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Authenticating Personal Identities Using Palmprint Recognition

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CERTIFICATE OF ORIGINALITY

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Abstract

Palmprint recognition technology is based on the identification of creases, wrinkles, ridges and hollows of the inner surface of the human palm. Palmprint recognition research, especially where it integrates fingerprint and hand geometry, is an area of great promise in the search for ever more reliable personal identity authentication and security systems. Our research over the last five years has made a number of major practical and theoretical contributions to the field of palmprint recognition. Our development of an online capture device has proven the feasibility of using palmprint recognition technology to identify people in real time. Our establishment of a palmprint database (ten thousand images collected from one thousand volunteers) has allowed us to thoroughly test the development of several novel palmprint positioning/segmentation, feature extraction/presentation and matching algorithms. We have proposed three palmprint positioning algorithms based on end points of the heart line and the outer boundary of the palm, on conjunction points between fingers, and on an inscribed circle. For the reference of researchers in the field, we also developed a number of feature extraction and matching methods: texture analysis, Fourier Transform and bi-directional matching of creases. This last proved itself 97.5% accurate and we are working on a new method to improve it. Finally, we also implemented a proof-of-concept palmprint verification system integrated with a smart card. Our publications include eight journal papers and five conference papers with one paper currently under review. In our future work we hope to improve the capture device, develop, test and compare other methods, enlarge our database, and find a way to locate and identify a palmprint in a free-of-scale image.Palmprint recognition shows great promise as a way to authenticate personal identities. With further research it will certainly become an established and accepted technology in the increasingly important fields of security and personal identity authentication.

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Chapter 1

Introduction to Biometrics

Biometrics, which refers to automatically recognizing people by their distinguishing traits (Biometrics Consortium [1]), is emerging as the most foolproof method for security systems. It is a broad market for this new technology especially after the terrorist attack of the World Trade Center on 11th September 2001. Law enforcement, boundary control, and financial services are showing to need biometrics as safe guard. Vendors are competing drastically. Unlike five years ago, nowadays people are accepting this new technique gradually. Though promising, it is still immature and researchers are fervidly probing into biometrics. Traditionally used biometrics such as fingerprint and signature are investigated thoroughly, meanwhile new attempts are given to body odor, gait and keyboard stroke, etc. Currently people have agreed on some basic concepts and notations on description and evaluation of a biometrics technique.

1.1. The Market for Biometrics

According to an International Biometric Group market report, biometric revenues grew from $399.4 million in 2000 to $523.9 million in 2001 and are expected to reach $1.9 billion in 2005 [2]. Till now, fingerprint and face recognition have been the high-growth areas, because of the rapid adoption of e-commerce and the increasing usage of security-enabled applications worldwide. The terrorist attack of the World Trade Center on 11th September 2001 has also served to wake the world out of a lackadaisical attitude towards security. The perception is that as the technology matures and the prices of devices come down, more and more security applications will become biometric-based [2]. There are three biometric markets -- a mature market focused on law enforcement, an emerging market focused on authentication, and a potential market focused on financial services [4].

1.1.1 Law Enforcement

Automatic fingerprint identification systems have been used with great success by law enforcement agencies since the 1980s. Fingerprints are by far the most widely used biometric today, and the most widely respected. Most people take it as a matter of faith that each person has his own unique fingerprint and that a computer can rapidly search out one person's fingerprint from a database of millions [5]. Presently, many AFIS (Automatic Fingerprint Identification System) systems are being used around the world. The police stations in Connecticut State [6], Harris County, Texas [7], San Francisco [8], the city of Henderson, Nevada [9] and Canberra, Australia [10] have all installed AFIS systems to fight crime.

1.1.2 Authentication

A. Driver's License

Currently five U.S. states - California, Colorado, Georgia, Hawaii and Texas, have legislation in place allowing fingerprint biometric data to be added to a driver's license. This legislation enables these states to provide an increased level of identification and security for driver's license holders. The use of biometrics is a key to eliminating duplicate and fraudulent driver's licenses and interoperability between states will provide tremendous benefits to state law enforcement agencies [11-12].

B. Visa

The Bush administration is establishing a national biometrics identification system to prevent terrorists from gaining legal entry into the country and says international standards should be established [13]. By October 26, 2003, the Attorney General and the Secretary of State will have issued to aliens machine-readable tamper-resistant visas and travel and entry documents that use biometrics identifiers [14].

C. Airport

San Francisco International Airport uses handprint readers and identification card readers to restrict employee access to secure areas, and Thales Fund Management in Manhattan relies on eyeball recognition before allowing admittance to its offices. U.S. News & World Report (Feb. 18, 2002) finds airports in Boston, Palm Beach, and Dallas-Ft. Worth implementing face-scan technology that compares faces against an FBI image database of suspected terrorists and wanted felons [15].

1.1.3 Financial Services

A. Banks

By 2004, the financial services market will spend about $1.8 billion annually on biometric technology, according to IDC in Framingham, Manual Analysis Scan System. Increasing fraud rates and heightened security concerns in the wake of the Sept. 11 terrorist attacks have helped boost interest in biometrics. CITIBANK is looking into the feasibility and cost of using biometric technology as a more efficient and secure method of identifying its customers. Meanwhile, Huntington Bancshares Inc. is studying the impact of identity theft and fraud on biometrics as a possible approach to reducing the chronic problem. Deutsche Bank AG in Frankfurt and New Yorkbased Citibank have been using biometrics for several years for employee access to computer server rooms [17].

B. Retailer

Major retailers are putting biometrics in payment systems. Paying for products with a fingerprint, rather than with checks, cards or electronic devices, is one of the cashless options at checkouts. West Seattle Thriftway - the grocery store's cashiers scan the goods, then customers scan their right index finger to activate the payment process. Kroger - the No. 1 supermarket chain has tested the technology for the past month in three stores in Houston. McDonald's - a location in Fresno, Calif., took fingerprints for payment [18].

1.2. Biometrics Companies and Products

More than 200 companies are competing for the biometrics market. In order to survive, companies must continually upgrade their technologies enable their products easy integration with other devices as well as best meet the needs of the marketplace [19]. Now only a few companies won the big private and government contracts and other smaller companies didn't make much profit from biometrics technology. It is predicted that after years of competition, only a handful companies will survive and hundreds of small biometrics companies will likely have gone out of business or merged with other companies.

The most widely deployed biometric security technologies are face recognition, finger scanning, finger and hand geometry, iris and retina recognition, palm-print recognition, voice recognition, and signature (the handwritten type) recognition. Each requires special equipment and ongoing maintenance and calibration procedures. For example, voice recognition calls for a microphone and a PC sound card. Fingerprint scanners and eye scanners require specialized network and desktop hardware (though some vendors are starting to offer fingerprint-scanning keyboards and panels for laptops). For face recognition, you need a digital camera [20]. See Appendix for a list of biometrics companies.

1.3. People's Attitude to Biometrics

When fingerprint verification system was first adopted, people were worrying about the disclosure of their privacy and reluctant to have their fingerprint captured. But now the majority of public believes it is acceptable to use biometric technologies [3]. Generally, people may accept biometric checking when 1) checking the identity of an individual buying a gun against a database of convicted felons; 2) verifying the identity of those making credit card purchases; 3) withdrawing funds from an ATM; 4) accessing sensitive files, such as medical or financial. When biometrics traits are checked, 1) people should be fully informed about the uses an organization will make of their biometric ID and why it is needed; 2) organizations should not use biometric IDs for any purpose other than those originally described to the individual, unless the organization is required to do so by law or each person in the system has been informed and given his or her consent; 3) organizations collecting biometric IDs should automatically code the ID formula and not provide the key to any other organization unless required to do so by law or expressly authorized by the individual; 4) except in national security situations, an individual should be told whenever their biometric identifier is being collected — it should not be collected secretly.

1.4. Progress of Biometrics Technology

Computer based personal identification began in the 1970s. At that time, the first commercial system called Identimat was developed, which measured the shape of a hand and looked particularly at finger length. In the meantime, fingerprint based automatic checking systems were widely used in law enforce. Retina and iris based systems were introduced in the mid 1980s. Today's speaker identification biometrics have their roots in technological achievements of the 1970s; while signature identification and facial recognition are relative newcomers to the industry [22]. Any situation that allows an interaction between man and machine is capable of incorporating biometrics. Such situations may fall into a range of application areas such as computer desktops, networks, banking, immigration, law enforcement, telecommunication networks and monitoring the time and attendance of staff [23-25].

Hundreds of research papers on biometrics have been published in recent years. Some of them are discussing the general opinions of biometrics [105-112], but most are on specific technology. Table 1-1 gives an index of the researchers and their papers grouped by the biometrics features. Here we just list some of researchers in the area and the list is incomplete.

Table 1-1 List of researchers and their papers

Biometrics feature	Researchers	Papers
Fingerprint	Q. Xiao A.K. Jain N.K. Ratha A. Senior L. Hong D. Maio A.R. Roddy R. Bolle S. Pankanti	[27-67] [113-138]
Iris	R.P. Wildes J.G. Gaugman	[139-144]
Retina	G. Lawton	[145]
Signature	K. Huang G. Dimauo Q.Z. Wu E. Mandler M. Parizeau	[146-158]
Face	J. Zhang S.H. Jeng Q. Chen J. Huang A.J. Colenarez	[159-174]
Voice	J.P. Cambell R.C. Rose Q. Lin N.Z. Tishby	[175-181]
Palmprint	D. Zhang W. Shu W.X. Li J. You C.C. Han G. Lu	[69-78]

1.5. Biometrics Classification

Historically, different parts of human beings are used in personal identification. Here we summarized some major ones:

1.5.1 Fingerprint Recognition

Fingerprints have been used by police forces as a means of crime detection since they were introduced by Scotland Yard in the late 19th Century. Classification of fingerprints is based on certain characteristics (arch, loop, whorl). The most distinctive characteristics are the minutiae, the forks, or endings found in the ridges and the overall shape of the ridge flow [21]. Fig. 1-1 shows a sample of fingerprint.

Fig. 1-1 Fingerprint sample

1.5.2 Palmprint Analysis

Palmprints, like fingerprints, are unique to each individual. Creases, skin tone and swirls can be detected by a video camera and digitized. The digitized output is then compared with an image, which has been stored for each authorized user of the system. Access time is relatively fast, and false rejection rates are less than 1%, with false acceptance rates being extremely low. Fig. 1-2 shows a palmprint sample.

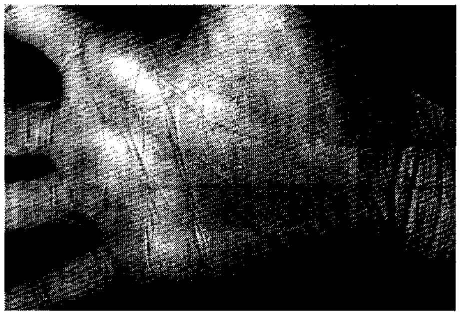


Fig. 1-2 Palmprint sample

1.5.3 Hand Geometry

One problem posed by using fingerprint or palmprint analysis techniques is that it is believed that it may be possible to forge fingerprints or palmprints, by using a latex solution to take an imprint of the fingerprint of the authorized user. Whilst it is by no means certain that this is the case, it means that other biometric measures, which are harder to forge are also used to control access to systems. One such method is hand geometry. The measurement of the length of the four fingers on each hand, and the translucency of fingertips and the webbing between fingers, can be used to identify individuals. These measurements take time and will therefore not allow rapid access to a system [23].

1.5.4 Face Recognition

The premise of this approach is that face characteristics (e.g. size of nose, shape of eyes, chin, eyebrows, mouth) are unique revealing individuals identity. The facial applications are well suited for a one-to-many compare to identify a person. Fig. 1-3 shows a face image sample.

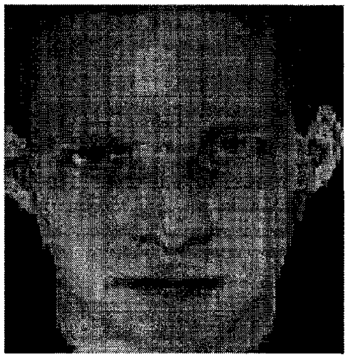


Fig. 1-3 Face sample

1.5.5 Signature Identification

Handwritten signatures have long been accepted as a valid means of authentication, for example on checks or contracts. Traditional signature verification has relied on visual inspection of the signature after it has been written and comparison with an original. The principle behind use of signature verification is that signatures are written so frequently that they become a reflex action, not subject to deliberate muscular control. Automatic verification of signatures is based on the shape of the completed signature and the dynamics of signature production (e.g. pressure deviation, acceleration, time to complete segments.) The signature is usually input using an electronic pen, and the measurements that are derived from the input are compared with pre-stored values for the purported owner of the signature. However, automatic recognition of signatures written using a traditional pen will also be useful in banking and other similar applications. Automatic signature verification is used both in access control and in transaction authorization. Fig.1-4 shows a sample of signature.

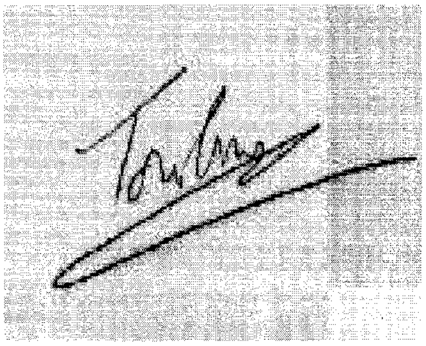


Fig. 1-4 Signature sample

1.5.6 Voice Authentication

A voice print of each authorized user can be recorded and is analyzed by measuring the zero crossings in two frequency ranges: 300-1000Hz and 1000-4000Hz. These measurements are believed to be characteristic to each individual, and are not easily forged, even by someone who to the human ear is performing a good imitation of the individual concerned.

1.5.7 Iris / Retina Recognition

The blood vessels at the back of the eyeball, on the retina, form a pattern which is both stable and detailed, and which is believed to be impossible to forge. The patterns are believed to be unique and as such provide an ideal way for preventing unauthorized access. The iris can be scanned using a low-level infrared eye camera. The output from the camera is digitized and compared with a stored image for each authorized user. Fig. 1-5 shows a sample of retina and Fig. 1-6 shows a sample of iris.

Fig. 1-5 Retina

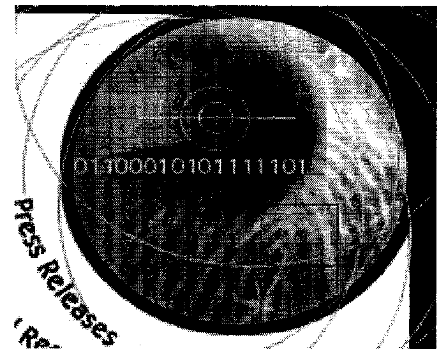


Fig. 1-6 Iris

1.6. Organization of the thesis

The rest of the thesis is organized as follows: Chapter 2 gives the general introduction to palmprint recognition – the definitions of concepts, the significance, key issues and difficulties, current status of palmprint recognition and summarizes the major contributions of the thesis. Chapter 3 gives the definitions of palmprint features and presents the architecture of the online palmprint capture device. Chapter 4 describes the offline recognition methods including alignment, feature extraction and matching algorithms. Chapter 5 includes the online palmprint recognition methods. Two palmprint positioning algorithms and three different feature extraction and matching methods are presented in details. Chapter 6 summarizes and compares all the proposed methods. Chapter 7 concludes the whole thesis, highlights the major achievements and attaches a list of publications on the work of this thesis.

Chapter 2

Introduction to Palmprint Recognition

This chapter gives a general description to palmprint recognition. First basic concepts and potential applications of palmprint recognition are introduced. Followed by the analysis of the limitations of existing biometrics techniques and the advantages of palmprint recognition. Then the key issues and difficulties in palmprint recognition are discussed and the researchers and their major publications on palmprint recognition are listed. At the end, the major contributions of this thesis are summarized.

2.1. Definitions of Concepts in Palmprint Recognition

2.1.1 Palmprint Recognition

Palmprint Recognition refers to the technique that automatically checks palmprint samples and gives the answer whether the samples are from the same palm source.

2.1.2 Offline and Online Palmprint Recognition

There are two means to get a digital palmprint image – offline and online. Offline palmprint images are got by covering the inner surface of a palm with ink and putting the palm on a white paper to get the palmprint on the paper and then using a scanner to turn the palmprint into a digital image. We call it **offline palmprint recognition** when using offline palmprint images. Online palmprint images are got by a digital camera or a special capture device that directly connected to a computer and when a live palm is put in front of the camera or put in the capture device, a digital image is stored in the computer immediately. Palmprint recognition based on online captured images is called **online palmprint recognition**.

2.1.3 Palmprint Identification and Verification

Palmprint recognition techniques are used in two types of applications – identification and verification. A **palmprint identification** system usually has a database and two sub systems – registration system and identification system. The registration system is used to register the authorized palmprints into the database as palmprint templates. The identification system deals with real time checking. If a newly captured palmprint is presented, the identification system answers whether the palm represented by the new palmprint has been registered and if yes, the system tells the registration number in the database. **A palmprint verification** system directly compares two given palmprint samples and answers whether they are from the same palm source. Both identification and verification systems need high accuracy and efficiency algorithms for palmprint comparison. A palmprint identification system also demands high speed of database searching when the database grows larger.

2.1.4 Palmprint Positioning and Alignment

Palmprints may exhibit some degree of distortion (rotation, shift, transform, etc.) due to their being captured at different times, and under varying conditions of temperature, humidity, brightness, etc. To compare two palmprints, a common coordinate system is needed to determine which part of a palmprint is going to match with a similar part in another palmprint. Here, we define **palmprint positioning** as the process of determining a coordinate system on a palmprint image. When the coordinate system on each palmprint is determined, we may move and rotate palmprints to make some certain points of the palmprints locate on the same position on their images so that algorithms such as feature extraction and feature matching can take the same parameters. We define the process of moving and rotating the images to their expected positions and directions as **palmprint alignment**.

2.1.5 Palmprint Central Part Extraction

In some palmprint recognition methods, not the whole captured image is used for feature extraction and matching. Usually only the central parts of the images are used. The process of cutting the central part of a palmprint image is called **palmprint central part extraction**.

2.1.6 Palmprint Feature and Feature Extraction

In palmprint recognition, we usually match palm creases, texture analysis results or characteristics on frequency domain to determine whether two palmprints are from the same palm source instead of comparing the original images directly. We call the information used in palmprint matching as **palmprint features**. Palmprints from same palm source have similar feature sets and those from different palms have their feature sets different enough. The process of getting the feature set from an original palmprint image is called **feature extraction.**

2.1.7 Palmprint Feature Representation

Depending on the nature of feature extraction methods, palmprint features can be represented by an integer, a series of binary code, a series of integer, a 2-Dimentional matrix of binary code or integer or other format.

2.1.8 Palmprint Feature Matching

Palmprint feature matching measures the similarity of two palmprint feature sets. The word '**distance**' is used to tell the similarity of two palmprint feature sets. In this thesis, distance is represent by an integer. The smaller the distance, the more similar the two feature sets are. Ideally the distance between two palmprints from same palm source is smaller than a certain threshold and that of different palms should be larger than the threshold. Therefore we can use the threshold to classify palmprints from same and different palm sources.

2.1.9 Palmprint Identification Rate

In a palmprint identification system, we use **identification rate** to tell how accurate/correct the system is. Identification rate is denoted as $IdentificationRate = \frac{Succ}{Attempts}$, where *Attempts* means how many times you feed the system with a query palmprint sample and ask the system to search in the database for a template that comes from the same palm source as the query palmprint; *Succ* means the times that the system gives the correct answer. We may use statistical method to calculate a system's identification rate, but the result is depending on the number of templates in the database, the number of attempts and the quality of the query palmprints. The designs of some particular experiments are given in chapter 4, 5 and 6.

2.1.10 False Acceptance Rate (FAR) and False Rejection Rate (FRR)

False Acceptance Rate (FAR) represents how often a system says that two palmprints are from the same palm source when the two palmprints are from different palms and False **Rejection Rate (FRR)** represents the rate that a system tells that two palmprints are from different palms when actually they are from the same palm source. FAR and FRR can be calculated using statistical method. The designs of experiments for calculating FAR and FRR are given in chapter 4, 5 and 6.

2.1.11 Equal Error Rate (EER)

When calculating the distance between two palmprint feature sets, we usually use a threshold to decide whether they are from the same palm source. When the distance is smaller than the threshold, we say the two palmprint feature sets are from the same palm, otherwise, they are from different sources. If we give a larger threshold, we may have more palmprint feature set pairs recognized as from same palm source. This decreases the possibility of misclassified palmprint pairs from same palm but increases the possibility of misclassified pairs from different sources. Therefore when increasing the threshold, FAR goes down but FRR goes up. Similarly when the threshold decreases, FAR goes up and FRR goes down. When a threshold makes the FAR equal to FRR, we call the FAR/FRR as **Equal Error Rate (EER)**. Sometime we also call the EER.

2.1.12 Receiver Operating Characteristic Curve

The FAR/FRR curve pair excellently describes the changing of FAR/FRR along with the threshold and can help to determine a suitable threshold for an identification system. However, it is not that effective when comparing different identification algorithms or systems due to the different explanations of thresholds. In order to reach an effective comparison of different systems, a description independent of threshold scaling is used which is **Receiver Operating Characteristic (ROC)**. In a ROC curve, FRR values are directly plotted against FAR values, thereby eliminating threshold parameters. The ROC, like the FRR, can only take on values between 0 and 1 and is limited to values between 0 and 1 on the X axis (FAR). It has the following characteristics:

- The ideal ROC only has values that lie either on the x axis (FAR) or the y axis (FRR); i.e., when the FRR is not 0, the FAR is 1, or vice versa.
- The highest point (linear scale under the definitions used here) is for all systems given by FAR=0 and FRR=1.
- As the ROC curves for good systems lie very near the coordinate axis, it is reasonable for one or both axis to use a logarithmic scale:

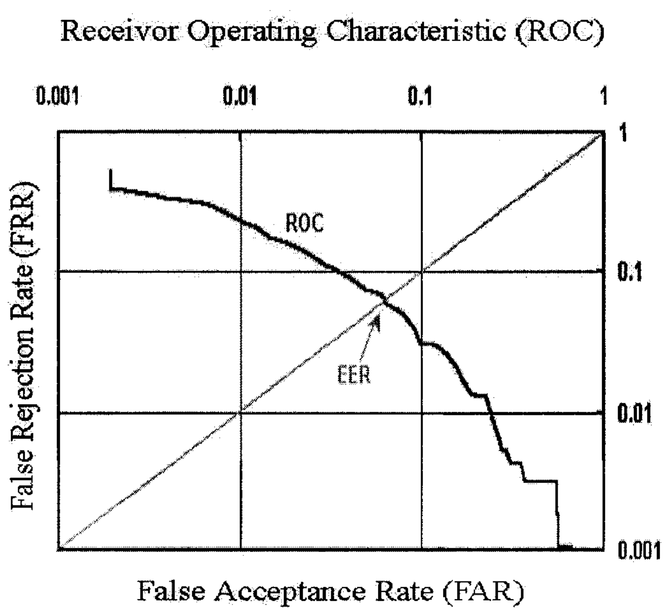


Fig. 2-1 ROC curve

2.2. Significance of Palmprint Recognition

2.2.1 Law Enforcement

It is estimated that unknown prints are found at about 60 percent of crime scenes, and that 30-35 percent of these are palmprints [25]. Manual searching of palmprints requires the examiner to compare a mark to every print in the archives a tedious job even if the archive is well organized. So before automatic palmprint matching system is introduced, palmprint checking was performed only in some major cases. Right now many police organizations have introduced automatic palm matching systems [7-10]. It shows that in a few years almost every police AFIS around the world is going to include palm identification system. It will be a large market for automatic palmprint identification systems.

2.2.2 Access Control

Though fingerprint plays a remarkably important role in police identification work, it is not to deny the enormous real and potential value of other techniques for access control or security purposes, such as face shape, iris and retina patterns, ear prints, teeth, voice and speech properties, wrist veins and hand geometry, handwriting and signature production, walking or gait characteristics, foot impressions, DNA, body odors, and of course palmprint.

2.2.3 Limitations to the Existing Methods

Though research on the issues of fingerprint identification and speech recognition has drawn considerable attention over the last 25 years [5-6] and recently issues of face recognition and iris-based verification have been studied extensively [7-8], there are still some limitations to the existing applications. Some people have their fingerprints worn away by working with their hands and some are born with unclear fingerprints. The existing iris based identification system has not been proved to be adaptive to eastern people who have quiet different iris patterns from those of western people. Face and voice based identification systems are less accurate and easy to mimic. Efforts to improve the current personal identification methods continue and new methods are under investigation.

2.2.4 Advantages of Palmprint Recognition

The inner and side surfaces of a palm are covered with a network of papillary friction ridges in exactly the same way as a finger or the underside of a foot. These ridges suffer from the same interruptions of flow as in a finger, producing an analogous pattern of ridge features or minutiae, and can be similarly used for personal identification. No two persons have ever been found to have exactly the same arrangement of detailed ridge features on their palms [21]. Like fingerprints, palmprint has been used as a powerful means in law enforcement for criminal identification because of its stability and uniqueness. The rationale to choose hand features as a basis for identity verification is originated by its user friendliness, environmental flexibility and discriminating ability. People do not feel uneasy to have their hand images and prints taken for testing. More importantly, these hand features are stable and uniquely represent each individual's identity.

2.3. Key Issues and Difficulties in Palmprint Recognition

An on-line palmprint identification system consists of a database, a registration system and an identification system. The database stores all the palmprint images and their features. The registration system is used to register palmprints and store their features as templates in the database. The identification system is used in real time when a personal authentication is demanded. A typical registration process involves palmprint capturing, feature extraction and on-line identification. The identification process involved palmprint capturing, feature extraction and best-match searching in the database.

2.3.1 Palmprint Capturing

Palmprint capturing is a key step in the whole identification process. The palmprint identification process starts with data capturing, which measures the inner surface of a palm and stores the palmprint as a digital image. The quality of original images has a direct impact on the efficiency of a system. Response time, image quality and price were the main factors we considered in designing a capture device.

Suppose that if we may get the same images from every person in different capture time, then everything is done. Everybody is different in some way - more or less. At any rate, the same images will present the certain person and we don't need any further check. Unfortunately, we don't have such a capture device and human beings don't act the same at different capture times. Therefore we need algorithms to classify the original samples so that under our defined measure system, samples from the same person would be similar enough and those from different persons may exhibit larger variances. This process involves palmprint registration, feature extraction and similarity measurement.

