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Multifeature-Based HR (High-Resolution) Palmprint Recognition

S. Gandhimathi Research Scholar, Department of Computer Science, Gobi Arts & Science College (Autonomous), Gobichettipalayam-638453.

P. Narendran Associate Professor & Head, Department of Computer Science, Gobi Arts & Science College (Autonomous), Gobichettipalayam-638453.

ABSTRACT

There has been a high demand for personal identification and verification for security reasons. Biometric computing o4ers an effective approach to identify personal identity by using individual's unique, reliable and stable physical or behavioral characteristics. The main importance of biometrics includes the positive authentication and verification of a person and ensuring confidentiality of information in storage or in transit. In the field of biometrics, palmprint is a novel but promising technology. Palmprint recognition has considerable potential as a personal identification technique. But for high-security applications (e.g., forensic usage), high-resolution palmprints (500 ppi or higher) are required from which more useful information can be extracted. In this paper, we propose a novel recognition algorithm for high-resolution palmprint. This research work mainly focuses on the usage of a novel fusion scheme for an identification application which performs better than conventional fusion methods. Extreme Learning Machine is used in this approach for novel fusion approach. The performance of the proposed approach is compared with the existing novel fusion approaches such as SVM, Neyman-Pearson rule.

KEYWORDS:

I. Introduction

Authentication and security become much popular because of the arrival of new upcoming technologies like electronic banking, e-commerce, and smartcards and an increased emphasis on the privacy and security of information stored in various databases, automatic personal identification has become a very important field in the area of biometrics. Accurate automatic personal identification is now needed in a wide range of civilian applications involving the use of passports, cellular telephones, automatic teller machines, and driver licenses. Traditional techniques like knowledge-based (password or Personal Identification Number (PIN)) and token-based (passport, driver license, and ID card) identifications are prone to fraud because PINs may be forgotten or guessed by an imposter and the tokens may be lost or stolen [1].

It's comparably much difficult to use conventional knowledge-based and token-based approaches, since these techniques are easily overcome by electronically interconnected information society. It's very critical to have accurate automatic personal identification in a variety of applications in our electronically interconnected society [2]. Generally, Biometrics, is the study of identification based on physical or behavioral characteristics, is being increasingly adopted to provide positive identification with a high degree of confidence [3, 4].

Recently, biometric features play a vital role in personal authentication applications because they possess the physiological properties like universality, uniqueness, permanence, collectablilty, performance, acceptability, and circumvention. Biometrics features are the features extracted from human biological organs or behavior.

Today Biometrics are computerized methods of recognizing an individual based on their physiological (e.g., fingerprints, face, retina, iris) or behavioral characteristics (e.g., gait, signature). Each biometric feature has its own strengths and weaknesses and the choice typically depends on the application. This research focuses on the palmprint biometrics.

Palmprint recognition has considerable potential as a personal identification technique. Palmprints share most of the discriminative features with fingerprints and, in addition, possess a much larger skin area and other discriminative features such as principal lines. For access control usages, scanning the palmprint is not only fast but also highly acceptable for the public. Palmprint recognition also has a significant role in forensic applications as about 30 percent of the latents recovered from crime scenes are from palms. One of the most important goals of the FBI's Next Generation Identification System is to develop a national palmprint identification system [5].

There are two basic features in a palmprint: ridges and creases. Ridges are formed by the arrangement of the mastoid in the dermal papillary layer. They come into being during the three-tofour months of the fetal stage and are fixed in the adolescence stage [6]. The ridge pattern of the palm is unique for an individual, just like the finger tip. But unlike the fingerprint, there are many creases in the palmprint. They can be further classified as immutable and mutable creases.

But, for high-security applications (e.g., forensic usages), high-resolution palmprints are required in which the highly discriminative ridge feature can be observed. Moreover, certain ridge patterns are acceptable in a court of law, which facilitates its use in forensic applications. Further, the prints lifted from a crime scene usually have poor quality and a complex background which warrants extraction of features in addition to texture in order tomakea reliable identification.

