A Fast and Efficient Palmprint Identification Method for a Large Database

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ABSTRACT

This paper proposes a fast and efficient palmprint identification method for a large database. The process is accelerated as a result of our efficient palmprint classification and matching scheme. Palmprint classification method is based on principle lines which are life line, head line and heart line. Palmprints' features are extracted with Log-Gabor filter and matched with Hamming distance in the most potential palmprint group/category, and if necessary, continues orderly to the less potential ones. Experiments are done with 2 hand databases, Visgraph database and CU-CGCI hand database. Experimental results show that the proposed method can greatly reduce the number of template matching from 100% (as in general identification methods) to 33.2-38.2% while maintaining the equivalent EER as the general identification method.

Keywords: Palmprint Identification, Large Database.

1. INTRODUCTION

Biometric is a means for automatic recognition of people based on their distinctive anatomical characteristics (e.g., face, fingerprint, iris, retina and hand geometry) and behavioral characteristics (e.g., signature and gait). At present, biometric is widely used for identifying or verifying people in today's information society mostly for security purposes. Palmprint has been considered as an alternative choice for automatic personal authentication due to its unique physical characteristic, visible stable features and low initial cost. In addition, palmprint capture devices are much cheaper than others (e.g. iris and fingerprint devices).

Palmprints consist of distinctive features, such as principle lines and wrinkles, which can be easily extracted from low-resolution images [1, 2]. Generally, palmprint identification approaches compare a claimer's palmprint with every palmprint in a database [3-8]. Consequently, it is rather time-consuming. In order to solve this problem, many researchers have proposed to categorize palmprints into small groups to reduce the number of data in the matching process [9, 10]. Hierarchical palmprint identification for a large database is another approach that has been researched lately [11-13].

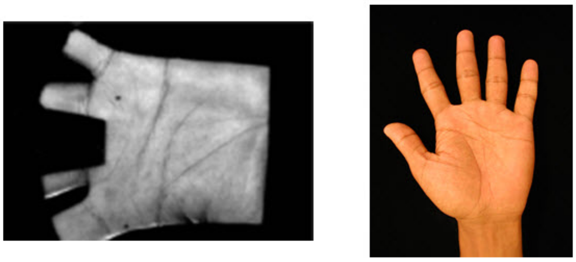
In this work, we propose a fast palmprint identification method for a large database. Enrolled palmprints are pre-classified into several well-distributed groups by the principle lines' simple and clear characteristics which can be easily extracted from low-resolution images. In the identification process, palmprints' features are matched within the most potential group, and if necessary, continues to less potential ones respectively.

This paper is organized as follows: Related works and their problems are presented in section 2. Section 3 illustrates our proposed method. Experiments and results are presented in section 4. Finally, discussion and conclusion of this work are illustrated in section 5.

2. RELATED WORK

In this paper, we categorize palmprint identification researches into 2 groups: general palmprint identification researches that do not emphasize on a large database and those that are designed for a large database.

It is noticed that, in palmprint identification researches, there are 2 types of palmprint images. The first one consists of fixed-positioned hand images that are acquired with some special devices to fix the hand position as shown in figure 1 (a). The other consists of unfixed-positioned hand images as can be seen in figure 1 (b) respectively.



(a) (b)

Fig.1: Example of hand images. (a) A fixed-position [3] and (b) an unfixed-position hand images from image acquisition [14].

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2.1 General Palmprint Identification

As mentioned earlier, in this paper, general palmprint identification refers to the work that does not emphasize on a large database. Most of them proposed and discussed their methodology and results.

In 2002, W. K. Kong et at. [3] proposed a method for personal identification by utilizing 2D Gabor filter to extract palmprint's feature and Hamming distance, to compare with the templates. The results show that FAR (False Acceptance Rate) was 0% when threshold value was fixed at 0.335 and FRR (False Rejection Rate) was 0.9% for image resolution of only 65 dpi.

