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Personal Identification Using Left and Right Palmprint Images by Steerable Filters

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Abstract - *Palmprint recognition is one of the biometrics available at present. Palmprint is the one of the important biometrics characteristics with higher user acceptance. Biometric systems are used to authenticate or identify by measuring the physiological and/or behavioral characteristics. In this paper, a novel framework is proposed to perform multi biometrics by comprehensively combining the left and right palmprint images. This framework integrates three kinds of scores generated from the left and right palmprint images to perform matching score level fusion. The first two scores were generated from left and right palm images respectively. Whereas, the third score is generated by finding the similarity between left and right palm. It is generated from right and reverse left palmprint images. Steerable filters are used to obtain the edges in different angles, thus improving the efficiency of the system.*

Key Words: **Biometrics, Multi-biometrics, Palmprint recognition, and Steerable filter**

1. INTRODUCTION

Biometrics is the study of automated methods for recognizing a person based on his physical or behavioral characteristic. Biometric systems can be divided into two categories- identification systems and verification systems. Identification systems tell "who you are?"and verification system tells "are you the one who you claim to be? "There are different human traits that can be used by a biometric system. Many human characteristics proposed as biometric traits have both advantages and disadvantages. Biometric systems use different physiological or behavioral traits of an individual for verification/identification. Different biometric traits have different characteristics and potential applications. Fig. 1 shows some of the most used biometric characteristics and the category into which they fall. Physiological methods try to identify the user by some sort of physical trait that is typical to the user. Examples include fingerprint, face, iris, retina etc. On the other hand, behavioral try to identify a user based on some sort of behavior that is typical for a user like the way they walk, or the way they hold the pen while writing or the way they press the keys while entering the PIN etc.

The palmprint contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint and marks which can be used for comparing one palm with another palm. Palmprint can be used for criminal, forensic or commercial applications. Palmprint refers to an image acquired of the palm region of the hand. It can be either an online image (taken by the CCD or a scanner) or offline image where the image is taken with the ink and paper.

Multibiometrics give better results than single biometrics. In this paper left, right and cross matching of left and right palmprints is used. In the framework, three types of matching scores, which are respectively obtained by the left palm, print matching, right palmprint matching and crossing matching between the reverse left query and right training palmprint, are fused to make the final decision. The framework not only combines the left and right palmprint images for identification, but also properly exploits the similarity between the left and right palmprint of the same subject. Extensive experiments show that the proposed framework can integrate most conventional palmprint identification methods for performing identification and can achieve higher accuracy than conventional methods.

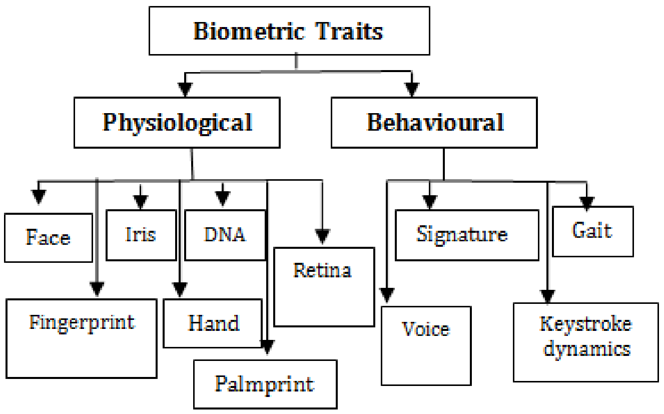

Fig1: Different Biometric Traits

2. LITERATURE

Generally speaking, the principal lines and texture are two kinds of salient features of palmprint. The principal line based methods and coding based methods have been widely used in palmprint identification. General palmprint recognition system is shown in figure 2.

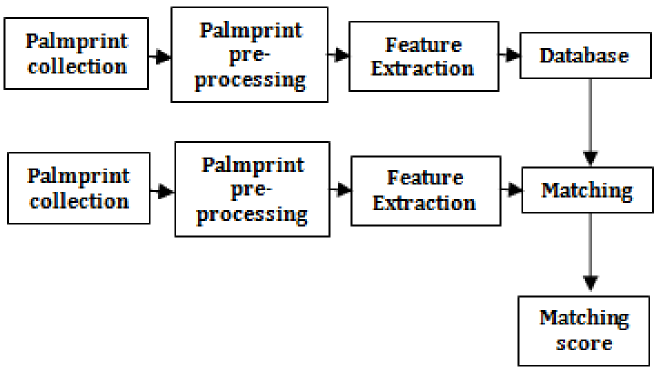

Fig. 2 Palmprint recognition system

The palmprint contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palmprint identification is able to achieve a high accuracy because of available rich information in palmprint [2]–[8].

