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A Palmprint Recognition Method Using LS-SVM Based on Finite Ridgelet Transform

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Abstract. A multi-scale palm print classification method based on FRIT (finite ridgelet transform) and LS-SVM (least square support vector machine) was proposed. The multi-scale feature extraction of FRIT was utilized to extract the palmprint feature, and then the LS-SVM was combined with identify palm types. Firstly, palmprint image with preprocessing was decomposed into some ridgelet coefficients in different scales and various angels by FRIT. The important linear feature of palmprint was included in the low frequency coefficients of FRIT decomposition coefficients. Then the decomposition coefficients were transformed into feature vectors. Finally, the eigenvectors were input into LS-SVM classifier for palmprint type classification. The experiments were performed in PolyU palmprint database. Experiment results show that this proposed method not only can effectively extract fault features, but also has shorter classification time compared with SVM network.

Keywords: Finite ridgelet transform (FRIT), Least square support vector machine (LS-SVM), Palmprint recognition

1. Introduction

Biometric recognition technology has been paid more and more attention as a new method for identity authentication. Palmprint recognition has become a research hotspot due to the fact that palm is unique in many domestic and foreign researchers, the details are permanent, the information is rich and the collection of palm is convenient. In the palmprint identification process, the accuracy rate of recognition is largely determined by the uniqueness and robustness of feature extracted. Commonly some schemes for palmprint identification are line or point feature extraction for model matching [1]. A BDPCA developed from PCA which can reduce the dimension of the original image matrix in both column and row directions [2]. The success of wavelets is mainly due to the good performance for piecewise smooth functions in one dimension. In paper [3], authors integrated the wavelet analysis method and ICA to represent the palmprint features. In the paper [4], they proposed to use the wavelet energy feature of the scalable detailed sub-images. Unfortunately, such is not the case in two dimensions. For two-dimensional linear, surface singularities functions, the wavelet can not approximate them very well. The lack of the wavelet makes researcher try to seek the other harmonic analysis tools. The concept of the ridgelet is proposed by E. Candès and D.L. Donoho professor in 1998. It is very well at representing the smooth functions with line singularities. And the concepts and methods of modern harmonic analysis are used to deal with structural problems in neural network. Ridge transform not only retains the characteristics of multi-scale in wavelet method, but also has anisotropic characteristics, also can be a good approximation of singular curves. Ridgelet get sparser than the wavelet representation in some aspects of image processing. The palmprint recognition based ridgelet transform was first proposed in Literature [5], which used ridgelet transform and threshold method to extract palmprint feature information. Experiment obtained 95.25 percent correct recognition rate that similar with conventional wavelet method in PolyU palmprint database.

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A multi-scale palmprint classification method based on discrete ridgelet transform and least squares support vector machine was proposed. Ridgelet transform is employed to get the representation basis of palmprint image normalized, and then use LS-SVM (least square support vector machine) to improve recognition speed.

2. Basic Principles

2.1. Finite Ridgelet Transformation and the Converse

The image is projected onto the FRAT (finite Radon transform) domain through finite Radon transform, and then finished the one-dimensional orthogonal transformation, which satisfy the Z condition, according to each column. This gives an orientation orthogonal basis for the image. In image processing which have obvious characteristics of line singularity, and good distinguishing result has been obtained. Here, it will be used to extract the feature of the palm lines as complete as possible.

Suppose the image is composed of $p \times p$ matrix, p is a prime number. Defined set $Z_p = \{1, 1, \ldots, p\text{-}1\}$, Z_p^2 is a finite region that generated by template p. Thus, the FRAT that can put a discrete picture f on finite mesh is defined as follow:

$$r_k[l] = FRAT(k,l) = p^{-1/2} \sum_{(i,j)\in L_{KJ}}^{p} f(i,j) \tag{1}$$

Where: L_{KJ} representation a dot set in linear, it composed between slope k and intercede l on mesh Z_p^2 (When k equal p, it is vertical linear.).

Transform by using finite Radon transform for specific size of the discrete finite grid Z_p^2, will produce a finite Radon transform sequence in each direction, corresponding to a column of the output matrix. Then one-dimensional discrete wavelets transform can be executed in each column of Radon coefficient matrix. Finally, ridgelet coefficient matrix can be obtained. The whole process is called discrete finite ridgelet transformation [6].