In 2003, D. Zhang et al. [4] presented an online palmprint personal identification approach. This research also used low resolution images of 75 dpi. Palmprint's texture extracted via 2D Gabor filter was chosen as a feature. Hamming distance was used as the distance measure in the matching step. They reported that EER (Equal Error Rate) was 0.6%. The total time for personal identification was 1.1 second with a database that contained images for 100 persons registered with 3 palmprint images each. It should be noted that this work is often referenced.

In 2004, L. Zhang et al. [5] proposed another personal identification by using palmprint characteristic and extracting feature with Wavelet transform. The image resolution was 65 dpi. The results of FIR (False Identification Rate) and FRR were 2% and 0%, respectively.

In 2005, J. S. Noh et al. [6] applied Hu invariant moments and Otsu binarization for palmprint identification. They computed the moments in 3 levels and compared the results from each level with Euclidean distance. The FAR and GAR (Genuine Acceptance Rate = 100-FRR) were 0.038% and 98.1%, respectively. This research used low resolution image of 75 dpi with the image size of 135 × 135 pixels.

In 2006, F. Li et al. [7] proposed a palmprint matching method by Modified line-based Hausdorff Distance. Hausdorff distance is used to compare line characteristic on the palm. This approach has about 95% accuracy for personal identification

In 2006, X. Wang et al. [8] used the palmprint database from UST_HK which did not fix the hand position. They proposed a palmprint identification approach using boosted local binary pattern based classifiers. The palmprint area was scanned with a scalable sub-window from which local binary pattern histograms were extracted to represent the local features of a palmprint image. AdaBoost algorithm was used to select those sub-windows. The weights of chi-square distance were learned by applying the statistical learning algorithm-AdaBoost. From their experiments, EER was reported at 2%.

2.2 Palmprint Identification for a Large Database

In 2002, J. You et al. [11] proposed hierarchical palmprint identification via multiple feature extraction. This research used 2 features; global texture energy and interesting points. The global texture energy was used to guide the dynamic selection of a small set of similar candidates from the database at coarse level for further processing. An interesting point based image matching was performed on the selected similar pattern at fine level for final confirmation. They reported that the effectiveness of this hierarchical search guided by global palmprint texture feature selection scheme was that on the average 91% of the candidates in the database were classified as distinctive from the input data. In the worst case, the elimination rate of the candidates was 72% and hence, only 28% of the samples remained for further identification at fine level by image matching.

In 2004, J. You et al. [12] proposed a hierarchical multifeature coding scheme to facilitate coarse to fine matching for palmprint identification in a large database. In this research, there were 4 level features: global geometry-based key point distance (Level-1 feature), global texture energy (Level-2 feature), fuzzy interest line (Level-3 feature), and local directional texture energy (Level-4 feature). The use of level-1, level-2, and level-3 features was able to remove candidates from the matching process by 9.6%, 7.8%, and 60.6%, respectively.

In 2006, J. Wu et al. [13] presented a hierarchical palmprint identification method without ROI extraction. For the coarse-level feature extraction, they measured hand geometry and angle values and used them to train their k-NN (k-Nearest Neighbors) classifier. They divided the hand image into subimages and used unit information entropy of each subimage to describe grayscale distributions as their fine-level feature. Accuracy up to 99.24% was reported when using 6 samples per class for training.

However, we have noticed that the results from most work mentioned above are quite impressive (with FAR, FRR, EER close to 0%) [3-7, 11-12] while that of X. Wang et al. [8] is not as good (with EER 2%). This is perhaps caused by the fixed-position of hand in the palmprint image acquisition process.

3. OUR PROPOSED METHOD

In our research, we do not fix the hand's position in the image acquisition process. A hand must lay flat on a black background as shown in figure 2.

This section illustrates our proposed method which consists of system overview, ROI (region of interest) and principle lines' characteristics, our palmprint classification method and our palmprint identification approach.