Various palmprint identification methods, such as coding based methods [7]–[9] and principle curve methods [11], have been proposed in past decades. In addition to these methods, subspace based methods can also perform well for palmprint identification. For example, Eigen palm and Fisher palm [12]–[15] are two well-known subspace based palmprint identification methods. In recent years, 2D appearance based methods such as 2D Principal Component Analysis (2DPCA) [16], 2D Linear Discriminant Analysis (2DLDA) [17], and 2D Locality Preserving Projection (2DLPP) [18] have also been used for palmprint recognition.

Further, the Representation Based Classification (RBC) method also shows good performance in palmprint identification [19]. Additionally, the Scale Invariant Feature Transform (SIFT) [20], [21], which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palmprint identification.

Lines are the basic feature of palmprint and line based methods play an important role in palmprint verification and identification. Line based methods use lines or edge detectors to extract the palmprint lines and then use them to perform palmprint verification and identification. In general, most palms have three principal lines: the heart-line, headline, and lifeline, which are the longest and widest lines in the palmprint image and have stable line shapes and positions. Thus, the principal line based method is able to provide stable performance for palmprint verification. Palmprint principal lines can be extracted by using the Gabor filter, Sobel operation, or morphological operation.

3. PROPOSED SYSTEM

3.1 ROI extraction

Locating the ROI of palmprint images is a popular problem in biometrics and image processing. This is the primary step in developing a biometric system based on palmprint recognition. The method employed is simple and aimed to provide an efficient calculation. However, further optimizations should be possible since these requirements were not looked into in this version. The image is first smoothed by using a Gaussian filter and then by finding the centroid and updating it according to the crests and troughs .The distance to the centroid and minimum and maximum peaks is determined. Rectangular shape is considered for the detection of Region of Interest. The blue dot indicates the centroid. And finally ROI is extracted which is as shown in figure 3.

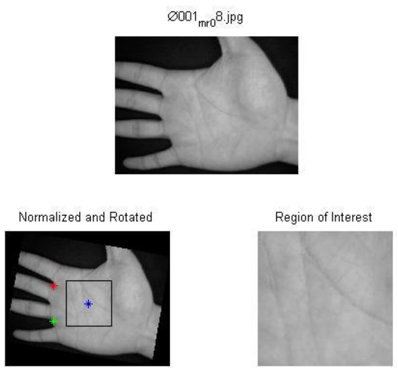

Fig 3: Illustration of pre-processing

3.2 Methods

3.2.1 Steerable Filters

A steerable filter is an orientation selective convolution kernel used for image enhancement and feature extraction. Oriented filters are used in many vision and image processing tasks, such as texture analysis, edge detection, image data compression, motion analysis, and image enhancement. In many of these tasks, it is necessary to apply filters of arbitrary orientation under adaptive control, and to examine the filter output as a function of both orientation and phase. We use the term "steerable filter" to describe a class of filters in which a filter of arbitrary orientation is synthesized as a linear combination of a set of "basis filters".

The process by which the oriented filter is synthesized at any given angle is known as steering. The oriented first order derivative can be obtained by taking the dot product of a unit vector oriented in a specific direction.

Consider the 2-dimensional, circularly symmetric Gaussian function, G, written in Cartesian coordinates, x and y:

$$G(x, y) = e^{-(x^2+y^y)}$$

Where scaling and normalization constants have been set to 1 for convenience. The first derivative of a Gaussian

$$G_1^{0^o} = \frac{\partial\ e^{-(x^2+y^2)}}{\partial x} = 2xe^{-(x^2+y^y)}$$

The same function rotated by 90 degrees,

$$G_1^{90^o} = \frac{\partial\ e^{-(x^2+y^2)}}{\partial y} = 2ye^{-(x^2+y^y)}$$

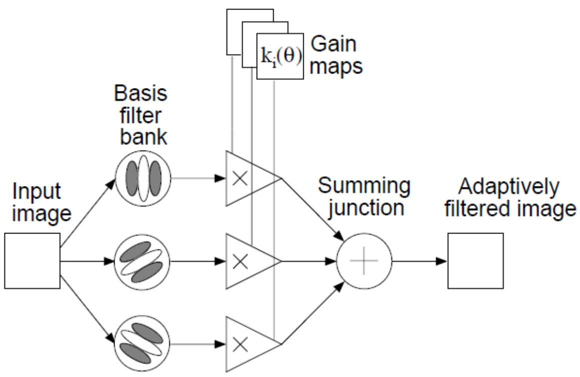

Fig.4 Steerable filter Architecture.

The outputs are multiplied by a set of gain maps which adaptively control the orientation of the synthesized filter.