Based on discrete finite ridgelet transformation, we can obtain 2-D image of the main linear features. By the way of inverse transform on the ridgelet coefficient matrix. The inverse transformation of FRAT can be expressed as follows:

$$IFRAT(i,j) = FBP_r(i,j) - \frac{1}{p} \sum_{(i',j')\in Z_p^2} f(i',j') \tag{2}$$

Where: the minuend is an average of all pixel gray value on the original discrete finite mesh, when it is zero, then *f(i,j)=FBP(i,j)*. FBP is finite back projection.

Therefore, every pixel on Z_p^2 should subtract the mean of pixel before making finite Radon transform, as the pending discrete finite grid. Finally, using the result between the pixel value of finite back projection and the mean, image restoration can be done.

2.2. The Least Square Support Vector Machine Algorithm

SVM is one of the methods which the statistical learning theory can be introduced to practical application. It has its own advantages in solving the pattern recognition problem with small samples, nonlinearity, and higher dimension. SVM can be easily introduced into learning problem such as palm classification. Uykens and Vandewalle (1999) presented the least square support vector machine (LS-SVM) approach. It is an improvement upon the traditional support vector machine method. It substitutes the in-equation constraint with an equation constraint in the support vector machine method and adapts the square error and loss function as the experience loss in the training set. The square planning problem is thus transformed into a linear function group problem. Therefore, the problem can be solved faster with a higher converging accuracy.

Compared with traditional support vector machine, the LS-SVM theory caters mostly to the 2-class case. As for the multiple classification case, the basic idea is to transform the problem into a 2-class problem, which is usually implemented using a combined classifier. A poll is carried out for all these 2-class classifiers and the class with the most polls is determined as the class that the point being analyzed belongs to.

When the sample x is fed into the 2-class classifier constructed from the *m-th* class sample and the *n-th* class sample, the classifying function is:

$$f_{mn}(x) = sign[\sum_{s}(w^{mn})^T K(x_i, x) + b^{mn}] \tag{3}$$

In which sign is the signed function, W^{mn} is the vertical vector on the classifying hyper plane, $K(x_i, x)$ is the kernel function, b^{mn} is the location of the hyper plane and s is the support vector.

If x is determined to be a member of the *m-th* class by $f_{mn}(x)$, one poll is added to the *m-th* class. Otherwise, one poll is added to the *n-th* class. After all the N(N-1)/2 2-class classifiers have made the decision for x , the class that has the most polls is determined to be the one x belongs to.

2.3. Classification Rules in the Paper

In this paper, "one to many approach" [7] is used to finish the palm classify, which is converted to two kinds of problems. There need construct hyperplane between the first k classes and other $k-1$ classes. In this way, the system only need to build k classes LS-SVM classifiers, each LS-SVM classifier will identify a class of data from other classes.

Classification rules are as follows. Suppose there are C classes in the identify sample, denoted by $s_1, s_2, ..., s_c$. Design a LS-SVM classifier y_i $(i=1, 2, ..., c)$, which each y_i to use a class sample s_i as positive training samples, while all other samples s_j $(j \neq i)$ as a negative training samples. For the positive and negative samples, the system output is +1, -1 respectively. In the test stage, each test sample input to C classifiers, If only one y_i output is +1, then the specimen was placed into cluster i. If p $(p>1)$ classifiers output are +1, and then use nearest neighbor classification technique which is calculate the distance between the test sample and the training samples represented by p classifier, the test samples identified as the minimum value corresponding to that category. If all classifiers outputs are -1, then the test sample identified as a new sample.

3. Experiments and Result Analysis

3.1. Preparations for the Experiment

This work is carried on the PolyU palmprint database in order to verify the effectiveness of the proposed method. The database includes 100 different palms, and each of these palms has twenty images，which are grey-scale image in BMP file format. The samples for each palm were collected in two sessions, which means that the first ten samples were captured in one session and the other ten samples in another session.

In order to construct LS-SVM network, five people’s palm image were random selected from the palmprint database in this paper. Training images set contains thirty images which are each of these six sample palms, another four palm prints of them and others 100 images as a test images set, total 120 images. After preprocessing of palmprint image, we got the ROI region of some palms that size is 128×128. Some of these are shown in figure 1.