3.1 System Overview

Our proposed palmprint identification method aims for use with a large database. Palmprints in the database are pre-classified into several categories by the clear and simple characteristics of principle lines. By this proposed approach, palmprint matching process is done only in the necessary palmprint group(s). Hence, identification can be achieved quickly. Figure 2 illustrates our proposed system.

3.2 ROI and Principle Lines' Characteristics

Region of Interest (ROI) on a palmprint and the characteristics of palmprint principle lines in this research are described in this section.

3.2.1 ROI

From a binarized palmprint image, as shown in figure 3, we segment the palm, and define some reference points and the ROI as follows:

V1, V2, and V3 are the points among forefinger, middle finger, ring finger and little finger.

O is a point on the line from V2 that is orthogonal to the line connected between V1 and V3 (V1V3). The length of OV2 is predefined and fixed.

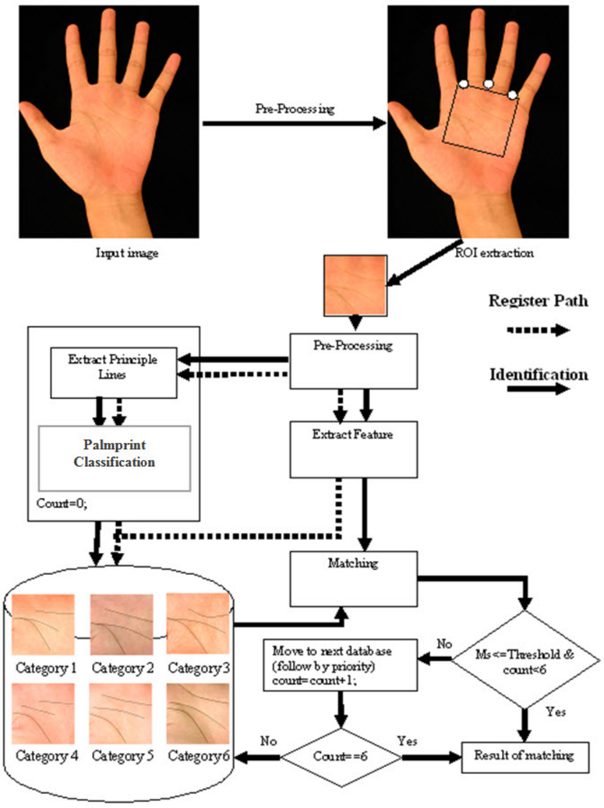
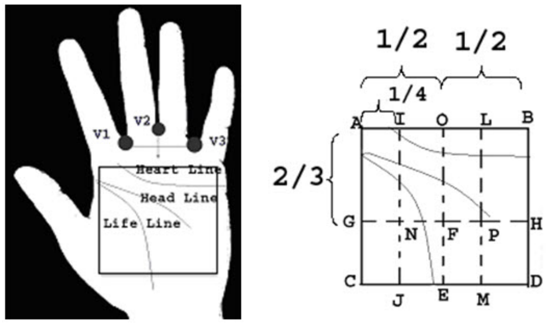


Fig.2: *Our proposed palmprint identification system overview.*



(a) (b)

Fig.3: *The positions and key points that are used in this research.*

A and B are two points on the line which passes through O and parallel to line V1V3. The lengths AO and OB are equal and predefined.

The square ABDC is formed and used as the ROI in this research.

IJ, OE and LM are the lines which divide the ABDC into 4 equal parts.

AG and BH have the ratio of 2/3 of line AC and BD, respectively.

3.2.2 Principle Line Characteristics

In this research, the three principle lines which consist of heart line, head line and life line in ROI as shown in figure 3 are defined by their locations as follows:

1) *Heart line* is the line which has an endpoint on the right side of rectangle LBHP and must pass through line OF.

2) *Head line* has an endpoint on the left side of rectangle AING. The position of this endpoint is either above or the same as that of a *life* line and must pass through line OF.