We want to find the conditions under which any function, f (x; y), steers, i.e., when it can be written as a linear sum of rotated versions of itself.

Any type of identification method mentioned in section 2 can be used whereas in this paper steerable filters are used.

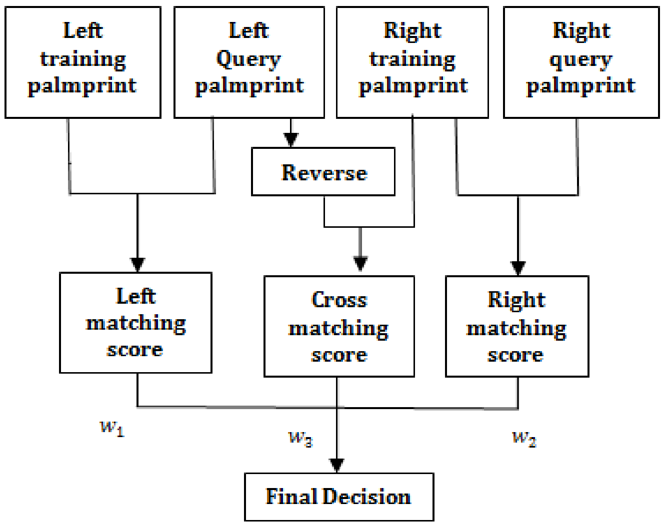

Fig. 5 Fusion at the matching score level of the proposed framework

3.2.2 Sobel edge detection

Image edge detection is a process of locating the edge of an image which is important in finding the approximate absolute gradient magnitude at each point I of an input grayscale image. The Sobel operator performs a 2-D spatial gradient measurement on images. Transferring a 2D pixel array into statistically uncorrelated data set enhances the removal of redundant data; as a result, reduction of the amount of data is required to represent a digital image. The Sobel edge detector uses a pair of 3 x 3 convolution masks, one estimating gradient in the x-direction and the other estimating gradient in y–direction. The Sobel detector is incredibly sensitive to noise in pictures, it effectively highlight them as edges. It involves smoothing, enhancing, detection, localization. The Sobel edge detection output is shown in Fig.10. And then the matching is done using and operation between the test and train inputs.

3.3 Matching

The palmprint identification is done based on the Euclidean distance. The Euclidean distance function measures the 'as the-crow-flies' distance. Matching done when there is least distance. The formula for this distance between a point X (X1, X2, etc.) and a point Y (Y1, Y2, etc.) is:

$$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

The formula to use AND gate is

$$S = \sum_{i=1}^{n}(x_i \& y_i)$$

Matching is done where there is largest score.

The left, right and cross matching scores are determined respectively by using steerable filter features. This implies similarity between the left and right palmprints. For most of the persons similarity occurs or if not it will be as accurate as conventional methods.

3.4 Matching score level fusion

The final decision making is based on three kinds of information: the left palmprint, the right palmprint and the cross matching between the left and right palmprint. Fusion in multimodal biometric systems can be performed at four levels. In the image (sensor) level fusion, different sensors are usually required to capture the image of the same biometric. Fusion at decision level is too rigid since only abstract identity labels decided by different matchers are available, which contain very limited information about the data to be fused. Fusion at feature level involves the use of the feature set by concatenating several feature vectors to form a large 1D vector. The integration of features at the earlier stage can convey much richer information than other fusion strategies. So feature level fusion is supposed to provide better identification accuracy than fusion at other levels. However, fusion at the feature level is quite difficult to implement because of the incompatibility between multiple kinds of data.

Moreover, concatenating different feature vectors also lead to a high computational cost. and the weight-sum score level fusion strategy is effective for component classifier combination to improve the performance of biometric identification. The strength of individual matchers can be highlighted by assigning a weight to each matching score. Consequently, the weight-sum matching score level fusion is preferable due to the ease in combining three kinds of matching scores of the proposed method.

The final matching score is generated from three kinds of matching scores. The first and second matching scores are obtained from the left and right palmprint, respectively. The third kind of score is calculated based on the crossing matching between the reverse left and right palmprint. w_i *(i* = 1, 2, 3*)*, which denotes the weight assigned to the i^{th} matcher, can be adjusted and viewed as the importance of the corresponding matchers.

The weighted fusion scheme $f_i = w_1 s_i + w_2 t_i + w_3 g_i$, where $0 \le w_1, w_2 \le 1$ and $w_3 = 1 - w_1 - w_2$, is used to calculate the score.

4. EXPERIMENTAL RESULTS

The database consists of eight individuals. It consists of 8 left and right palmprints of persons respectively.
The following images depict the ROI extraction of the database images.