2.3.2 Palmprint Registration

Palmprint registration provides the foundation for feature extraction and matching. Palmprints may exhibit some degree of distortion (rotation, shift, transform, etc.) due to their being captured at different times, and under varying conditions, such as temperature, humidity, or brightness. To compare two palmprints, a common coordinate system is needed to determine which part of a palmprint is going to match with a similar part in another palmprint. After the coordinate system is determined, palmprints are moved and rotated to their expected position with certain direction – this is called palmprint alignment that is a crucial issue in palmprint recognition. Using this alignment operation, a certain palmprint sub-area can be obtained so that the corresponding palmprint feature extraction and matching can be carried out.

2.3.3 Feature Extraction/Representation

Feature extraction/representation is the kernel of palmprint recognition. Features depict the 'real' contents of a palmprint – effective features possess a large variance between different classes while maintaining high compactness within the class. Sometimes it is even possible to identify distinctive features before palmprint capturing. When we know clearly what features are to be used in identifying a person, an informed choice of capture device can enhance the demanded features. That is to say feature extraction may be conducted via both hardware and software.

In fact, several factors must be taken into account: feature definition, feature enhancement and feature representation. Feature definition is to determine the feature set and establish to what extent such a feature set is able to represent the samples of different groups. Feature enhancement aims at removing the noises and correcting the distortions thereafter the features are left. We may measure the effectiveness of feature enhancement algorithm by comparing the output of the algorithm with the predefined feature criteria. Feature representation concerns the feature dimensionality and matching cost.

2.3.4 Similarity Measurement

Similarity measurement plays an important role when feature extraction is not very satisfied. We are not always able to precisely extract the correct features – for example, extracting palmprint creases may not get all the genuine creases. But we still need to make decision whether two samples are from the same person. We may design various similarity measurement algorithms to calculate the distance between two images or two shapes. Here similarity measurement is associated with some classification criteria.

2.3.5 Database

A large database is the essential for palmprint recognition research. In general, palmprint recognition is a problem of classification – to classify samples of same palm into one class and assign samples of different palms to different classes. On one hand, we need a large quantity of samples to learn the feature distribution and measure the effectiveness of features in classification, on the other hand, we also demand enough testing data to measure the palmprint recognition algorithms and prove the around truth of the algorithms. With such a large database, we may perform various experiments to verify our algorithms.

2.4. Current Status of Palmprint Recognition Research

Palmprint identification research began five years ago [69] and is a relatively new area of biometrics. Research into palmprint identification is still in its initial stage.

In 1999, Zhang and Shu [69] presented their initial work on palmprint verification, which registered the palmprints by invariant feature points and used some masks to extract the line features from 40 samples (20 pairs) of inked palmprint images and then matched the end points of those lines. In 2001, Li, Zhang et al [70] introduced their texture-based palmprint feature extraction method, which is used in similar palmprints selection. Totally 200 inked palmprints from 100 palms (each palm provides 2 palmprints) are used in the experiment. In 2001, Li, Zhang, et al [71] presented their first attempt on online palmprint identification. They captured 1000 palmprints from 200 different palms (each palm 5 samples) with their self-designed capture device. The identification was based on both global and local features obtained by texture analysis. In 2001, Wei Shu and Zhang, et al [72] extended their work of [69] by adding palmprint classification. They classified the palmprints into six classes using different types of outside region pattern of core and delta points. 354 inked palmprints are involved in the classification algorithm testing. In 2002, Duta et al. [73] tried to extract the key points of creases on a palm without extracting the crease line to test about 30 inked palmprint images from three persons. In 2002, Li and Zhang introduced their Fourier Transform based on-line palmprint identification method [74], which a palmprint capture device was introduced and 2,500 live scan palmprint images from 500 different palms were collected. They translated the original images into the frequency domain in which the feature extraction and matching were conducted. Also in 2002, Jou, Li and Zhang [75] published their texture analysis and interesting point based offline palmprint identification method, which was an extension to the work described in [70]. In 2003, Han, Cheng and et al [76] introduced their research findings in palmprint identification. Their method was based on wavelet-based segmentation, Sobel edge detection and back-propagation neural network. The samples used in their experiment are palmprints captured by a scanner. In 2003, Li and Zhang and et al [77] introduced an offline palmprint alignment algorithm for automatic palmprint registration. Inked palmprint samples were used in the experiment. In 2003, Lu, Zhang and Wang presented their eigenpalm based feature extraction method [78]. K-L transform was used in their method and a high identification rate was reported on their database of online captured 3056 palmprints. Based on these palmprint research reports, we can conclude:

1) Palmprint recognition research is not investigated broadly yet though it is a promising method for personal identification;
2) Researchers are working on their own database and therefore their work is not easy to compare in terms of identification rate;
3) Palmprint sensor is not discussed sufficiently though is a very important part of personal identification.

2.5. Major Contributions of the Thesis

In the past five years, the work of the thesis involves almost all the aspects related to palmprint recognition, and proposed a series of algorithms to tackle the crucial problems.

2.5.1 Online Palmprint Capture Device

In order to capture palmprint images in real time, we designed and developed a palmprint capture device. When developing the device, we mainly considered three factors: response time, quality of image, and price. Some key parameters in adjusting the equipment include distance between camera and palm, light, brightness and contrast of the lens and resolution of the image.

2.5.2 Algorithms for Palmprint Alignment

For offline/inked palmprints, the author proposed to use two invariant features – outer boundary and end point of heart line to decide the coordinate system of a palmprint and shift and rotate the images to align the palmprints. For online captured palmprint images, the author proposed two positioning and segmentation methods – square based and circle based.

2.5.3 Algorithms for Palmprint Feature Extraction

The author first proposed a layered texture-based algorithm for palmprint feature extraction and matching. The searching of same palm sample of the input is carried out in a layered fashion. Then used Fourier Transform to convert the images to frequency domain and in which we perform feature extraction and matching. With this method, we achieved a similar identification rate as the layered texture based method. Crease extraction and matching method are also tested and this method is adopted together with the inscribe-circle-based segmentation method and obtained the acceptable recognition result.

2.5.4 Algorithms for Palmprint Matching

For layered texture based method and Fourier Transform based method, the features are represented by an array of integers and the similarity measurement of two feature sets is to calculate the linear coefficient of two integer arrays.

Crease features are stored as binary maps with all pixels on the edge points with number 1 and other pixels with number 0. The author proposed a novel bi-directional matching method to match two crease maps in two directions and this method surprisingly improved the identification rate.

2.5.5 Palmprint Database Setup

For offline palmprint recognition, we performed our experiments on a database (200 inked palmprint images from 100 palms) that set up by W. Shu, who together with D. Zhang published the first paper on palmprint verification.

For online palmprint identification, we organized several times of data capture activities in the campus and collected more than 10,000 palmprint images. Most users are undergraduate students of age 18-21 and a few are faculties of age 30-70. About 1/3 of them are female and 2/3 are male. All of our online palmprint experiments are conducted on this database. In case that the palmprint samples are collected in three-year period, our experiments are carried out only to partial of the database.

2.6. Conclusion

Palmprint recognition refers to identifying personal individuals by checking their unique body or behavioral characteristics. Law enforcement, access control systems and banks can integrate palmprint recognition technique as part of their security systems. Due to the difference of data capturing methods, palmprint recognition is classified into two categories – offline palmprint recognition and online palmprint recognition, which use different techniques. The general process of palmprint recognition involves data capturing, preprocessing, feature extraction and feature matching. Currently only a few researchers are working on palmprint recognition and the research on this topic is still in its infancy. In this thesis, the author gives some novel algorithms for offline and online palmprint recognition.

Chapter 3

Palmprint Definitions and Acquisition

This chapter gives the definitions of various palmprint features and introduces different types of palmprint acquisition methods. A novel design of online palmprint capture device is described in detail and the captured palmprint samples and their storage format in the database are given.

3.1. Palmprint Features

Feature extraction plays an important role in image identification and verification. Many features are exhibited in a palm. There are three principal lines caused by flexing hand and wrist in the palm, which are named as Heart line, Head line and Life line respectively [69]. Fig. 3-1 shows the layout of a palm, where a palm is divided into three regions, namely finger-root region (I), inside region (II) and outside region (III). The three marked curves, 1, 2 & 3 represent the three principal lines (heart line, head line and life line) respectively. The two endpoints, a and b, are determined by the intersections of life line (curve 3) and heart line (curve 1) with the both sides of a palm. Due to the stability of the principal lines, the locations of endpoints and their midpoint o in a palm remain unchanged in respect to rotation of the hand and the change of time. Therefore, these feature lines are regarded as reliable and stable features for distinguishing one person from another.

In addition to the principal lines and datum points (two endpoints and midpoint) as described above, many other features such as wrinkles and ridges are associated with a palmprint. The following lists these features (Fig. 3-2 shows palmprint's major lines; Fig. 3-3 shows different types of ridge patterns; Fig. 3-4 shows delta points on a palmprint):

- Geometry Features: width, length and area are the geometry features in accordance to a palm's shape.
- Principal Line Features: because of their stability and uniqueness, in distinguishing individuals.
- Wrinkle Features: thin and irregular lines and curves different from principal lines.
- Delta Point Feature: the center of a delta-like region in a palmprint, which is normally located in finger-root region and out side region.
- Minutiae Features: significant feature measurement of ridges existing in a palm.

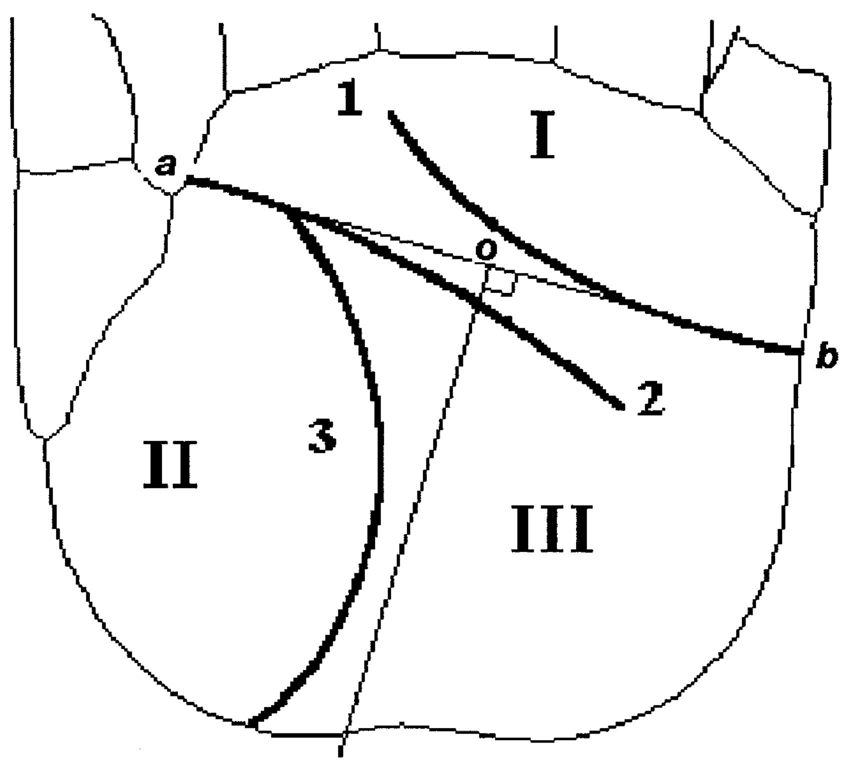


Fig. 3-1. The layout of a palmprint (1 – the heart line; 2- the head line; 3 – the health line. a is the end point of 3; b is the end point of 1; o is the mid-point of ab; I, II, III are three regions on the palm)

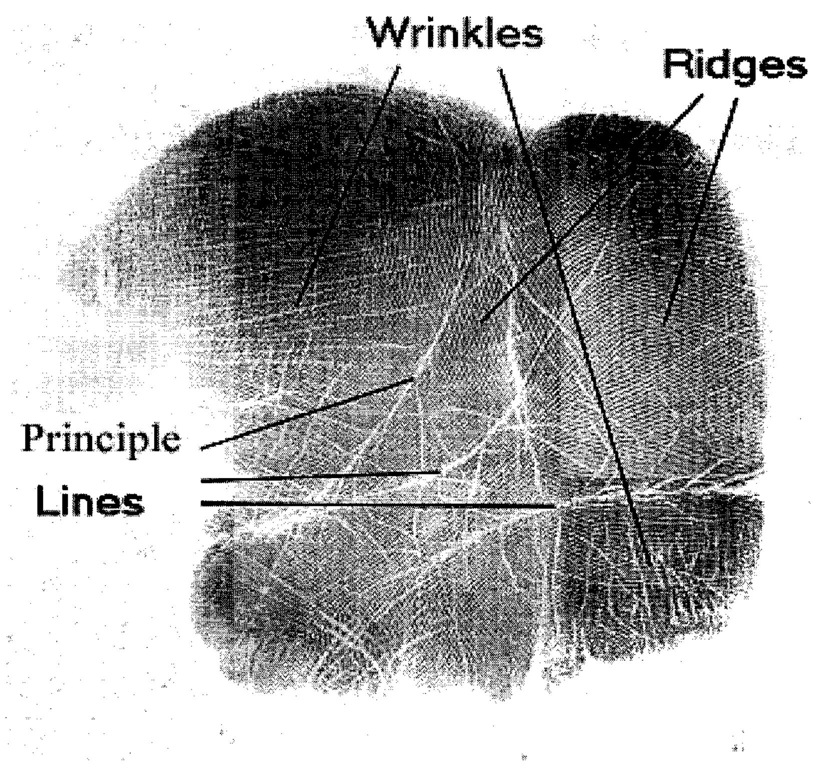


Fig. 3-2. The line patterns of a palmprint (principle refers to the three major lines on a palm, wrinkles are weaker than principle lines and ridges are the skin pattern similar to fingerprint)

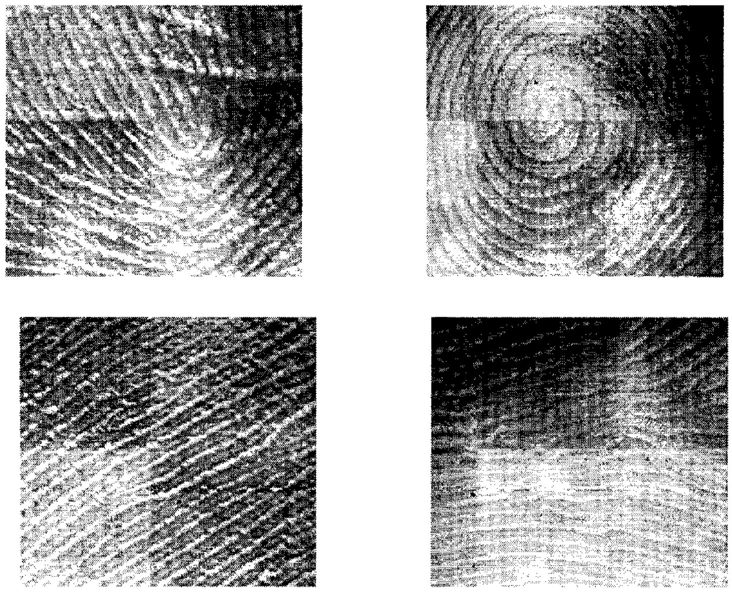


Fig. 3-3 Different ridge patterns on a plam

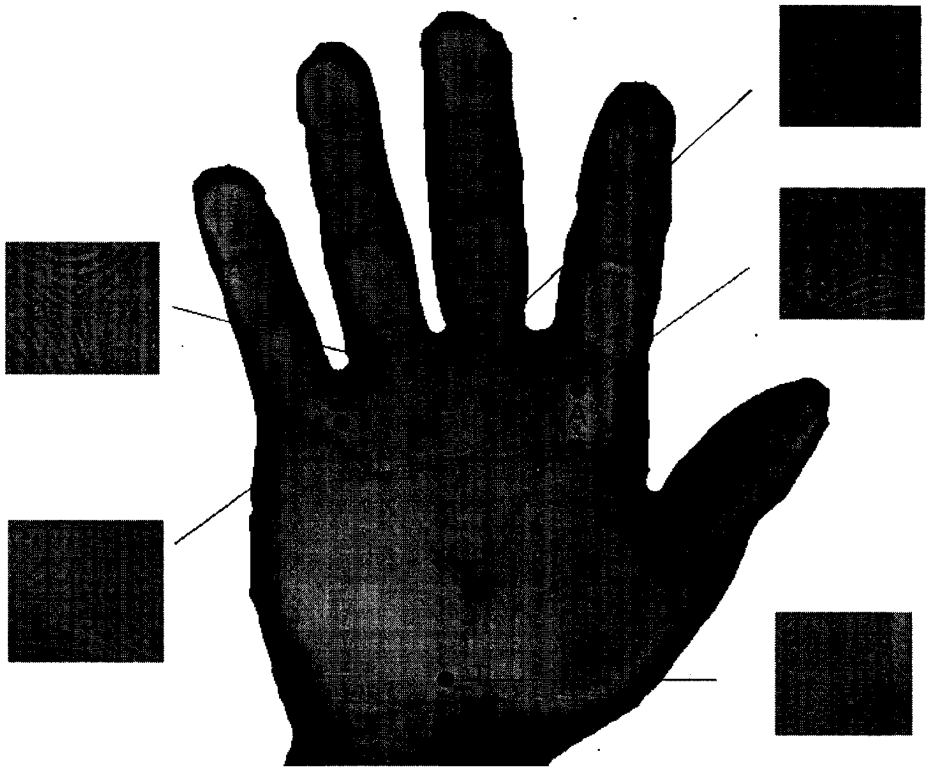


Fig. 3-4 Delta points on a palm (A, B, C, D, T are five delta points on the palm)

3.2. Palmprint capturing Methods

Generally there are two types of palmprint capture methods: online and offline. For offline capturing, there are two types: inner surface up and inner surface down. Online capturing methods include scanning, inner surface up photograph and inner surface down capturing.

3.2.1 Inner Surface Up Offline Capturing

Thoroughly ink the inner surface and then put a white paper on the palm – ensure the paper makes full contact with the inner surface, then scan the paper and get a digital palmprint image. The advantage of this method is that it captures all the details including the center of a palmprint. Fig. 3-5 gives the palmprint sample captured in this way.

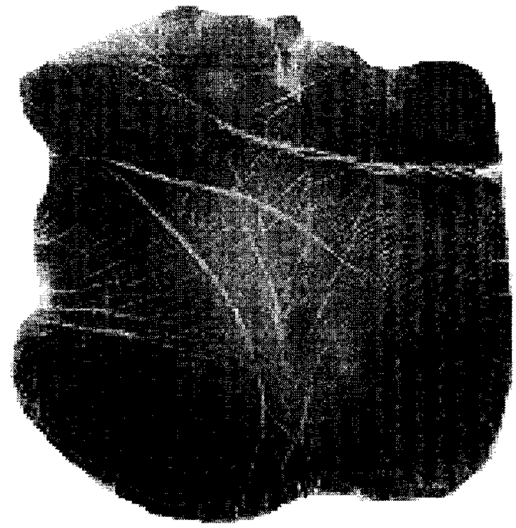


Fig. 3-5 Offline palmprint sample captured with the palm facing up

3.2.2 Inner Surface Down Offline Capturing

A box like rubber with top covered by ink is used in palmprint capturing. Put the palm on the rubber and get the inner surface fully contacted with ink. Put the inked palm on a white paper with the palm inner surface down. Then scan the paper with a scanner and get the digital image. Fig. 3-6 shows the palmprint sample captured with palm inner surface down.

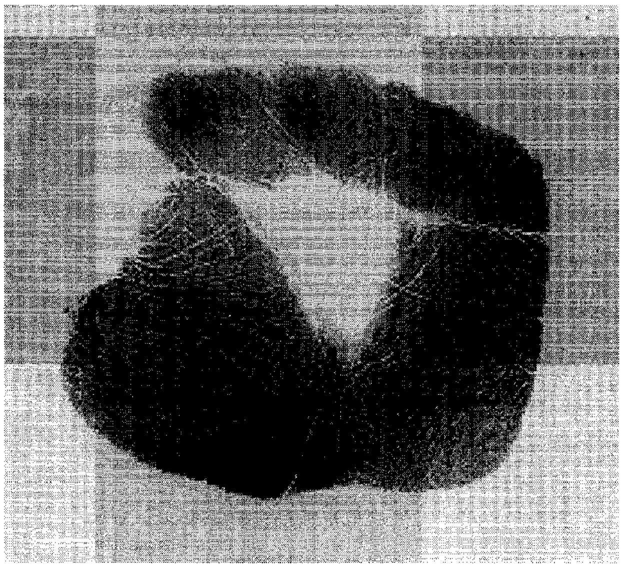


Fig. 3-6 An offline palmprint sample captured with the palm inner surface facing down

3.2.3 Inner Surface up Online Photographing

Use a camera to photograph palmprints. Fig. 3-7 is an image captured by a camera.

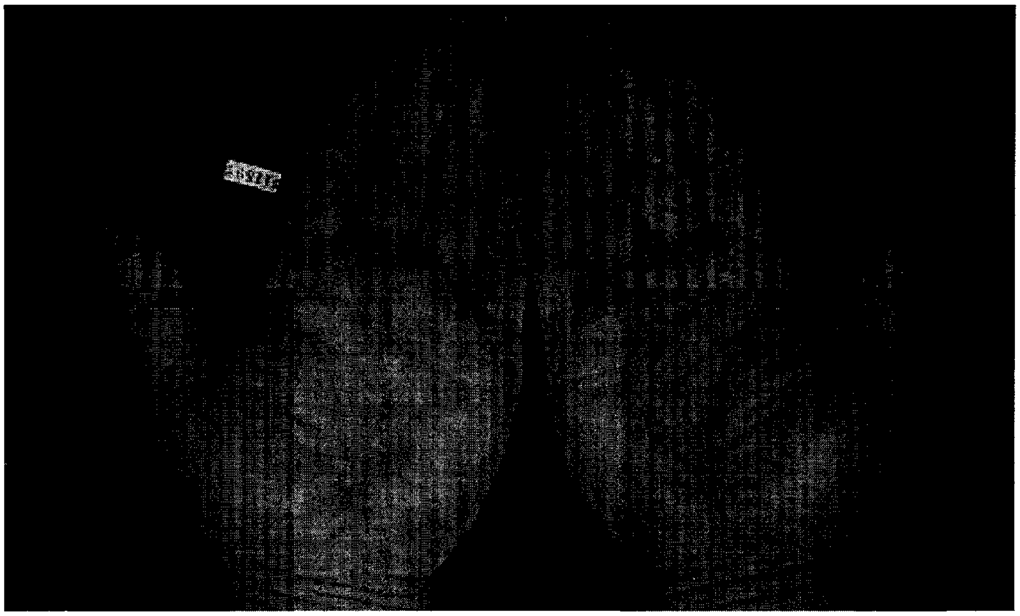


Fig. 3-7 Palmprint captured by a camera

3.2.4 Palmprint Scanning with a Standard Scanner

A simple way for online pamprint capturing is to use a scanner. Fig. 3-8 gives a sample captured in this way.

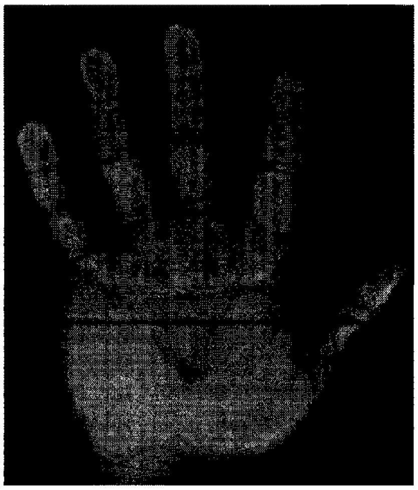


Fig. 3-8 Palmprint sample captured by a scanner

3.2.5 Inner Surface Down Online Capturing

Use a special palmprint capture device to capture the palmprints. Fig. 3-9 shows a sample captured by a special palmprint capture device.

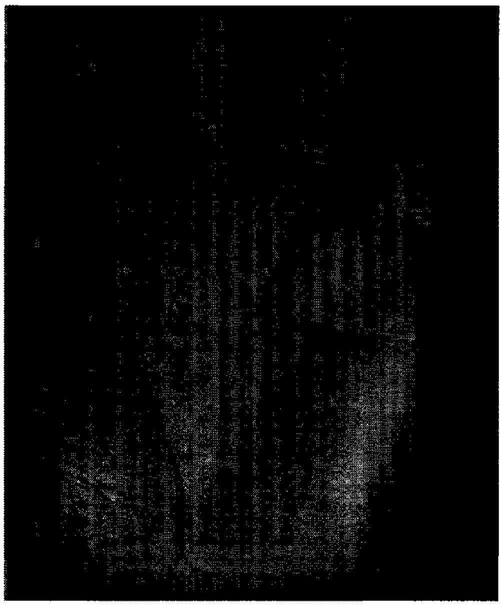


Fig. 3-9 A palmprint sample captured by an online capture device

3.3. Online Palmprint Capture Device

The author coperated with other researchers developed an online palmprint capture device. Three factors are put into consideration in the device designing – response time, image quality and price. Fig. 3-10 shows the appearance of the capture device and Fig. 3-11 shows the structure of the palmprint capture device, which consists of a CCD camera and a mirror. The CCD camera photographs a palmprint and directly transfers the image into a computer system. This novel design does not require participants to place their hands on a glass so that the inner surface of a palm retains its natural shape.

