mobile phone camera.
4. The proposed system should be robust when distorted images are used.

6.4.2 Comparison

It is difficult to compare the proposed system with other method comprehensively, since different approaches have different strengths and weaknesses, and hence each test data set has been designed to highlight capability of each particular system. Furthermore, a fair comparison has to be under same experiment conditions, which is usually not easy to guarantee.

Chapter 7 Interesting Application: Fortune Telling

Among the applications of the biometric identification based palm print analysis, fortune telling is an interesting one. The fact that fortune telling[136] is a topic that most people know of as fortune telling is a field that is explored by different culture in attempt to predict and prepare for the unknown of the future, be it health, career or marriage of the individual.

The process of fortune telling usually involves traditional one to one interaction. The reader examines the palm of the individual and attempts to interpret the unknown future of the individual with the characteristic of the palm as shown in Figure 7.1[137].

Figure 7.1: Regions of a palm and the main palm lines [137].

7.1 Traditional Fortune Telling Process

The general process flow of traditional palm reading and fortune telling is shown in Figure 7.2.

Figure 7.2: Traditional Fortune Telling process

In Figure 7.3[138], the lady is the customer and the man is the reader providing fortune telling services.

Figure 7.3: Traditional fortune telling performed with magnifying glasses.

One of the biggest disadvantage of the traditional fortune telling is that the palmprints are examined by human eyes, sometimes the reader will miss out some fine details on the lines on the palm. The lines that are missed were not taken into consideration as part of the data analysis. It makes the result of the traditional way to be less accurate. The result might also be inaccurate as reader might be bias towards the way the reader interpret the lines on the palm, more inclined to interpret based on the reader's experience.

7.2 Fortune Telling using Palm Print Recognition

System

A palm print identification system is integrated into the traditional way of fortune telling. The process flow of traditional way of fortune telling is shown in Figure 7.2. Using the fortune telling system that utilizes the palm print recognition is a more accurate alternative to the traditional way. With the scanning of the customer's palm, the system will be able to capture all the finer details on the palm. The method of scanning also makes the fortune telling process more efficient when compared to in traditional way, the reader using magnifying glasses to slowly examine one part by one part of the palm of client. The image of the palm and the results of the output could be stored and viewed again after the scanning has taken place. This information can be stored under the profile of the person so that there is some basic profiling is done for recording down customer's information.

The 3 principal lines on the palm are the life line, head line and heart line. It is believed that certain principal lines on the palm of a person will reflect his

characteristics and events that might happen to the person in the field of fortune telling. Thus the main motivation of doing fortune telling is an attempt for humans to predict and deal with the unknown future and is always a much sought solution when the person is seeking an advice for possible problems might happen in the future like marriage and career.

The fortune telling system is similar to the palm print recognition system. The only difference between the two systems is that only principal lines are extracted and used for matching in fortune telling system instead of 50% of longest lines.

The general overflow of fortune telling using palm print recognition system:

Figure 7.4: General Overflow of Fortune Telling System

After identifying the ROI region, we need to perform feature selection by extracting only the information that was needed for fortune telling inside the ROI region. Thus the 3 principal lines in the palm print image, the life line, the head line and the heart line were extracted. Only the data from the 3 principal lines was used.

After the relevant data were extracted out, the algorithm of pairwise relative

angle difference Hausdroff distance was applied to analyze the relationship of the 3 principal lines of the image compared to the 3 principal lines of the models in the database.

7.2.1 *Principal Lines Extracting*

Extraction of principal lines from a scanned image of a palm proves to be a challenge itself. When a raw palm print image is received, there are many different lines on the palm print itself intersecting one another. However not all the lines on the palm print image are useful or needed in the application like the fortune telling system where it only use the 3 principal lines for analysis. However, when the line intersects and connects to other lines, the lines tends to get mixed up and it is hard to separate lines that are useful from the other lines that are not. Thus the Hough Transform[139, 140] was proposed as a way to try and solve the problem of line extraction from palm print.

As Hough transformation works with straight lines, all the lines on the palm print image must be approximated to straight lines segments.

