一种用于掌纹识别的线特征表示和匹配方法*

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An Approach to Line Feature Representation and Matching for Palmprint Recognition

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Abstract: A palmprint is a relative new biometric feature for personal authentication. Palm-lines, including the principal lines and wrinkles, are one of the most important features used in palmprint recognition. This paper proposes a novel approach of line feature representation and matching for palmprint recognition. To represent palm-lines, a vector, called line feature vector (LFV), is defined by using the magnitude and orientation of the gradient of the points on these lines. A LFV contains information about both the structure and thickness of the lines, thus its capability to distinguish between palmprints, including those with similar line structures, is strong. A correlation coefficient is employed to measure the similarity between LFVs of palmprints during the matching phase. 99.0% and 97.5% accurate rates are obtained in the one-to-one matching test and one-to-many matching test, respectively. The results show that LFV is robust to some extent in rotation and translation of the images. The accuracy, speed and storage of the proposed approach can meet the requirements of an online biometric recognition.
Key words: biometrics; palmprint recognition; line feature representation and matching

摘 要: 作为一种较新的生物特征,掌纹可用来进行人的身份识别.在用于身份识别的诸多特征中,掌纹线,包括主线和皱褶,是最重要的特征之一.本文为掌纹识别提出一种有效的掌纹线特征的表示和匹配方法,该方法定义了一个矢量来表示一个掌纹上的线特征,该矢量称为线特征矢量(line feature vector,简称 LFV).线特征矢量是用掌纹线上

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各点的梯度大小和方向来构造的.该矢量不但含有掌纹线的结构信息,而且还含有这些线的强度信息,因而,线特征矢量不但能区分具有不同线结构的掌纹,同时也能区分那些具有相似的线结构但各线强度分布不同的掌纹.在掌纹匹配阶段,用互相关系数来衡量不同线特征矢量的相似性.实验表明,LFV 方法无论是在速度、精度,还是在存储量方面都能满足联机生物识别的要求.

关键词: 人体生物特征;掌纹识别;线特征的表示与匹配
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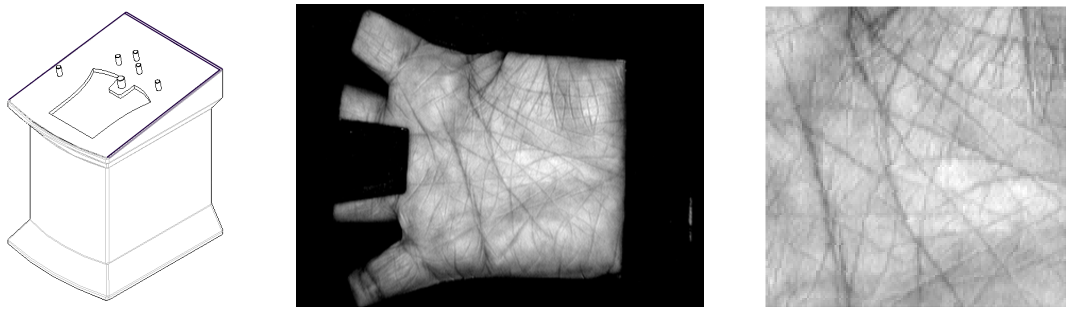
1 Introduction

Computer-Aided personal recognition is becoming increasingly important in our information society. Biometrics is one of the most important and reliable methods in this field. The most widely used biometric feature is the fingerprint and the most reliable feature is the iris[1]. However, it is very difficult to extract small unique features (known as minutiae) from unclear fingerprints and the iris input devices are very expensive[1]. Other biometric features, such as the face and voice, are less accurate and they can be mimicked easily. A palmprint, as a new biometric feature, has several advantages compared to other available features: low-resolution images can be used, low cost capture devices can be used, it is very difficult or impossible to fake a palmprint, and the line features of the palmprints are stable, etc. It is for these reasons that palmprint recognition has recently attracted an increasing amount of attention from researchers[2~4]. Zhang *et al*.[2] proposed to use a palmprint as a biometric feature for identity recognition and obtained good results in offline palmprint verification. Duta *et al*.[3] extracted some feature points lying along the palm-lines and verified the identity by matching these points. Zhang[4] used 2-D Gabor filters to extract the texture features from low-resolution palmprint images captured using a CCD camera and employed these features to implement a highly accurate online palmprint recognition system.