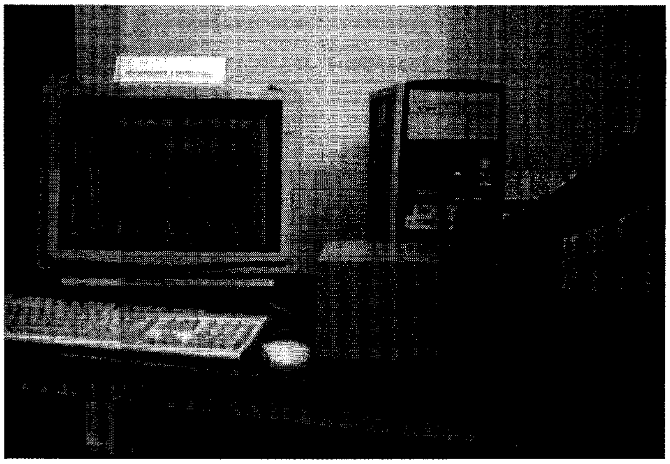


Fig. 3-10 Palmprint capturing with the proposed capture device

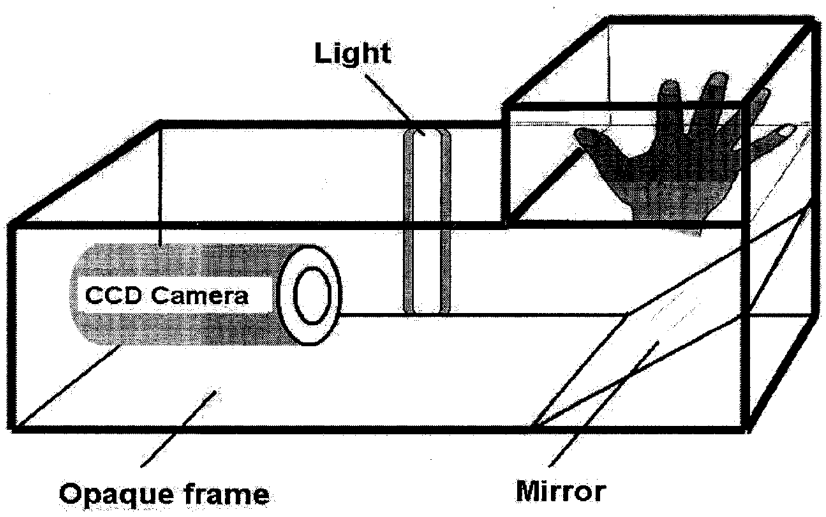


Fig. 3-11 The online palmprint capture device

3.4. Database

Online captured palmprints are stored in two tables, one to store the user information and the other to store the extracted palmprint features. The original palmprint images are stored separately in image files and the file names are stored in the database table. The table schemas are listed in Table 3-1 and Table 3-2.

Table 3-1 User Information Table:

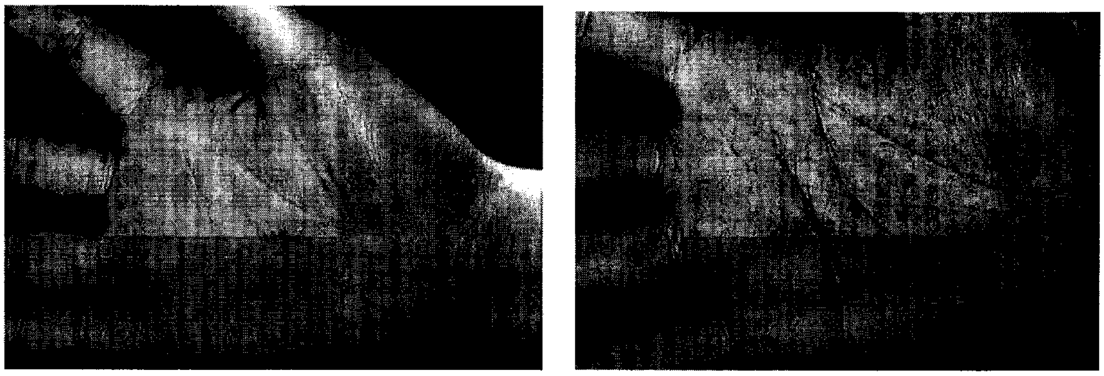
User ID	Sex	Age	Occupation	Image location
Stanley	Male	21-30	Teacher	D:\palm\001.jpg
Mary	Female	31-40	Student	D:\palm\002.jpg
May	Female	21-30	Marketing sales	D:\palm\003.jpg

Table 3-2 Feature Extraction Table:

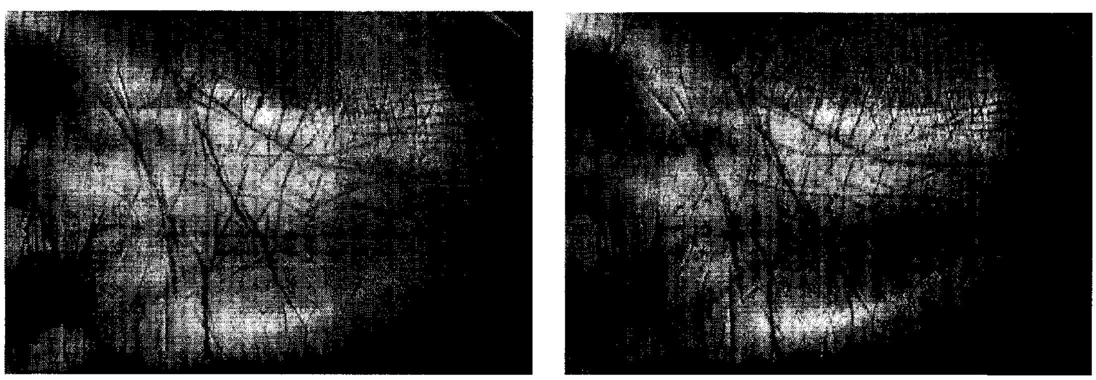
User ID	Record Number	Date Create	Date Update	Feature A	Feature B	Feature C	Feature D
Stanley	1	01/01/2000	Nil	123	5	1	92
Mary	2	01/02/2000	Nil	25	2	65	279
May	3	01/03/2000	02/03/2000	46	3	8	21

When collecting the samples, we asked each participant to put his/her right hand into the device 10 times and obtained 10 samples. We did not capture all 10 pictures at one time when the hand was in the capture device because we wanted to capture user's habit of putting his/her hand on a device. We observed that different participants did give out their hands differently: some had their fingers closed and some widely stretched, while others had them placed neither closed nor stretched. We organized several palmprint capture activities and about 1,000 students provided their palmprints with 10,000 images for the research. Usually in the 10 palmprints from a same hand, the first three were not good enough for palmprint identification because the user needed practice to get used to the capture device. The last three were not good either because the user had performed the same action for too many times or they got bored and tired and wanted to finish as soon as possible. In some cases, the hand became stiff and sweaty.

Several typical palmprint images captured by the capture device are given in Fig. 3-12 Fig. 3-12(a) shows two samples from different palms and Fig. 3-12(b) shows two samples from the same palm.



(a)



(b)

Fig. 3-12 Typical palmprint samples in our database (a) two samples from different palms. (b) two samples from the same palm.

3.5. Conclusion

Palmprint features include priciple lines, wrinkles, minutiae and geometry parameters. Both offline and online methods are used in capturing a palmprint image. Offline capturing is to get the inner surface of a palm inked and get the inked palm on a paper, and then the palmprint on the paper is scanned into a computer. Online capturing is basically using a camera to photograph the palmprint and transfer the image into a computer at the capturing time. In an online palmprint capture device, a CCD camera is put in a special box with light inside. The special box is controlling the light at capturing time and the position between the camera lens and the palm inner surface. Palmprint images are stored in a database together with their extracted features for future use.

Chapter 4

Offline Palmprint Recognition

Offline palmprint recognition refers to identify personal individuals by checking their offline palmprint images. This chapter introduces the key issues of offline palmprint recognition and analyzed the difficulties of offline palmprint recognition research. Several algorithms – offline palmprint alignment, texture energy based global feature extraction and matching, interesting point based local feature extraction and matching, layered searching algorithms are described in detail. Experiments are designed and performed to test the effectiveness of the proposed algorithms and experimental results are listed and analyzed.

4.1. Introduction

In order to tell whether two palmprint samples are from the same palm source, four key issues must be addressed – alignment, feature extraction, feature matching and making decision. Palmprint alignment serves to make all the palmprints locate in their images at the same location with the same direction. Feature extraction is the process to extract the unique features from each palmprint and represent the features with smaller storage space than the original image. Feature matching describes how to measure the similarity of two feature sets and gives the distance between two feature sets. In making decision, a strategy must be predefined that under which condition, we can draw a conclusion that two palmprints are from the same palm source.

In order to test the performance of various algorithms for palmprint recognition, a database must be set up. Till now there is no large offline palmprint database for public access and the process of capturing offline palmprint images is not as convenient as online images. Therefore, the progress of offline palmprint recognition is not as fast as online palmprint recognition, though it is started earlier than online research. In this chapter, all the experiments are performed on a database of 200 palmprints.

4.2. Offline Palmprint Alignment

4.2.1 Literature Review of Image Alignment

Image alignment (also known as registration), which refers to establishing a common frame of reference for a set of images, is widely investigated in various contexts [79]. A framework for aligning images without needing to establish explicit feature correspondences was proposed in [80]. Two contour-based methods, which use region boundaries and other strong edges as matching primitives, were also presented [81]. In [82] and [83], sequential transforms were used to align two images. However, most proposed methods are focused on applications in multi sensor imaging area and aiming at solving problems like how to align one object captured from more than one sensor. Usually objects in different images have the similar contour shapes. For palmprint identification, the problem is somewhat different because palmprints not only have different qualities but also have different contour shapes. The existing alignment approaches are not suitable to solve our problem. As a result, a sound and reasonable palmprint coordinate system and an effective palmprint alignment algorithm are needed. Since the captured palmprints may have different locations with various directions, the first step of alignment will be to detect some key features on palmprints. Then, palmprints are rotated into the same direction and shifted into the expected location according to these key features.

4.2.2 Definition of the Coordinate System on a Palmprint

The objective of palmprint alignment is to put all the palmprints into the same location in their images. Here 'same location' means that the end point of Heart Line (o in Fig. 4-1) on each palmprint is located at a fixed location at its image and the outer boundary (L in Fig. 4.1) is vertical in the image. The palmprints that are not at this location must be moved and rotated automatically using Algorithm 4-1.

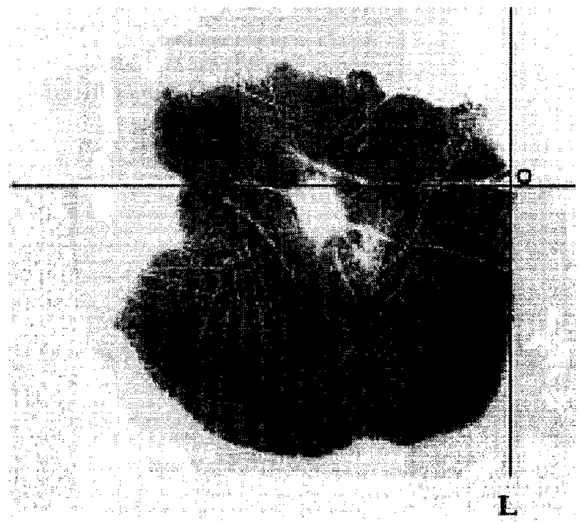


Fig. 4-1 A two-dimension orthogonal palmprint coordinate system using two palmprint features - outer boundary direction and end point of principle line.

The outside boundary of an offline palmprint is usually clear and stable and can be described by a line. Therefore can serve as the Y-axis of the coordinate system. The intersect point between the outer boundary and Heart line is relatively easer to extracted than other point features and it is defined as the origin of the orthogonal coordinate system, as shown in Fig. 4-1. Using this coordinate system, we may move all the palmprints to a certain position with the same direction in their images therefore different palmprints can be compared.

4.2.3 The Proposed Offline Palmprint Alignment Algorithm

Let $I_{N\times N}$ denotes the original $N \times N$ offline palmprint image and $I_{N\times N}$ '' denotes the image after alignment. The following algorithms describe the aligning process:

Algorithm 4-1: Offline Palmprint Alignment :

Input: Original Image - $I_{N\times N}$

Output: Image after alignment - $I_{N\times N}$''

- Step 1: determine the outer boundary of $I_{N\times N}$, L: $y = ax + b$, using ***Algorithm 4-2***,
- Step 1: rotate $I_{N\times N}$ to make L vertical and get image $I_{N\times N}$', using ***Algorithm 4-3***,
- Step 2: determine the end point of Heart Line on $I_{N\times N}$', O: (x_0, y_0), using ***Algorithm 4-4***,
- Step 3: shift $I_{N\times N}$' to move O to a fixed position and get $I_{N\times N}$'', using ***Algorithm 4-5.***

Algorithm 4-2: Outer Boundary Determination :

Input: Original Image - $I_{N\times N}$

Output: Outer Boundary Line - L: $y = ax + b$

- Step 1: turn $I_{N\times N}$ (Fig. 4-2(a)) into a binary map $B_{N\times N}$ (Fig. 4-2(b)) using the following formula:

$$B_{N\times N}(i,j) = \begin{cases} 255 & I_{N\times N}(i,j) > T \\ 0 & I_{N\times N}(i,j) \le T \end{cases} \tag{4-1}$$

  where T is a threshold to differentiate palmprint and background, $B_{N\times N}(i,j)$ is a point on the binary map and $I_{N\times N}(i,j)$ is the corresponding point on the original image,

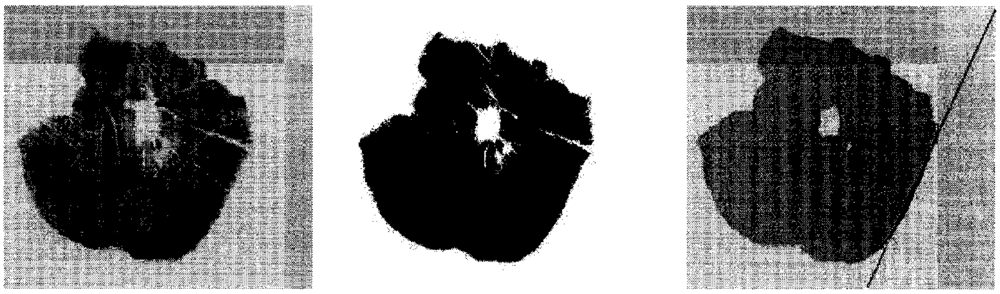
- Step 2: perform boundary tracing on $B_{N\times N}$ to get all the pixels on the outer boundary of the palm, $(x_i, y_i)(i = 1,2,..,n)$. A boundary tracing algorithm can be found in [100].
- Step 3: calculate a and b in L: $y = ax + b$ (Fig. 4-2(c)) with the following formula:

$$a = \bar{y} - b\bar{x} \quad , \quad b = \frac{l_{xy}}{l_{xx}} \tag{4-2}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \ , \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i \tag{4-3}$$

$$l_{xx} = \sum_{i=1}^{n}(x_i - \bar{x})^2 \ , \ l_{xy} = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}) \tag{4-4}$$

where $(x_i, y_i)(i = 1,2,..,n)$ are points on the edge of palmprint outer boundary.



(a) (b) (c)

Fig. 4-2 Main process for Y-axis determination (a) The original image (b) The binary image of original image (c) The boundary and direction determined with the proposed method

Fig. 4-2 illustrates the Y-axis determined by the given method. Fig. 4-2(a) is the original image and Fig. 4-2(b) is the binary image of Fig. 4-2(a) on which boundary tracing is performed. Fig. 4-2(c) shows the outer boundary and a line, which describes the palmprint's direction. Such a line thereafter is used in the palmprint rotation.

Algorithm 4-3: Palmprint Image Rotation :

Input: Original Image - $I_{N\times N}$ and outer boundary line L: $y = ax + b$

Output: Rotated image - $I_{N\times N}$' (rotation is around the center of $I_{N\times N}$)

- Step 1: calculate rotation degree θ as follows:

$$\theta = -(\arctan(a) - \frac{\pi}{2}) \tag{4-5}$$

- Step 2: rotate the original image $I_{N\times N}$ as follows:

$$I_{N\times N}'(i, j) = \begin{cases} 255 & i', j'\ areOutOfTheBoundaryOfI_{N\times N} \\ I_{N\times N}(i', j') & i', j'\ areWithinTheBoundaryOfI_{N\times N} \end{cases} \tag{4-6}$$

where,

$$i' = \cos\theta \times (i - \frac{N}{2}) + \sin\theta * (j - \frac{N}{2}) + \frac{N}{2} \tag{4-7}$$

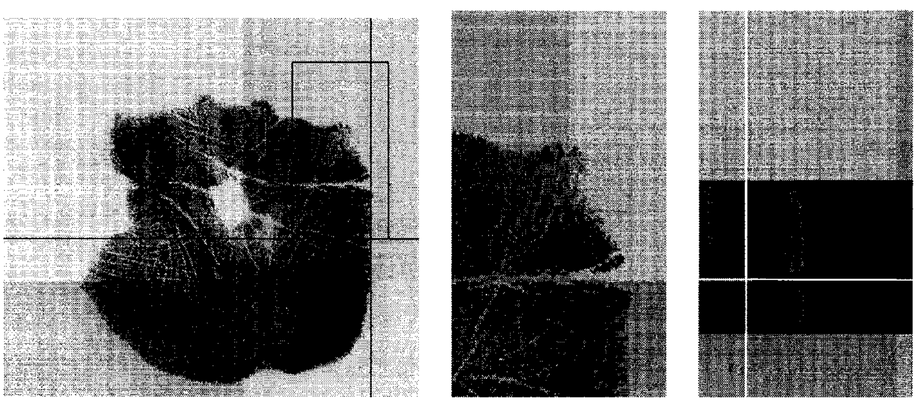
$$j' = -\sin\theta \times (x - \frac{N}{2}) + \cos\theta \times (y - \frac{N}{2}) + \frac{N}{2} \quad (4\text{-}8)$$

Algorithm 4-4: Determination of End Point of Heart Line :

Input: Rotated Image - $I_{N\times N}$'

Output: End point of Heart Line on $I_{N\times N}$' - O: (x_0, y_0),

- Step 1: extract a sub image which includes the end point from the upper right region of $I_{N\times N}$' (Fig. 4-3(a)) to get a rectangle shape image (Fig. 4-3(b)), the position and size of the rectangle is fixed to all palmprints and it is decided according to the observation to palmprint images,
- Step2: perform a horizontal projection of the gray level of the extract sub image to find the end point of Heart Line (Fig. 4-3(c)). Particularly, y_0 is determined by this projection and x_0 is already known due to it is on the outer boundary of $I_{N\times N}$'.



(a) (b) (c)

Fig. 4-3 Illustration of palmprint origin determination.

Fig. 4-3 shows the process of finding end point of Heart Line. Note that Fig. 4-3(a) is the rotated palmprint image and the rectangle on upper right corner is used to extract a sub image on which the origin of the palmprint coordination system is determined. The sub image extracted from Fig. 4-3(a) is enlarged in Fig. 4-3(b). As a horizontal projection map of

Fig. 4-3(b), we can get the largest energy on the intersection between the heart line and the outer boundary in Fig. 4-3(c).

Algorithm 4-5: Palmprint Image Shifting:

Input: Rotated Image - $I_{N\times N}$' and the end point of Heart Line O: (x_0, y_0)

Output: Image after alignment - $I_{N\times N}$''

- Step 1: shift $I_{N\times N}$' as follows:

$$I_{N\times N}''(i,j)=\begin{cases}255 & i',j'\,areOutOfTheBoundaryOfI_{N\times N}' \\ I_{N\times N}'(i',j') & i',j'\,areWithinTheBoundaryOfI_{N\times N}'\end{cases} \qquad (4\text{-}9)$$

where,

$$i'=i+x_0-X,\, j'=j+y_0-Y \qquad (4\text{-}10)$$

(X,Y) is a predefined position that the end point of Heart Line should be.

4.2.4 Experimental results

We conducted two experiments to verify the effectiveness of outer boundary determination and end point of Heart Line algorithms separately. Two hundred palmprint images (125 dpi, 432×432 pixels) from 100 palms are used in the experiments.

Experiment 4-1: Test of the outer boundary determination algorithm

- Step 1: perform Algorithm 4-2 to the two hundreds palmprint images to get the outer boundary line automatically. Fig. 4-4 shows some examples.

- Step 2: look at each palmprint, manually check whether the outer boundary line of each palmprint is determined correctly and record the number of images with acceptable outer boundary line.

The experimental result is that 192 out of 200 palmprints have their outer boundary lines determined acceptable and outer boundary lines in 8 images are identified incorrectly. The reason for the mistake is that some palmprints have round shape outer boundary other than a straight one. Fig. 4-5 shows the round shape boundary palmprint.

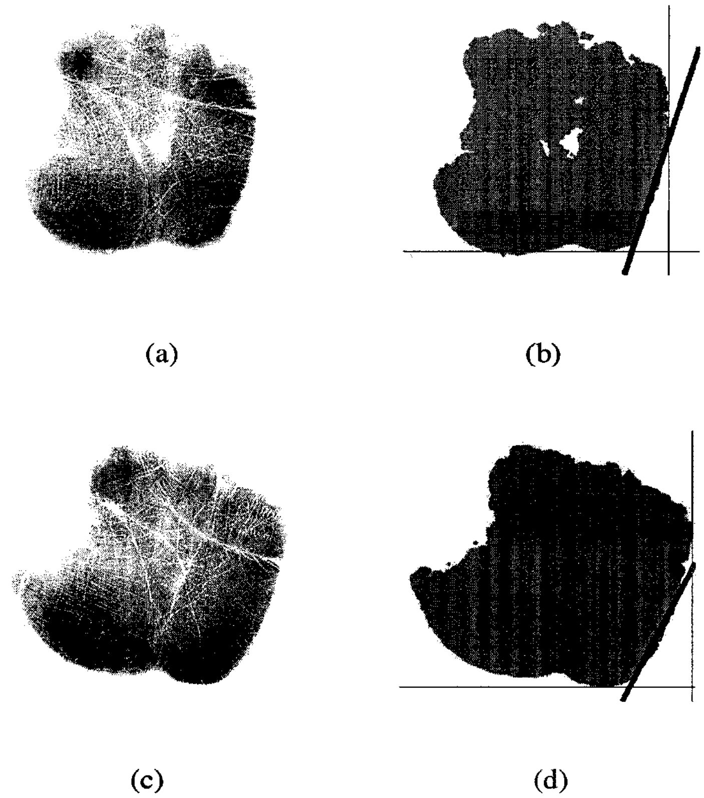


Fig. 4-4 Samples palmprints with outer boundary line determined. (a) (c) are two palmprint images and (b) (d) show their outer boundary lines respectively

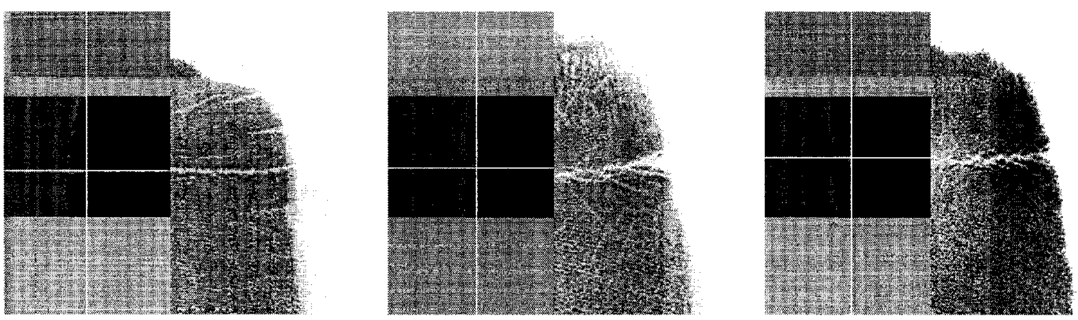
Fig. 4-5 Sample palmprint with round shape outer boundary.

- **Experiment 4-2: Test of the end point of Heart Line determination algorithm**

- Step 1: perform Algorithm 4-3 and 4-4 to the 192 pamprint images to get the end point of Heart Line automatically. Fig. 4-6 shows some successful examples.

- Step 2: look at each palmprint, manually check whether the end point of Heart Line of each palmprint is determined correctly and record the number of images with acceptable end point of Heart Line.

The experimental result is that 180 out of 192 palmprints have their end point of Heart Line determined acceptable and end point of Heart Line in 12 images are identified incorrectly. The reason for the mistakes is that some palmprints have not clear lines at the upper right region Fig. 4-7 shows a palmprint sample with incorrectly identified endpoint of Heart Line.



(a) (b) (c) (d) (e) (f)

Fig. 4-6 Sample palmprints with successfully identified end point of Heart Line.(b)(d)(f)are the upper right regions of three palmprints and horizontal white lines on (a)(c)(e) are the position of end point of Heart Lines on (b)(d)(f) respectively.

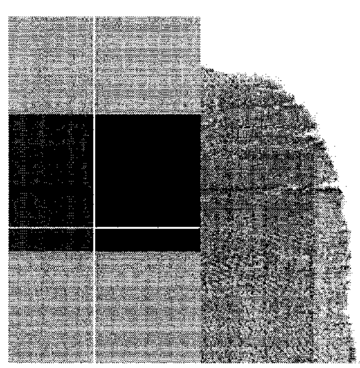
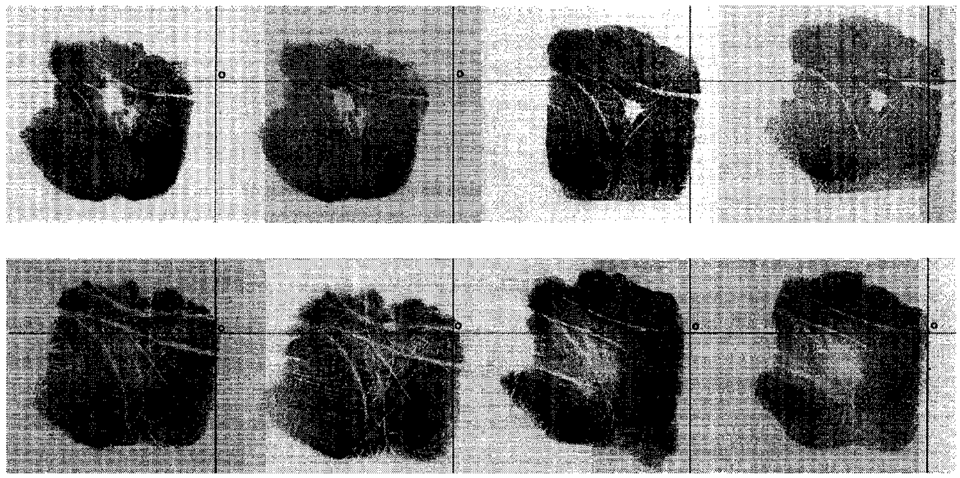
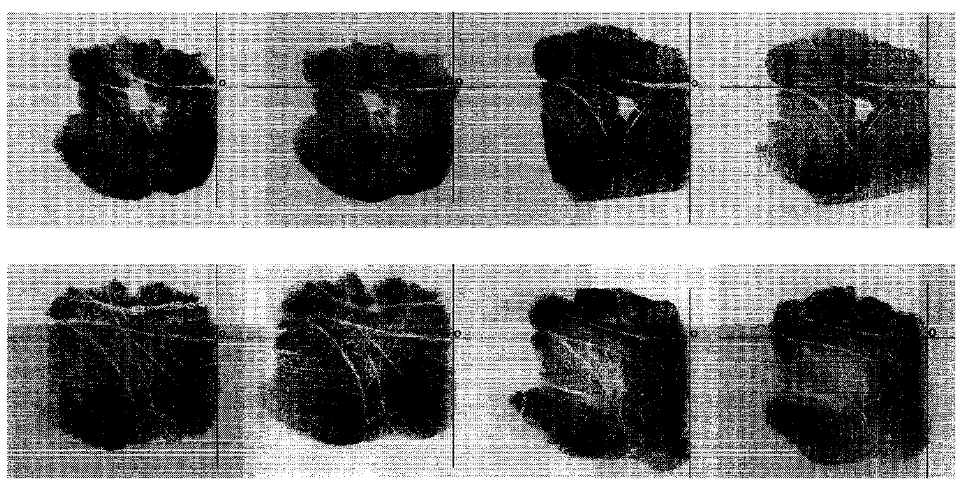


Fig. 4-7 Sample palmprint with incorrectly identified endpoint of Heart Line.