All the lines are then converted to points that exist on parametric space on the plane $(\rho - \theta)$ [141]. The conversion is shown in the diagrams below step by step.

The sample LEM in Figure 7.5 was converted into the $\rho - \theta$ plane according to the relationship illustrated in Figure 7.6. The conversion result is shown in Figure 7.7 which represented the result in a numeric way where else the presentation in Figure 7.8 was focused on providing 3D view to aid in visualization of the position of points in the space. The value in accumulator cells, $L_{\rho\theta}$, in Figure 7.7,

is the accumulated length of the lines whose distance to origin is ρ and the intersection angle to x-axis is θ , for the sample accumulator cell in Figure 7.7, $\rho=15$ and $\theta=5$, $L_{\rho\theta}=69$. It is observed that the line matching problem in image space can be converted into a point-matching problem in parametric $(\rho-\theta)$ space, making the problem faced initially much more simplified[142].

Figure 7.5: Sample LEM

Figure 7.6: x-y plane

Figure 7.7: Parameter space of $(\rho - \theta)$ plane

Figure 7.8: Frequency count of lines in $(\rho-\theta)$ space

Since it is highly feasible to convert the line segments to $(\rho-\theta)$ space, other features of the principal lines like its orientation and position on the palm can be represented in a vector $L = \{L_{\rho_{\min}\theta_{\min}}, \dots, L_{\rho\theta}, \dots, L_{\rho_{\max}\theta_{\max}}\}$. Since there can be many cells that can be represented by the vector, the $(\rho-\theta)$ space is evenly grouped into a few bins to reduce the number of cells.

To determine the number of groups, trial and error or even exhaustive experiments repeated with different values countless times until all the combinations are all tried. From there, the most efficient number of cells can be determined. In this research, the most efficient number of cells is 16x9 bins after exhaustive experiments. Feature vector L is then simplified to 16x9 integers to represent the global pattern of the palm print, which is 162B only for a 108KB image.

In traditional palm print reading and fortune telling, the process always involves the 3 principal lines, making it necessary to extract the 3 principal lines. Since the 3 principal lines are usually the longest curves found on the palm, a new proposed method parameter deviation filtering shown in Figure 7.9 was

suggested to approximate the points on the same curve. However, an assumption is made if parameter deviation filtering is used as parameter deviation filtering can only approximate accurately when there is no big deviation from the parameters in the line segments. If this condition is not satisfied, the accuracy of parameter deviation filtering will not be high.

Figure 7.9: Grouping line segments with similar line parameters

The following pseudo code gives a rough idea of how to implement of line parameter deviation filtering:

```

Function ParameterFilter()
Begin
Find 3 Peak Cells in  $\rho$ - $\theta$  plane as seeds
For 3 seeds  $P_i, i \in [1, 3]$ 
Sort Other Cells,  $C_j$  according to  $Distance(P_i, C_j)$ 
    For 3 links
        Merge into one with ascend  $Distance(P_i, C_j)$ 
        Keep first half of the combined link for seed growing
    For 3 seeds
        Merge Nearest Neighbours of current seed
End;
```

Thus after determining the three groups of bins shown in Figure 7.10, a principal line can be represented by three values, L , ρ , and θ . Take first group in figure below, which represents first principal line, as example. ρ and θ are the location of P_l . L is the accumulated value of all the four bins in this cluster. Therefore, by determining the grouped bins, one principal line k , which is corresponding to the k^{th} cluster in this ROI, is represented by three values, L_k , ρ_k , and θ_k . By determining large groups or cluster of cells gather at one are, we can conclude that it is a presentation of one of the 3 principal lines represented in ρ - θ space.

Figure 7.10: Grouping line segments

7.2.2 Fortune Telling Models

To be able to build a fortune telling system based on a palm print recognition system, we need understand how fortune telling using the principal lines on the palm works. Some sample models are shown in Figure 7.11.

Figure 7.11: Sample fortune telling models.

The general characteristics of the 3 principal lines are displayed and a palm analysis for fortune telling is done based on the general characteristics. We take the 4th model as example.