There are many features in a palmprint such as geometrical features, principal lines, wrinkles, delta points, minutiae, etc.[1]. However, geometrical features such as the width of the palm can be faked easily by making the model of a hand. Delta points and minutiae only can be extracted from the fine-resolution images. Principal lines and wrinkles, called line features[2], are very important to discriminate between different palmprints and they can be extracted from low resolution images. Therefore, line features are one of the most important features in automated palmprint recognition. Palm-lines can be efficiently detected by some edge detection algorithms[5,6]. Because the lines in a palm are irregular, it is impossible to represent them exactly by using some mathematical equations and difficult to match them directly. Zhang *et al*.[2] used several straight-line segments to approximate each palm-line and verified the palm by matching these straight-line segments. In this method, palm-lines were traced and linked before the approximation. These operations were very time consuming. Moreover, the connectivity of the lines affected the result of the approximation heavily. To overcome these problems, Duta *et al*.[3] adopted the isolated points lying along palm-lines, which were called feature points, and their orientations to represent the lines and verified palmprints by matching these feature points. A great deal of storage space was required to store the feature points and their orientations. Both of the above methods only considered the structural information about the lines, thus it was difficult for them to discriminate between palmprints with similar line structures. To solve these problems, a novel approach to line feature representation and matching is proposed in this paper. In this approach, the lines are represented by a vector, called line feature vector (LFV), which is defined by using the orientation and the magnitude of the gradient of the points forming these lines. LFV contains not only the structural information about the lines, but also the information about the thickness of the different lines. Thus, its ability to discriminate between palmprints, including those with a similar line structure, is strong. A correlation coefficient is used to measure the similarity between LFVs of palmprints during the matching phase.

In this paper, all of the palmprint images are captured by an online CCD-camera-based device. In this device, there are some pegs between fingers to limit the palm's stretching, translation and rotation (Fig.1(a)). These pegs separate the fingers, forming two holes between the forefinger and middle finger, and between the ring finger and the little finger. Figure 1 (b) is a sample captured by this device. We use the preprocessing technique described in Ref.[4] to align the palmprints. In this technique, the tangent of these two holes are computed and used to align the palmprint. The central part of the image, which is 128×128, is then cropped to represent the whole palmprint (Fig.1(c)). After this preprocessing, translation and rotation of the palmprints remain very little.



(a) Our palmprint capture device (b) A sample captured by this device (c) The preprocessing result

Fig.1 Palmprint device and preporcessing

The rest of this paper is organized as follows. Section 2 contains some definitions and notations. In Section 3, we introduce the proposed approach to line feature representation. Section 4 describes the line feature matching process. Experimental results and analysis are given in Section 5. In Section 6, we provide some conclusions and future work.

2 Definitions and Notations

The lines on a palm are a kind of roof edges. Many algorithms can be used for roof edge detection[5]. Most of these algorithms are based on finding the zero-crossing points of the first-order derivative of the gray-level profile of a roof edge. Based on those algorithms, however, the direction of the gradient of the edge points (zero-crossing), which will be used in our approach, is uncertain. Therefore, in this paper, we regard a roof edge as two step edges and use a step edge detection algorithm such as Canny's algorithm[6] to detect it.

Let I be an $M \times N$ image; Mag and $Angle$ be the magnitude and orientation angle of the gradient of I, where $-90^{\circ} \le Angle(i,j) < 90^{\circ}$, $0 \le i \le M-1$, $0 \le j \le N-1$. The values of the non-edge points in Mag are set to 0.

Each edge point, (i,j), can be regarded as an element of a line, l, that crosses this point and whose direction, $Ang(i,j)$, is perpendicular to the direction of the gradient at this point. That is,

$$Ang(i,j) = Angle(i,j) + 90^{\circ} \tag{1}$$

Obviously, $0^{\circ} \le Ang(i,j) < 180^{\circ}$. The edge point (i,j) is called a *directional line-element* (DLE) with a direction of $Ang(i,j)$.

Since the orientation of the gradient of the edge points can be any value in the interval $[-90^{\circ}, 90^{\circ}]$, according to Eq.(1), the orientation of the corresponding DLEs can be any value in the interval $[0^{\circ}, 180^{\circ}]$, which makes it very difficult to measure and describe these DLEs. To solve this problem, four fuzzy sets of DLEs are defined as follows.

Let U be a collection of all the DLEs in a palmprint. We define four fuzzy sets of DLEs, $F_{0^{\circ}}, F_{45^{\circ}}, F_{90^{\circ}}, F_{135^{\circ}}$, in U : $F_{0^{\circ}} = \{\mu_{0^{\circ}}(i,j)/(i,j)\}$, $F_{45^{\circ}} = \{\mu_{45^{\circ}}(i,j)/(i,j)\}$, $F_{90^{\circ}} = \{\mu_{90^{\circ}}(i,j)/(i,j)\}$, and $F_{135^{\circ}} = \{\mu_{135^{\circ}}(i,j)/(i,j)\}$, where

(i,j) is the coordinates of the DLE, $\mu_{0^\circ}(i,j), \mu_{45^\circ}(i,j), \mu_{90^\circ}(i,j)$, and $\mu_{135^\circ}(i,j)$ are the corresponding membership functions in $F_{0^\circ}, F_{45^\circ}, F_{90^\circ}$ and F_{135°, respectively:

$$\mu_{0^\circ}(i,j)=\begin{cases}\cos(2\times Ang(i,j)), & \begin{matrix}0^\circ \le Ang(i,j)<45^\circ \\ 135^\circ \le Ang(i,j)<180^\circ\end{matrix} \\ 0, & 45^\circ \le Ang(i,j)<135^\circ\end{cases} \tag{2}$$