3) Similar to the *head line*, a *life* line also has an endpoint on the left side of rectangle AING in the ROI. The position of this endpoint is either below or the same as that of the head line. Life line must exist in rectangle IOEJ.

3.3 Palmprint Classification Method

Our proposed criteria for palmprint classification are as follows: 'Do the head line and life line intersect?', 'Is the heart line straight or curved?' and 'if the heart line is straight, how flat is it?' Hence, there exist six categories as shown in figure 4. More detail of our palmprint classification method can be found in [15].

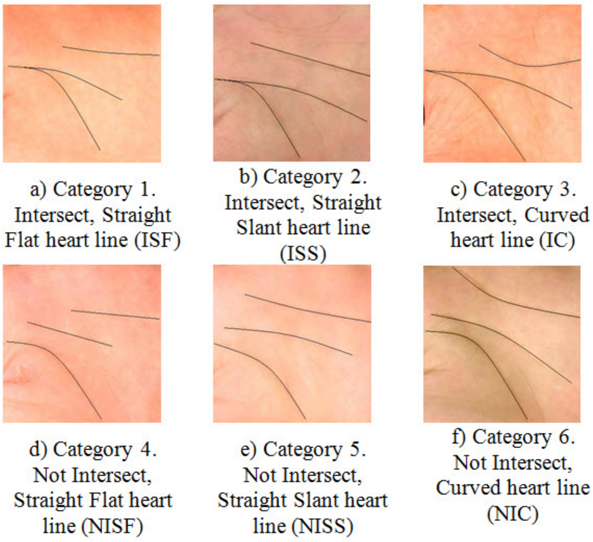


Fig.4: *Six palmprint categories from our proposed method. (The principle lines are highlighted for clear representation only.)*

This section consists of 3 parts. They are image pre-processing, principle line detection method, and feature extraction, respectively.

3.3.1 Image Pre-processing

It is the fact that, the principle lines are dark whereas, except pale white and yellowish colors (for Asians), palm areas consist of reddish color (reflecting from capillaries) and greenish color (reflecting from veins). Therefore, in this research, we neglect red and green color components and use only the blue component of hands' color images.

After obtaining ROI from hand images, we have normalized all ROI's in the database to reduce the effects of different brightness in the image acquisition process by the normalization method of L. Hong et al. [11] in equations 1 and 2. Noise is then eliminated with Gaussian filter [10]. Finally, the resolution of the image inside the ROI is decreased by half to reduce computation in the principle line detection and in the matching processes.

$$I'(x,y) = \begin{cases} \phi_d + \lambda \ ; & if\ I(x,y) > \phi \\ \phi_d - \lambda \ ; & otherwise \end{cases} \tag{1}$$

$$\lambda = \sqrt{\frac{\rho_d (I(x,y) - \phi)^2}{\rho}} \tag{2}$$

where $I'(x,y)$ is the normalized image.
ϕ_d and ρ_a are the average and standard deviation of the output image.
ϕ and ρ are the average and standard deviation of the input image.

3.3.2 Principle Line Detection

Since palmprints' lines are darker than other areas, principle lines can be detected by checking the gray level profiles in a small window of size 3×3 in 4 directions, which are 0°, 45°, 90° and 135°. (For clarity, figure 5 illustrates gray level profiles in a window of size 9×9 in all 4 directions.) These profiles in 3×3 window can be classified as 3 cases; a valley, a slope and an unidentified case. The characteristics of each pattern are shown in table 1.