HeartLine = Straight and Long Heart Line

HeartLine_Description = People who has a straight and long heart line usually tend to be good welfare workers, as they have a heart for those unhappy people.

HeadLine = Long Head Line

HeadLine_Description = Most commonly found in people who thinks and give a lot of thought before taking action on anything

LifeLine = Curved Life Line

LifeLine_Description = A curved life line often indicates a person passionate about life and who lives life to the maximum.

7.2.3 Identification Process

The Identification phase is responsible for the matching between the input image and the model. The technique to extract line features and matching between two images are described in details in Chapter 4. The feature extraction for all the models in the database are done prior to program execution to reduce the time needed for execution of the program. The model with the highest similarity with the input image is considered the genuine category. The description of personal character of the corresponding category will display to the user. The whole process cost about 2s. The palm analysis result is then displayed as shown in Figure 7.12.

Figure 7.12: Palm analysis result of the input palm. (a) Principal lines detected from input image. (b) Matched model. (c) General characteristic of the model.

7.3 Reflection

Palm reading is subjective so we can only verify the results visually. Palm reading has been used for centuries in different cultures, and there are many variations of the interpretation. We have 10 template models in our database, which is not sufficient to be a professional fortune telling system. We explored the way to move hand analysis into the realm of computer science. We will expand the model database to differentiate varied categories better.

Chapter 8 Registration of 3D Brainstem Surfaces

Adolescent idiopathic scoliosis (AIS) is a three-dimensional structural deformity of the spine that occurs during adolescence, and the prevalence is about 4% of the adolescent population worldwide. Due to the lack of generally accepted scientific theory on the etiology of AIS, the treatment and prognosis of AIS are limited [15]. Many experiments and evidences point toward the nervous regulation of the postural balance in the idiopathic scoliosis patients. The brainstem and vestibular system are two key organs in the balance control system. Significant anomalies of the balance function, proprioception and oculomotor reflexes have been reported[16], and morphological difference has been found in the vestibular system[17]. However, there is no reported work on studying the morphological alterations in brain stems in the AIS subjects in an objective and quantitative way. Motivated by this, we are interested in developing mathematical models which facilitate the morphometry of brainstem surfaces in AIS and normal controls.

In order to perform shape analysis effectively, meaningful one-to-one correspondences between different brainstems must be obtained. Such a process is called *surface registration*. Landmark-matching based registration approaches have been commonly applied, in which landmark features were required to be consistently matched to guide the registration. Landmark-matching registration

has shown to be effective in obtaining accurate point-wise correspondences between 3D medical data. On brainstem surfaces, there are no medical features defined by neuroscientists that can be used as a constraint to establish good correspondences. Therefore, in order to register brainstems effectively, meaningful landmark features that describe the global geometry of the brainstem surfaces must firstly be extracted. With these obtained features, landmark-matching registrations can then be computed to obtain accurate point-wise correspondences.

In this work, we introduce an algorithm to automatically register brainstem surfaces based on the discrete Ricci flow method. Four consistent features are firstly extracted automatically to guide the surface registration. These features effectively describe the global geometry of the brainstem surface. Using the discrete Ricci Flow method, brainstem surfaces are parameterized conformably onto the quadrilaterally-faced hexahedron, of which the extracted feature landmarks are mapped to the edges. Surface registrations between brainstems can then be obtained through the parameterization, which consistently match the feature landmarks. With the obtained registration, a shape energy can be defined to measure the local shape difference between different brainstem surfaces, which is useful to study shape variation between brainstems for the purpose of disease analysis. We tested our algorithm on real brainstem surfaces extracted from MRIs of 15 normal subjects and 15 AIS patients. Experimental results show the efficacy of the proposed algorithms to register and detect the local shape difference between different brainstem surfaces.

Our contributions are two-folded: first, we propose to delineate four salient features on brainstems that describe the global geometry; second, by mapping the

four detected landmarks to the four side edges of a hexahedron, we propose an efficient algorithm to conformally parameterize the brainstem surface, which naturally induces the registration among brainstem surfaces. Our registration algorithm can guarantee the exact landmark feature correspondence.

