Palmprint Identification Using Discriminative Frequency Components and Extreme Learning Machine

Burhan ERGEN and Vedat Tümen

***Abstract*—** This paper proposes a novel fusion method for palmprint identification based on frequency component analysis, autoregressive signal modeling and extreme learning machines. After determining frequency components by means of a two dimensional Fourier Transform (2DFT), the components are evaluated in three parts; imaginary, real, and absolute values. The 2D components are converted 1D signal using spiral scanning scheme. Then, autoregressive (AR) signal modeling is used to find out dominant components that they are the input for extreme learning machines (ELM) based classifier. This scheme is applied for each part of the frequency component. Experimental result on reliable well known PolyU palmprint database shows the effectiveness of the proposed method with %95 correct recognition rate.

***Keywords*—**Palmprint identification, descriptive frequency components, extreme learning machines.

I. Introduction

The need of personal identification has made the use of a password, a secret code or a personal identification numbers (PINs). Those methods are unsafe and not user-friendly since they can be easily forgotten, shared, observed. For this reason, biometric systems have recently become indispensible to solve security problems for personal identification. The main advantage of a biometric recognition system is that the person should be physically at the point of authentication. Palmprint support reliable properties to identify a person because the palmprint patterns are not duplicated in other people, even in monozygotic twins that demonstrate an advantage.

Palmprint recognition methods commonly use two approaches to analyze an image and extract the features for characterization; structural approach, and statistical approaches. The structural approach uses principal lines, wrinkles, ridges and minutiae points to constitute feature vector [1-3]. Since the determination of the structural features is hard, the statistical methods assuming palmprint as textural image are commonly preferred in literature. There are many proposed methods analyzing textural properties of palmprints such as Eigenpalm, Fisherpalm, traditional Fourier Transform (FT), discrete wavelet transform (DWT), Gabor wavelet transform (GWT), discrete cosine transform (DCT), and some local texture energy based methods [4-9]. Eigenpalm and fisherpalm methods uses principal components [10], FT and DCT analyze the frequency components [4, 11], and DWT and GWT decompose the image into low and high frequency components [7, 12, 13].

However these methods have some success, their realizations in real world application is very low. These methods contain the algorithm having very high complexities in order to obtain reliable and short feature vector [14]. To obtain short and reliable feature vector, many applications mix many algorithm to present reliable features and use principal component analysis (PCA) to find most deterministic and short feature vector. PCA based method contains eigen value decomposition calculation which increases the time and memory complexity. Whereas, the basic signal processing methods work adequately and have fast algorithms. FT is one of the basic and reliable methods to find out frequency representation of one or two dimensional (2D) signal. There are many proposed algorithms to realize FT such as radix algorithms. Therefore, we have proposed a fusion method which combines FT and parametric signal modeling techniques. To deal with the complexity of eigen decomposition, we use autoregressive (AR) signal modeling to present short and discriminative feature vector.

As a parametric signal modeling method in signal processing, AR is the most preferred method because it produces peaks in its spectra for significant and discriminative components of input signal [15, 16]. The algorithms to find optimal AR parameters have low memory complexity because of iteratively working. In addition, an extreme learning machines based classifier is used to overcome the training time and memory complexity like feed forward or back forward neural network and k-nearest neighbor classifiers. Therefore, we have proposed a fusion method to make a practically implementable palmprint identification system.

II. Proposed Method

A pattern recognition system can divided into three steps; preprocessing, feature extraction, and classification. A preprocessing step commonly consists of image enhancement and determination of ROI. In fact, the feature extraction step is the most important process in a recognition system because it presents feature vector distinguishing the image to be recognized. The last stage, classification, puts forward a class label for the unknown given input. This can be called as

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decision for recognition. The proposed method consists a noise reduction and cropping ROI in preprocessing step, two dimensional Fourier transform (2D-FT), spiral scanning scheme, and autoregressive (AR) signal modeling in feature step, and extreme learning machines (ELM) based classifier in classification step. Fig. 1 depicts the proposed system as a flow chart.