This research focuses on multifeature-based high resolution palmprint recognition system in which minutiae, orientation field, density map, and principal line map are reliably extracted and combined to provide more discriminatory information.

II. Literature Survey

Existing research on palmprint recognition mostly concentrates on low-resolution (about 100 ppi) images [7], which are mainly captured by contactless devices. For low-resolution images, palmprint ridges cannot be observed, and the matching is mainly based on crease and texture features. Shu and Zhang [8] extracted the hand shape and principal line features to build the palmprint recognition system. Zhang and Shu [9] presented the datum point invariance and line feature matching characteristics in palmprint verification. Duta et al. [10] tried to represent and match the principal lines with feature points which locate on the principal lines and are extracted by a series of morphological operations. You et al. [11] matched the principal lines by the interesting points, which are extracted by the Plessey operator [12]. In [7], Zhang et al. proposed a contactless low-resolution palmprint acquisition device using a CCD camera and a 2D Gabor phase encoding scheme is proposed to extract palmprint textures. In [13], Huang et al. highlighted the discriminative power of principal lines and used those to design a palmprint verification system. Sun et al. [14] proposed the ordinal palmprint representation and unified several low-resolution palmprint recognition algorithms into a framework. In [15], Yue et al. proposed a modified fuzzy C-means cluster algorithm for competitive codebased palmprint recognition.

Palmprint nonlinear discriminant feature extraction and recognition is proposed in [16] by using a kernel discriminant analysis based on NSCT and palm recognition method. NSCT transformation is applied to palm images and new palm images were obtained with multiresolution and multidirectional. Then mapping the palm images to the kernel space, according to the kernel discriminant capacity to choose the new palm images with high discriminant capacities and used them to extract the discriminant features.

You et al. [17] proposed a hierarchical palmprint identification system. In the first stage of the system, based on global texture energy, it is determined are the two palms similar enough to belong to the same person. If they are, the system proceeds with a finer matching stage in which interest points are located on both palmprints and matched. An average recognition rate of 95% was obtained on the database of 200 images of 100 persons.

III. The Composite Orientation Field Estimation

It is crucial for the palmprint recognition system to reliably estimate the orientation field. It is used in ridge enhancement and minutiae validation, making it very important in minutiae extraction. Various orientation estimation algorithms have been proposed for fingerprints.

These algorithms consist of two main steps: initial estimation and post-smoothing. Lots of postsmoothing methods have been designed, including the hierarchical gradient method, the model-based method, the region growing algorithm, etc. But no matter how powerful these smoothing algorithms are, they all rely on the results provided by the initial estimation. If there are overwhelming errors in the initial estimation results, no smoothing algorithms can generate reliable results magically.

There are three commonly used initial estimation methods, namely, the gradient-based method, the discrete Fourier transform (DFT), and the Gabor-filterbank method. The basic idea of the gradient-based method is that the ridge and valley can be seen as black-and white stripes and the ridge's direction is perpendicular to the gradient direction. As for the Fourier transform method, it assumes that sine waves can effectively represent the black and-white stripes, so the peak in the frequency domain of a local area corresponds to the central lines of the stripes in the image. The Gabor-filter-bank method shares the same basic assumption with the Fourier transform method. In the frequency domain, the Gabor-filter-bank method multiplies the frequency spectrum of the local area with a series of Gabor filters and selects the direction of the Gabor filter with the strongest response as the local ridge direction. This method is very time-consuming and is not suitable for processing prints with a large image size or online applications.

The above-mentioned methods perform well on the prints with few creases. But they cannot reliably estimate the orientation of palmprints with many creases. Basically, they focus on the change of grayscale and treat the black and white stripes equally, so the direction information of the black and white stripes would both influence the result. If there are no or few creases, both of them will provide correct information. However, for palmprints containing lots of creases, the amount of white stripes will greatly increase, bringing much noise for the estimation algorithm. As a result, when the creases are overwhelming in a local region, the output of the above estimation algorithms will be wrong [18].