The proposed alignment method can automatically put all the palmprints into close if not the same location and direction, which are acceptable in palmprint identification. Some typical examples before and after the automatic alignment are shown in Fig. 4-8.



(a)



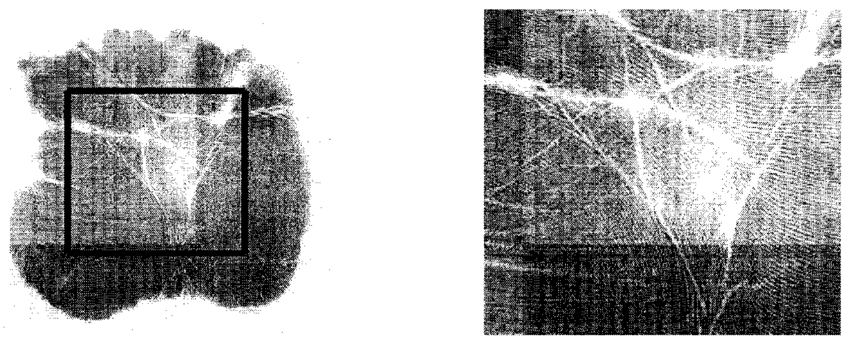
(b)

Fig. 4-8 Experimental results of a group of palmprints before and after alignment.

(a) palmprints before alignment, (b) palmprints after alignment

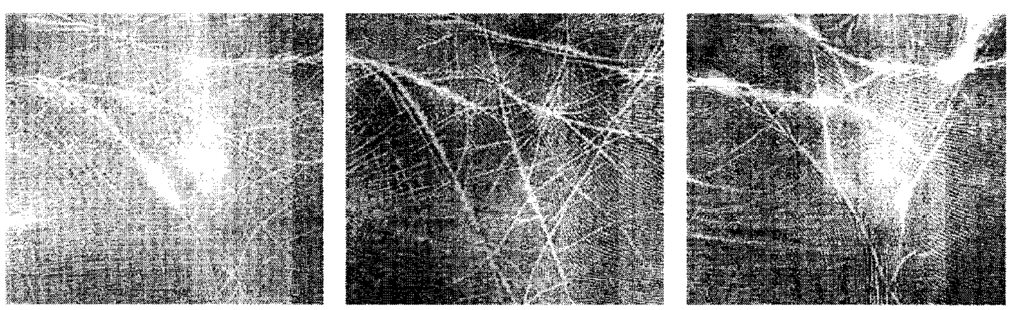
4.3. Aligned Palmprint Processing before Feature Extraction

The alignment process makes all the palmprints locate on the same position at their images. Therefore we may use a fixed window to extract a sub image from each palmprint. Fig. 4-9 shows a palmprint sample and its sub image extracted using a fixed window in the center of the image.

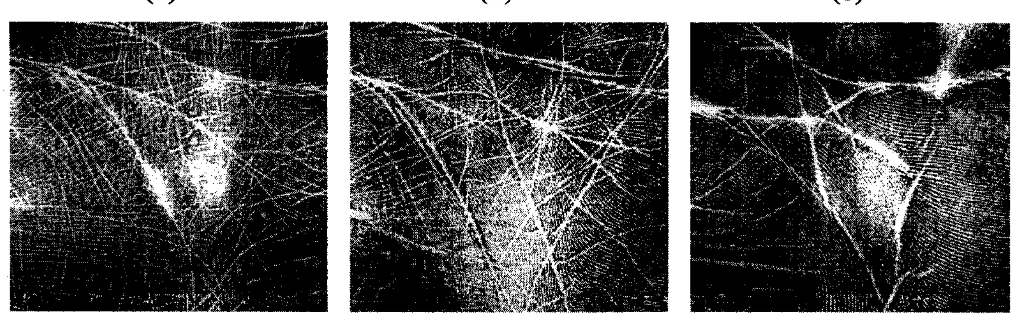


(a) (b)

Fig. 4-9 A palmprint image and its central part sub image; (a) is the original image and the black square is its central part; (b) is the extracted central part image which will be used in feature extraction and matching



(a) (b) (c)



(d) (e) (f)

Fig. 4-10 Palmprint sub image samples and their respective images after histogram equalization.; (a)(b)(c) are three sub palmprint images and (d)(e)(f) are the results of histogram equalization processing of (a)(b)(c) respectively.

The central part sub images are used in feature extraction and matching. Fig. 4-10(a)(b)(c) lists three sub image samples. The qualities of different palmprint samples are different, which makes it difficult for automatic feature extraction. Here we adopt histogram equalization algorithm to make the palmprint wrinkles look clearer. Fig. 4-10 (d)(e)(f) are the results of histogram equalization of Fig. 4-10(a)(b)(c) respectively.

4.4. Texture-based Global Feature Extraction and Matching

Palmprints consist of large numbers of thin and short line segments represented in forms of wrinkles and ridges. Such patterns can be well characterized by texture. Therefore the global texture energy is introduced to define the global features of a palmprint. Though can not serve to precisely determine whether two palmprints are from the same palm, global features can be used to fast generate a small candidate set for further matching of local features.

4.4.1 Texture Feature Measurement

We calculate the global texture energy and let it directly function as global features. Such a statistical approach is notable for its computational simplicity [88]. Let $I_{M\times N}$ denotes a palmprint image with size of $M \times N$, and $I(i,j)$ denotes a point on image $I_{M\times N}$. Global texture energy of $I_{M\times N}$ is denoted as GTE_I. Then GTE_I is defined as:

$$GTE_I = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} E(i,j)}{M \times N} \tag{4-11}$$

$$E(i,j) = \frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n} | F(k,l) | \tag{4-12}$$

$$F(i,j) = A(i,j) * I(i,j) \tag{4-13}$$

$$= \sum_{k=-a}^{a}\sum_{l=-a}^{a} A(k,l) I(i+k, j+l) \tag{4-14}$$

where $A(i, j)$ is a zero sum mask with size $2a+1$ by $2a+1$, in this case, the size of the mask $A(i,j)$ is 5×5 and * denotes 2D convolution.. $E(i,j)$ is calculated through $F(i,j)$ within a $2n+1$ by $2n+1$ window at point (i,j) , in this case, it is 15×15. Here we use four masks to capture the global palmprint texture features which are more sensitive to horizontal lines, vertical lines, 45° lines and -45° lines respectively. Fig. 4-11 lists the four masks. Such a texture energy measurement for global palmprint feature extraction has the following characteristics:

- Insensitive to noise,
- Insensitive to shift changes,
- Easy to compute,
- High convergence within the group and good dispersion between groups.

$$\begin{array}{ccccc} -1 & -2 & -4 & -2 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 4 & 8 & 4 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ -1 & -2 & -4 & -2 & -1 \end{array} \qquad \begin{array}{ccccc} -1 & 0 & 2 & 0 & -1 \\ -2 & 0 & 4 & 0 & -2 \\ -4 & 0 & 8 & 0 & -4 \\ -2 & 0 & 4 & 0 & -2 \\ -1 & 0 & 2 & 0 & -1 \end{array}$$

Horizontal Line Vertical Line

$$\begin{array}{ccccc} 0 & -1 & -4 & 0 & 2 \\ -1 & -6 & 0 & 8 & 0 \\ -4 & 0 & 12 & 0 & -4 \\ 0 & 8 & 0 & -6 & -1 \\ 2 & 0 & -4 & -1 & 0 \end{array} \qquad \begin{array}{ccccc} 2 & 0 & -4 & -1 & 0 \\ 0 & 8 & 0 & -6 & -1 \\ -4 & 0 & 12 & 0 & -4 \\ -1 & -6 & 0 & 8 & 0 \\ 0 & -1 & -4 & 0 & 2 \end{array}$$

45° Line -45° Line

Fig. 4-11. The four masks used in palmprint global texture feature extraction

4.4.2 Candidate Set Generation by Global Feature Matching

The global texture energy exhibits high similarity of inner-palm samples and good dispersion of inter-palm ones. Fig. 4-12 shows four palmprint samples from four different individuals with distinctive texture features and Fig. 4-13 demonstrates the distribution of global palmprint texture energy measurements.

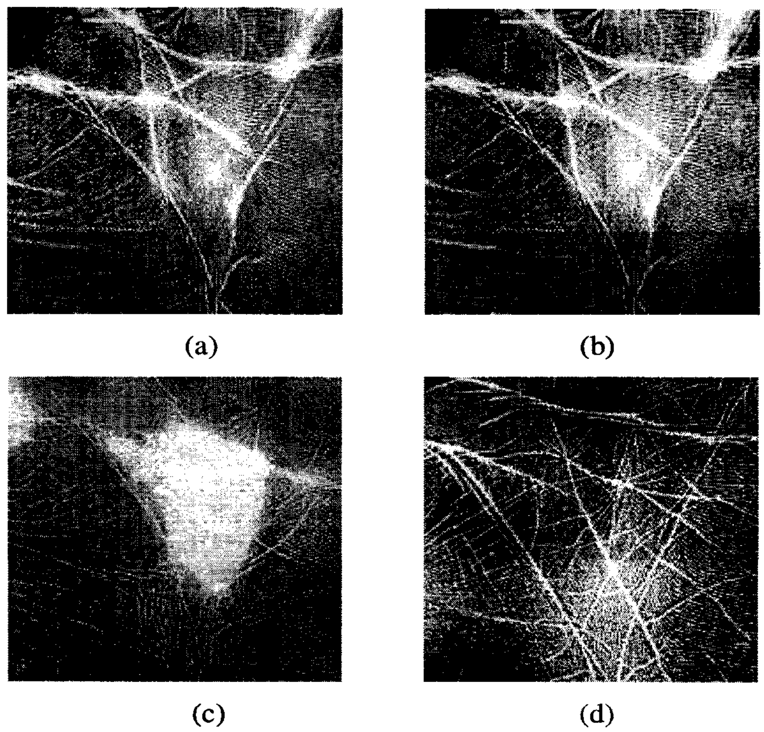


Fig. 4-12 Samples of different palmprint patterns with distinctive texture features (a) strong principle lines (b) full of wrinkles (c) less wrinkles (d) strong wrinkles

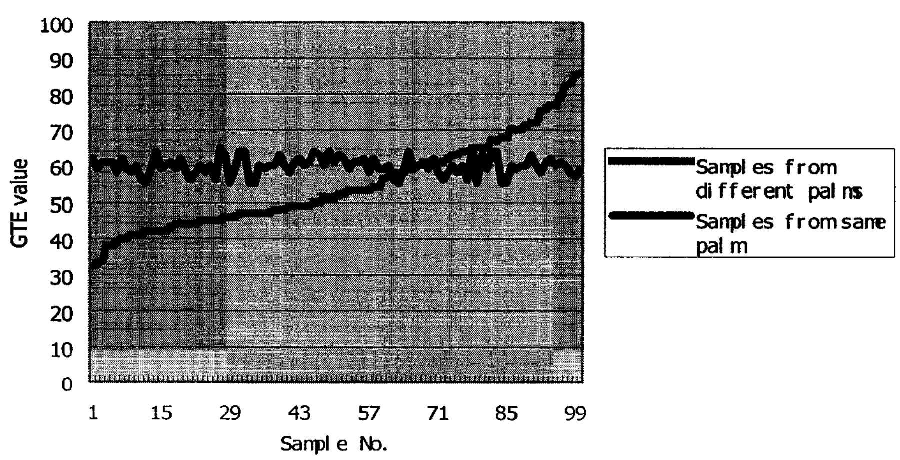


Fig. 4-13 The comparison of palmprint GTE distribution: inter-palm dispersion vs. intra-palm convergence

The global features are used in eliminating those candidates with large GTE differences and generating a list of the very similar candidates with very close GTEs. The following summarizes the main steps for implementation:

Algorithm 4-6 Candidate Selection by Global Texture Energy

- Step 1: Convolve the sample palmprint image I_{sample} with the four masks A_i, $i=1,2,3,4$ and obtain the corresponding global texture energy $GTE_{sample}(i)$, $i=1,2,3,4$.
- Step 2: Compare the sample with each candidate in the database in terms of GTE and calculate their difference d, where d is given by:

$$d = \sum_{i=1}^{4} | GTE_{sample}(i) - GTE_{sample}(i) | \tag{4-15}$$

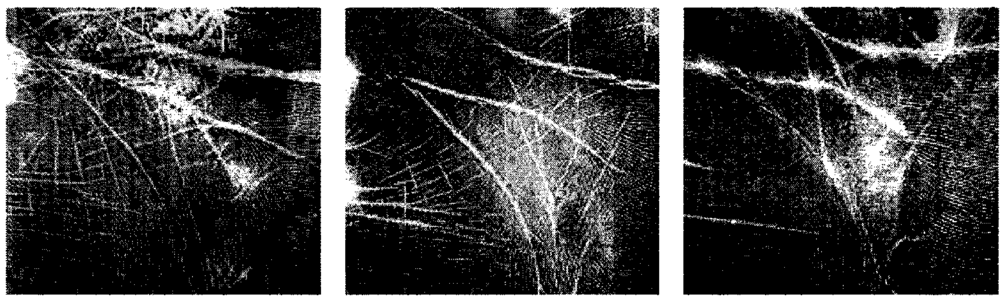
- Step 3: If d is smaller than the pre-defined threshold value, this candidate is added to the list for further matching.
- Step 4: Go to Step 2 and repeat the same procedure until all of the candidates are considered.
- Step 5: Provide the final list of candidates to guide the search by local features at fine level.

4.5. Interesting-point-based Local Feature Extraction and Matching

Although different individuals have different palmprint patterns, some of these patterns are so similar that it is very difficult, if at all possible, to classify them based on the global texture features alone. Fig. 4-14 shows samples of similar palmprint patterns from different groups. Therefore we need to extract local feature for matching at fine level. Unlike the traditional image matching methods, which are based on the detection of edge points, we proposed to detect interesting points in textured images to achieve high performance.

Sample A-1 Sample A-2 Sample A-3

(a)



Sample B-1 Sample B-2 Sample B-3

(b)

Fig. 4-14 Samples of the similar palmprint patterns from different groups (a) Group A: Similar palmprint samples (b) Group B: Similar palmprint samples

4.5.1 Feature Points -- Interesting Points vs. Edge Points

Most matching algorithms are based on binary images to identify the interested object(s). Therefore, the original image, either grayscale or color images, should be converted into a binary image. Traditional methods that convert an original image into a binary image rely on edge detection. Even though edge detection has been successfully used for many years mostly due to its simplicity, it has some problems, which prevent it from being applied on a real-time image matching scheme, such as

- It is susceptible to noise in the image.
- Feature points may not be well distributed.
- It produces a large number of feature points for an image, many of the points however are redundant.

The redundant information limits the possible speedup in subsequent operations since the time consumption of a matching algorithm, such as Borgefors' hierarchical chamfer matching [91], and the Hausdorff distance [92], is directly related to the number of feature points used in matching. Therefore, it is desirable to use an algorithm which extracts only those feature points that

- Are representative and distinctive, such as corners, and without redundancy, and
- Are robust to "noise" .

This has prompted the research in [93] to use interesting point detectors rather than edge detectors to extract feature points from a given image for matching. The previous research [93] indicates that the Plessey operator is superior to the Moravec operator according to the criteria set above. Hence, the Plessey operator is chosen as the interesting point detector in this work. Fig. 4-15 shows the comparison of edge points and interesting points in representing the original image. Fig. 4-15(a) is a histogram equalized image of size 232×232 ranging from 0 - 255 in gray scale, Fig. 4-15(b) shows edge points detected by Prewitt operator and Fig. 4-15(c) shows interesting points detected by Plessey operator.

(a) orignal (b) edge detection (c) interesting points

Fig. 4-15 Comparison of palmprint feature point detection: edge vs. interesting points

The algorithm of interesting point detection using Plessey operator is given below:

Algorithm 4-6: Interesting Point Detection Using Plessey Operator

Input: The palmprint image $I_{N\times N}$ on which the interesting points are detected

Output: The map of interesting points detected $I_{N\times N}$''

- Step 1: For each pixel on $I_{N\times N}$ - $I(i, j)$, calculate $G_x(i, j)$ and $G_y(i, j)$ using the following formula:

$$G_x(i, j) = \sum_{k=-1}^{1} - I(i+k, j-1) + \sum_{k=-1}^{1} I(i+k, j+1) \tag{4-16}$$

$$G_y(i, j) = \sum_{k=-1}^{1} - I(i+k, j+1) + \sum_{k=-1}^{1} I(i+k, j-1) \tag{4-17}$$

- Step 2: Calculate template matrix $I_{N\times N}$'(i, j) using the following formula:

$$I'(i, j) = \frac{G_x{}^2 + G_y{}^2}{2 \times G_x G_y} \times k \tag{4-18}$$

where k is a fix value which can be set according to the quality of images and here it takes a value of 100.

- Step3: Change the $I_{N\times N}$'(i, j) to a binary map which is the interesting point map $I_{N\times N}$'' using a threshold:

$$I''(i, j) = \begin{cases} 1 & I'(i, j) > threshold \\ 0 & I'(i, j) \le threshold \end{cases} \tag{4-19}$$

where *threshold* is determined by statistical method.

4.5.2 Distance Measurement for Interesting-point-based Local Features

Given two images, a matching algorithm determines the location of the template image on the target image and places a value on their similarity at this point. The value determines the degree of similarity. Based on Huttenlocker *et al* [92], we use a Hausdorff distance algorithm to search for portions, or partial hidden objects. This feature also allows us to partition the target image into a number of sub images, and then carry out the matching process simultaneously on these sub images in order to accelerate the process. Instead of using edge points, we use interesting points as a basis for computing the Hausdorff distance [93]. The objective is to reduce the computation required for a reliable match.

The hierarchical guided matching scheme was first introduced by Borgefors [91] in order to reduce the computation cost required to match two images. We extended it by using interesting points rather than edge points in a similar fashion, i.e., an interesting point pyramid is created and the matching starts from the lowest resolution and the results of this match guides the search on the possible area of the higher resolutions. We further extend it by using the Hausdorff distance as a measure of similarity. The advantage of using Hausdorff distance in a matching process is its on the capability of searching for portions of images, which allows us to partition the target image into a number of sub images and simultaneously match the template image on these sub images.

The Hausdorff distance is a non-linear operator which measures the mismatch of the two sets. In other words, such a distance determines the degree of the mismatch between a model and an object by measuring the distance of the point of a model that is farthest from any point of an object and vice versa. Therefore, it can be used for object recognition by comparing two images which are superimposed. The key points regarding this technique are summarized as below.

Given two finite point sets $A = \{a_1,...,a_m\}$ and $B = \{b_1,...,b_n\}$, the Hausdorff distance D_H between these two sets is defined as

$$D_H = \max(d_{AB}, d_{BA}) \tag{4-20}$$

where d_{AB} is the distance from set A to set B expressed as

$$d_{AB} = \max_{a_i \in A}(d_{a_iB}) \tag{4-21}$$

while d_{a_iB} is the distance from point a_i to set B given by

$$d_{a_iB} = \min_{b_j \in B}(d_{a_ib_j}) \tag{4-22}$$

The Hausdorff distance D_H is the maximum of d_{BA} and d_{BA} which measures the degree of mismatch between two sets A and B.

In general, image data are derived from a raster device and represented by grid points as pixels. For a feature detected image, the characteristic function of the set A and B can be represented by a binary array $A[i,j]$ and $B[i,j]$ respectively, where the $(i, j)th$ entry in the array is non-zero for the corresponding feature pixel in the given image. Therefore, distance array $D[i,j]$ and $D'[i,j]$ are used to specify for each pixel location (i,j) the distance to the nearest non-zero pixel of A or B respectively, where $D[i,j]$ denotes the distance transform of A and $D'[i,j]$ denotes the distance transform of B. Consequently, the Hausdorff distance as a function of translation can be determined by computing the point-wise maximum of all the translated D and D' array in the form of:

$$F(i,j] = \max(\max_a, \max_b) \tag{4-23}$$

where

$$\max_a = \max_a D[a_i - i, a_j - j] \tag{4-24}$$

$$\max_b = \max_b D\,[b_i + i, b_j + j]. \tag{4-25}$$

4.5.3 A Guided Matching Scheme

The hierarchical image matching scheme was first proposed by Borgefors [91] in order to reduce the computation required to match two images. This section details our extension of this scheme by introducing a guided search strategy to avoid the blind searching for the best fit between the given patterns. In order to avoid the blind searching for the best fit between the given patterns, a guided search strategy is essential to reduce computation burden. Our extension of the hierarchical image matching scheme (H.I.M.S) was based on a guided searching algorithm that searches first at the low level, coarse grained images, to the high level, fine grained images. To do this we need to obtain a Hausdorff distance approximation for each possible window combination of the template and target image at the lowest resolution. Those that returned a Hausdorff distance approximation equal to the lowest Hausdorff distance for those images were investigated at the higher resolution. The following summarizes the key steps involved in a H.I.M.S algorithm.

Algorithm 4-7 Hierarchical Image Matching Scheme

- Step 1 create image pyramid
- Step 2 for all combinations of windows

  at lowest level

  get value of match for this combination

  if low value add to lowest list

  end-for
- step 3 for each remaining level

  remove area from lowest list

  get match value for this area

  if low value add to lowest list

  end-for

4.6. Experimental Results

The palmprint image samples used for testing are 232×232 size with the resolution of 125 dpi and 256 grayscales. In our palmprint image database, a total of 180 images (90 pairs) from different individuals are stored. Two experiments are conducted: one is for testing the performance of global-feature-based candidate selection algorithm and the other is for testing the interesting-point-based local feature matching. The experimental processes are documented as below:

Experiment 4-3: Global-feature-based Candidate Selection Algorithm Testing

- Step 1: Take one of each pair of palmprints and put them into the database as registered templates.

- Step 2: One by one use the left palmprints as testing data, and for each test data, generate a candidate list for it according to the global feature extraction method described in section 4.4.1 and matching algorithm 4-6.
- Step 3: Record all the candidate lists and the number of templates in each candidate list.
- Step 4: Draw the eliminate rate graph as shown in Fig. 4-16.

As shown in Fig. 4-16, for a given test palmprint sample, at the best case, 99% templates are eliminated. on average, 91% of the templates are classified as distinctive from the input data and filtered out. In the worst case, the elimination rate of the candidates is 72% and only 28% of the samples are remained for further checking by local feature matching.

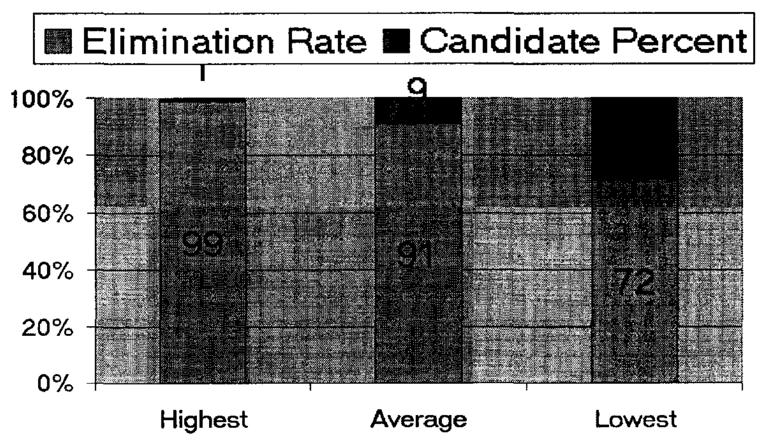


Fig. 4-16. The performance of the global feature based selection scheme: elimination rate vs. candidate percentage

Experiment 4-4: Interesting-point-based Local Feature Matching Algorithm Testing

- Step 1: For testing data, compare it with each template in the candidate list generated in experiment 4-3 using the interesting point detection algorithm described in algorithm 4-6 and the matching method presented in section .4.5.3 and 4.5.4.
- Step 2: For each testing data, finally determine one best matching and count the number of correct matching of palmprint pairs.

The average accuracy rate is 95%. Since the majority samples have been filtered out from by the coarse classification, the execution speed of fine identification has been increased significantly.

4.7. Conclusion

Offline palmprint recognition is based on inked palmprint images. The data capturing for offline images is not as convenient as online capturing. Before feature extraction and matching, all the palmprint are aligned under the same coordinate system. The coordinate system is defined by palm outer boundary and the end point of Heart Line. Two layers of feature extraction are conducted – global feature extraction and local feature extraction. The global feature is based on the calculating of global texture energy. The local feature extraction is based on interesting point detection which uses a Plessey detector. When matching two palmprints, global features are used first to decide whether they are similar enough. If two palmprints are similar, local features are matched to find the final result. In general, offline palmprint recognition research is difficult than online palmprint due to the difficulty of image capturing. In the next chapter, online palmprint recognition algorithms are introduced.

Chapter 5

Online Palmprint Recognition

Though online and offline palmprint recognition both aiming at identify entities by checking their palmprints, they use different techniques. For online palmprint recognition, a capture device is used to capture the palmprints from live persons. Therefore the palmprint qualities are quiet different from those of offline palmprints. This chapter introduces the online palmprint positioning, feature extraction and matching algorithms.

5.1. Introduction

The problem of palmprint based personal recognition is described as: given an input palmprint, query for the template in the database, which is from the same palm as the input. The searching process involves input image processing (positioning and feature extraction) and matching the input with all the templates in the database to find out the most similar one. The criteria to measure the searching are accuracy and efficiency - measurements of whether the system can find the right answer in a short response time. Fig. 5-1 shows several typical palmprints in our database. Palmprints in the database are stored together with their features and searching is based on matching of these features.

In section 5.2, we introduce the online palmprint positioning algorithms and in section 5.3 we explain the feature extraction and matching algorithms.