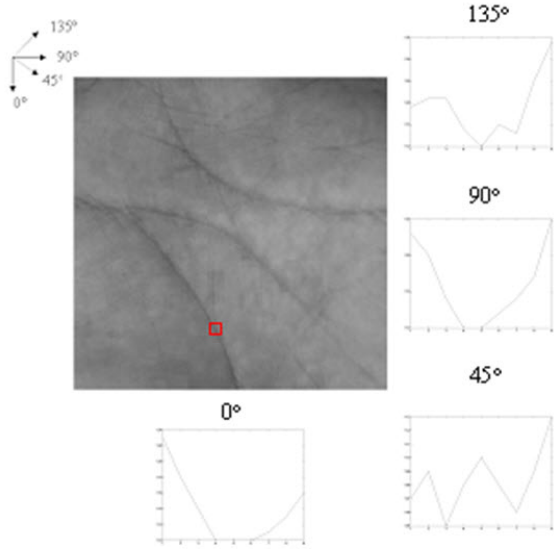


Fig.5: *Principle lines' characteristics and the profiles of gray values in 4 directions. For clarity, the window size shown here is* 9×9.

Table 1: *Profile characteristics used in principle line analysis.*

Profile characteristics	Pattern		
Valley	+0+	00+	+00
Slope	+0-	-0+	
Unidentified case	000		

Let "0" represent the pixel in consideration or the case of the same gray level as that of the pixel in consideration, "+" represent the case of higher gray values and "-" represent the case of lower gray values.

A pixel is classified as it is in a principle line if it satisfies one of these rules.

1) Profiles in more than 2 directions are valley.
2) Profiles are 2 valleys and 2 unidentified cases.
3) Profiles are 2 valleys, 1 slope and 1 unidentified case.

Figure 6 (b) represents an example of principle line extraction from original image in figure 6 (a). A morphological closing filter is applied to eliminate noise and smooth the image. End points of fragmented lines are detected by convex hull algorithm [10]. Fragmented lines are linked afterwards as shown in figure 6 (c).

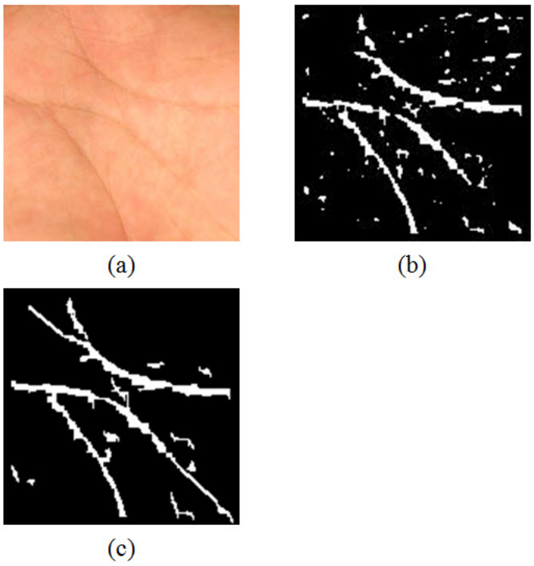


Fig.6: *Principle lines extraction.*

3.3.3 Feature Extraction

As mentioned earlier, the criteria for palmprint classification in this research are: 'Do the head line and life line intersect?', 'Is the heart line straight or curved' and 'if the heart line is straight, how flat is it?'

1) Intersection between head line and life line

Line(s) from endpoint(s) on the left side of rectangle AING are detected using chaincode [13]. Checking whether they are the head line and/or the life line is done by using the length and the definitions in section 3. Intersection is identified afterwards.

2) Heart line: straight or curved?

As defined in section 3, the heart line is the line which starts at the right side of rectangle LBHP, and must pass through OF. Chaincode is applied to track the line. Small branches are eliminated. If the tracked line does not fulfill the heart line definition, e.g. it does not pass through OF, linking fragmented lines are needed.

A straight line equation (3) is fitted to the extracted heart line to classify it as being "straight" or "curved". Errors are calculated with equation (4).

$$y = mx + c \tag{3}$$

$$error = \sum (X_i - \mu_i)^2 / \mu_i \tag{4}$$

where X_i is the position on the extracted heart line.
μ_i is the position from the equation.

If the extracted line is classified as a straight line, then we sub-classify the straight line as a "flat line" if the slope is less than 10 degrees, or a "slant" otherwise.