3.1. Methodology

Following this experience, we propose a novel orientation estimation algorithm for palmprints. A new initial estimation method is developed to reliably estimate the orientation field even in regions having many creases. But its computational cost, like the Gabor-filter-bank-based method, is much higher than the traditional gradient-based and the DFT method. In order to reduce the computational cost, we develop a composite algorithm. In this algorithm, first, the creases in a palmprint are located; for the regions with few creases, the traditional method is employed, whereas the designed initial estimation method is used for the regions with many creases. This effectively combines the robustness of the novel and efficiency of the traditional methods. As a postsmoothing procedure, the region growing algorithm is applied.

The first stage of the composite algorithm consists of estimation of ridge quality and determination of the initial estimation algorithm to be applied. In this stage, we use the crease extraction algorithm proposed in [13] to extract creases. In order to reduce the computational complexity, the image is divided into 16 x 16 pixel blocks and the crease features are computed for each of these blocks. The output of the crease extraction algorithm contains the crease orientation, ID, and the crease energy, IE. The crease orientation associated with a crease refers to the direction parallel to the crease, whereas crease energy corresponds to the width of the crease. The quality value for each block is computed as a sum of crease energy values for all of the creases present inside a 64x64 pixel neighboring region around the block under consideration.

The conventional DFT method is applied for the blocks whose crease energy is smaller than a threshold. Here, we determine k most likely orientations of the block, denoted as $X = [X_1, X_2, \ldots\ldots, X_K]^T$ $X = [X_1, X_2, \ldots\ldots, X_K]^T$, $X_i = (\theta_i, f_i)$ $X_i = (\theta_i, f_i)$, where θ_i θ_i is the ridge direction and f_i is the ridge density. Assuming that the ith peak in the frequency spectrum is at (u_i, v_i) (u_i, v_i), then the corresponding candidate solution, $X_i = (\theta_i, f_i)$ $X_i = (\theta_i, f_i)$ is given by

$$\begin{cases} \theta_i = \arctan \dfrac{v_i}{u_i} - \dfrac{\pi}{2} \\ f_i = \dfrac{\sqrt{u_i^2 + v_i^2}}{64} \end{cases}$$

For the block with a large number of creases, a Radon transform-based method (RTBM) is developed to focus on ridges and find out their directions, ignoring the disturbances from white stripes.

IV. Feature Extraction

By using the composite algorithm, the orientation field can be reliably extracted. Now, we will introduce the extraction of minutiae, density map, and principal line map.

4.1. Minutiae

With reliable orientation field and density map information, a series of image processing steps can be performed to extract minutiae. First, the ridges are enhanced by the Gabor filter according to the local ridge direction and density. Second, the image is binarized and thinned to get the skeleton ridge image. Finally, minutiae are extracted as the endings and bifurcations points of ridge lines. The initial minutia set is denoted by $M = \{m_1, m_2, \ldots, m_k\}$, where $m_i = \{x_i, y_i, \theta_i\}$ $m_i = \{x_i, y_i, \theta_i\}$. x_i, y_i and θ_i represent the ith minutia's x-coordinate, y-coordinate and direction respectively.

4.2. Radon-Transform-Based Orientation Estimation

For a pixel on the ridge, it should be a part of a low intensity stripe. As the ridge direction is slowly varying, a ridge can be approximated by a straight line in a local area. The Radon transform is a robust method to detect lines in the image, which is defined as

$$R(r,\theta)[I(x,y)] = \sum_{x=0}^{W}\sum_{y=0}^{H} I(x,y)\delta(r - x\cos\theta - y\sin\theta)$$

where $I(x,y)$ is the gray level at the location (x,y), W is the image width, H is the image height, r is the vertical distance from the line to the origin, and is the inclination. Then, the problem of detecting lines is changed to voting for the best parameters.