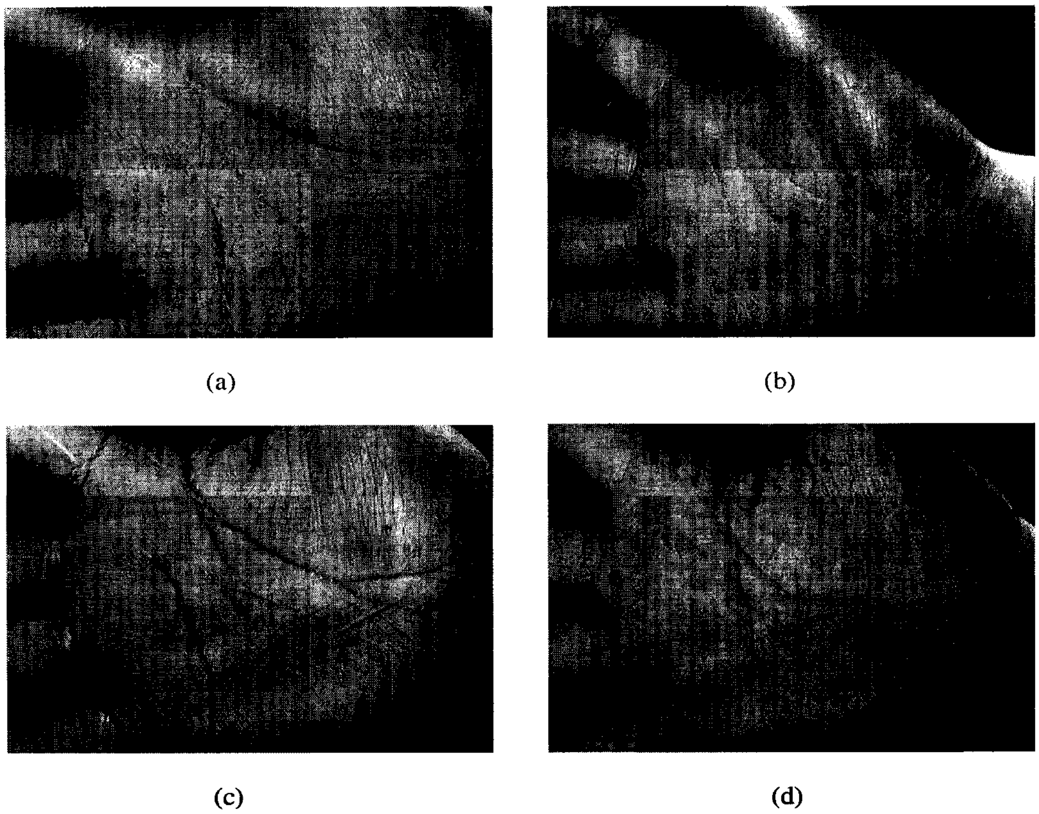


Fig. 5-1 Online palmprint samples in our database

(a) and (c) are from two boys and (b) and (d) are from girls

5.2. Palmprint Positioning

Palmprints may exhibit some degree of distortion (rotation, shift, transform, etc.) due to their being captured at different times, and under varying conditions of temperature, humidity, brightness, etc. To compare two palmprints, a common coordinate system is needed to determine which part of a palmprint is going to match with a similar part in another palmprint. Here, we define palmprint positioning as the process of correcting distortions and putting all palmprints under the same coordinate system so that the expected area of each palmprint can be extracted. So, three key issues are involved in palmprint positioning. 1) How to define the coordinate system? 2) How to decide the key points of the defined coordinate system on each palmprint image? 3) How to define and extract the useful part of a palmprint?

In this section, we introduce square-based and circle-based palmprint positioning methods. First the contour of a palmprint is determined. Then the square based method decides three key points between four fingers and setup an orthogonal coordinate system. Based on the coordinate system, a fixed size of palmprint is extracted from a certain position of the central part of the palmprint. The circle-based method calculates the biggest inscribed circle of the palmprint contour and the center of the circle is defined as the palmprint center. Later palmprint feature extraction and matching are based on the extracted square or circle part of the palmprint.

5.2.1 Square-based Positioning Method

The main idea of square-based positioning method is to first define three key points on a palmprint, then decide an orthogonal coordinate system using the three points (see Fig. 5-2), last extract a fixed size square from a predefined position under the coordinate system. The size and position of the square are determined according to the statistics of many palmprints. The basic rule in determining the size and position of the square is to ensure that the part of the image to extract is available in every palmprint.

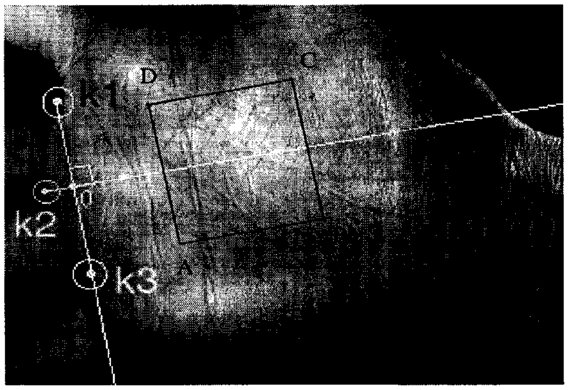


Fig. 5-2 Orthogonal coordinate system on a palmprint (K1, K2, K3 are midpoints between two fingers; ABCD is the square in the central part of the palm)

In Fig. 5-2, K1 is the midpoint between the index finger and the middle finger. K2 is the midpoint between the middle finger and the ring finger and K3 is the midpoint between the ring finger and the small finger. Line K1-K3 is the Y-axis of the palmprint coordinate system.

Make a line through K2, perpendicular to the Y-axis, the intersection point is the origin of the palmprint coordinate system. Here, we suppose that the fingers are not stuck together and at least four fingers (index, middle, ring and small finger) are present in an image. Therefore, the three gaps between the fingers are obtained, and the three key points are found.

The following summarizes the square-based positioning algorithm:

Algorithm 5-1: Square-based Positioning

Input: Online palmprint image $I_{M \times N}$

Output: Extracted central part of original image $C_{K \times K}$

- Step 1: Use a threshold, α, to convert the original gray image $I_{M \times N}$ (Fig. 5-3(a)) into a binary map $B_{M \times N}$ (see Fig. 5-3(b)).

$$B(i,j) = \begin{cases} 1 & I(i,j) \geq \alpha \\ 0 & I(i,j) < \alpha \end{cases} \tag{5-1}$$

- Step 2: Smooth the binary map by a Gaussian filter in Fig. 5-3(c)

$$B' = B * A \tag{5-2}$$

  where A is the Gaussian filter.

- Step 3: Trace the boundary of the holes between the fingers as shown in Fig. 5-3(d).
- Step 4: Calculate the center of gravity of the holes and decide the key points – k1, k2, and k3 (see Fig. 5-3(e)).
- Step 5: Line up k1 and k3 to get the Y-axis of the palmprint coordinate system and then make a line through k2, perpendicular to the Y-axis to determine the origin of the palmprint coordinate system, as shown in Fig. 5-3(f).
- Step 6: Extract a fixed size sub-image of the central part of a palmprint. In Fig. 5-2, the square "*ABCD*" is the area to extract. The position of "*A*" in the coordinate system and the size of "*ABCD*" are fixed in all palmprints, and these are predefined according to

many observations and experiments. Once the central part is extracted, a rotation of the image is performed; therefore, a square rather than a diamond-shaped image is obtained.

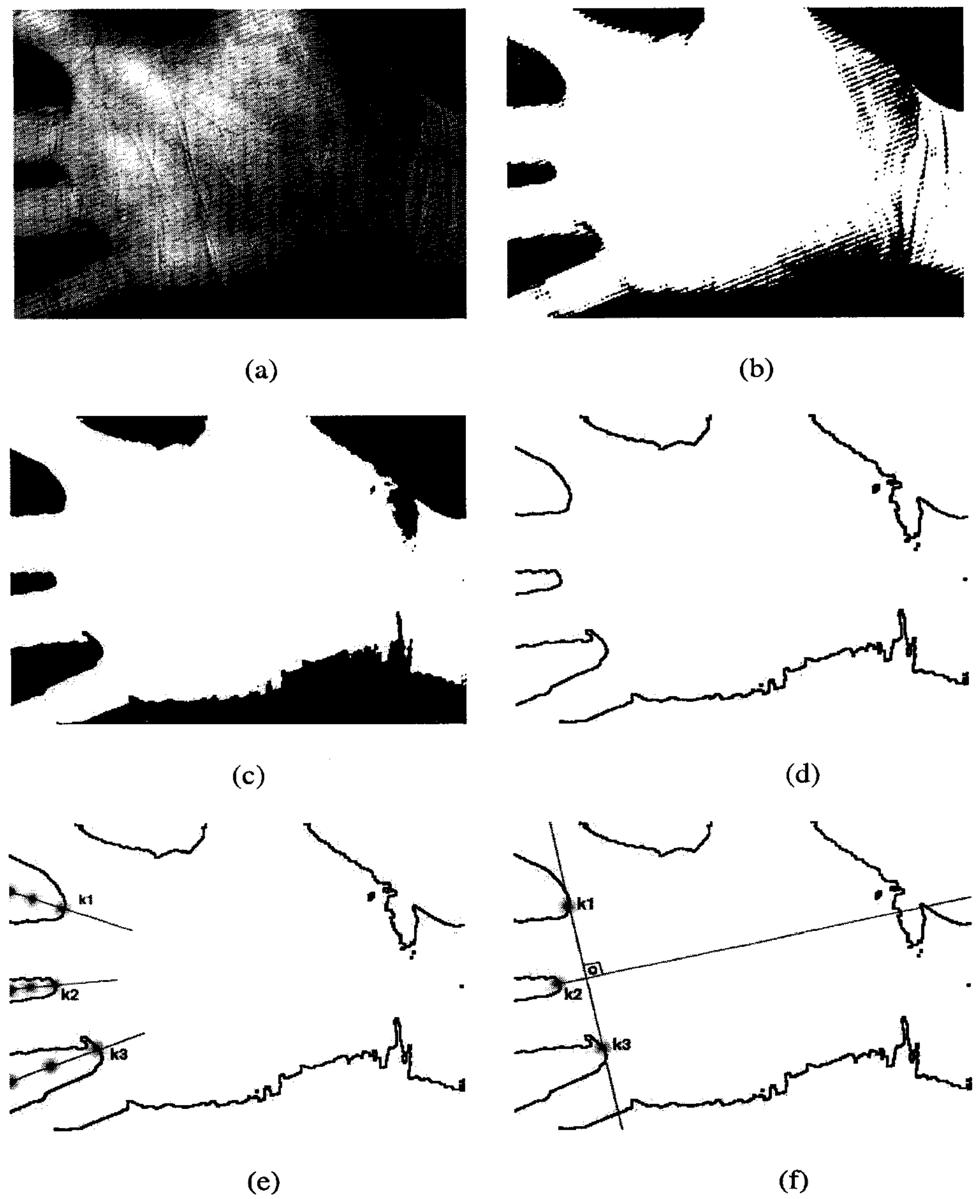


Fig. 5-3 Determination of K1, K2 and k3 (a) the original image (b) the binary map of the original image (c) smoothed map of (b) (d) palmprint boundary (e) determination of K1, k2 andK3 (f) determination of the coordinate system

Fig. 5-4 shows some palmprint segments extracted using **algorithm 5-1**.

Fig. 5-4 Palmprint segments extracted by square-based method.

A limitation of the square-based segmentation method is that when the three hubs between the fingers are not determined precisely, the whole method fails. The image is then regarded as a bad sample and it has to be thrown away, despite the fact that the palm area might be clear enough for identification.

5.2.2 Circle-based Positioning Method

In contrast to the square-based segmentation method, the method based on an inscribed-circle extracts the central part of a palmprint using a circle; therefore a round image is obtained rather than a square. Fig. 5-5 shows the square and circle on the same palm.

Fig. 5-5 Square and circle on the same palmprint

The basic idea of using an inscribed circle is to calculate the inscribed circle that meets the boundary of a palm so that it can extract as large an area as possible from the central part of the palmprint (see Fig. 5-6).

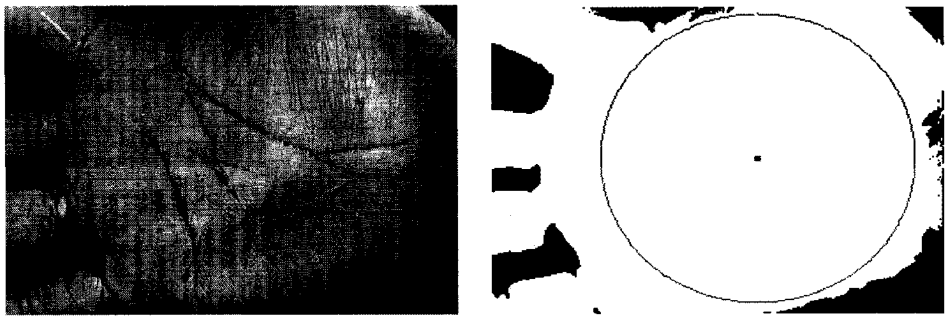


Fig. 5-6 The process of circle-based segmentation

The following describes the details of this method:

Algorithm 5-2: Circle-based Positioning

Input: Online palmprint image $I_{M \times N}$

Output: Extracted central part of original image C_r

- Step 1: The same as Step 1 in Algorithm 5-1.
- Step 2: The same as Step 2 in Algorithm 5-1.
- Step 3: Calculate the biggest inscribed circle for the contour of the palmprint and obtain its center and radius using a blind search algorithm.
- Step 4: Extract all pixels inside the inscribe circle. Fig. 5-7 shows several successfully segmented palmprints.

Fig. 5-7 Extracted samples with inscribed circle based segmentation method.

Because different palms have different sizes, the radiuses may be different. Samples of the same palm have circles with similar radiuses and centers. When matching two palmprints, we first check the radiuses. If the radiuses are not close to each other, we can conclude immediately that the two palmprints are from different palms. Otherwise, further matching is needed within the circle. We suppose that the centers of two palmprints are close but not necessarily exactly at the same point on a palm. Therefore, the matching needs to shift and rotate one of the palmprints to make the match.

5.2.3 Comparison of the Square and Circle Based Positioning Method

Palmprint segmentation serves to find the useful part of an image. Two criteria are used in evaluating a segmentation method. 1) How precisely it extracts the required part? 2) Can the algorithm deal with more distortions in an image? The following experiments are designed and performed to compare the two positioning methods:

5.2.3.1 Accuracy Test

A. Definition

Commonly, there are three main creases on a palm. Here, we define two key points on a palm according to where two of the creases flow out of the palm – A and B in Fig. 5-8 respectively.

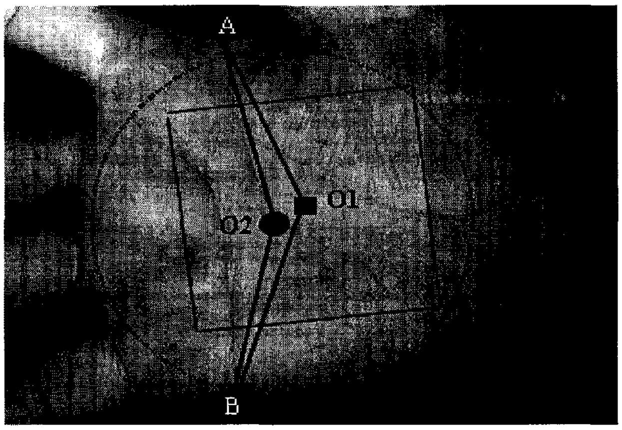


Fig. 5-8 Definitions for accuracy test (A, B are two points that creases flow out; O1 is the center of the square and O2 is the center of the circle)

In Fig. 5-8, we also define the center of the square as O1 and the center of the circle as O2. The distance between O1 and A is denoted as $D_{square\text{-}a}$, and the distance between O1 and B is $D_{square\text{-}b}$. The distance between O2 and A is $D_{circle\text{-}a}$, and distance between O2 and B is $D_{circle\text{-}b}$.

B. Design of the Experiment

We obtained 400 palmprints from 80 palms, and manually decided the two key points (A,B) of all palms. Then automatically calculate $D_{square\text{-}a}$, $D_{square\text{-}b}$, $D_{circle\text{-}a}$ and $D_{circle\text{-}b}$. We then generated the experimental results and compared the two methods.

C. Experimental results

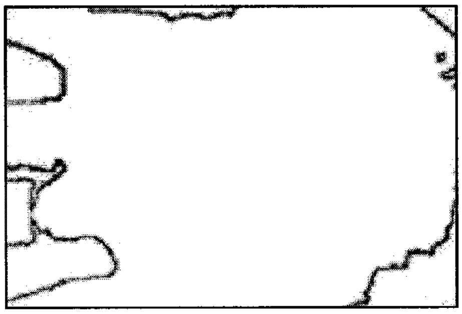
There are five palmprint samples of each palm. It is expected that the extracted parts from each sample include the same area of the palm. We calculate the average distance between the centers of five squares and circles to decide which one moves by the least amount. Our experimental results show that both the shifts of $D_{square\text{-}a}$ and $D_{square\text{-}b}$ are 6 pixels, and the shifts of $D_{circle\text{-}a}$ and $D_{circle\text{-}b}$ are 5 pixels, respectively. Therefore, we can conclude that the circle-based method as precise as the square-based method.

5.2.3.2 Tolerance to Palmprint Images of Different Quality

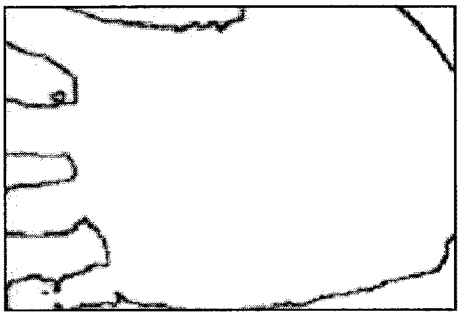
In some cases, an image cannot be segmented correctly using the square-based method but it can be processed using the inscribed circle. In our database, there are about 10,000 palmprint images. Only 4/5 of them can be correctly segmented using the square-based method, but all of them can be segmented correctly using the circle-based method. Fig. 5-9(a) shows a sample in which the index finger has a ring. Fig. 5-9(c) is the binary map of Fig. 5-9(a) that the holes between the fingers cannot be identified correctly due to the ring, therefore this palmprint can not be correctly segmented using square based method. But it can be successfully segmented using circle-based method and segmented part is shown in Fig. 5-9(e). In Fig. 5-9(b), the small finger cannot be segmented correctly because it is too dark and cannot be identified from the background. Fig. 6-9(d) gives the binary map of Fig. 5-9(b) and it shows that the hole between ring finger and small finger is not traced correctly. So Fig. 5-9(b) was not satisfactorily segmented using square based method. The circle based method can segmented it and the round part segment of Fig. 5-9(b) is put there as Fg. 5-9(f).

(a)

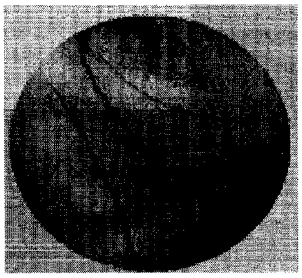
(b)



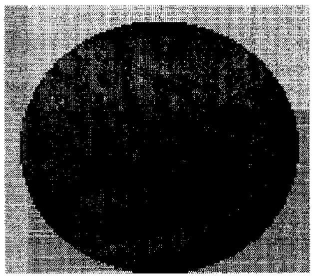
(c)



(d)



(e)



(f)

Fig. 5-9 Correctly segmented using inscribed circle but not squared-based method (a) a palmprint with a ring on the unnamed finger; (b) A palmprint sample with the small finger merged into the background; (c) The boundary of (a) which is not correctly identified; (d) The boundary of (b) which is not correctly determined; (e) Correctly segmented of (a) using the circle based method; (f) Correctly segmented of (b) using the circle based method.

5.3. Palmprint Feature Extraction and Matching

Palmprint feature extraction is the process to represent a palmprint's unique feature using a smaller space than the original image. Different feature representations may have different similarity measurement methods. In section 5.3.1-5.3.3, palmprints are preprocessed using square-based positioning method before feature extraction and in section 5.3.4, circle-based positioning method is adopted.

5.3.1 Global Texture Based Feature Extraction and Matching

5.3.1.1 Global Texture Energy (GTE)

A palmprint consists of various lines with different widths and directions, which are classified into three categories - principle lines, wrinkles and ridges. Three principle lines are defined as Heart line, Head line and Life line. Ridges are the tiny regular lines that cover the surface of the palm. Global texture energy (GTE) to represent a palmprint's feature is defined as follows:

For an image I with $n \times n$, $E_A(I)$ represents its GTE over a mask, A, by

$$E_A(I) = \frac{1}{n \times n} \sum_{i=a+1}^{n-a} \sum_{j=a+1}^{n-a} F(i,j), \tag{5-3}$$

$$F(i,j) = \left| \sum_{k=-a}^{a} \sum_{l=-a}^{a} (I(i+k, j+l) \times A(k,l)) \right|, \tag{5-4}$$

where A is the convolution mask for the capture of palmprint texture feature. In the proposed approach, four kinds of masks are defined in Fig. 5-10, which are suitable for describing palmprint's features. These masks highlight an image's energies in horizontal, vertical, 45° line and 135° line directions, respectively. Therefore, GTE values calculated with the four masks also reflect the image's directional features. For example, given a palmprint image, *I*, using Eqs. (5-3)-(5-4) and the masks shown in Fig. 5-10, we can obtain each GTE value, $E_i(I)(i=1,2,3,4)$, where $E_1(I)$ reflects how likely I is consisting of horizontal lines and $E_2(I)$ reflects how likely I of vertical lines, and so on.

-4 0 8 0 -4	-8 -16 -32 -16 -8	16 0 -12 -8 0	0 -8 -12 0 16
-8 0 16 0 -8	0 0 0 0 0	0 24 0 -16 -8	-8 -16 0 24 0
-16 0 32 0 −16	16 32 64 0 -4	-12 0 32 0 -12	-12 0 32 0 -12
-8 0 0 0 0	0 0 0 0 0	-8 -16 0 24 0	0 24 0 -16 -8
-4 0 -4 -2 -1	-8 -16 -32 -16 -8	0 -8 -12 0 16	16 0 -12 -8 0
(a) Horizontal line	(b) Vertical line	(c) 135° angle line	(d) 45° angle line

Fig. 5-10 Four masks used to calculate global texture energy

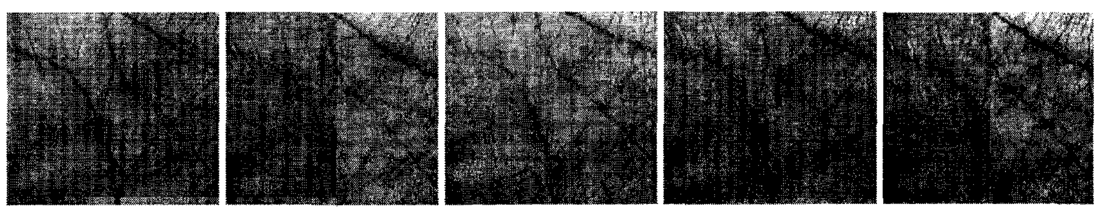
5.3.1.2 Global Feature Extraction Based on GTE

Global features describe a palmprint's overall attribute and local features give more detailed information of a palmprint. In general, some palmprints are so different that can be identified by global features, but some palmprints are similar and can be recognized only by their local features.

Using the four masks listed in Fig. 5-10 and Eqs. (5-3)-(5-4), four global features are calculated for each palmprint, which are normalized as the corresponding numerical representations (0-100). The bigger number means a larger energy. These numbers describe the palmprint's texture energies in horizontal, vertical, 45° and 135° directions, respectively. Although the calculation of global features loses the position information, it gives a general texture description of a palmprint.

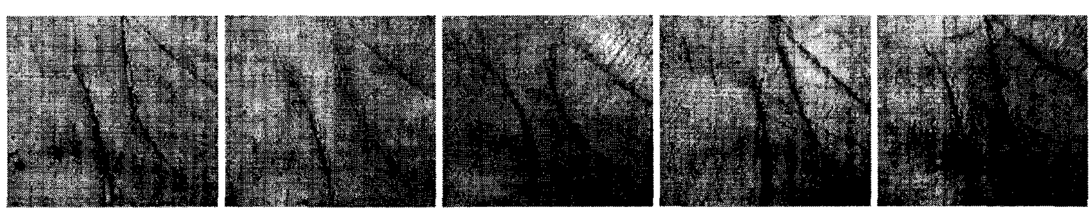
Global features can be defined by a vector, $E_i\,(i=1,2,3,4)$, which builds up a relationship between a palmprint image and 4-dimensional space. This mapping is not one-to-one. Two palmprints may correspond to the same point in the feature space and not all the points in the space have their corresponding palmprints. Feature points of similar palmprints are closed to each other in the feature space and neighbor points in the feature space are also associated with similar palmprints if any.

Fig. 5-11 shows this relationship between palmprints and their global features listed under each palmprint, where Fig. 5-11(a) is a group of palmprints from the same palm, Fig. 5-11(b) shows the similar palmprints from different palms and Fig. 5-11(c) shows the palmprints with significant difference. In our experiments, the average differences between any two palmprints in Groups (a)-(c) are shown in Table 5-1. The difference between samples of the same palm is much smaller than that of significantly different palms, but the difference between samples of similar palms is small too.