$$\mu_{45^\circ}(i,j)=\begin{cases}\sin(2\times Ang(i,j)), & 0^\circ \le Ang(i,j)<90^\circ \\ 0, & 90^\circ \le Ang(i,j)<180^\circ\end{cases} \tag{3}$$

$$\mu_{90^\circ}(i,j)=\begin{cases}0, & \begin{matrix}0^\circ \le Ang(i,j)<45^\circ \\ 135^\circ \le Ang(i,j)<180^\circ\end{matrix} \\ -\cos(2\times Ang(i,j)), & 45^\circ \le Ang(i,j)<135^\circ\end{cases} \tag{4}$$

$$\mu_{135^\circ}(i,j)=\begin{cases}0, & 0^\circ \le Ang(i,j)<90^\circ \\ -\sin(2\times Ang(i,j)), & 90^\circ \le Ang(i,j)<180^\circ\end{cases} \tag{5}$$

where $Ang(i,j)$ is the angle of the DLE at point (i,j). The membership functions (Eqs.(2)~(5)) have the following properties:

For each DLE, at least two of its membership grades are zeros. For example, let the orientation of the DLE at point (i,j) be α, where $45^\circ \le \alpha < 90^\circ$, according to Eqs.(2) and (5), $\mu_{0^0}(i,j)=0$ and $\mu_{135^\circ}(i,j)=0$. When α varies from 45° to 90°, $\mu_{45^\circ}(i,j)$ decreases from 1 to 0, whereas $\mu_{90^\circ}(i,j)$ increases from 0 to 1 (see Eqs. (3) and (4)).

According to its membership grade in the fuzzy sets of a DLE, the energy of the DLE at (i, j) in fuzzy set F_α, called a *fuzzy energy of DLE*, is defined as follows:

$$e_\alpha(i,j)=(Mag(i,j)\times\mu_\alpha(i,j))^2,\ \alpha=0^\circ, 45^\circ, 90^\circ \text{ and } 135^\circ \tag{6}$$

3 Line Feature Representation

3.1 Line feature vector

The edge image of a palmprint is divided equally into $M\times M$ blocks and then labeled as $1,\dots,M\times M$. For the block labeled as p, a four-dimensional vector ($E^p_{0^\circ}, E^p_{45^\circ}, E^p_{90^\circ}, E^p_{135^\circ}$) can be computed as follows:

$$E^p_\alpha=\sum_{k=1}^m e_\alpha(x_k,y_k)=\sum_{k=1}^m (Mag(x_k,y_k)\times\mu_\alpha(x_k,y_k))^2,\ \alpha=0^\circ,\ 45^\circ,\ 90^\circ \text{ and } 135^\circ \tag{7}$$

where m is the total number of points in this block and $(x_1,y_1),(x_2,y_2),\dots,(x_m,y_m)$ are the coordinates of these points. Since each block has four dimensions, the vector of a whole palmprint has $M\times M\times 4$ dimensions, i.e.

$$V=(E^1_{0^\circ},E^1_{45^\circ},E^1_{90^\circ},E^1_{135^\circ},E^2_{0^\circ},E^2_{45^\circ},E^2_{90^\circ},E^2_{135^\circ},\dots,E^{M\times M}_{0^\circ},E^{M\times M}_{45^\circ},E^{M\times M}_{90^\circ},E^{M\times M}_{135^\circ}) \tag{8}$$

In order to remove the effect of the illumination variance, this vector is normalized by using the maximum and minimum values of its components:

$$\widetilde{V}=(e^1_{0^\circ},e^1_{45^\circ},e^1_{90^\circ},e^1_{135^\circ},e^2_{0^\circ},e^2_{45^\circ},e^2_{90^\circ},e^2_{135^\circ},\dots,e^{M\times M}_{0^\circ},e^{M\times M}_{45^\circ},e^{M\times M}_{90^\circ},e^{M\times M}_{135^\circ}) \tag{9}$$

$$e^k_\alpha=\frac{E^k_\alpha-E_{\min}}{E_{\max}-E_{\min}} \tag{10}$$

where $k=1,\dots,M\times M$; $\alpha=0^\circ,45^\circ,90^\circ,135^\circ$; $E_{\max}$ and $E_{\min}$ are the maximum and minimum values of the components of V, respectively. The normalized vector $\widetilde{V}$ is called a *line feature vector* (*LFV*).

According to the definition, a LFV represents the strength of the lines in different directions at different spatial positions on a palm. That is, it contains the information about both the structure and thickness of palm-lines. Therefore, LFVs can discriminate palmprints captured from different palms, even those with similar line structures. Figure 2 shows an example of the LFV extraction.