Note that the original Radon transform is performed on the whole image, whereas we just want to search for ridges in a small local area. So, we utilize the modified finite Radon transform to detect the ridge lines. The procedure of the proposed Radon-transform-based method is demonstrated in Fig. 3. First, all of the pixels in the current block's 64×64 pixel neighboring area τ are scanned and those whose grayscales are lower than G_r are selected. Let the pixel at the location (x_0, y_0) be one of the selected pixels. Then, normalization is performed in a circular region Δ centered at (x_0, y_0) in the radius of 27 pixels by subtracting the mean of gray levels from every pixel.

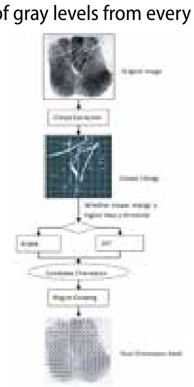

Figure 1: The flowchart of the composite algorithm

V. Multifeature Fusion

After the steps described, we get the matching scores of multiple features, including minutiae, orientation field, density map, and principal line map. In this section, we describe the techniques to combine them to measure the final similarity of two palmprints. Several fusion technologies have been proposed for the low-resolution palmprint recognition. Wang et al. [19] fused the palmprint image and palm vein image at the feature level. In [20], Kumar and Zhang fused multiple feature scores at the decision level and proposed a product of sum rule. In [21], Hennings-Yeomans et al. used the product rule for palmprint classification. Due to the differences in the nature of the application scenarios, we consider separate fusion techniques for verification and identification. For verification, we use some conventional statistical learning methods for the classification of the genuine and imposter matches. For identification, a novel heuristic rule is proposed to achieve a higher identification rate.

5.1. Statistical Methods for Verification

Given the similarity scores of various features between two palmprints, the verification system should decide whether they are from the same palm. The performance of verification is usually evaluated using the curve of the Receiver Operating Characteristic (ROC), which is a graph of FRR versus FAR. The simplest fusion technique is to compute the linear weighted sum of all of the similarity scores $S = \sum_i^k w_i S_i$ and set a threshold S_T. If S is higher than S_T, it is deemed a genuine match or else an imposter one. This is equivalent to separating two classes by a hyperplane in the feature space. But in most cases, the genuine and imposter matches are not linearly separable.

In order to accommodate nonlinearly separable densities, we learn the probability that a given match S^* is genuine $P(G|S^*)$ or imposter $P(I|S^*)$ and use a threshold-based classification for the two densities. Here, G denotes the genuine scores and I denotes the impostor scores.

In the existing approach, SVM classifier is used for classifier. But due to the drawbacks of SVM classifier, this approach uses ELM classifier approach.

5.2.Drawbacks of SVM Classifier

A common disadvantage of non-parametric techniques such as SVMs is the lack of transparency of results. SVMs cannot represent the score of all companies as a simple parametric function of the financial ratios, since its dimension may be very high. It is neither a linear combination of single financial ratios nor has it another simple functional form. The weights of the financial ratios are not constant. Thus the marginal contribution of each financial ratio to the score is variable. Using a Gaussian kernel each company has its own weights according to the difference between the value of their own financial ratios and those of the support vectors of the training data sample.

5.3. Proposed ELM Approach for classification

Extreme Learning Machine (ELM) meant for Single Hidden Layer Feed-Forward Neural Networks (SLFNs) will randomly select the input weights and analytically determine the output weights of SLFNs. This algorithm tends to afford the best generalization performance at extremely fast learning speed.

The structure of ELM network is shown in figure 1. ELM contains an input layer, hidden layer and an output layer.

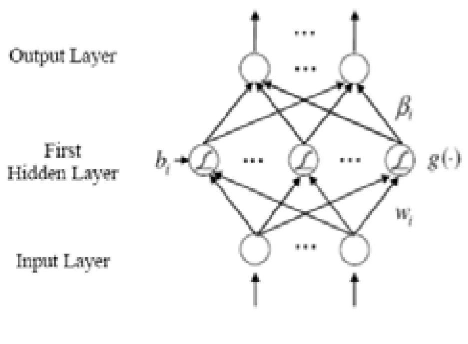

Figure 2: Structure of ELM

Thus, a simple learning method for SLFNs called Extreme Learning Machine (ELM) can be summarized as follows:

Algorithm ELM: Given a training set
$\aleph = \{(x_i, t_i) | x_i \in R^n, t_i \in R^m, i = 1, \dots, N\}$, activation function $g(x)$, and hidden node number N

Step 1: Randomly assign input weight w_i and bias b_i, $i = 1; \dots, N$.