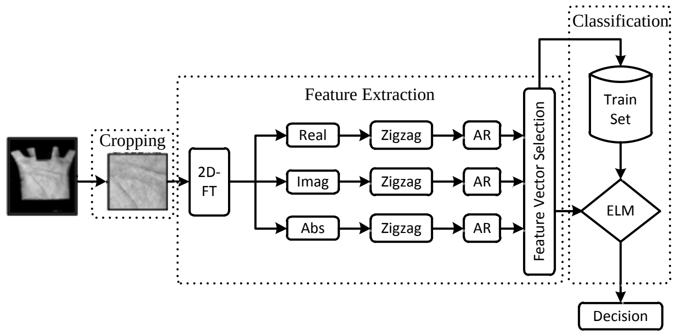

Fig 1. Flow chart of the proposed palmprint identification.

A. Preprocessing

A typical palmprint image and its region of interest (ROI) are given in Fig.2a and b, respectively. A ROI is the convenient part which consist the structural and textural features.

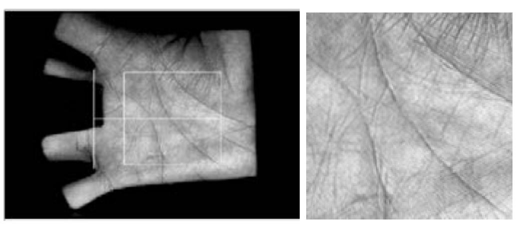

Fig. 2. A typical palmprint, and its region of interest (ROI).

The central part of a palmprint considered as ROI, which extracted in the preprocessing stage after filtering for noises reduction and some alignments. In feature extraction stage, the 2D-FT is used to determine frequency components to distinguish the palmprint images. However the Fourier transform is most well known and powerful tool to determine frequency components, it has a disadvantage because of producing complex values. The frequency components are used in three manner; real, imaginary, and absolute values. The recognition system is tested for each part of frequency components.

B. Fourier Transform And Scanning Scheme

If 2D-FT is applied on an image, low frequency components are concentrated at the corners on the frequency representation of given image. These components are shifted to the center of the representation to make visualization and extraction easier. The shifting procedure is shown in Fig. 3a and b, an example of an image is given in Fig. 1b.

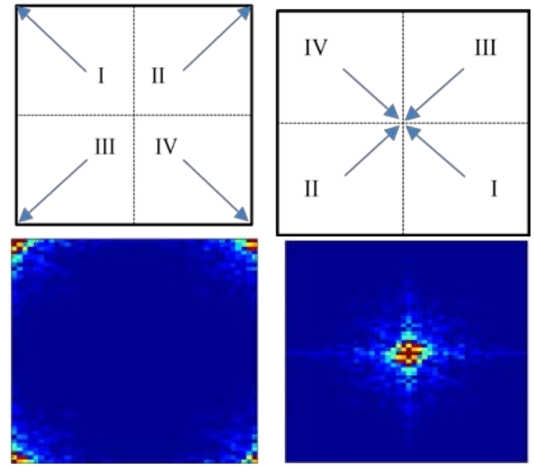

Fig. 3. Shifting procedure of frequency representation; a) Before shifting, b) After shifting, c) 2D-FT frequency representation, d) Centered representation.

The 2D-FT representation of an image of MxN size can be given as follows;

$$F(u,v)=\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}f(x,y)exp\left\{-j2\pi\left(\frac{ux}{M}+\frac{vy}{N}\right)\right\} \quad (1)$$

where f(x,y) and F(u,v) denotes input image and its frequency representation using FT. In recognition systems, it commonly considered that features of an input image are presented as a vector to the classifier in the recognition system. Therefore, the frequency representation of an image should be converted into a one dimensional (1D) signal. In a 2D-FT representation, significant components spread out from the center toward the edge. High-frequency components are naturally weaker than in the pictures. The coefficients of high frequency components are smaller and the low frequency components are larger. To construct an appropriate 1D decreasing signal, it is obvious that the frequency components should be scanned from the center to the edges. Fig. 4a represents spiral scanning scheme. Fig. 4b is show a small part of the absolute valued 1D signal form of the image given in Fig. 1b.