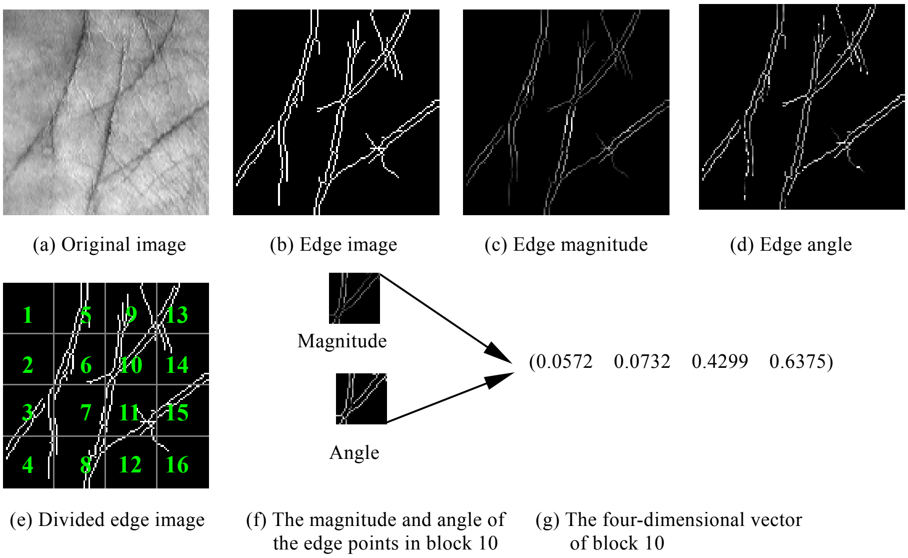


Fig.2 An example of LFV extraction

3.2 Fuzzy division

As described in the sub-section above, to construct a LFV, the palmprint image is divided into $M \times M$ blocks definitely. Each of the DLEs has only two states: either it belongs to a block or not. Because it is impossible to remove all of the translation and rotation during the preprocessing stage, the points around the boundaries of the blocks in an image may not be in the same block of the image captured from the same palm at different times. To avoid this problem, the fuzzy block and fuzzy division are defined in this subsection.

Let $2l$ be a positive integer, and U be the collection of all points in a palmprint. Then, a fuzzy block, FB_k, whose central point is (x_k, y_k), can be defined as follows:

$$FB_k = \{\mu_k(i,j)/(i,j)\} \tag{11}$$

where (i,j) is the coordinates of a point in the image and $\mu_k(i,j)$ is the corresponding membership function in the FB_k:

$$\mu_k(i,j) = \begin{cases} 1, & d \le l/2 \\ \dfrac{2(l-d)}{l}, & l/2 < d < l \\ 0, & d \ge l \end{cases} \tag{12}$$

where

$$d = \max(|i - x_k|, |j - y_k|) \tag{13}$$

According to Eqs.(12),(13), the membership grade of a point in a fuzzy block is computed by examining the distance from it to the central point of the block.

We call $M \times M$ fuzzy blocks, which are labeled as $(0,0), (0,1), ..., (i,j), ..., (M-1, M-1)$, a $M \times M$ *fuzzy division* of an image with size $N \times N$ if and only if

$$x_i = l + \frac{3}{2} \times i \times l, \quad y_j = l + \frac{3}{2} \times j \times l \tag{14}$$

$$x_{M-1}=y_{M-1}=l+\frac{3}{2}\times(M-1)\times l=N-l \tag{15}$$

where (x_i,y_j) is the center point of block (i,j) ($i,j=0,...,M-1$); M and $2l$ are two positive integers.

In a fuzzy division of an image, each fuzzy block overlaps $\frac{l}{2}\times 2l=l^2$ pixels of each adjacent block, thus there is no definite boundary between the fuzzy blocks. Eq.(15) can be rearranged as:

$$M=\frac{2N-l}{3l} \tag{16}$$

Because both M and $2l$ are positive integers, and N=128 in this paper, M only has four values: 85, 21, 5 and 1, which can satisfy Eq.(16). That is, there exist four fuzzy divisions, i.e. 85×85 fuzzy division, 21×21 fuzzy division, 5×5 fuzzy division and 1×1 fuzzy division. The length of the corresponding LFVs is 85×85×4 = 28 900, 21×21×4 =1 764, 5×5×4=100 and 1×1×4=4, respectively. Obviously, the 1×1 fuzzy division is not suitable for palmprint. Because the storage requirements and the computation complexity are a direct ratio to the length of the vectors, the LFVs of 85×85 and 21×21 fuzzy division are too long to be used in palmprint recognition. Therefore, 5×5 fuzzy division is employed in the following sections.

For the fuzzy block, p, Eq.(7) can be modified as follows:

$$\widetilde{E}_{\alpha}^{p}=\sum_{i=0}^{N}\sum_{j=0}^{N}[Mag(i,j)\times\mu_{\alpha}(i,j)\times\mu_{p}(i,j)]^2 \tag{17}$$

where the palmprint image is of size $N\times N$, $\alpha=0^\circ,45^\circ,90^\circ$ and 135°. Replacing $E_{0^\circ}^k,E_{45^\circ}^k,E_{90^\circ}^k,E_{135^\circ}^k$ with $\widetilde{E}_{0^\circ}^k,\widetilde{E}_{45^\circ}^k,\widetilde{E}_{90^\circ}^k,\widetilde{E}_{135^\circ}^k$ in Eqs.(8)~(10), we can obtain the definition of the LFV for the fuzzy division of the palmprint.