8.1 Algorithm

8.1.1 Overview

Given the brainstem surface M , we first detect four salient geometric features on M . We then apply the discrete Ricci flow method to parameterize the brainstem surface onto a quadrilaterally-faced hexahedron, through which the four feature curves on the brainstem are mapped to the four vertical sides of the hexahedron which is shown in Figure 8.2. As our parameterization method naturally segments the brainstem surface into six patches, we can easily register two different brainstems by finding a diffeomorphism between each corresponding patches. In the following, we explain each step in details.

8.1.2 Landmark Extraction

As brainstem surfaces have very strong geometric features, we extract the landmarks by computing the ridge-valley lines [143], a powerful shape descriptor on a surface along which the surface bends sharply. Suppose k_1 and k_2 are the maximal and minimal principal curvatures respectively, where $k_1 \geq k_2$. Let $\mathbf{t}_1$ and $\mathbf{t}_2$ be the corresponding principal directions. Consider the directional

derivatives $e_i = \frac{\partial k_i}{\partial t_i}$, $i=1,2$. Then, the ridge-valley lines are defined as the extrema of the principal curvatures along their principal directions, i.e.,

Input: Two brainstem surfaces $M1$ and $M2$

Output: The homeomorphism $\phi : M_1 \rightarrow M_2$ with guaranteed landmark correspondence

1. Extract the four landmarks from the brainstem surfaces;
2. Cut the brainstem surfaces open along the detected landmarks;
3. Set the prescribed Gaussian and geodesic curvatures to each mesh vertex and run discrete Ricci flow;
4. With the resulting metric, embed the brainstem surfaces into quadrilaterally-faced hexahedral, which naturally induces a segmentation of $M1$ and $M2$ into six patches.
5. For each pair of patches $F_1^i \in M_1$ and $F_2^i \in M_2$, find the bijective map $\phi_i : F_1^i \rightarrow F_2^i$ by computing harmonic functions with Dirichlet boundary conditions;
6. Output the map $\phi = \bigcup_{i=1}^6 \phi_i$.

Algorithm 1: Brainstem surface registration algorithm with guaranteed landmark correspondence.

$$\text{ridges: } e_1 = 0, \partial e_1 / \partial t_1 < 0, \quad k_1 > |k_2|, \quad (1)$$

$$\text{valleys: } e_2 = 0, \partial e_2 / \partial t_2 > 0, \quad k_2 < -|k_1|, \quad (2)$$

The ridge and valley lines can then be computed by solving Equations (1) and (2) on the given mesh as shown in Figure 8.3(A) and (B). These lines are smoothed out if necessary to reduce artifacts caused by the noise and/or poor

triangulation. Ridge or valley lines are merged to each others, if they are close to each other and the tangent directions on the end points are within the user-specified threshold. Next, we measure the strength of each feature by computing the length of the detected ridge-valley line. The longer the curve, the stronger the feature. We then find the two strongest ridges and valleys, which are chosen as landmark features. On brainstem surfaces, there are consistent umbilic points and high-curvature points. These points are chosen as the endpoints of the landmark features. Examples of the four extracted features on different brainstems are shown in Figure 8.1.

Figure 8.2: Landmark extraction. (A) and (B) show the computed ridge and valley lines respectively. The two strongest ridge and valley lines are chosen as landmarks, as shown in (C). (D) shows the four consistent features extracted on brainstems of a normal and an AIS subject.

Figure 8.3: (A) The universal covering space. (B) The fundamental domain. (C) The parameterization naturally induces a segmentation of the brainstem surface into six patches. (D) The checkerboard texture mapping shows the parameterization is conformal.

8.1.3 Parameterization using Discrete Ricci Flow

To ease the computation process, we parameterize the brainstem onto a domain in R^2 . The ideal parameter domain for such surface is the quadrilaterally-faced hexahedron, of which each landmark is mapped to an edge of the hexahedron. Discrete Ricci flow method is used to obtain the parameterization.