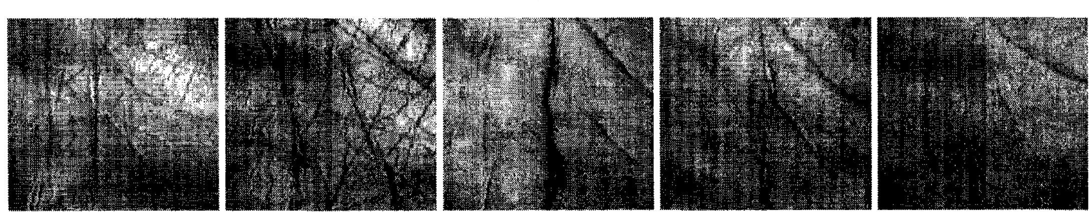
(51, 69, 48, 49) (48, 67, 49, 45) (54, 71, 49, 52) (56, 69, 50, 51) (52, 72, 48, 51)

(a)



(60, 68, 46, 54) (52, 59, 41, 50) (55, 71, 54, 49) (58, 67, 48, 48) (55, 68, 49, 49)

(b)



(70, 74, 52, 57) (91, 95, 74, 71) (55, 61, 45, 45) (48, 58, 40, 44) (43, 52, 32, 41)

(c)

Fig. 5-11 Relationship between palmprints and their global features. (a) palmprints from the same palm; (b) similar palmprints from different palms; (c) palmprints with significant difference

Table 5-1 Comparison of the average difference, E_i (i =1,2,3,4), for three kinds of the groups defined in Fig. 5-11

	Group (a)	*Group (b)*	*Group (c)*
Average difference of E_1 (0-100)	2.24	2.40	15.28
Average difference of E_2 (0-100)	1.52	3.04	13.20
Average difference of E_3 (0-100)	0.64	3.28	11.52
Average difference of E_4 (0-100)	2.08	1.60	9.92

5.3.1.3 Similarity Measurement Based on Global Features

Suppose I_i and I_j represent two palmprints and their global features are E_{ik} and E_{jk} $(k = 1,2,3,4)$, respectively. The distance between I_i and I_j is defined as follows:

$$D(I_i, I_j) = \begin{pmatrix} D_1(I_i, I_j) \\ D_2(I_i, I_j) \\ D_3(I_i, I_j) \\ D_4(I_i, I_j) \end{pmatrix} = \begin{pmatrix} |E_{i1} - E_{j1}| \\ |E_{i2} - E_{j2}| \\ |E_{i3} - E_{j3}| \\ |E_{i4} - E_{j4}| \end{pmatrix}. \tag{5-5}$$

$D(I_i, I_j)$ decides whether two palmprints may come from the same palm. A threshold vector, T_k (*k=1,2,3,4*), is used to make the decision. The decision rule is defined as:

If $|E_{ik} - E_{jk}| > T_k$ (*k=1,2,3,4*), then I_i and I_j are from different palms; otherwise, the same one. T_k (*k=1,2,3,4*) is obtained by using a statistical method. If we collect M samples from one palm and get M global feature vectors, E_{1k}, E_{2k}, ..., E_{Mk} (*k=1,2,3,4*), the threshold, T_k (*k=1,2,3,4*), can be decided by calculating both the average and largest distance between any two samples in the group, i.e.,

$$T_k = ((\frac{1}{2M}\sum_{i=1}^{M}\sum_{j=1}^{M}|E_{ik} - E_{jk}|) + \mathop{Max}_{i=1}^{M}\mathop{Max}_{j=1}^{M}|E_{ik} - E_{jk}|)/2 \quad (k=1,2,3,4). \tag{5-6}$$

5.3.2 Image Shrinking Based Feature Representation and Matching

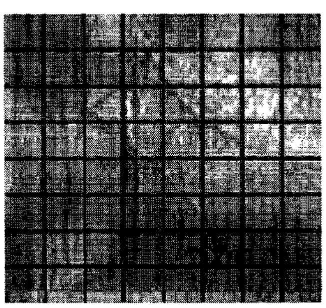
As mentioned above, although global features are good enough to classify most palmprints, they cannot differentiate a palmprint from all similar ones. Therefore, it is necessary to extract local features. The following describes the process of image shrinking based feature representation and matching algorithm.

Algorithm 5-3: Image Shrinking Based Feature Representation

Input: Central part of the palmprint image $I_{N\times N}$ (here N is 128)

Output: K bytes array representing the palmprint feature(here K is 64)

- Step 1: Segmenting the Image into Small Tiles. In order to reserve the local information of a palmprint, $I_{N\times N}$ is divided into 8×8 tiles, each is a 16×16 sub-image as shown in Fig. 5-12.
- Step 2: Averaging the hues of all the pixels in each tile. The average value is represented as the tile's attribute.
- Step 3: Lining up the attributes in the tiles to get an array of the numbers to describe the local features of a palmprint, as shown in Fig. 5-12, where the 8×8 numbers are lined into a 1-dimensional array that represents the palmprint's unique feature.



67	171	73	90	100	94	77	76
87	93	78	90	102	92	82	83
80	88	87	94	104	105	95	103
77	70	78	86	98	104	94	100
72	69	81	97	105	105	111	96
66	61	87	106	109	115	116	106
62	66	90	105	115	120	113	98
59	66	90	102	116	113	100	83

67	171	73	90	100	94	77	76	87	93	78	90	102	92	82	83	80	···

Fig. 5-12 The process of local feature extraction.

Algorithm 5-4: Image Shrinking Based Feature Matching

Input: Two feature set $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$, here n is 64.

Output: d_{xy} - distance between two feature sets.

- Step 1: Calculating the average for $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i. \tag{5-7}$$

- Step 2: Calculating the average deviation of $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$:

$$l_{xx} = \sum_{i=1}^{n}(x_i - \bar{x})^2, \; l_{yy} = \sum_{i=1}^{n}(y_i - \bar{y})^2, l_{xy} = \sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y}), \tag{5-8}$$

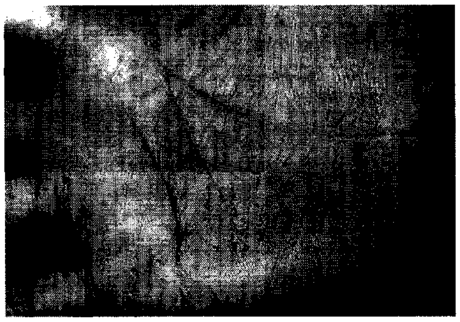
- Step 3: Calculating the correlation of $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$:

$$r_{xy} = \frac{l_{xy} l_{xy}}{l_{xx} l_{yy}}, \tag{5-9}$$

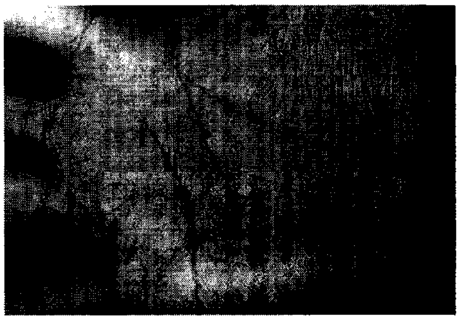
- Step 4: Calculating the distance between $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$:

$$d_{xy} = 1 - r_{xy}, \tag{5-10}$$

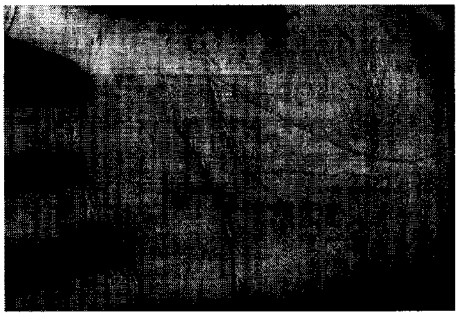
Fig. 5-13 illustrates the local feature matching algorithm, where Figs. 5-13(a)-(b) are two samples from person A, and Figs. 5-13(c)-(d) from person B. Their features are shown in Fig. 5-13(e). Table 5-2 shows the distances between each sample pair. The distance between two samples from the same person (A or B) is less than 3; however, the distance from the different person is larger than 14. Therefore, a threshold can be set to decide whether two samples are from the same palm. If the distance, d_{xy}, is smaller than a threshold, T, two palmprints are from the same palm; otherwise, different palm sources. T is determined by using a statistical method.



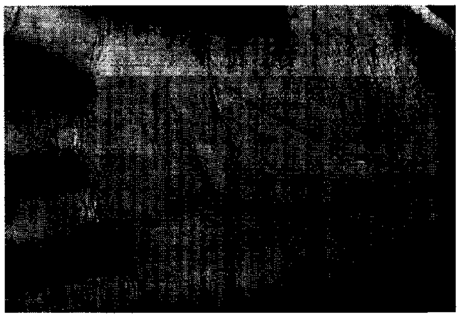
(a) Person A – sample 1



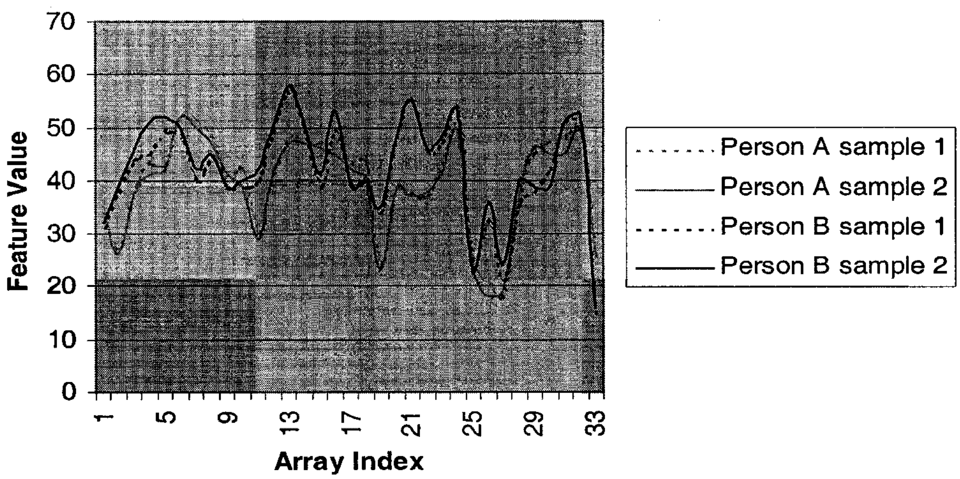
(b) Person A – sample 2



(c) Person B – sample 1



(d) Person B – sample 2



(e)

Fig. 5-13 Similarity measurement to similar palmprints based on local features

Table 5-2

	A1-A2	A1-B1	A1-B2	A2-B1	A2-B2	B1-B2
Distance (0-100)	1	15	16	18	17	2

5.3.3 Fourier Transform Based Feature Representation and Matching

In this section, we introduce a feature extraction method that converts a spatial domain palmprint image into a frequency domain image using the Fourier Transform to represent palmprint features in the frequency domain. The extracted features are used as indexes to the palmprint templates in the database. All the palmprints are preprocessed and segmented using the square-based method introduced in chapter 4. Therefore we perform the feature extraction and matching on the square central part of palmprints.

5.3.3.1 Fourier Transform

Fourier Transform is one of the most popular and useful transforms in image processing applications. Discussions of this topic spread in many papers and books [96]. Its major applications involve image enhancement and feature extraction. The Fourier Transform includes Transform and inverse Transform. The former converts an image from the spatial domain into the frequency domain and the later changes it from the frequency domain back. A two-dimensional discrete Fourier Transform is defined as:

$$F(u,v) = \frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} f(m,n)\exp[-j2\pi(\frac{mu}{M}+\frac{nv}{N})] \qquad (5\text{-}11)$$

where $f(m,n)$ is an image with $M \times N$, $j = \sqrt{-1}$, $u = 0,1,\ldots,M-1$; $v = 0,1,\ldots,N-1$.

The inverse Transform is defined as:

$$f(x,y) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} F(u,v)\exp[j2\pi(\frac{mx}{M}+\frac{ny}{N})] \qquad (5\text{-}12)$$

In [96], the calculation of the Fourier Transform is described in detail. It is natural to use the Fourier Transform to do the image enhancement. While high pass filter is supposed to the edge lines and low pass filter is used to smooth the image. Fig. 5-14 shows the results of both high pass and low pass filters to the palmprint image. The Fourier Transform does not add more value to the palmprint feature extraction.

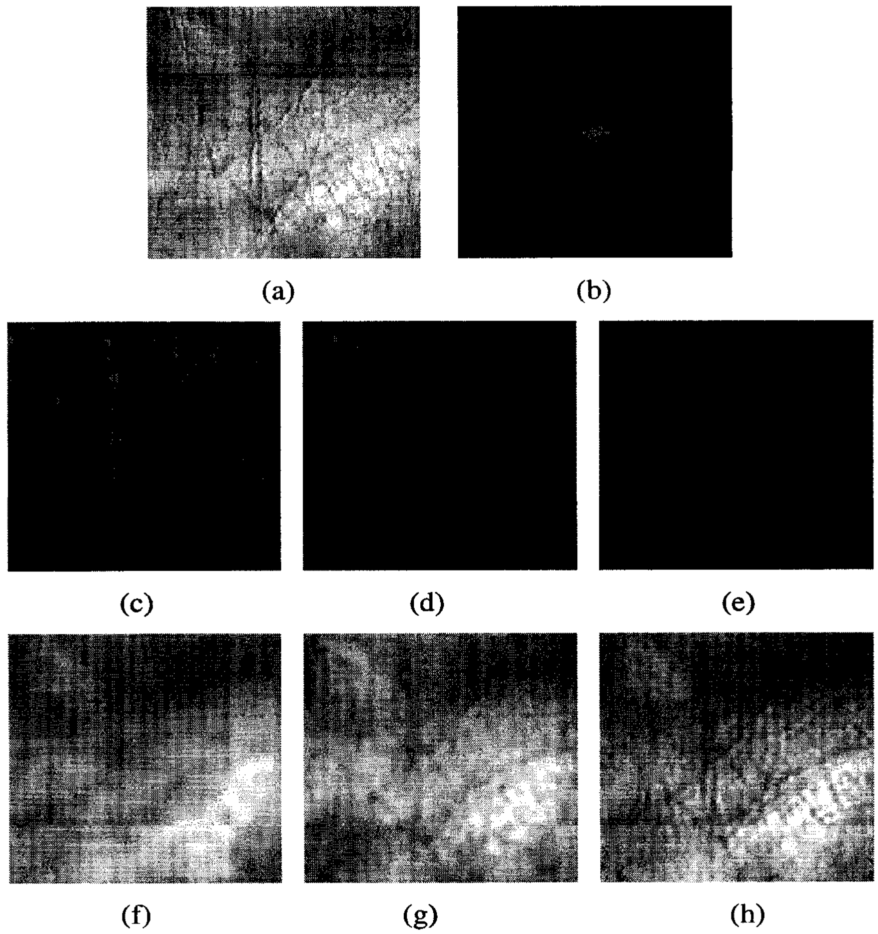
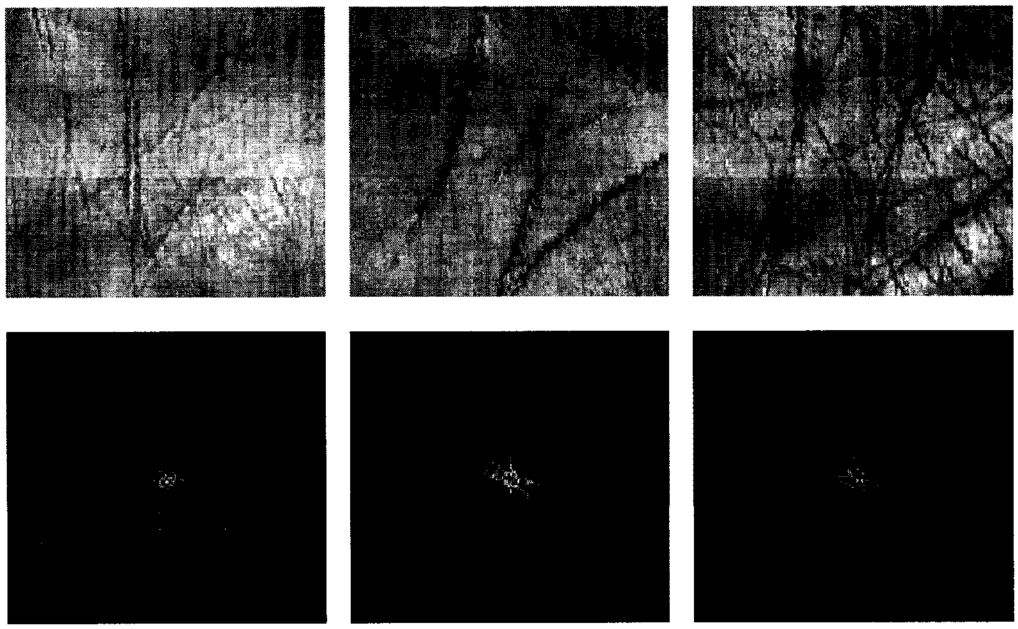


Fig. 5-14 High pass and low pass of the palmprint images. (a) The original palmprint image. (b) The frequency domain image. (c) – (e) High pass filter (r>0,1,2). (f) - (h) Low pass filter (r<10,20,30).

5.3.3.2 Palmprint Features Exhibited In the Frequency Domain

In palmprint identification, the Fourier Transform is used in feature extraction. There exist some correspondences between palmprint features on a spatial domain image and those on a frequency domain image. In general, the stronger the creases are on a spatial domain image, the less compact the information is on a frequency domain image. If a palmprint image in the spatial domain has a strong line, there will be more information in the line's perpendicular direction in the frequency domain.

Fig. 5-15 shows three typical palmprints and their correspondence frequency domain images, where Fig. 5-15(a) is a palmprint without strong creases and its frequency domain image shows that the information is centralized in the center, which is the low frequency area; Fig. 5-15(b) is a palmprint with two clear and strong creases and its frequency domain image shows that there exists rich information on the direction perpendicular to the creases; and Fig. 5-15(c) is a palmprint with full of strong creases and its frequency domain image shows that the information is not as centralized as that in Fig. 5-15(a).



(a) (b) (c)

Fig. 5-15 Different palmprints and their corresponding frequency domain images. (a) Palmprint without strong creases. (b) Palmprint with two clear, strong creases. (c) Palmprint full of strong creases.

In palmprint identification, if feature extraction is conducted in the frequency domain, it is important that similar palmprints maintain their resemblance when converted into frequency images. Fig. 5-16 shows three groups of palmprints and their correspondent frequency images. They are from the same palm, similar palms, and different palms.

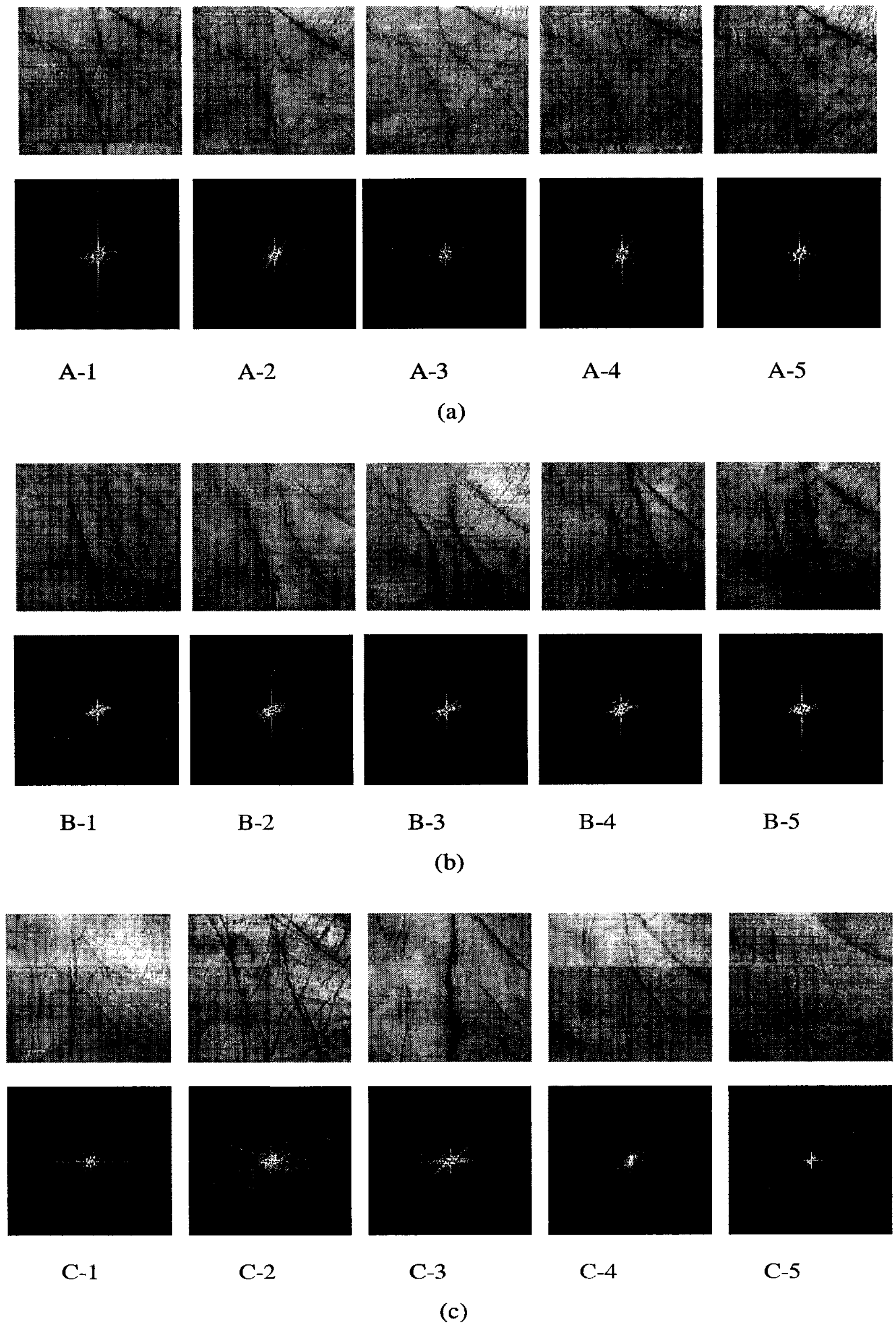


Fig. 5-16 Comparison of various frequency domain images. (a) Samples from the same palm. (b) Samples from similar (but different) palms. (c) Samples from different palms (looks different).

5.3.3.3 Palmprint Feature Representation

Palmprint feature representation is used to describe the features in a way that is concise and easy to compare. If we use polar coordination system (r,θ) to represent the frequency domain images, the energy change tendency along r shows the intensity of a palmprint's creases and that along θ shows the directions of a palmprint's creases. Therefore, we may use a statistical method to represent palmprint's features.

The image can be converted from an orthogonal coordinate system into a polar coordinate system by

$$I'(r,\theta) = I(64 + r\cos\theta, 64 + r\sin\theta), 0 \le r \le 64 \quad 0 \le \theta \le \pi \qquad (5\text{-}13)$$

where I is the image under orthogonal coordinate system and I' is the image under polar coordinate system.

In order to represent a palmprint's crease intensity, the frequency domain image is divided into small parts by a series of circles which have the same center, as shown in Fig. 5-17(a). The energy in each ring like area is defined as

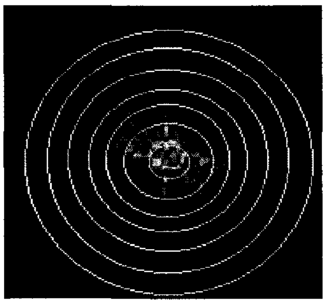
$$R_i = \sum_{\theta=0}^{\pi} \sum_{r=8(i-1)}^{8i} I'(r,\theta), \qquad (i = 1,2,\ldots,8) \qquad (5\text{-}14)$$

where I' is the sub image under polar coordinate system. In the following of this section, $R_i (i = 1,2,\ldots,8)$ is called R feature.

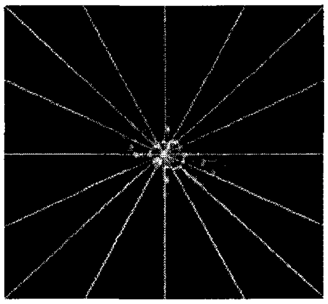
In order to represent a palmprint's crease direction, the frequency domain image is divided by a series of lines that go through the center of the image, as shown in Fig. 5-17(b). The energy in each fan like part is defined as

$$\theta_i = \sum_{\theta=(i-1)}^{i} \sum_{r=0}^{64} I'(r, \theta\pi/8), \qquad (i = 1,2,\ldots,8) \qquad (5\text{-}15)$$

In the following of this section, $\theta_i (i = 1,2,\ldots,8)$ is called θ feature.



(a)



(b)

Fig. 5-17 Palmprint feature representation: (a) R feature and (b) θ feature

5.3.3.4 Feature Matching and Palmprint Identification

Feature matching computes the distance between two palmprint feature sets. Because a palmprint is represented by R feature and θ feature, feature matching is calculating the distance between R features and θ features.

Let $RX_i (i = 1,2,..,8)$ and $RY_i (i = 1,2,...,8)$ represent two R feature sets. The distance DR_{xy} between $RX_i (i = 1,2,...,8)$ and $RY_i (i = 1,2,...,8)$ is defined as:

$$DR_{xy} = \frac{1}{8}\sum_{i=1}^{8} | RX_i - RY_i | \tag{5-16}$$

Let $\theta X_i (i = 1,2,...,8)$ and $\theta Y_i (i = 1,2,...,8)$ represent two θ feature sets. The distance $D\theta_{xy}$ between $\theta X_i (i = 1,2,...,8)$ and $\theta Y_i (i = 1,2,...,8)$ is defined as:

$$D\theta_{xy} = (1 - \frac{l_{xy} l_{xy}}{l_{xx} l_{yy}}) \times 100 \tag{5-17}$$

where

$$l_{xx} = \sum_{i=1}^{8} (\theta X_i - \frac{1}{8}\sum_{i=1}^{8} \theta X_i)^2 \tag{5-18}$$

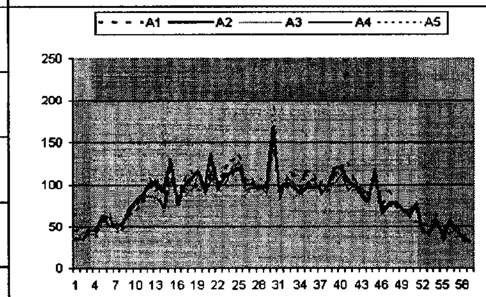
$$l_{yy} = \sum_{i=1}^{8} (\theta Y_i - \frac{1}{8}\sum_{i=1}^{8} \theta Y_i)^2 \tag{5-19}$$

$$l_{xy} = \sum_{i=1}^{8} (\theta X_i - \frac{1}{8}\sum_{i=1}^{8} \theta X_i)(\theta Y_i - \frac{1}{8}\sum_{i=1}^{8} \theta Y_i) \tag{5-20}$$

The scope of $D\theta_{xy}$ is between 0 and 100. The smallest distance is 0 and the largest distance is 100.