Figure 3 shows three groups of palmprints that are captured from the same palm and palms with similar/different line structures. The LFVs of these palmprints are plotted in Figs.4(a)~(c), and the standard deviations of the components of the LFVs for each group are shown in Fig.4(d). Obviously, the results show that the differences among the LFVs computed from images of the same palm are much less than those computed from the images of the different palms with similar or dissimilar line structures. Therefore, the LFV is suitable for representing the line features in palmprint recognition.

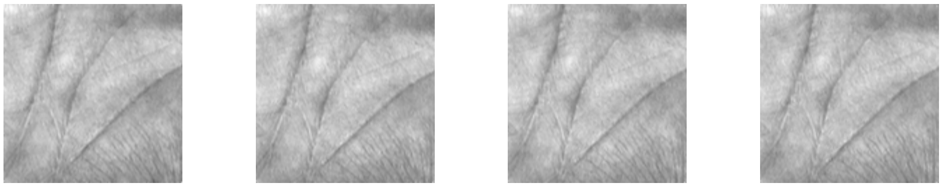
4 Line Feature Matching

A correlation coefficient is a criterion used to measure the similarity between two vectors. We use the correlation coefficient of LFVs as a matching score of the corresponding palmprints. Suppose that $X=(x_1,x_2,...,x_n)$ and $Y=(y_1,y_2,...,y_n)$ are two LFVs, and their correlation coefficient is defined as follows:

$$R_{XY}=\frac{\sum_{i=1}^{n}(x_i-\mu_X)(y_i-\mu_Y)}{\sigma_X\sigma_Y} \tag{18}$$

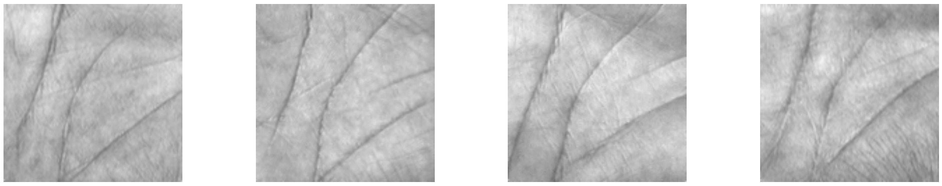
where μ_X, μ_Y, σ_X and σ_Y are the mean and standard deviation of the components of X and Y, respectively.

The value of R_{XY} is between −1 and 1. If X and Y are LFVs obtained from two images of the same palmprint, R_{XY} will be close to 1. Otherwise, R_{XY} will be far from 1. The matching scores of Groups A~C in Figure 3 and their average scores are listed in Table 1. Obviously, the scores of the palmprints from the same palm are very close to 1 (the average score is 0.969 6), whereas the scores of the palmprints from different palms with different line structures are very far from 1 (the average score is 0.4541). The average score of the palmprints with similar line structures is 0.7281, which is small enough to allow them to be distinguished.