Given a brainstem surface, we first cut it open along the detected feature lines. As a result, the open brainstem surface is of genus 0 with 4 boundaries, denoted by $\gamma_i, i=1, \dots, 4$. We then set the target curvatures to be $-\pi/2$ at the end points of the landmarks and zero elsewhere. Using the discrete Ricci flow method [126], we can parameterize the brainstem surface onto the universal covering space embedded in R^2 .

To visualize the parameterization, we cut the brainstem surface along the geodesics (i.e. line segments) $e_1^1 e_2^1$, $e_2^1 e_3^1$, and $e_3^1 e_4^1$ (see Figure 8.3(C)), under the

new metric $\overline{g}$. Intuitively speaking, we cut along the edges of the bottom face to make the hexahedron open. Now the brainstem surface becomes a genus-0 surface with only one boundary.

We compute the layout of the parameterized mesh by isometrically embedding all the triangles with the new metric $\overline{g}$. Figure 8.3 shows the universal covering space of the brainstem surface with the highlighted fundamental domain. One can see that each landmark is mapped to the straight side of the hexahedron. This feature allows us to easily compute the high quality registration with guaranteed exact landmark matching, which will be described in the next subsection.

Figure 8.4: (A) Registration between two normal brainstems. (B) Registration between the brainstems of a normal and AIS subject. Landmark features are matched exactly. (C) shows the average shape of 15 AIS brainstems using our registration. The sharp features are well-preserved after averaging, meaning that our registration matches salient features well. (D) shows the average shape using the curvature-based registration without landmarks [144]. Note that the sharp features are smoothed out.

8.1.4 Registration

The above discrete Ricci flow method parameterizes each brainstem surface to a hexahedron, such that the four landmarks are mapped to the four vertical edges. The hexahedron naturally induces a segmentation of 6 patches. With these, we can easily register two brainstem surfaces in a piecewise manner.

Let F_1^i (resp. F_2^i), $i=1, \dots, 6$, denote the six patches of M_1 (resp. M_2) induced by the parameterization. We want to find a diffeomorphism (i.e., a C^∞ -smooth and bijective map) $\phi_i: F_1^i \rightarrow F_2^i$ between each pair of patches F_1^i and F_2^i . Let f_1 (resp. f_2) denote the Ricci flow parameterization that maps F_1^i (resp. F_2^i) to a quadrilateral D_1^i (resp. D_2^i). Let us also denote the corners of the 3D patch and 2D quadrilateral by p^j and q^j , $j=1, \dots, 4$, respectively. Then we map each quadrilateral Q to a unit disc D by a harmonic function $g: Q \rightarrow D$ such that $\Delta g = 0$ with Dirichlet boundary condition $g(\partial Q) = \partial D = S^1$. Let $r^j = f(q^j)$, $j=1, \dots, 4$, denote the images of the corners on the unit circle. Next, we compute another harmonic function $h: D_1^i \rightarrow D_2^i$ between the two unit discs D_1^i and D_2^i , i.e., $\Delta h = 0$. We set the boundary condition $h(\partial D_1^i) = \partial D_2^i$ by enforcing the exact feature correspondence, i.e., the corners r_1^j are mapped to corners r_2^j . Therefore, a map ϕ_i between the patches F_1^i and F_2^i can be obtained by the composite map $\phi_i = f_2^{-1} \circ g_2^{-1} \circ h \circ g_1 \circ f_1$ (See Figure 8.5).

A homeomorphism $\phi: M_1 \rightarrow M_2$ can then be obtained by $\phi = \bigcap_{i=1}^6 \phi_i$. Note that landmarks are exactly matched for each patches. So, our algorithm guarantees the exact correspondence between the landmark features.

Proposition. The proposed brainstem surface registration algorithm produces a homeomorphism ϕ between M_1 and M_2 , which guarantees the exact correspondence between the landmarks $\phi(\gamma_1^j) = \gamma_2^j, j=1, \dots, 4$.