Step 2: Calculate the hidden layer output matrix H.

Step 3: Calculate the output weight β

$\beta = H^{\dagger} T$

Where $T = [t_1, \dots, t_N]^T$

5.4. Advantages of ELM

The main advantage of this algorithm is in dividing the computational time by hundreds and making the learning process of the neural network rather simplistic.

VI. Experimental Results

In this section, the performance of the proposed ELM learning algorithm is compared with the popular algorithms of feedforward neural networks like the conventional BP algorithm and support vector machines (SVMs) on quite a few benchmark real problems in the function approximation and classification areas.

Up to now, there has been no publicly available highresolution palmprint database. To test the algorithm, we built a large-scale palmprint database containing 14,576 full palmprints from 13,736 palms, which is referred to as THUPALMLAB. The database's size is much larger than the database used in [8]. The image size is 2040 x 2040 pixels with 500 ppi resolution and 256 grayscales. The database contains both full and partial palmprints. The set of full palmprints consists of two parts; 120 × 8 of them are collected from 120 different palms by using a Hisign palm scanner.

6.1. Performance Evaluation

A. False Acceptance Rate(FAR) and False Rejection Rate(FRR)

Table 1: Evaluation FAR and FAR

Threshold	Trail 1		Trail 2	
	FAR (%)	FRR (%)	FAR (%)	FRR (%)
0.320	0.0049	3.69	0.0098	1.80
0.325	0.0439	2.93	0.088	1.34
0.330	0.15	2.29	0.28	1.025
0.335	0.37	1.90	0.68	0.72
0.340	0.84	1.51	1.43	0.57

Table 1 shows the FAR and FRR values for the palmprint considered. It is observed from the table that the results are very significant. Two trails are taken and the results are very efficient with less FAR and FRR.

6.2. Performance of the Classifier

The existing approach uses SVM classifier and the proposed approach uses ELM classifier. Table 1 shows the accuracy of the classifiers.

It is observed from the table that the proposed ELM fusion based Palmprint recognition technique attains the accuracy of 91%, where as the Neyman-Pearson rule and SVM attains the accuracy of 83% and 86% respectively.

Table 2: Accuracy of Classifier

Classifiers	Overall Classification Accuracy (%)
Neyman-Pearson rule	83
SVM	86
ELM	91

Table 2 shows the time comparison of the propsed ELM fusion based palmprint recognition approach. The time taken for ELM classifier is 2.9 seconds, where as the time taken by Neyman-Pearson rule and SVM is 5.8 seconds and 5.2 seconds respectively.

Table 3: Time Comparison

Classifiers	Time taken for Classification (sec)
Neyman-Pearson rule	5.8
SVM	5.2
ELM	2.9

VII. Conclusion

This research work focused on developing a novel high-resolution palmprint recognition system which can handle palmprints with a large amount of creases, leading to much higher accuracy than the previous systems. The main contributions are as follows:

- Using multiple features for palmprint recognition to significantly improve the matching accuracy.
- Designing a quality-based and adaptive orientation field estimation algorithm. It can reliably estimate the ridge direction by adaptively choosing suitable estimation method according to the image quality.
- Using a novel heuristic rule for identification applications to combine different features.
- The discriminative power of different feature combinations is analyzed and we find that density is very useful for palmprint recognition.

The proposed approach can accurately identify a person in real time, which is suitable for various civil applications such as access control. Experimental results reveal that the proposed approach can identify 400 palms with a low FAR of 0.02%. For verification, the system can operate at a FAR of 0.017% and a FRR of 0.86%.

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