	R Feature (Average Distance = 3.7)							
A-1	57	48	63	59	56	62	56	60
A-2	56	53	62	59	58	58	48	57
A-3	52	50	57	54	52	57	53	60
A-4	56	43	57	56	58	62	57	56
A-5	59	47	59	58	67	59	57	61

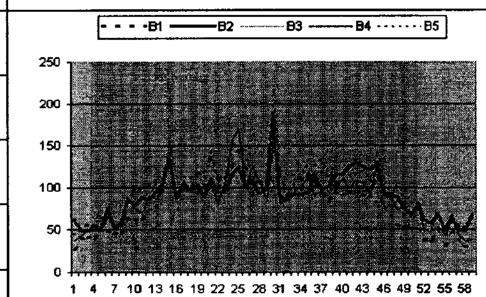
θ Feature



(a)

	R Feature (Average Distance = 9.4)							
B-1	43	39	45	55	53	63	62	74
B-2	45	54	56	60	67	72	67	67
B-3	63	49	56	58	52	58	53	51
B-4	65	39	54	49	52	68	57	69
B-5	55	49	61	56	66	81	76	80

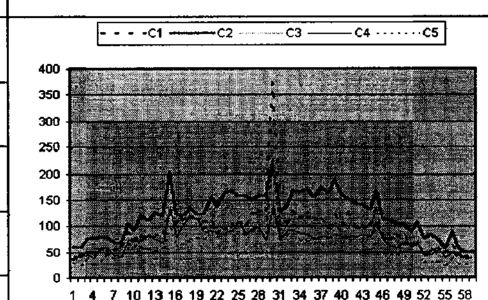
θ Feature



(b)

	R Feature (Average Distance = 20.0)							
C-1	48	46	56	68	69	64	62	64
C-2	66	77	91	89	87	87	77	80
C-3	63	46	55	47	54	62	61	61
C-4	50	36	48	47	49	54	49	51
C-5	33	30	37	40	43	44	43	49

θ Feature



(c)

Fig. 5-18 Comparison of both R and θ feature values of the palmprint samples in Fig. 5-16 (a) Distance between R and θ feature values from samples of the same palm. (b) Distance between R and θ feature values from samples of similar palms. (c) Distance between R and θ feature values from samples of different appearance palms.

Fig. 5-18 shows R and θ features of those palmprints shown in Fig. 5-16. For group A, which includes the samples from the same palm, the average distance of R features is 3.7 and the θ features are very close to each other. For group B, which includes the samples from similar palms, the average distance of R features is 9.4 and the θ features are close to each other. For group C, which includes the samples from palms with different appearances, the average distance of R features is 20.0 and the θ features are far from each other. Both R feature and θ feature can be used in feature matching and palmprint identification.

5.3.4 Crease Based Feature Extraction and Matching

In this section, we present a crease extraction and bi-directional matching method. This method applies crucial feature set identification and bi-directional matching (which lower the impact of unstable creases). All the palmprint images are preprocessed using the circle-based segmentation method described in section 5.2.2 so that the crease feature are extracted and matched within the central area of the palmprints.

The major steps of the crease and bi-directional matching method are: 1) inscribe a circle to define the 'center' and the central part of a palmprint; 2) extract creases in the central part (we refere to the crease map as a 'whole feature set'); 3) within the whole feature set identify strong creases as a 'crucial feature set'; 4) match the crucial feature set of one palmprint with the whole feature set of the other; 5) do matching of step 4) in the other direction; 6) average the two matching scores obtained in 4) and 5) to get the final matching result.

5.3.4.1 Palmprint Crease Feature Extraction

Crease feature extraction is performed on the extracted central part of palmprints. Here we use a classical Canny edge detection method to get crease features. The detailed description of the Canny method can be found in [182]. Fig. 5-19 shows a palmprint segment and its crease features.

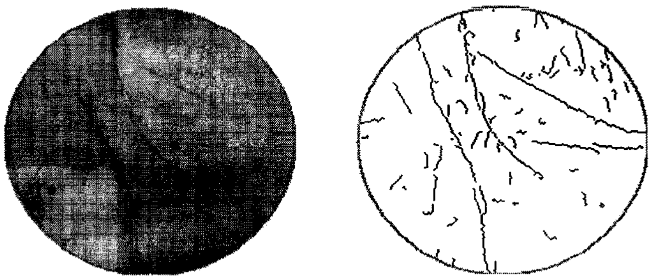


Fig. 5-19 A palmprint segment and its crease features

5.3.4.2 Palmprint Crease Feature Matching

A. Whole Feature Set Matching

Calculate the distance between two palmprints by matching their whole feature sets, as shown in Fig. 5-20. The matching is to count the number of pixels that overlapped on the two palmprint images. The matching score is normalized to 0-100.

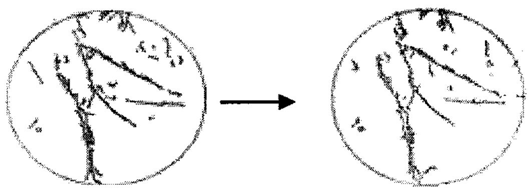


Fig. 5-20 Illustration of matching with whole feature set

B. Matching Crucial to Whole Feature Set

Calculate the distance between two palmprints by matching one palmprint's crucial feature set to the other's whole feature set, as shown in Fig. 5-21. The matching is to calculate the number of pixels on the crucial feature set that correctly matched with the whole feature set on the other image. The matching score is normalized to 0-100.

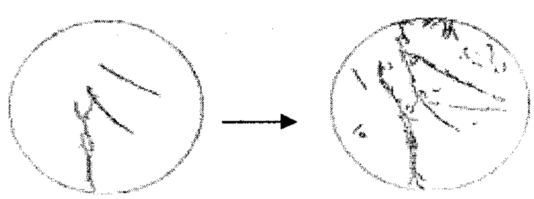


Fig. 5-21 Illustration of matching with crucial feature set

C. Matching Crucial to Whole Feature Set in Two Directions

Calculate the distance between two palmprints A and B by matching A' crucial feature set to B's whole feature set, and then matching B' crucial feature set to A's whole feature set and average the matching scores, as shown in Fig. 5-22. The matching score is normalized to 0-100.

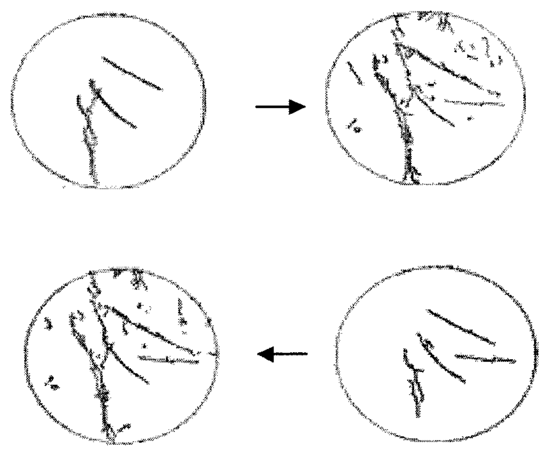


Fig. 5-22 Illustration of bi-directional matching

5.3.4.3 Experimental Results

The experiments were performed on 130 palmprint images (65pairs). The images are 320*240 pixels in size with the resolution of 100dpi. The programming language is Visual C++ and operating system is Windows NT. First, all the 130 palmprints are processed by a feature extraction program and their whole and crucial feature sets are stored together with the original palmprint images. Then, three groups of experiments are performed.

A. Whole Feature Set Matching

We used the whole crease set matching method that described in 5.3.4.2 *A* and got the relationship of threshold, FAR(False Acceptance Rate) and FRR(False Rejection Rate), as shown in Fig. 5-23. When the threshold is set to 30, FRR is 32% and FAR is 54%; when the threshold is set to 40, FRR is 55% and FAR is 23%.

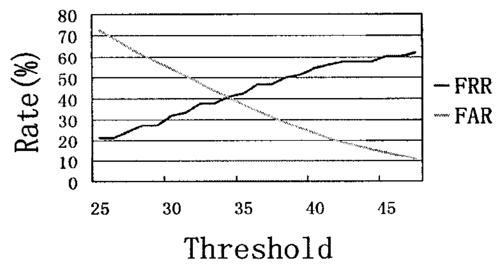


Fig. 5-23 Relationship of FRR, FAR and Threshold of *Whole Feature Set matching*

B. Matching Crucial to Whole Feature Set

The result of the matching method described in 5.3.4.2 *B* is shown in Fig. 5-24.

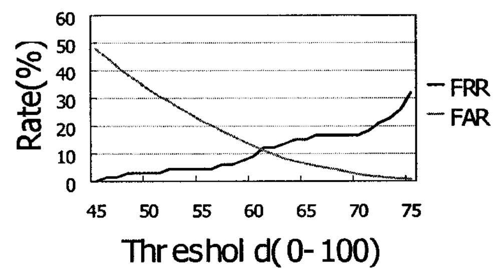


Fig. 5-24 Relationship of FRR, FAR and Threshold of *Matching Crucial Set to Whole Feature Set*

When the threshold is set to 60, FRR is 9% and FAR is 13%; when the threshold is set to 65, FRR is 15% and FAR is 6%.

C. Bi-directional matching

The result of the matching method described in 5.3.4.2 *C* is shown in Fig. 5-25. When the threshold is set to 50, FRR is 3% and FAR is 4.5%; when the threshold is set to 53, FRR is 4.5% and FAR is 1.75%.

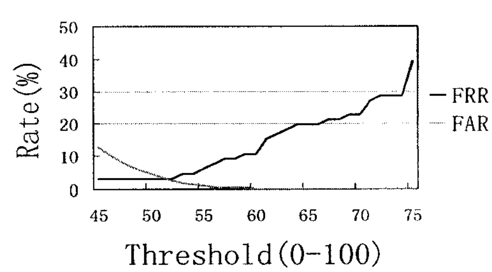


Fig. 5-25 Relationship of FRR, FAR and Threshold of *Bi-directional Matching*

D. Comparison of Matching Methods

Table 5-3 documents the comparison of the above three matching methods. The matching score is normalized to 0-100 for 100 meaning perfect match and 0 meaning no pixel is matched.

Table 5-3. Comparison of the three matching methods

Test No.	*A*	*B*	*C*
Threshold(0-100)	35	62	52
FRR(%)	41.0	12.12	3.03
FAR(%)	41.0	9.66	2.53
EER(%)	41	11	3
Recognition rate(%)	59	89	97

For experiment A, when the threshold is set to 35, FRR and FAR are close – FRR is 41.0% and FAR is 41.0%, so the recognition rate is about 59%. For experiment B, when the threshold is set to 62, FRR and FAR are close – FRR is 12.12% and FAR is 9.66%, so the recognition rate is about 89%. For experiment C, when the threshold is set 52, FRR and FAR are close – FRR is 3.03% and FAR is 2.53%, so the recognition rate is about 97%. Therefore we get the conclusion that the bi-directional matching method improves the recognition rate significantly.

5.4. Conclusion

Online palmprint recognition involves positioning, feature extraction and matching. Palmprint positioning can use either square-based or circle-based methods. While square-based method defines a coordinate system according to the positions of finger hubs and circle-based method defines the coordinate system based on the biggest inscribed circle. Global texture energy is calculated for global feature extraction but it uses different masks from the offline palmprint feature extraction due to different quality of images. Shrink images are served as local features. Fourier Transform provides a means for feature extraction and matching in the frequency domain. Crease extraction and bi-directional crease matching are proved to be effective for palmprint recognition. In the next chapter, a summary and comparison of all the proposed algorithms are presented.

Chapter 6

Comparison and Analysis of the Proposed Methods

In the former chapters, three positioning algorithms and three feature extraction algorithms for palmprint recognition are introduced. This chapter summarizes these algorithms and analyses their advantages and disadvantages. A performance test is designed to compare the three palmprint recognition methods (texture based, Fourier Transform based and bi-directional matching of creases) on the same testing data set and under the same hardware and software environment.

6.1. Summary of the Proposed Algorithms

6.1.1 Offline Palmprint Positioning

The basis of this method is the precise determination of two key features of a palmprint – the outer boundary and the end point of the Heart Line. The method assumes that a palm's outer-boundary can be described by a line and this line can be regarded as the Y-axis of the palm. The end point of Heart Line is regarded as the origin of the orthogonal coordinate system. The process of determining the Y-axis requires to turn the palmprint image into a binary map, trace the outer boundary and calculate a line according to the outer boundary. In order to decide the end point of the Heart Line, we project the gray levels of pixels to the Y-axis and the point that gained the largest energy is determined to be the end point of the Heart Line. This method is described in detail in section 4.2.

This method has two major problems. First, the boundaries of about 4% of palms are round rather than straight so for them this method is not suitable and second, the Heart Lines about 3% of palms are vague and their end points are difficult to determine.

6.1.2 Conjunction Points Between Fingers Based Positioning

Because it is relatively easy to obtain the palmprint boundary of online captured plamprint images and because conjunction points between fingers are relatively stable, we determine the point between index finger and middle finger and denote it as K1; the point between middle finger and ring finger and denote it as K2; and the point between ring finger and small finger and denote it as K3. We line up K1 and K3 to get the Y-axis of the palmprint and make a line perpendicular to K1K3 from K2 and denote the intersect point as the origin of the palmprint. By doing so we decide an orthogonal coordinate system on a palmprint and which makes it easy to extract and match features.

The major problem to this method is that if a candidate is wearing a ring on his or her ring finger or closes the fingers together, the holes between the fingers cannot be correctly determined.

6.1.3 Inscribed Circle Based Positioning

This method is to calculate the largest inscribed circle of the boundary map of a palmprint image. The center of the circle is then regarded as the origin O of coordinate system. The point K2 between the middle and ring finger is another key point of this method. We line up O and K2 to get the X-axis of the coordinate system.

The major limitation of this method is that some people have a rectangular palmprint area and for different samples, the circle may shift forth and back.

6.1.4 Texture Based Feature Extraction and Matching

The texture based feature extraction method is associated with the square-based positioning and segmentation algorithm and the feature extraction and matching are performed to the central square (128*128) of palmprints.

We defined four 5*5 masks to describe the horizontal, vertical, 45 degree line and 135 degree line and convolved these masks with the palmprint images to get four global texture energies expressed as numbers. These four numbers are defined as a palmprint's global feature. We then split the 128*128 image into 8*8 tiles and calculate the average hue in each tile. Later the 8*8 tiles are lined up to a 64 bytes code, which we call local feature. The palmprint identification is conducted in a layered fashion: first the global features are used to eliminate most templates in the database until only a small set of similar candidates is left. Local features are then measured for similarity to determine the output of the searching. Linear coefficient is used to measure the similarity of two local features.

6.1.5 Fourier Transform Based Feature Extraction and Matching

The square area in the center of a palm is extracted and used in feature extraction and matching. All the images are first converted to the frequency domain and the feature extraction and matching are performed in the frequency domain. Palmprints with strong creases have more energy in the frequency domain and those with weak creases have less energy. Therefore, by calculating total energy falls in different frequencies may reveal differences between two images with strong or weak creases.. A strong line in a palmprint image may also exhibit higher energy in its perpendicular direction in the frequency domain. The existence of this characteristic allows us to split the frequency domain image into fan like areas and calculate the total energy in each area. This establishes the distribution of the directions of creases on a palm, which could be used to identify palms.

6.1.6 Crease Extraction and Bi-directional Matching

Creases are the main identifying features of a palm, but until now no perfect crease extraction method has been proposed for palmprint identification due to the complexity of creases. The major problem is that some creases may not present when capturing a palm in the second time, so we proposed a bi-directional crease matching method to lower the impact of the noises introduced in the capturing phase. We identify several long and strong creases as major feature set and regard them as stable feature set. When we compare two crease maps, the matching is performed in two directions: use A's major feature set matching with B's whole feature set and then use B's major feature set matching with A's whole feature set and average the matching scores. Our experimental results show that even using the same edge detection algorithm, this bi-directional matching method significantly improves identification accuracy.

We tried the Canny edge detection algorithm and our self-designed edge detection method with this bi-directional matching algorithm and the recognition results of both were satisfactory.

6.2. Advantages and Disadvantages of the Proposed Algorithms

Each of the proposed algorithms has advantages and disadvantages. Table 6-1 documents the comparison information of palmprint positioning algorithms and Table 6-2 gives that of feature extraction and matching algorithms. Table 6-1 shows that the most promising method is the inscribed circle based positioning method. In order to solve its problem of shifting, we may later try an inscribed ellipse based positioning method or define the distance between center of the circle and the conjunction point between middle finger and ring finger. We may also combine the three algorithms as a way to better positon palmprints.

Table 6-1 Comparison of the positioning algorithms

	Advantages	Disadvantages
Invariant Feature Based	1. Easy to compute 2. Do not need all of boundary to be clear	1. Fail when the boundary is not straight 2. Fail if the Heart Line is not clear
Conjunction Points between Fingers Based	1. Easy to compute 2. Precise	1. Fail when the quality of image is not good enough 2. Fail if the user not to open all the fingers
Inscribed Circle Based	1. Easy to compute 2. Precise in determining palm direction 3. May obtain larger size of palmprint segments 4. Not sensitive to image quality 5. The radius is also a feature in classifying palmprints	1. The circle may shift in different samples

Table 6-2 Comparison of the feature extraction and matching algorithms

	Advantages	Disadvantages
Layered Texture Based	1. Easy to compute 2. Small feature size 3. Easy to improve by changing masks 4. Quick response of matching	1. Not precise
Fourier Transform	1. Easy to represent feature in frequency domain 2. Insensitive to shift distortion	1. Longer response time 2. Lost of position information
Bi-directional Matching of Creases	1. Precise 2. Easy to analysis the matching result 3. Easy to improve by updating edge detection method	1. Larger feature size 2. Longer matching time

In general, the bi-directional matching of creases method may achieve a higher identification rate but the feature size is larger while the texture-based method uses smaller feature size and could be used in indexing the palmprint database for quick searching in first round. Fourier Transform based method though applicable, is not very good for identification.

6.3. Performance Testing

We designed and implemented a performance testing system to automatically test the performance of the three algorithms. For each algorithm, its Equal Error Rate, registration time and match time are recorded.

6.3.1 Database

The database is 90 (numbered from 1 to 90) palms wide (w) and 9 impressions per palm deep (d) (810 palmprints in all); Table 6-3 summarizes the global features of the two databases and Fig. 6-1 shows some sample images in the database.

Table 6-3 The database

Sensor Type	Image Size	Wide	deep	Resolution
Optical Sensor	320*240	90	9	100 dpi

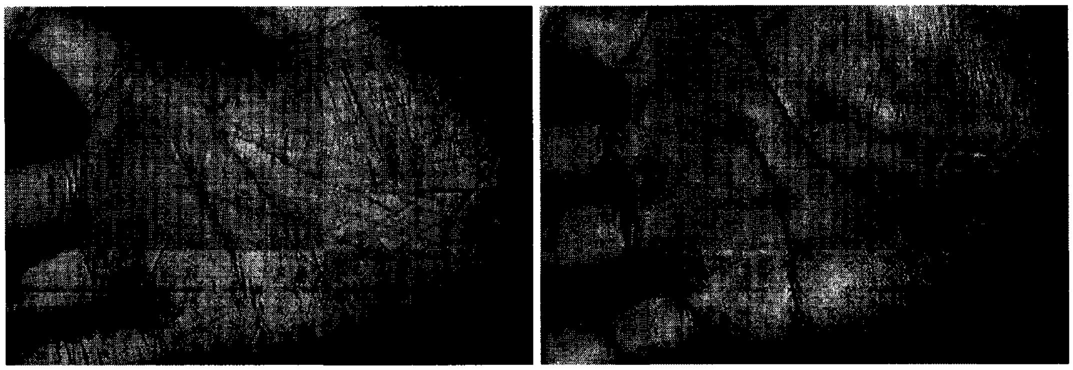


Fig. 6-1 Palmprint samples in the testing database

To summarize, the database has the following features:

- Ninety percent samples are from 18-20 year-old students.

- Sixty percent palmprints are from male.
- Palmprints are all from right hand.
- All images were taken from untrained people and for each person it took five minutes to finish the capturing.
- All the images from the same individual were acquired by a new positioning of the palm – after finishing one sample, the participant was asked to remove his or her palm from the device and to then place the palm for a next capturing.
- The position and direction of the samples from the same palm are not exactly the same. But the rotation is between −15 to +15 degree.
- It was not guaranteed that the stretch degree and the relationship of fingers are the same for samples from the same palm.
- It is guaranteed that the full palm was presented in the images for all samples.

6.3.2 Performance Evaluation

We will refer to the *j*th palmprint sample of the *i*th palm as P_{ij} , $i = 1...90$, and $j = 1...9$, and to the corresponding template (computed from P_{ij}) as T_{ij}.

For each algorithm:

The templates T_{ij}, $i = 1...90$, and $j = 1...8$ are computed from the corresponding P_{ij} and stored on a disk;

- Each palmprint template T_{ij} is matched against the palmprint image P_{ik} ($j < k <= 9$) and the corresponding *Genuine Matching Scores* gms_{ijk} are stored. The number of matches (denoted as NGRA – Number of Genuine Recognition Attempts) is ((9*8)/2)*90 = 3240.
- Each palmprint template T_{i1}, $i = 1...90$ is matched against the first palmprint image from different palms P_{k1}($i < k <= 90$) and the corresponding Impostor Matching Scores ims_{ik} are stored. The number of matches (denoted as NIRA – Number of Impostor Recognition Attempts) is ((90*89)/2) = 4005.

- The genuine matching score distribution and the impostor matching score distribution are computed (actually, the term "distribution" denotes a histogram) and graphically reported to show how the algorithm "separates" the two classes. In palmprint verification, higher scores are associated with more closely matching images.
- The FAR(t) (False Acceptance Rate) and FRR(t) (False Rejection Rate) curves are computed from the above distributions for t ranging from 0 to 1. Given a threshold t, FAR(t) denotes the percentage of ims_{ik} >=t, and FRR(t) denotes the percentage of gms_{ijk}< t:

$$FAR(t) = \frac{card\{ims_{ik} \mid ims_{ik} \geq t\}}{NIRA},$$

$$FRR(t) = \frac{card\{gms_{ijk} \mid gms_{ik} < t\}}{NGRA}$$

where *card* denotes the cardinality of a given set.

- The Equal Error Rate EER is computed as the point where FRR (t) = FAR (t) (see Fig. 10-2); in practice, the matching score distributions (histograms) are not continuous and a cross point might not exist. In this case, we report the average of EER_{low} and EER_{high}.

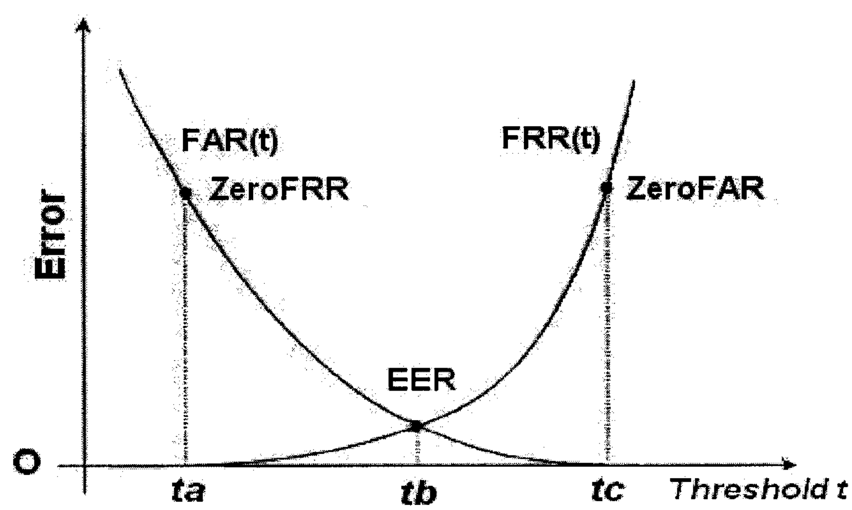


Fig. 6-2 An example of FAR/FRR curve, where the points corresponding to EER, ZeroFAR and ZeroFRR are highlighted.

- ZeroFAR is defined as the lowest FAR at which no False Acceptance occur and ZeroFRR is defined as the lowest FRR at which no False Rejections occur (Fig. 6-2):

$$ZeroFAR(t) = \min_t \{FRR(t) \mid FAR(t) = 0\}$$

$$ZeroFRR(t) = \min_t \{FAR(t) \mid FRR(t) = 0\}$$

  Both ZeroFAR and ZeroFRR may not exist.

- The average enroll time is calculated as the average CPU time for a single enrollment operation, and average match time as the average CPU time for a single match operation better template and a test image.

6.3.3 Results

This section reports the performance of the tested algorithms (Table 6-4). The notation introduced in Section 6.3.2 is used in both the graphics and tables. For each algorithm, detailed results are listed in Fig.6-3, Fig. 6-4 and Fig. 6-5.

Table 6-4 Algorithm performance sorted by EER

Algorithm	EER (%)	Avg Enroll Time (Sec.)	Avg Match Time (Sec.)
Crease Matching	2.9	0.05	2.01
Texture Analysis	7.42	0.093	0.005
Fourier Transform	10.01	3.24	0.004

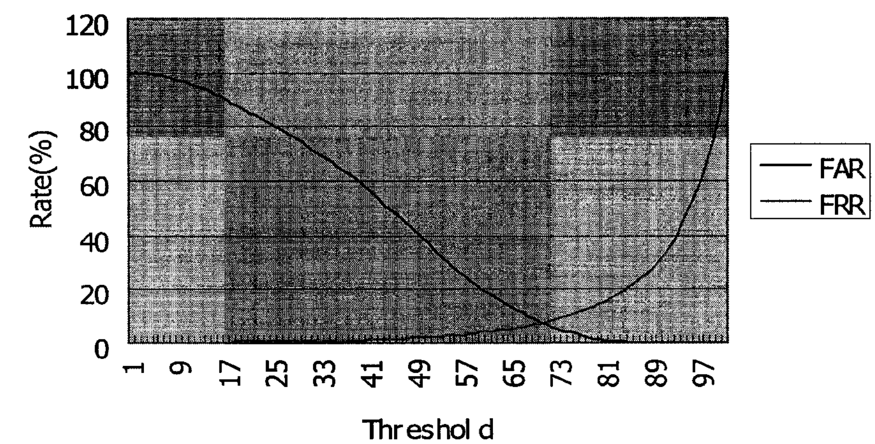


Fig. 6-3 FAR and FRR of texture ananlysis

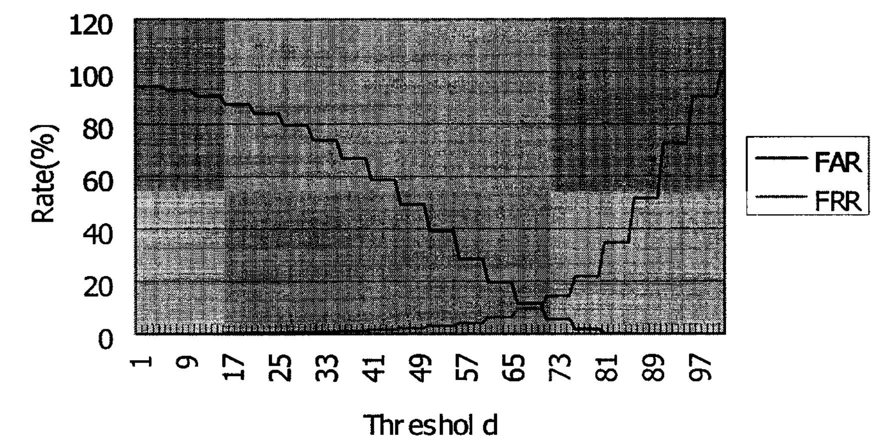


Fig. 6-4 FAR and FRR of Fourier Transform

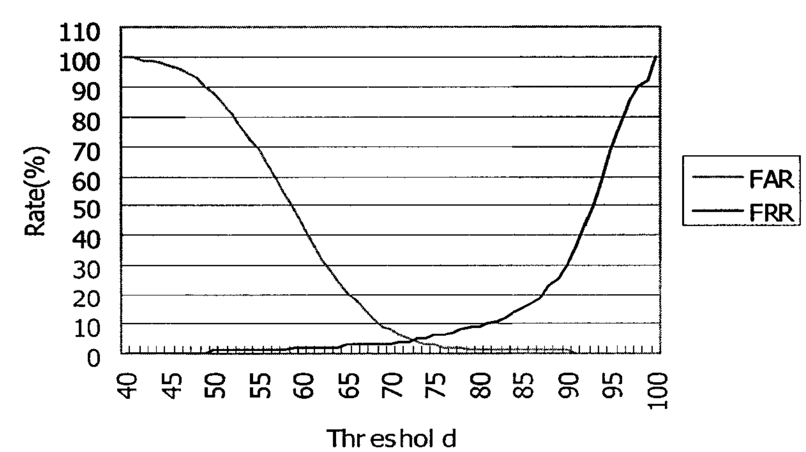


Fig. 6-5 FAR and FRR of crease matching

6.3.4 Analysis of the results

The three algorithms are not 100 percent accurate. Some palmprints are classified as faulty. Some palmprints are quite similar and some samples from the same palm have visible differences, which are the main reason for false recognition. Fig. 6-6 shows some similar but different palmprints and Fig. 6-7 shows the samples of a same palm that are not correctly identified.