Proof. We first show that the resulting map ϕ is a homeomorphism. Observe that the discrete Ricci flow induced parameterization f_1 and f_2 are diffeomorphism [125]. According to the classical result, a harmonic function, which maps a $\Omega \subset \mathbb{R}^2$ to some convex region Ω' and maps the the boundary $\partial\Omega$ homeomorphically into the boundary $\partial\Omega'$, is diffeomorphic. As Q_j and $D_j, j=1,2$, are convex and the boundary conditions in g_j and h are homeomorphic, all the harmonic functions g_1 , g_2 and h are diffeomorphic. Therefore, the map $\phi_i = f_2^{-1} \circ g_2^{-1} \circ h \circ g_1 \circ f_1$ is a diffeomorphism (see Figure 8.5). By gluing the maps $\phi_i, i=1, \dots, 6$, together, the resulting map $\phi = \bigcap_i \phi_i$ is homeomorphic, since the boundaries of ϕ_i are matched in C^0 manner.

Second, we show that the map ϕ preserves the correspondence between the landmarks. By setting the prescribed geodesic curvature on γ_1^j and γ_2^j to zero, $j=1, \dots, 4$, the metric $g(\infty)$ obtained by discrete Ricci flow can guarantee each landmark is mapped to a *line segment* (see Figure 8.3(b)). Then with harmonic functions, g_1 and g_2 , each line segment is mapped to an arc of the unit circle. Note that the exact feature correspondence are set when computing the harmonic function $h: D_1 \rightarrow D_2$ between two unit disks. Therefore, the composite function ϕ_i maps the boundary ∂F_1 homeomorphically to ∂F_2 and also sends each corner of F_1 to the corresponding corner of F_2 . Thus, the map ϕ_i sends the

landmark of F_1 to the corresponding landmark of F_2 . As a result, the map ϕ preserves the exact correspondence between the landmarks $\phi(\gamma_1^j) = \gamma_2^j, j=1, \dots, 4$.

Putting it together, the map $\phi: M_1 \rightarrow M_2$ is a homeomorphism with guaranteed landmark correspondence.

Figure 8.5: Computing the map $\phi_i: F_1^i \rightarrow F_2^i$.

8.1.5 Shape Variation Detection

With the obtained registration between brainstems, we can define a shape energy which detect local shape variations. According to Riemannian geometry theories, the local geometry of a Riemann surface can be described by its mean curvature and Gaussian curvature. Let B_1 and B_2 be two brainstem surfaces. Suppose $f: B_1 \rightarrow B_2$ is the registration between B_1 and B_2 . We can define a shape energy E_{shape} as follows: $E_{shape}(f) = \alpha \int_{B_1} |H_1 - H_2(f)| + \beta \int_{B_1} |K_1 - K_2(f)|$, where H_1 and K_1 (resp. H_2 and K_2) are the mean curvature and Gaussian curvature of B_1

(resp. B_2). $E_{shape}(f)=0$ if and only if B_1 and B_2 are equal up to a rigid motion. Therefore, E_{shape} measures the local shape difference between B_1 and B_2 effectively. This allows us to examine the region of significant shape difference for the morphometry of the brainstems.

Figure 8.6: (A)-(D): Grid texture is drawn on the control brainstem. It is mapped to three different brainstems of the AIS subjects using our proposed registration algorithm. The grid pattern illustrates that our registration result is indeed a homeomorphism. (E)-(H): Detection of shape variations.

8.2 Experimental Results

Subject and data acquisition:

We tested our proposed algorithms on 30 brainstem surfaces, which are extracted from the MRIs. The MRI brain data were acquired from 15 AIS subjects and 15 age-matched normal controls using a 1.5T MRI scanner (Sonata, Siemens, Erlanger, Germany) using a quadrature head-coil. The segmentation of the brain stems was achieved automatically. Two experienced operators verified the segmentation results.