3.4 Palmprint Identification Approach

In this section, our palmprint identification approach is described in 2 subsections. They are feature extraction and matching, and lastly, our template matching scheme.

3.4.1 Feature Extraction and Matching

After filtering out the noise from the ROI, feature is extracted by applying Log-Gabor filter which has been proposed by D. Field in 1987 [18] as shown in equation 5. The 2D palm image is broken up into several 1D signals, transformed to frequency domain and then convolved with 1D Log-Gabor filter.

$$G(f) = \exp\left\{-(\log(f/f_0))^2 / 2(\log(\sigma/f_0))^2\right\} \tag{5}$$

Where f_0 represents the center frequency, and σ is the bandwidth of the filter.

The palm's ROI in spatial domain and the palmcode (1D Log-Gabor feature) are shown in figure 7. It is noted that the palmcode is a binary 2D array since the result from the filter is thresholded to 0 and 1. The palmcode array is twice the width but the same height of the original image because, from this filter, 2 values (from real and imaginary parts) are obtained per 1 pixel.

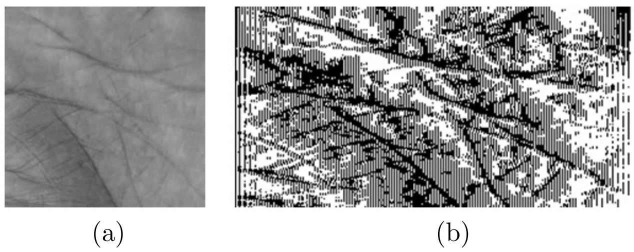


Fig.7: *(a) Original palmprint image and (b) palmcode obtained from Log-Gabor filter.*

In this work, Hamming distance is used for comparing the features between two palmprints as shown in equation 6.

$$HD = \frac{1}{N - \sum_{K=1}^{N} Xn_k(or)Yn_k} \sum_{j=1}^{N} X_j(xor)Y_j (and)\acute{X}n_j(and)\acute{Y}n_j \tag{6}$$

Where X_j and Y_j are the two palmcodes from two palmprints,

Xn_j and Yn_j are the corresponding noise masks for X_j and Y_j,

$X\acute{n}_j$ and $Y\acute{n}_j$ are the invert of Xn_j and Yn_j respectively,
N is the number of bits represented by each pattern.

If two patterns/palmcodes are derived from the same palm, the Hamming distance between them is close to 0.0 since they are highly correlated.

In this research, we calculate many Hamming distances of the overlapping between the claimer's palmcode and a registered template to compensate image translation. The least distance is chosen as the matching distance.

3.4.2 Our Template Matching Scheme

In this paper, we propose a technique to accelerate palmprint identification for a large database. In the database, palmcodes, which are used as our palmprint templates, are pre-classified into 6 categories as mentioned earlier.

For our template matching scheme, a claimer's hand image is categorized by our classification criteria. The extracted palmcode is matched with the templates in the highest potential category in the database. If the matching result is satisfied, the matching process stops and the identification result is encountered. If not, the matching process continues to the next highest potential category, and so on.

The chart in figure 8 illustrates our classification criteria. The relationship of each category can be easily seen from this chart. For example, if a claimer's palmprint is classified as in category 2 (ISS, Intersect-Straight-Slant), the order of matching groups is from catergories 2, 1, 3, 5, 4 and 6 respectively.