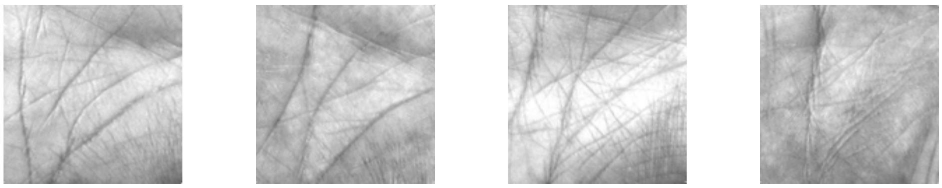
A-1 A-2 A-3 A-4

Group A: Palmprints from the same palm



B-1 B-2 B-3 B-4

Group B: Palmprints from palms with similar line structures



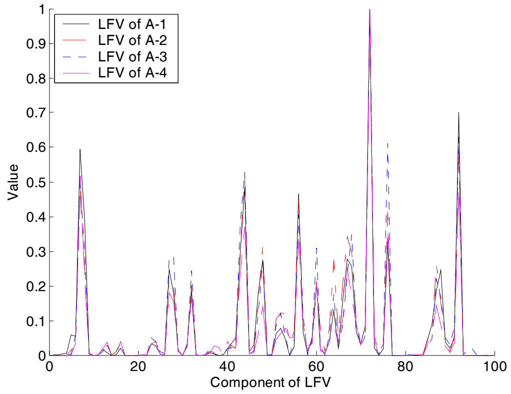
C-1 C-2 C-3 C-4

Group C: Palmprints from palms with different line structures

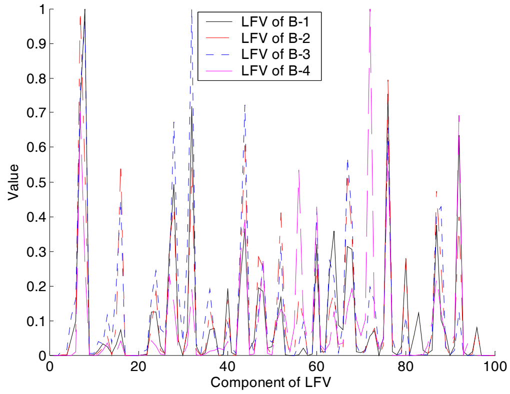
Fig.3 Some typical palmprint samples

5 Experimental Results and Analysis

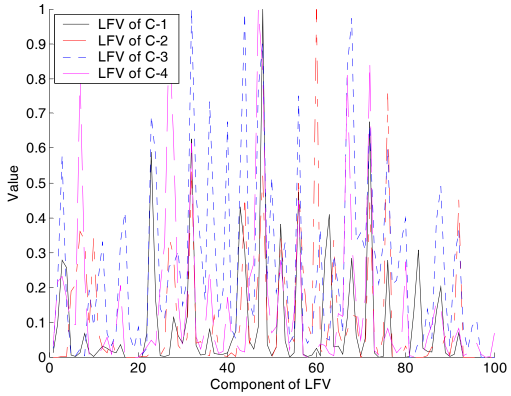
We have collected images of palmprints from 320 individuals with both sexes and different ages, using our CCD-based palmprint device, to establish a palmprint database. The subjects were asked to provide 10 images of their right palms. Therefore, there are 3,200 palmprints in our database. The resolution of the original palmprint images is 384×284 pixels. The central part of the image with 128×128 is cropped using the method described in Ref.[4] to represent the whole palmprint. Some of the palmprints used in our experiments are shown in Fig.5. Canny's algorithm[6] is used for line edge detection in our experiments. The variance σ in this algorithm is chosen as 1 and the threshold is decided automatically using Otsu' method[7]. Six images of each palm are selected randomly as the training samples to form a template. 5×5 fuzzy division of the images is used, thus the length of the LFVs is 100. The average of the LFVs of the training samples is stored as the template for each palm. For comparison, the straight-line segments (SLS) based on method[2] is also implemented in our experiments.



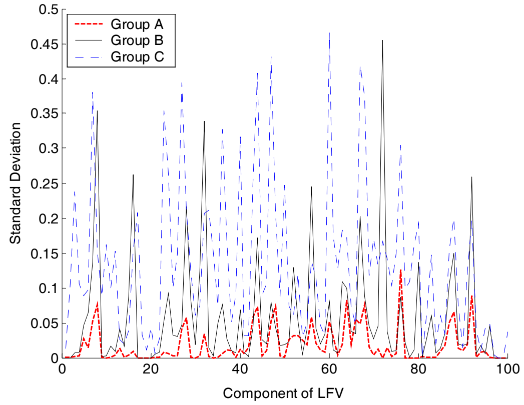
(a) Group A



(b) Group B



(c) Group C



(d) Comparison between Groups A, B and C

Fig.4 Comparison of the component values of the LFVs of the palmprints shown in Figs.3(a) , (b) and (c) are the LFV of Group A, Group B and Group C, respectively, and (d) is the standard deviation of (a)~(c).

Table 1 Matching score of groups A~C in Fig.3

Matching scores of group A		A-2	A-3	A-4	Average
	A-1	0.974 7	0.965 4	0.970 3	
	A-2	–	0.974 4	0.967 7	0.969 6
	A-3	–	–	0.964 9	
Matching scores of group B		B-2	B-3	B-4	Average
	B-1	0.863 2	0.864 9	0.598 5	
	B-2	–	0.885 2	0.633 8	0.728 1
	B-3	–	–	0.522 9	
Matching scores of group C		C-2	C-3	C-4	Average
	C-1	0.431 1	0.595 8	0.434 7	
	C-2	–	0.370 8	0.409 3	0.454 1
	C-3	–	–	0.483 2	

5.1 Rotation and translation test

Though the rotation and translation of the palmprints from the same palm are very little after preprocessing, it is impossible to remove all of them. To quantificationally investigate the robustness of LFVs to rotation and translation, 50 palmprints captured from different palms are selected randomly from our palmprint database. These images are translated and rotated using different distances and angles. Then, the translated and rotated palmprints are matched with the original ones by using our proposed approach. Some of the testing palmprints and their rotated and translated versions are shown in Fig.6. The average matching scores are shown in Figures 7–8. For comparison, the average score (0.9479) among the palmprints captured from the same palm (average within-class score), which is computed by using all of the samples in the palmprint database, is also plotted in these figures. According to Fig.7, when the rotational angle is between −6° and 6°, the average scores between the rotated and original palmprints are larger than the average the score. Therefore, our approach is robust when the rotational angle is within this range. From Fig.8, when the translational distance is within the range [−5, 5] pixels, the approach is also robust.