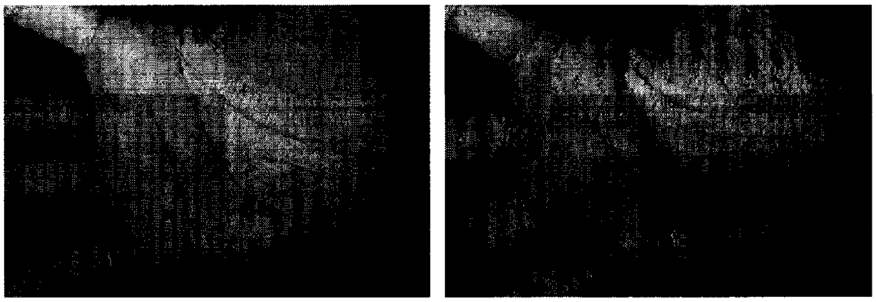


Fig. 6-6 Similar palms

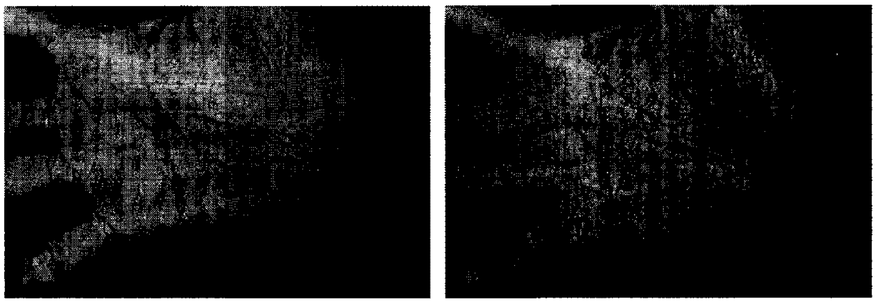


Fig. 6-7 Samples from the same palm

6.4. Conclusion

This chapter brings together all the algorithms introduced in former chapters. Each algorithm has its advantages and disadvantages. Table 6-1 and Table 6-2 document the comparison of the algorithms. The experimental results show that the crease extraction and matching method is more promising than the other methods. All the analysis provides the foundation for further investigation into this area.

Chapter 7

Conclusion and Future Work

Biometrics computing is emerging as a premier technology in a variety of automated security systems. Different biometric features, such as fingerprint pattern, speech quality, face feature, signature manner, hand geometry and iris characteristics, have been proposed as means for individual identification.

Palmprints are different from other biometrics trait because they are reliable, easy to capture, rich in personal features and can be seamlessly integrated with fingerprint and hand geometry to provide a more robust and accurate identification system.

Key issues and major difficulties in palmprint identification include palmprint capturing, positioning, feature extraction and matching. In order to test and verify the proposed algorithms, a large database is also essential. This thesis tackled all of these problems.

The major contributions of this thesis include:

1. Collected a relatively large palmprint image database, which provides the foundation for researchers to further investigation in this area.
2. Cooperated with others to design and develop a palmprint capture device and a prototype system to prove the feasibility of palmprint based personal identification for security systems.
3. Proposed several image positioning/segmentation, feature extraction and matching methods, which can be referenced by researchers in similar areas. The positioning

algorithms include Heart Line end point and outer boundary based, conjunction points between fingers based and inscribed circle based. The feature extraction methods include texture analysis, Fourier Transform and Bi-directional matching of creases. The experimental results demonstrate the effectiveness of the proposed methods on the online captured palmprint database.

Future work

1. Improving the capture device so that more clear palmprint images can be gotten. Related work includes changing the color, brightness, direction of light in the capture device to see what could be the best configuration for a palmprint capture device and trying some more physical methods such as those have been used in fingerprint capture devices.
2. Collecting more palmprint images to verify the proposed identification methods. Currently the palmprints are basically from undergraduate students. The next data collection activity aims at different group of people with different ages and occupations.
3. Setting up a palmprint database tracing the palmprint images from the same group of people in a long period of time (1-2 years) to observe the possible changing of palmprints.
4. Improving the proposed feature extraction and presentation methods and try some new approaches to get an applicable online palmprint recognition method. Wavelet and Bayes Network are two methods showing promise to palmprint recognition.
5. Integrating the palmprint with fingerprint and hand geometry methods. Develop a device to capture the palmprint and fingerprints at the same time, so as to combine the features from fingerprint and palmprint.
6. Planning to try the palmprint recognition that the images are captured by a common camera connected to the computer and the hand is just to put in front of the lens without any equipments for the positioning and light control. This is similar to the face detection

and face-based recognition system. Our idea is that if you just put your hand in front of the door and then the door opened automatically. That would be a wonderful application.

7. Working on the classification of palmprints so that an efficient searching algorithm can be developed and it becomes easier to search in a large quantity of palmprints.

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Appendix

A . Research Labs

1. Michigan State University Biometrics Research Homepage

http://biometrics.cse.msu.edu/

2. Purdue's Automatic Identification and Data Capture (AIDC) Homepage

http://www.tech.purdue.edu/it/resources/aidc/

3. San Jose State University's Biometric Identification Research Effort

http://www-engr.sjsu.edu/~graduate/biometrics/

4. West Virginia University/FBI Forensic Identification Degree Program

http://info.news.wvu.edu/news/forensic.html

B. Journals

1. ACM Special Interest Group on Security, Audit and Control

http://www.acm.org/sigs/sigsac/

2. Automatic I.D. News

http://www.autoidnews.com/

3. Biometric Digest

http://www.biodigest.com/

4. Biometrical Journal: Journal of Mathematical Methods in Biosciences

http://journals.wiley.com/wilcat2-bin/ops/ID1/0323-3847/prod

5. BIOMETRICS: A Journal of the International Biometric Society

http://stat.tamu.edu/Biometrics/

6. Biometrika (Britain)

http://www.oup.co.uk/biomet/

7. Biometric Technology Today, The Biometrics Report, etc.

http://www.sjb.co.uk/

8. EE Times

http://www.eetimes.com/

9. Electronic Commerce (EC) Today

http://www.ectoday.com/

10. Infosecurity News

http://www.westcoast.com/

11. Info World

http://www.infoworld.com/

12. Journal of Agricultural, Biological, and Environmental Statistics

http://www.amstat.org/publications/jabes/

13. IEEE Transactions on Speech and Audio Processing

http://www.ieee.org/pub_preview/sa_toc.html

14. IEEE Transactions on Pattern Analysis and Machine Intelligence

http://ada.computer.org:80/tpami/

15. National Institute of Justice's Headlines and Technology News Update

http://www.nlectc.org/headline.html

16. PC Week

http://www.nlectc.org/techhed.html

17. PIN's Advanced Card & Identification Technology Sourcebook, Ben Miller's annual publication

http://www.pcweek.com/

18. Secure Computing

http://www.ctst.com/f_sourcebook.html

19. Security Management (ASIS)

http://www.infosecnews.com/

20. Security Solutions Online

http://www.securitymanagement.com/

22. Speech Communication

http://www.elsevier.nl/eee/specom/

C. Associations

1. American Association of Motor Vehicle Administrators (AAMVA)

http://www.aamva.org/

2. American Statistical Association

http://www.amstat.org/

3. Association for Biometrics (AfB), UK

http://www.afb.org.uk/

4. Australian Biotechnology Association

http://www.aba.asn.au/

5. Automatic Identification Technology Commerce and Education - About Biometric ID

http://www.aitworld.com/

6. BioAPI Consortium -- Industry group working to define an API for biometrics

http://www.aitworld.com/techvalley/biometrics.html

7. Biometrics In Human Services User Group

http://www.bioapi.org

8. Biometric Testing Services (BIOTEST) - a European project aimed at developing standard metrics for measuring/comparing performance of biometric devices, and establishing testing services

http://www.dss.state.ct.us/digital/faq/dihsug.htm

9. Commercial Biometrics Developer's Consortium (CBDC)

http://www.npl.co.uk/npl/sections/this/biotest/

10. Committee on Computing, Information, and Communications R&D... Technology Policy

http://www.icsa.net/services/consortia/cbdc/

11. Subcommittee

http://www.hpcc.gov/ccic/

12. Financial Services Technology Consortium (biometric fraud prevention)

http://www.fstc.org/

13. International Association for Identification (IAI)

http://www.iaibbs.org/

14. International Biometric Industry Association (IBIA)

http://www.ibia.org

15. National Center for Indentification Technology

http://www.ncit.org/

16. NATO Advanced Study Institute (ASI) on Face Recognition: From Theory to Applications

http://chagall.gmu.edu/faces97/natoasi/

17. Security Industry Association (SIA)

http://www.siaonline.org/

18. The Biometric Consortium

http://www.biometrics.org

19. The Human Identification Project

http://www.asti.dost.gov.ph/

20. UK Police Information Technology Organisation (PITO)

http://www.pito.org.uk

21. 1997 Automated Fingerprint Identification System (AFIS) Committee

http://www.iaibbs.org/afis.htm

22. 1998 Glossary of Biometric Terms (AfB & ICSA)

http://www.afb.org.uk/glossuk1.html

23. American National Standards Institute

http://www.ansi.org:80/

24. International Standards Organization

http://www.iso.ch/

D. Companies

Biometric Consultants & System Integrators

1. International Biometric Group, Inc.

   http://www.biometricgroup.com

2. DARPA's Internet for Security Professionals

   http://isp.hpc.org/

3. EDI HotLinks (standards, etc.)

   http://www.wpc-edi.com/resource.html

4. EAGLES' Assessment of Speaker Verification Systems

   http://coral.lili.uni-bielefeld.de/~gibbon/EAGLES/slwghand-t/node54.html

5. East Shore Technologies (check the EST Challenge)

   http://www.east-shore.com/

6. Fingerprint Technologies

   http://www.fingerprint.com/

7. FingerPrint USA

   http://www.fpusa.com/

8. GSA's Federal Security Infrastructure Program (for secure applications: tokens, keys, and authorization)

   http://www.gsa.gov/fsi/

9. GSA's SmartGov

   http://policyworks.gov/smartgov/

10. I/O Software, Inc. - a distributor, consultant, SI and custom developer for the Sony fingerprint identification unit. The first self-contained unit that compares and enrolls in a device the size of a mouse.

http://www.iosoftware.com

11. International Biometric Group (IBG)

http://www.biometricgroup.com/

12. Justice Technology Information Network (JUSTNET)

http://www.nlectc.org/

13. Julian Ashbourn's Technology Corner

http://members.aol.com/teknotalk/home.htm

14. National Information Assurance Partnership (NIAP)

http://niap.nist.gov/

15. NIST's Computer Security Resource Clearinghouse

http://csrc.ncsl.nist.gov/

16. Physical Security Equipment Action Group

http://www.vitro.bloomington.in.us:8080/pseag/

17. Q&A Consulting

http://www.communinet.org/QA/

18. The Biometric Consulting Group, LLC

http://biometric-consulting.com

19. 20G4 Multi-technology Automated Reader Card (MARC) Project

http://www.vitro.bloomington.in.us:8080/marc/

Biometric Vendors/Consultants (Fingerimaging)

20. AuthenTec - identification and security products: biometrics. PO Box 37, MS 11MC/1743, Melbourne, FL 32902. (tel) 407.727.4872 (fax) 407.729.3499

http://www.authentec.com

21. Biometric Access Corporation

http://www.biometricaccess.com/

22. Biometric Identification, Inc.

http://www.biometricID.com/

23. Cambridge Neurodynamics

http://www.camneuro.stjohns.co.uk/

24. Cogent Systems

http://www.cogentsystems.com/

25. Compaq

http://207.18.199.108/im/fit/

26. Crosscheck Corp.

http://www.xcheck.com/

27. East Shore Technologies

http://www.east-shore.com/

28. Fingerprint Technologies

http://www.fingerprint.com/

29. Fingerprint USA

http://www.fpusa.com/

30. Harris Semiconductor, Melbourne, Fla.

http://www.harris.com

31. Ideamation, Inc. - a supplier of customized fingerprint identification systems and services to businesses world-wide. IDeas International

http://users.ids.net/%7emikedn/idea

32. Identicator Corporation

http://www.parlant.com/ideas/ideas.htm

33. Identification Systems

http://www.identicator.com/

34. Identix

http://www.gotnet.net/home/idyou

35. ID TEC

http://www.identix.com/

36. ImEdge - Edgelit Holography Fingerprint Imaging

http://www.idtek.com/

37. I/O Software, Inc

http://eastview.org/ImEdge/

38. LEX Solutions, Inc.

http://www.iosoftware.com

39. Mitsubishi Electric Corp.

http://www.lexsolutions.com/

40. Mytec

http://www.mbnet.or.jp/melsys/fingre03.html

41. The National Registry, Inc. (NRI) - finger-imaging, fingertip scanners,software.

http://www.mytec.com/

42. Net-ID, Inc.

http://www.netid.com/

43. Neurotechnologija, Ltd.

http://www.neurotechnologija.com/

44. Polaroid Corporation

http://www.polaroid.com/

45. Printrak International

http://www.printrakinternational.com/

46. SAC Technologies Inc., Edina, Minn.

http://www.sacman.com

47. Saflink Corporation (NRI)

http://www.saflink.com/

48. Sagem Morpho, Inc.

http://www.morpho.com

49. Startek Engineering, Inc.

http://www.w3bit.com/www_star.html

50. The National Registry Inc.,Tampa, Fla.

http://www.tcs.thomson-csf.com/Us/fingerchip/FC_home.htm

51. Thomson-CSF Inc.

http://users.ids.net/~tms/

52. Totally Managed Security, Inc. -- company(thrum-print based)

http://www.marketplace.unisys.com/bioware

53. UNISYS, Inc

http://www.veridicom.com/

54. Veridicom

http://www.vitrix.com/

55. Vitrix, Inc.

http://www.whovision.com/

56. Who?Vision

http://www.cjis.com/

Biometric Vendors/Consultants (Facial Imaging)

57. CJIS

http://www.wp.com/IVS_face/

58. Intelligent Vision Systems

http://www.miros.com/

59. Miros

http://www.polaroid.com/

60. Polaroid Corporation

http://www.viisage.com/

61. Viisage Technology

http://www.faceit.com/

62. Visionics

http://www.graphcotech.com

Biometric Vendors/Consultants (Voice)

63. Graphco Technologies Inc., West Trenton, N.J.

http://www.imaginenation.com

64. Imagine

http://www.intelitrak.com/

65. Intelitrak Technologies, Inc.

mailto:jmarkowitz@pobox.com

66. J. Markowitz, Consultants

http://www.keywareusa.com/

67. Keyware USA

http://www.speakerkey.com/

68. SpeakerKey, Inc.

http://www.verivoice.com/

69. VeriVoice, Inc.

http://www.aeat.co.uk/pes/ancc/counter

Biometric Vendors/Consultants (Handwriting)

70. AEA Technology - find out about the most extensively tested dynamic signature verification biometric, Countermatch, which has already been demonstrated as a Smart-card holder verification method.

http://hwr.nici.kun.nl/

71. Handwriting Recognition Group

http://www.penop.com/

72. PenOp

http://www.quintetusa.com/

73. Quintet Signature Verification

http://www.iriscan.com/

Biometric Vendors/Consultants (Iris scan)

74. IriScan

http://www.sensar.com/

75. Sensar

http://www.recogsys.com/

Biometric Vendors/Consultants (Hand Geometry)

76. Recognition Systems

http://innotts.co.uk/~joerice/

Biometric Vendors/Consultants (Veincheck)

77. Veincheck Biometric Homepage

http://www.comsec-solutions.com

Biometric/Cryptographic Countermeasures

78. COMSEC Solutions

http://www.cadix.com

E . Important Events on Biometrics

1. September 1997, Proceedings of IEEE published a special issue on automated biometrics.

2. 1997, The Biometric Consortium established the National Biometric Test Center (NBTC) at San Jose State University in the spring of 1997. The Center is a testing, learning and educational organization, created for the development, documentation, dissemination, promotion and teaching of scientifically/mathematically sound, "real-world" performance standards, testing protocols. Working cooperatively with manufacturers, government and non-government users, the NBTC will test and certify any such devices to these standards, on behalf of the Biometric Consortium (BC) for the biometric industry. [1]

3. 1998, AFB was setup. The Association for Biometrics is an organization that aims to promote the awareness and development of biometrics related technologies. It provides an international forum for research and development, system design and integration, application development, market development and other issues. [2]

4. 1998, Association for Biometrics (AfB) and International Computer Security Association (ICSA) published the Glossary of Biometric Terms. [3]

5. August 16-20 1998, '14th Int'l Conference on Pattern Recognition', has a tutorial on automated biometrics. [4]

6. From 1997, San Jose University began to provide a course "Biometric Identification Science and Technology" to graduate students. [5]

7. In February 1997, Oracle Corp., of Redwood City, Calif., Began offering Indentix Inc.'s fingerprint reader and firmware along with Version 7.3 of it database, as well as all subsequent versions.[6]

8. In May of 1997, IBM published a "challenge to the biometric industry" to show that large-scale identification systems (enrollment on the order of 25 million people) are technically feasible.[7]

9. April 1998, BioAPI was established. The BioAPI Consortium was formed to develop a widely available and widely accepted API that will serve for various biometrics technologies. [8]

10. September 1998, IBIA was set up. The International Biometric Industry Association (IBIA) is a trade association founded in September 1998 in Washington, D.C., to advance, advocate, defend and support the collective international interests of the biometric industry. [9]

11. Oct. 1998, Banking on Biometrics '98 was convened. It is a Biometrics Conference for financial institutions, Banks, Credit Unions, S&Ls, Card Processors, Integrators, Biometrics Vendors, Brokers & Investors, Hardware Manufacturers. [10]

References

[1] http://www-engr.sjsu.edu/~graduate/biometrics/

[2] http://www.afb.org.uk/

[3] http://www.afb.org.uk/glossuk1.html

[4] http://www.cssip.elec.uq.edu.au/~icpr98/

[5] http://www-engr.sjsu.edu/~graduate/biometrics/engr297.html

[6] http://www.bioapi.org/

[7] http://www.dss.state.ct.us/digital/news11/bhsug11.htm

[8] http://www.zdnet.com/pcweek/news/0112/12bio.html

[9] http://www.ibia.org/

[10]http://webusers.anet-stl.com/~wrogers/biometrics/conf/bob/98/

F . Glossary

Now some Biometrics associations such as Biometrics Consortium, BioAPI Consortum, Association For Biometrics, International biometric Industry Association and National Biometric Test Center, are working for standards and data exchange in both industry and academia. The definition to basic concepts in biometrics has been in agreement in the majority. The following lists the frequently used notations (referenced [26]):

A. Biometrics

Biometrics is the science of measuring an individual's physical properties such as fingerprint, palmprint, face, hand geometry, iris and retina.

B. Identification

In an **identification,** the recorded biometric feature is compared to *all* biometric data saved in a system. If there is a match, the identification is successful, and the corresponding user name or user ID may be processed subsequently

C. Verification

In a **verification**, the user enters her/his identity into the system (e.g., via a keypad or card), then a biometric feature is scanned. The biometric trait must only be compared to the *one* previously saved reference feature corresponding to the ID. If a match occurs, verification is successful.

D. Enrollment

A prerequisite for authentication is enrollment, in which a biometric feature is saved as a personal reference either decentralized on a chip card or PC, or centrally in a database. Since the quality of the enrollment essentially determines the performance of the authentication, it must be implemented carefully. The enrollment must take place in a trustworthy environment.

During an authentication, a new scanning of the biometric feature is required. This time it is not saved; instead, it is compared to the reference feature. If the comparison is positive, access to the appropriate applications can be granted.

Most biometric systems show the following procedure in detail:

- Taking a data set (e.g., image or sound) which includes the features to be extracted using an appropriate sensor
- Examination of the data quality; if it is insufficient, the data are rejected immediately or appropriate user guidance is given to improve the quality
- Extraction of the desired features from the data set and generation of a template
- For enrollment: Storage of the template as "reference template" in the "reference archive"
- For authentication: Comparison of the actual (request) template with the reference template using a "matcher" and generation of a score value which determines the degree of coincidence. For authentication: Exceeds the score value a predetermined threshold, access is granted, otherwise the request is rejected

E. Template

A template is comprised of the extracted unique features of the biometric data. The template is generated during the process of feature extraction, which frees the raw data coming from the biometric sensor from redundant information. By this way, both the storage requirements and the matching expense are reduced. Here, the definition of the template does not depend on its usage as reference or for a verification request. (Several authors only call the reference template a template. The request template is called a "sample".)

F. Sensor

For recording and converting biometric traits to usable computer data, one needs an appropriate sensor. Of course, costs can greatly vary for different sensors. However, we can't forget that many technical devices already have sensors built in, and therefore offer possibilities to measure biometric features nearly free of cost.

G. Features, biometric

Biometric traits develop:

- through genetics: **genotypic**
- through random variations in the early phases of an embryo's development: **randotypic** (often called phenotypic)
- or through training: **behavioral**

As a rule, all three factors contribute to a biometric trait's development, although to varying degrees. Biometrics traits used in personal identification include fingerprint, signature, facial geometry, iris pattern, retina, hand geometry, finger geometry, vein structure of the back of hand, ear form, voice, DNA, odor and keyboard strokes.

H. Performance

A biometrics based authentication system's performance is measured by **False Acceptance Rate (FAR) / False Match Rate (FMR) , False Rejection Rate (FRR) / False Non-Match Rate (FNMR)., Failure To Enroll rate (FTE, also FER) , False Identification Rate (FIR) ,**

I. Failure To Enroll Rate (FTE/RER)

The FER is the proportion of people who fail to be enrolled. FER is a non-stationary statistical quantity which does not only show a strong personal correlation, it can even be determined for each individual feature (called personal FER). Those who are enrolled yet but are mistakenly rejected after many verification/identification attempts count for the Failure To Acquire (FTA) rate. FTA can originate through temporarily not measurable features ("bandage", non-sufficient sensor image quality, etc.). The FTA usually is considered within the FRR and need not be calculated separately, see also FNMR and FMR.

J. Fault Acceptance Rate (FAR)

The FAR is the frequency that a **non authorized** person is **accepted** as authorized. Because a false acceptance can often lead to damages, FAR is generally a security relevant measure. FAR is a non-stationary statistical quantity which does not only show a personal correlation, it can even be determined for each individual feature (called personal FAR).

K. Fault Rejection Rate (FRR)

The FRR is the frequency that an **authorized** person is **rejected** access. FRR is generally thought of as a comfort criteria, because a false rejection is most of all annoying. FRR is a non-stationary statistical quantity which does not only show a strong personal correlation, it can even be determined for each individual feature (called personal FRR).

L. Equal Error Rate (ER)

Biometrics is the science of measuring an individual's physical properties such as fingerprint, palmprint, face, hand geometry, iris and retina.

M. Receiver Operating Characteristic (ROC)

The FAR/FRR curve pair is excellently suited to set an optimal threshold for the biometric system. Further predictors of a system's performance, however, are limited. This is partially due to the interpretation of the threshold and similarity measures. The definition of the similarity measures is a question of implementation. Almost arbitrary scaling and transformations are possible, which affect the appearance of FAR/FRR curves but not the FAR-FRR values at a certain threshold. A popular example is the use of a "distance measure" between the reference feature and the scanned feature. The greater the similarity, the smaller the distance. The result is a mirror image of the FAR/FRR curves. A favorite trick is to stretch the scale of FAR/FRR curves near the EER (Equal Error Rate: FAR(th) = FRR(th)), (i.e., using more threshold values) thus making the system appear less sensitive to threshold changes.

In order to reach an effective comparison of different systems, a description independent of threshold scaling is required. One such example from the radar technology is the *Receiver Operating Characteristic (ROC),* which plots FRR values directly against FAR values, thereby eliminating threshold parameters. The ROC, like the FRR, can only take on values between 0 and 1 and is limited to values between 0 and 1 on the x axis (FAR). It has the following characteristics:

- The ideal ROC only have values that lie either on the x axis (FAR) or the y axis (FRR); i.e., when the FRR is not 0, the FAR is 1, or vice versa.
- The highest point (linear scale under the definitions used here) is for all systems given by FAR=0 and FRR=1.
- The ROC cannot increase
- As the ROC curves for good systems lie very near the coordinate axis, it is reasonable for one or both axis to use a logarithmic scale:

M. False Identification Rate (FIR)

The False Identification Rate is the probability in an identification that the biometric feature is falsely assigned to a reference. The exact definition depends on the assignment strategy; namely, after feature comparison, often more than one reference will exceed the decision threshold.

Brief Curriculum Vitae

Wenxin Li is a Ph.D student at the Department of Computing, the Hong Kong Polytechnic University. She received her B.S. and M.S. degree in Computer Science in 1990, 1993 from Peking University. She is now an associate professor at the Department of Computer Science and Technology, Peking University.

During her study in the Hong Kong Polytechnic University, she was awarded Two Tuition Scholarships for Research Postgraduate Studies by The Hong Kong Polytechnic University in 1999 and 2000. She was also awarded the HKAUW Thomas HC Cheung Postgraduate Scholarship in the academic year 1999/2000.