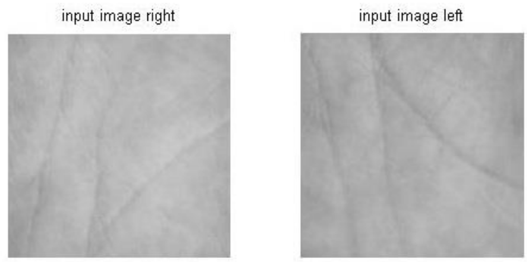

Fig. 6 ROI of test inputs

Once the ROI are extracted, the images are sent to steerable filter to extract the features in different orientations. These features are stored as the database. Once a test image is given, the ROI is extracted followed by steerable feature extraction or Sobel.

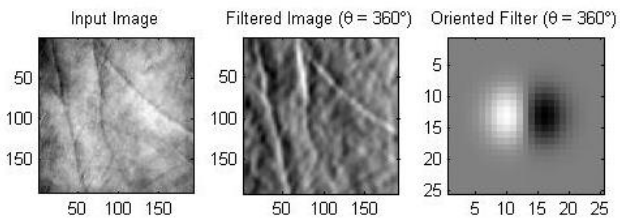

Fig. 8 Steerable filter feature extraction for left test palm at θ = 360 degrees.

Left and right test inputs are given and the scores are generated.
Based on the three scores person identification is done.

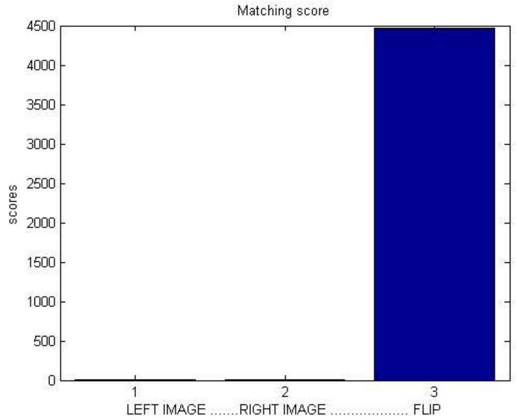

Fig. 9 Bar graph showing scores based on Euclidean distance

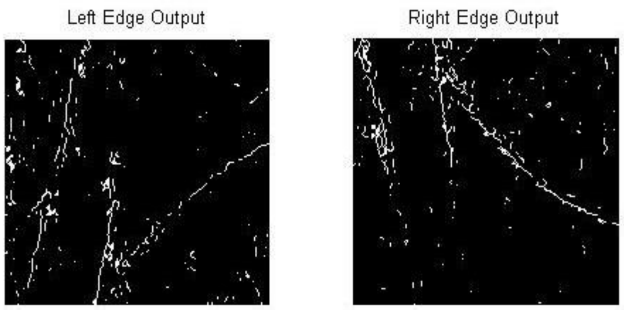

Fig. 10 Edges from Sobel edge detector

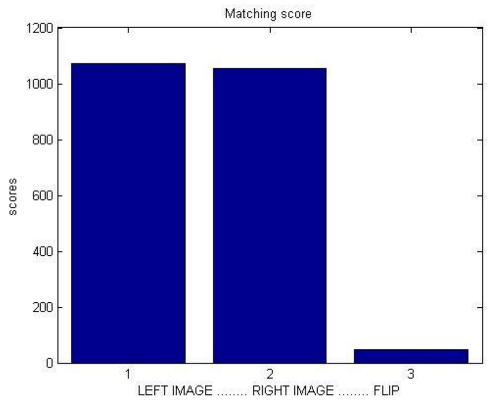

Fig. 11 Graph showing scores based on AND operation

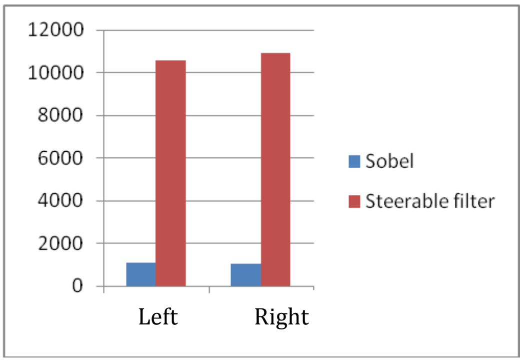

Fig. 12 Graph showing the features extracted

5. CONCLUSIONS

This study shows that the left and right palmprint images of the same subject are somewhat similar. The use of weighted fusion scheme of three scores for the performance improvement of palmprint identification has been explored in this paper. The proposed method carefully takes the nature of the left and right palmprint images into account, and designs a method to evaluate the similarity between them. Meanwhile, using of steerable filters extracts features in different orientations.

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