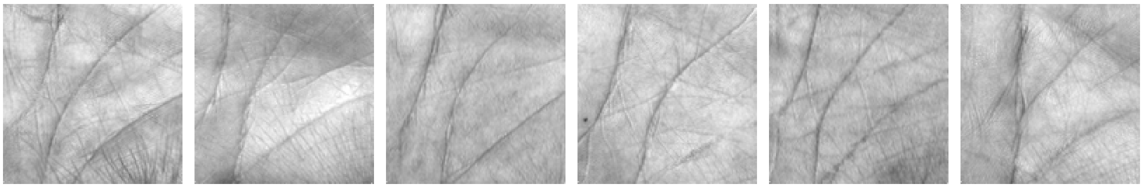
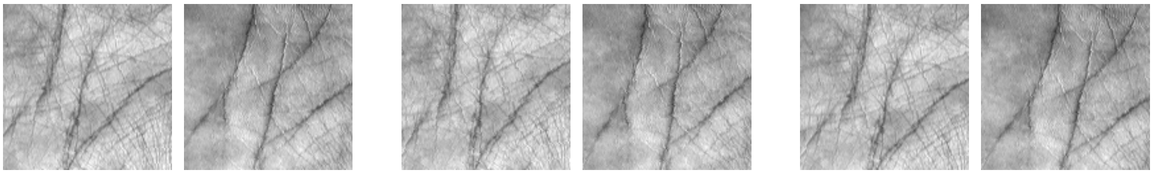


Fig.5 Some samples from the palmprint database used in our experiments



(a) Original images (b) Rotated images (c) Translated images

Fig.6 Some palmprints and their rotated and translated versions

5.2 One-to-One matching test

One-to-one matching, also called palmprint verification, involves answering the question "Whether this person is whom he claims to be" by examining his palmprint. The remaining four palmprints of each palm are used as the testing samples for our approach. To obtain the performance of the proposed approach, the LFV of each testing sample is compared with each template in the database. Therefore, 409 600 comparisons are conducted. The performance of a verification system is often measured by the false accept rate (FAR) and false reject rate (FRR). These two rates are contradictory to each other and cannot be lowered at the same time. Hence there should be a tradeoff which depends on the applications. In order to see the performance of a system with respect to this tradeoff, we usually plot the so-called receiver operating characteristic (ROC) curve, which plots the FAR against the FRR[8]. The ROC curves of the LFV approach and SLS method are plotted in Fig.9. Their equal error rate (EER, where FAR=FRR), 1.0% (LFV) and 4.1% (SLS), are also shown in this figure. In the method based on feature points (FP)[3], Duta used 30 images captured from three persons in their experiments and about 5.0% error rate was obtained. Obviously, our approach is much better than the SLS and FP methods.

5.3 One-to-Many matching test

One-to-many matching, also called palmprint identification, is to answer the question "Who is this person?" according to his/her palmprint. The process of one-to-many matching is as follows. The line features of the input palmprint are extracted and represented, and then they are compared with all of the templates in the database. Finally, the label of the most similar template is found as the result. The testing samples used in this subsection are the same as those used in the one-to-one matching test. The one-to-320 matching accuracy of our approach and the

SLS method is 97.5% and 92.3%, respectively. That is, the accurate rate of our approach is about 5.2% higher than that of the SLS method.

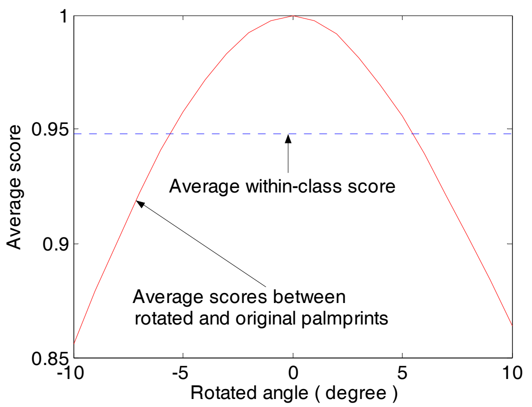


Fig.7 The average matching scores between the rotated and original palmprints

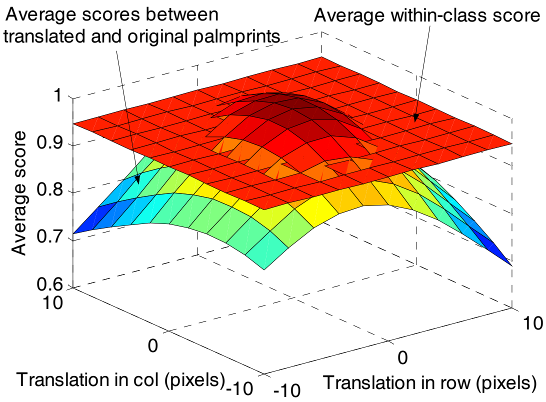


Fig.8 The average matching scores between the translated and original palmprints

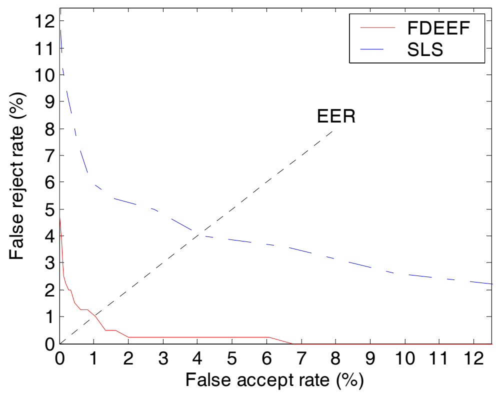


Fig.9 The ROC curves of LFV approach and SLS method

5.4 Comparison of speed

Speed is a very important parameter for an on-line biometric system. All of our experiments are conducted using the Microsoft Windows 2000 and Matlab 6.1 with image processing toolbox on a personal computer with an Intel Pentium III processor (500MHz). The average time taken by our approach for line feature representation and matching are 0.118s and 0.001s while those of the SLS method are 2.30s and 0.009s. Our approach is about 19.5 and 9 times faster than the SLS method for line representation and matching, respectively. This is because there is no the processes of line tracing, linking and straight-line segment approximation, which consume most of the time, in our approach.