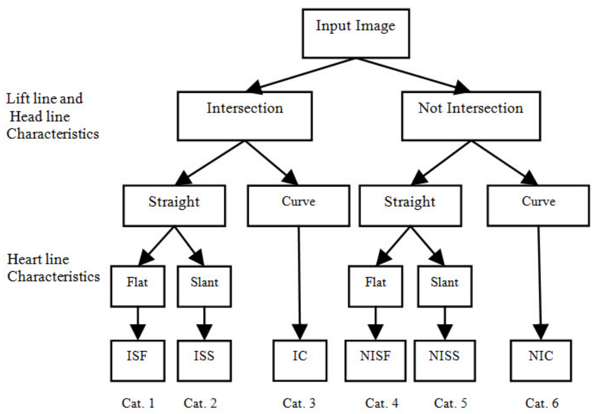


Fig.8: *Our classification chart.*

Table 2 shows all the matching order of all categories. It should be pointed out that a curve line (C) is more similar to a slant straight line (SS) than a flat straight line (SF). Hence, the order of matching group is from category 3 (or 6) to categories 2 and 1 (or 5 and 4).

Table 2: *Order of template matching.*

Claimer's category \ Matching category	Cat. 1	Cat. 2	Cat. 3	Cat. 4	Cat. 5	Cat. 6
Cat. 1 (ISF)	1	2	3	4	5	6
Cat. 2 (ISS)	2	1	3	5	4	6
Cat. 3 (IC)	3	2	1	6	5	4
Cat. 4 (NISF)	4	5	6	1	2	3
Cat. 5 (NISS)	5	4	6	2	1	3
Cat. 6 (NIC)	6	5	4	3	2	1

4. EXPERIMENTS AND RESULTS

Our palmprint identification approach is tested with two databases; Visgraph database [14], taken from people in Hong Kong, and the CU-CGCI hand database, from people in Thailand. The images in both databases are 24-bit RGB color image with resolution 960×1280. Visgraph database consists of 102 individuals, 10 hand images per individual. CU-CGCI hand database consists of 116 individuals, aged from 20 to 60 of both genders, and 10 images from each person. The algorithm has been implemented using Matlab 7.0 software and run on Intel Core2 Duo 2.66 GHz PC with 2 GB memory.

In CU-CGCI hand database image acquisition process, a hand's position was not fixed but it had to lay flat on a black background to lessen the effects of shadows from the hand itself and other objects. A Sony DSC-W5 compact camera fixed with a camera stand was used in both indoor and outdoor environments. The lighting was not restricted. However, it should be pointed out that about 90% of the images were taken indoor in several occasions and in different places.

In our experiments with Visgraph database, 70 people, 3 hand images per individual, are registered as genuine users. Tests are done with 490 genuine users' and 307 imposters' hand images.

Similar to the above experiments, the proposed method is tested with CU-CGCI hand database, 86 people, 3 hand images per individual, are used for registration. Tests are done with 602 genuine users' and 298 imposters' hand images.

For consistency, we run the experiments 3 times by both the general and our proposed identification methods with both databases by randomly choosing genuine users and imposters for each experiment. Experimental results are shown in tables 3, 4 and 5 and in figures 9 and 10.

It is found that the EER's from both methods in both databases are quite similar. For general identification method, a claimer's palmcode is matched with every palmcode in the database. Hence, the number of matching is 100%. With our proposed method, the average numbers of matching from all 3 experiments

Table 3: *Comparisons of the number of matching (for genuine users only) and the EER's from a general approach and from our proposed method (Visgraph Database).*

Method / Experiment number	General Method		Our Method	
	Number of Matching (Genuine)	EER (%)	Number of Matching (Genuine)	EER (%)
1	102,900	6.0	40,956	6.77
2	102,900	2.5	37,376	2.5
3	102,900	4.1	39,474	4.1
Average	**102,900 (100%)**	**4.2**	**39,268.7 (38.2%)**	**4.46**

Table 4: *Comparisons of the number of matching (for genuine users only) and the EER's from a general approach and from our proposed method (CU-CGCI hand Database).*

Method / Experiment number	General Method		Our Method	
	Number of Matching (Genuine)	EER (%)	Number of Matching (Genuine)	EER (%)
1	155,316	4.8	60,663	4.2
2	155,316	1.3	48,113	1.3
3	155,316	1.2	45,961	1.2
Average	**155,316 (100%)**	**2.4**	**51,579 (33.2%)**	**2.3**