Brainstem registration:

Using our proposed algorithms, we compute the registration between 30 brainstems of 15 normal subjects and 15 AIS patients. Experimental results show that our proposed method can compute the registration effectively with exact landmark-matching. Figure 8.4(A) shows the registration results between two normal brainstems. The registration result between the brainstems of a normal and AIS subject is shown in (B). Landmark features are exactly matched. In Figure 8.6(A)-(D), grid texture is drawn on the control brainstem. It is mapped to three different brainstems of the AIS subjects using our proposed registration algorithm. Note that grid patterns have no overlapping, indicating the registration is indeed a homeomorphism. The whole registration procedure can be computed efficiently. The feature landmarks (ridge and valley lines) are computed in real-time for brainstem meshes with 20K vertices. The Ricci flow based conformal parameterization for each brainstem mesh takes about 12 seconds, since the Newton's method with second order convergence rate is adopted in our implementation. The registration between brainstems through the parameterization takes about 5 seconds to compute. The whole process to obtain the landmark-matching brainstem registration takes less than 20 seconds. Hence, our proposed registration algorithm is quite efficient.

Detection of shape variations:

With the obtained registration f , the local shape difference between different brainstem surface can be detected from the shape energy $E_{shape}(f)$. Figure

8.6(E)-(H) shows the local shape differences of two brainstem (1 normal and 1 AIS subject) surfaces from the control. The color map is given by the shape energy, which measures their local shape difference. The red (resp. blue) color indicates a higher (resp. lower) degree of shape difference. The local shape difference of the AIS brainstem from the control tends to be more obvious than that of the normal brainstem. Figure 8.6(H) shows the statistical significance p-map measuring the local shape difference from the control between the normal ($n=15$) and AIS ($n=15$) groups, plotted on a control brainstem. The deep red color highlights regions of significant statistical difference. This method can be potentially used to study factors that influence shape changes of brainstems in AIS.

Comparison:

We also compare our registration algorithm with the existing curvature-based registration without landmarks [144]. The curvature-based registration without landmarks generally cannot match salient features. Figure 8.4(C) shows the average shape of 15 AIS brainstems using our registration. The sharp features are well-preserved after averaging, meaning that our registration matches salient features well. (D) shows the average shape using the curvature-based registration without landmarks. Note that the sharp features are smoothed out. It indicates the mismatching of salient features.

8.3 Summary

We present a rigorous algorithm to register brainstem surfaces for the disease

analysis of Adolescent Idiopathic Scoliosis. The basic idea is to extract four consistent features, which describe the global geometry of the brainstem, to guide the surface registration. Using the Ricci Flow method, brainstem surfaces are parameterized conformally onto quadrilaterally-faced hexahedron, which naturally induces the feature landmark-matching brainstem registration. Our registration algorithm can guarantee the exact landmark correspondence between brainstem surfaces. A shape energy can then be defined to measure the local shape variations between different brainstem surfaces. Experiments on real brainstem surfaces of 15 normal subjects and 15 AIS patients show the efficacy of our proposed algorithms to register and detect local shape differences between different brainstem surfaces. The proposed algorithm can potentially be used to study factors that influence shape changes of brainstems in AIS.

Chapter 9 Conclusion and Future Work

This chapter summarizes the work carried out and reported in this thesis. The limitations of the current approaches are also discussed. Finally, the major research issues remaining and their possible solutions are suggested for further study in the future.

9.1 Work Summary

Palmprint/vein patterns being used as biometric features in personal verification applications are of great interest. Particularly, an ideal technique can tackle the problem of unreliable alignment and poor image quality in general-used personal verification systems. A novel and unique local structure based image retrieval approach has been proposed in this work for speedy identification of input objects and retrieval of structurally similar models from large database.

The research identifies and investigates several major issues regarding the palmprint/vein pattern biometrics. These research issues are: (i). Obtainability of the palmprint/vein pattern data; (ii). Processing of the palmprint/vein pattern images; (iii). Identification of features for matching the palmprint/vein patterns; (iv). The discriminating power of the palmprint/vein patterns in biometric applications.

We have built one prototype system to demonstrate and investigate the

proposed matching scheme. The implementation employed line as a primitive. Each local structure is represented by a set of pair-wise geometric relationships, which are simple, invariant to translation / rotation, relatively robust to end-point-erosion, and sufficient for discrimination.

The system has been tested on PolyU palmprint database, mobile palmprint database and NIR hand vein database collected by our NTU research group. Excellent retrieval results have been obtained. The success of the system supports the idea that machine can interpret biometric features without strict device constraint.