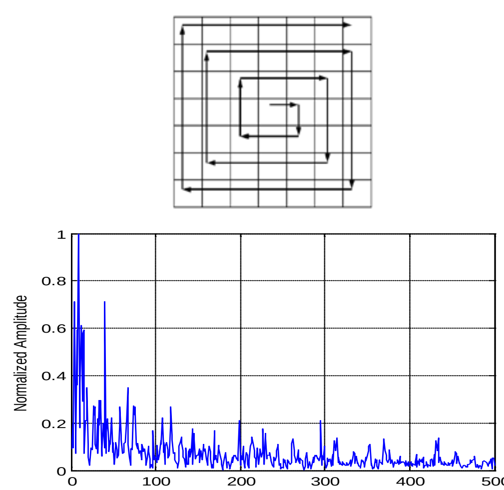

Figure 4. Spiral scanning scheme, and a 1D signal.

The conversion gives a long vector that is very hard to be used as a feature vector. Therefore, it is required a dimension reduction to obtain short feature vector. Here, we take advantage of AR signal modeling method. The result parameters of AR modeling provide a fixed and shorter length feature vector.

C. AR Signal Modeling

A signal is considered as a combination of current output value and past output values of a system in discrete signal processing. And, it is assumed that the input signal of the system is white noise having Gaussianity. The weights on previous outputs minimize the average square errors of the estimated AR parameters. If and indicate the zero mean white noise input and the output of a system, then AR model of the system can be given as;

$$x(n) = \sum_{k=0}^{p} a(k) y(k-n) \tag{2}$$

where a(k) indicates the AR parameters modeling the system, y(k) is the output signal of the system, and x(k) is the input signal assumed as white noise with power of 1 unit.

Many methods and algorithms have been proposed to discover the AR parameters. One of the most known and widely used methods for the estimation of the AR parameters is Yule-Walker method which is also named as autocorrelation method. In this method, the forward prediction error is minimized in the least square sense to fit the AR model to the given input data. The parameters are obtained by solving the autocorrelation function expressed as (Proakis 1996);

$$\sigma^2 = \frac{1}{N} \sum_{n=-\infty}^{\infty} \left| x(n) - \sum_{k=1}^{p} a(k) x(n-k) \right|^2 \tag{3}$$

Because the AR parameters carry the most important discriminative information, they can be used as a feature vector. In last stage, a feature matching procedure is performed using the AR modeling parameter via the ELM classifier. Consequently, the scanning scheme and AR modeling is used to produce a short feature vector.

D. Extreme Learning Machines

However feed forward neural networks have been successful in pattern recognition problems, its slow learning is still the main disadvantage. The main reason for this slow learning is that the neural network has a gradient-base learning algorithms and tunes them iteratively. Unlike conventional iterative learning algorithm, the weights and thresholds can be randomly generated, and the numbers of neurons in the hidden layer are adjusted. After learning, ELM can find out the optimal solution without setting any other. This method not only decreases the data processing time, but also increases generalized efficiency. The output of ELM can be given as (Huang, Zhu et al. 2006);

$$o_k(x) = \sum_{i=1}^{L} w_{oi} G(a_i, b_i, x_k) \tag{4}$$

where a, b, and L are the learning parameters and the bias of the i-th hidden layer neuron, respectively. Here, the i-th hidden layer neuron is connected to the output layer withw_{oi}. $G(.)$ refers to the output of the I-th hidden layer neuron. ELM output can be expressed in compact form as follows;

$$O = (W_o^T H)^T \tag{5}$$

Where H is the matrix of the hidden layer neurons, and a_(ki) refers to $G(a_i, b_i, x_k)$, which is the input in the k-th row and i-th column in the hidden layer output matrix H. H and W can be given as a matrix form as follows;

$$H = \begin{bmatrix} H_1(1) & \cdots & H_1(N) \\ \vdots & \ddots & \vdots \\ H_L(N) & \cdots & H_{L1}(N) \end{bmatrix} \text{ and } W = \begin{bmatrix} b_1 & b_1 & \cdots & b_1 \\ \vdots & \vdots & \vdots & \vdots \\ w_{11} & w_{11} & \dots & w_{11} \\ w_{11} & w_{11} & \cdots & w_{11} \end{bmatrix} \tag{6}$$

The ELM aims to minimize the training error and the norm of the output weight by calculating cost function given as;

$$CF = \|O - Y\| \tag{7}$$

where Y is the expected output matrix. The learning speed o ELM is very fast because there is no parameters need to be tuned during training phase. Similar to support vector machines, it can be integrate kernels in extreme learning machines. In this study, we use both the linear kernel and the RBF kernel.