Table 5: *Distribution of each category (Visgraph and CU-CGCI databases).*

Category / Databases	Cat. 1 (ISF)	Cat. 2 (ISS)	Cat. 3 (IC)	Cat. 4 (NISF)	Cat. 5 (NISS)	Cat. 6 (NIC)
Visgraph	25%	32%	26.7%	3.3%	5%	8%
CU-CGCI	34.8%	25.6%	27.5%	3.9%	1.2%	7%

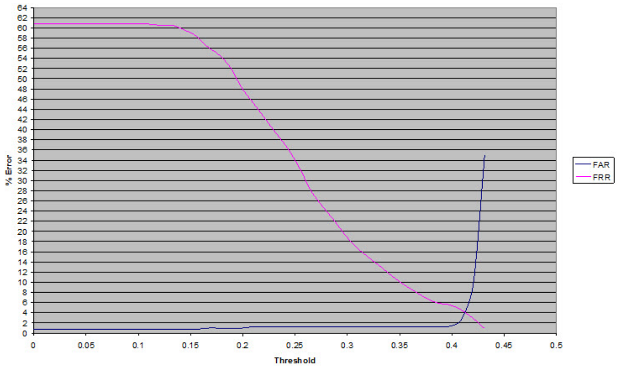


Fig.9: *EER from Visgraph database in experiment number 3 is 4.1%.*

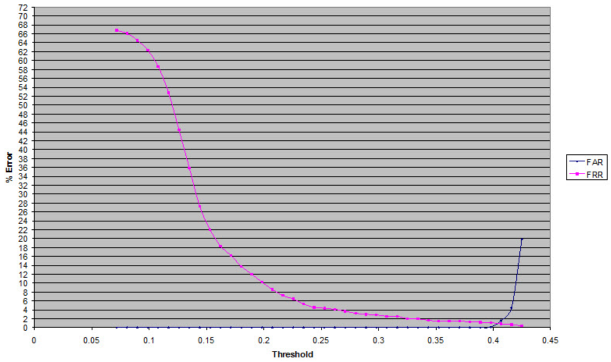


Fig.10: *EER from CU-CGCI hand database in experiment number 2 is 1.3%.*

are 38.2% for Visgraph database, and 33.2% for CU-CGCI hand database.

A whole identification process of our proposed method consists of ROI detection, principle line classification, palmcode feature extraction and finally, palmcode matching with the stored templates from the database. The processing time of each step is illustrated in table 6. However, the time consumption in the palmcode matching with Hamming distance varies upon two factors; the number of templates in the category being matched (palmprint distribution in each category is illustrated in table 5) and the number of categories needed to be matched. As pointed out earlier, it can be clearly seen from tables 3 and 4 that the numbers of matching with our proposed method are only 38.2% and 33.2% of the general method in Visgraph and CU-CGCI databases consecutively. The time consumption for one template matching as described in 3.4.1 is less than 0.1 second.

Table 6: *Processing time consumption of one palmprint image.*

Processing Step	Time consumption (sec)
Region of Interest Detection	2.28
Principle Line Classification	0.297
Palmcode Feature Extraction	0.128

5. DISCUSSIONS AND CONCLUSION

This paper presents a fast and efficient hierarchical palmprint identification method for a large database. It is done by using palmprint classification approach based on principle lines which are life line, head line and heart line. The palmprints in a database are classified by "the straight or curve characteristic of a heart line", "the degree of the straight heart line" and "the intersection of head line and life line".

From tables 3 and 4, it can be seen from the results of both databases that the numbers of palmcode matching from our proposed method are much less than those of a general identification method which generally matches a claimer's palmcode with all templates in the database. However, the EER's from both methods are comparable. Hence, our proposed method can greatly reduce the time consumption while maintaining the equivalent EER as the general method.

6. ACKNOWLEDGMENTS

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