Adolescent Idiopathic Scoliosis (AIS) characterized by the 3D spine deformity affects about 4% schoolchildren worldwide. Several studies have demonstrated the malfunctioning of postural balance, proprioception, and equilibrium control in patients with AIS. Since these functions are closely related to structures in and around the brainstem, the morphometry of the brainstem surface is of utmost importance. In this paper, we propose an effective method to accurately compute the registration between brainstem surfaces. Four consistent features, which describe the global geometry of the brainstem, are automatically extracted to guide the surface registration. Using the discrete Ricci flow method, brainstem surfaces are parameterized conformally onto the quadrilaterally-faced hexahedron, through which the brainstem registration can be obtained. Our registration algorithm can guarantee the exact landmark correspondence between brainstem surfaces. With the obtained registration, a shape energy can be defined to measure the local shape difference between different brainstem surfaces.

We have tested our algorithms on 30 real brainstem surfaces extracted from MRIs of 15 normal subjects and 15 AIS patients. Experimental results show the

efficacy of the proposed algorithm to register brainstem surfaces, which matches landmark features consistently. The computed registration can be used for the morphometry of brainstems. It has high potential to apply our proposed 3D surface registration to biomedicine and biometrics applications.

9.2 Contributions

The main contribution of the work is its capability to tackle the need of personal verification in unconstraint way and developed an effective and practical solution to register the brainstem surface. The following are contributions made in this thesis:

1. A novel prototype system has been built up, first of its kind, to tackle the need of “personal verification in unconstraint way”.
 - i. The system can collect vein pattern data with low cost and is able to achieve acceptable image quality.
 - ii. The system can work on low quality palmprint images captured by mobile phones with satisfactory accuracy.
2. Line is adopted as a primitive due to its efficient representation, low storage demand and consistency in being detected. In addition, we do not assume well segmented object outline or boundary. Each local structure is represented by a set of pair-wise geometric relationships, which are simple, invariant to translation and rotation, relatively robust to end-point-erosion, and sufficient for discrimination.
3. A subset division concept has been proposed to solve position information loss problem in pair-wise geometric relationships. By

dividing the palm lines into different subsets, it introduces the position information into system as well.

4. Fourier transform is used to distinguish the variations of palmprints/vein patterns in coarse-level to filter out incorrect matches quickly. This overcomes the problem of high computational complexity when the database size increases.
5. Principle lines are extracted using Hough Transform to apply palmprint matching system to palmistry. Its novelty and efficiency has been proved.
6. Four salient features are proposed to delineate on brainstems that describe the global geometry.
7. By mapping the four detected landmarks to the four side edges of a hexahedron, an efficient algorithm is proposed to conformally parameterize the brainstem surface, which naturally induces the registration among brainstem surfaces. Our registration algorithm can guarantee the exact landmark feature correspondence.

9.3 Future Research

Though promising results have been achieved on several key issues in the investigation of the potential of vein pattern biometrics, many possible extensions exist to further improve the system.

1. First of all, continuous efforts are to be put into the construction of a larger vein pattern image database to make it more representative for all possible population groups.

2. Palmprint and vein pattern biometrics are integrated to be a multi-modal biometric system.
3. The quality of image data is vital for the application; hence more work is needed in the data preprocessing stage.
4. Effort in reducing the computational complexity of this system is expected. Introducing indexing for this palmprints/hand vein matching system is a promising solution.
5. We will apply our proposed algorithms on more brainstem data to further investigate the relationship between the postural balance control problem and the occurrence of AIS. We would also like to point out that the proposed algorithm can be naturally extended for registration of other anatomical structures, such as hippocampus, cerebellum and the vestibular system, which will be investigated in our future work.

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Publication List

Journal paper

1. F. Li, M. K. Leung, "Line Extraction in Palmprint System", International Journal of Computer Theory and Engineering, IJCTE 2012, Vol. 4 (in press).
2. F. Li, M.K. Leung, "Making Palm Print Matching Mobile", International Journal Of Computer Science And Information Security, IJCSIS November 2009, Vol. 6 No. 2.

Conference papers

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