III. Experiments And Results

The experiments have done on the public palmprint database (PolyU-II Palmprint Database, 2006) which includes 7752 palmprint images from 386 different palms [17]. The experiment has been performed on whole database which consist of 7752 palmprint images. The images of the ten images for a person as the training samples and the remainder as the test samples are used to evaluate the performance. The ROI image are obtained as described in [18]. Since the AR parameters are used as a feature vector, P is also the number of the AR parameters. Table 1 shows the correct recognition rates (CRRs) for each part of frequency components respect to the length of feature. In this experiment, only one image per person is used as training sample. The rest of nine images are used as test images. The training and test images per person are chosen randomly.

Tablo 1. The CRR using real part of frequency components.

	10	25	50	100	200
Real	10.5930	41.0478	81.9804	96.9488	97.3805
Imag	15.5728	62.0610	84.2545	89.4358	90.0979
Abs	7.3115	34.7438	74.8129	95.2216	98.1865

It is observed that the CRRs increase respect to the length of feature vector. The results in the table do not show which part of the frequency components are discriminative such as real, imaginary or absolute value. However, it is observed that the real and absolute values produces higher CRRs for the relatively long feature vectors. The experiment is repeated for different ratios of training and test samples to determine how the number the training samples affect on CRRs. Table 2 shows the CRRs for each part of the frequency components according to the ratios. For this experiment, the length of the feature vector (p) is chosen as 200.

The results show that real and absolute values slightly gives more successful results. If the number of the training samples is increased, the CRRs of the method increase above 99%. As expected, if the length of the feature vector p is increased, the recognition rates achieve about 99. According to the results, one of the important inferences is that the proposed method has effectively reduces the length of feature vector. Table 3 represents a comparison that shows the superiority of our proposed method. The proposed method gives higher CRRs for all ratios.

Table 2. The CRRs for different ratios of training and testing images.

Ratio	Real	Imag	Abs
2:8	99.2552	97.5065	99.1256
3:7	99.5929	98.5566	99.4449
4:6	99.6978	98.9206	99.6546
5:5	99.6891	99.4819	99.7927

Table 3. A Comparison of CRRs of different methods.

Method	Training Samples per class			
	5	4	3	2
Traditional Gabor Method [19]	92.88	91.23	86.99	80.96
Gabor Local Invariant Features [7]	98.36	97.12	94.52	88.22
PCA [13]	95.00	94.00	89.50	70.25
$GB(2D)^2PCA$ [13]	99.00	98.50	96.00	94.50
W2D - DLPP [20]	-	94.91	89.8	81.80
Proposed Method	99.79	99.65	99.45	99.13

IV. Conclusion

This paper introduces a novel palmprint recognition system combining the 2D-FT, the AR signal modeling and ELM based classifier. The estimated AR parameters modeling the 2D-DFT coefficients of an input palmprint image are used as a feature vector representing the input image. Then, the ELM based classifier is used to measure similarities among the palmprint images. The novelty of our method is to use the AR parameters modeling the 2D-DFT coefficients of a palmprint image to constitute a practically implementable system. The results show that the proposed system has high successful CRRs. The AR modeling reveals the most distinctive information of the 2D-DFT, which is performed on the whole image so that it provides an easy implementation for practical applications. And also, we have used the nearest neighbor classifier due to the simplicity and the easy implementation at high accuracy. The CRRs achieving about 99% prove that the proposed system has high CRRs even if a small feature vector size is used. Because the methods in the study are not so complex, the proposed method can be used efficiently in practice implementations.

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