5.5 Comparison of the storage requirement

The amount of computer storage required is also a very important parameter for a biometric system. In the SLS method, the average number of straight-line segments for a palmprint in our database is about 85. Each segment has two endpoints and the coordinates of each endpoint have two components. At least one byte is used to store each component. Thus, to represent a palmprint, at least 85×2×2=340 bytes should be required. In the FP method, Duta et al. used about 300 feature points and their orientations to represent the lines on a palm. For each feature point, at least two bytes were used to store its coordinates and four bytes were used to store its orientation (floating point value). Therefore, the storage required for a palm was 300×(2+4) =1 800 bytes.

In our approach, each component of a LFV is in the interval [0,1], that is, at least a floating type number (4 bytes) should be used to store it. Therefore, the storage requirement for representing a palmprint is 100×4=400 bytes. In fact, the storage of each component (e_α^k) can be reduced as following process.

$$\tilde{e}_\alpha^k = [e_\alpha^k \times 65{,}535] \tag{19}$$

where [X] represents the rounded value of X, and 65,535 is the maximum unsigned integer that can be stored in two bytes. After we do this, $\tilde{e}_\alpha^k$ is an unsigned integer and $0 \le \tilde{e}_\alpha^k \le 65\,535$. Thus, it can be stored by using two bytes. We can restore the vector as follows:

$$e_\alpha^k = \frac{\tilde{e}_\alpha^k}{65535} \tag{20}$$

The error of each component that results from this process is

$$err = \left|\frac{\tilde{e}_\alpha^k}{65535} - e_\alpha^k\right| = \left|\frac{\tilde{e}_\alpha^k - 65535\times e_\alpha^k}{65535}\right| = \left|\frac{[65535\times e_\alpha^k] - 65535\times e_\alpha^k}{65535}\right| \le \frac{0.5}{65535} = 7.6295\times 10^{-6} \tag{21}$$

This error is so small that it can be regarded as noises. After this process, only 200 bytes are needed to store the LFV for a palmprint, which is much less than those of the SLS and FP methods. The comparisons among the LFV, SLS and FP methods are listed in Table 2.

6 Conclusions and Future Work

A novel approach to line feature representation and matching is proposed in this paper. A LFV, which is computed by using the magnitude and orientation of the gradient of the edge points forming the palm-lines, contains information about both the structure and thickness of the lines, thus its discriminability between palmprints, including those with similar line structures, is strong. It has been shown that LFV is robust to some extent in rotation and translation of the images. The experimental results show that the proposed approach is much better than other line feature based palmprint recognition methods in terms of its accuracy, speed and storage requirements. In the future work, we will investigate the effect of dirty palmprints on the proposed approach.

Table 2 Comparison of different line feature based palmprint recognition methods

Method	Our approach		Zhang's method[2]		Duta's method[3]
Database size	3 200 images (320 palms)		3 200 images (320 palms)		30 images (3 palms)
Line feature representation	Line feature vector		Straight-Line segments		Feature Points
Average storage requirement (bytes)	200		340		1,800
One-to-One matching accuracy (%)	99.0		95.9		95.0
One-to-Many matching accuracy (%)	97.5		92.3		Not presented
Average time	Line feature representation	Matching	Line feature representation	Matching	Not presented
	0.118	0.001	2.300	0.009	

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庆祝《软件学报》创刊 15 周年纪念活动预告

2004 年 9 月 16 日　北京

http://www.jos.org.cn

2004 年迎来了《软件学报》创刊 15 周年，为纪念《软件学报》所走过的 15 年风雨历程，并感谢长期以来支持《软件学报》工作的老一辈科学家、新一代科学家、历届编委会委员、广大的作者、读者以及主办单位、各级主管单位的领导等，我们将于 2004 年 9 月 16 日在北京举办纪念活动，并同时出版纪念专刊。纪念专刊将安排在《软件学报》2004 年第 9 期和第 10 期上发表。

现将有关事项预告如下：

一、专刊及大会报告内容

1．当前国际国内计算机软件(各学科方向)的发展动态和热点问题

2．有关《软件学报》的题词及照片等

二、重要日期

活动时间：2004 年 9 月 16 日

三、其他

1. 活动形式：纪念活动、表彰突出贡献人和优秀审稿人、大会报告、专题讲座、编委会；

2. 报告人：邀请国外著名大学学者及科学家和国内计算机专家做专题报告；

3. 参加活动人员：编委、特邀嘉宾、被表彰人员；

4. 详细议程待确定之后发布在《软件学报》网站上。