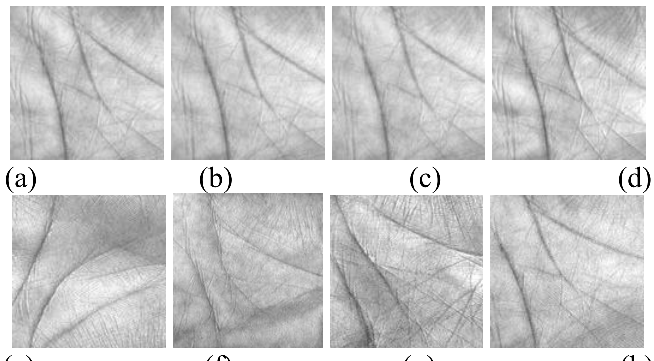

Fig. 1. Some samples after preprocessing: (a) ～ (d) from same palm; (e) ～ (h) from different people

3.2. Experimental Design

A basic detection and identification system about palmprint as illustrated.

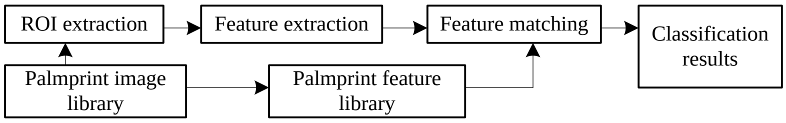

Fig. 2. Palmprint detection and recognition system architecture

Among them, the palmprint identification system consists of four parts, such as pre-processing module, feature extraction module, training module and identification module. This paper focuses on feature extraction and recognition modules. The algorithm based on FRIT and LS-SVM is summarized below:

Step 1: Image preprocessing. Extraction the ROI region into 128×128 refers to David Zhang's suggestion firstly. The ROI of sample image and test image should be geometric normalization and gray level normalization, the gray scale range of image is [0, 1] secondly. For convenience, we divide the ROI region into 16 blocks.

Step 2: Feature extraction. In this step, using FRIT to extract features for each sub-blocks of 16 training images respectively. First, we transform each block palm print into radon domain including training images and test images. And second, obtain the ridgelet transform coefficients by discrete wavelets transform [8].

Step 3: Constitute feature vector. The low-frequency coefficients of FRIT contain much important information about palm line, which can be used as feature vectors in training and classification in LS-SVM. The feature coefficients in the previous step combined to constitute feature vector. Coefficient matrix is $l \times l$, and the feature vector size is $l \times l^2$.

Step 4: Construction of k-class LS-SVM, the number of support vector is l^2.

Step 5: To learn and train for *k* classes LS-SVM respectively. All transform coefficients matrix after learning samples will be input to the *k-th* class LS-SVM alone.

Step 6: Palmprint classification test. The feature coefficients, obtained through FRIT from test image, are input to the trained LS-SVM in proper order, judged by the classification rules in section 2.

3.3. Experimental Results and Analysis

In order to assess the performance and effectiveness about the method, the test image set from the PolyU Palmprint Database was experimented by two types of different ways. The selected samples were randomly assigned to training and recognition in many times. The recognition rate reaches as high as 97.50 percent. To compare the performance of LS-SVM with that of another method, 120 samples are selected from the Database to be processed by both the LS-SVM network and the SVM network. The SVM algorithm program was used from the LIBSVM [9]. As shown in Table 1, the average accuracy of SVM classification has reached 94.50 percent, still lower than the average accuracy of LS-SVM classification. However, according to the single classification results, there are similar classification accuracy between SVM classifier and LS-SVM classifier.

Table 1. The Recognition rate of two methods

Test number	Recognition rate (%)					
	1	2	3	4	5	Average
FRIT & SVM	95.83	94.17	95.00	94.17	93.33	94.50
FRIT & LS-SVM	94.17	95.83	97.50	95.83	95.00	95.66

This experiment has been tried on the Intel® Core™2 Duo CPU E7400 @ 2.80GHz computer with Matlab language. When the number of test samples is larger, there are some rules at the time in table 2. From this table, we can observe that the recognizing time spent by two methods is longer with the increase number, while the recognizing time of SVM network, grow faster, is twice as many about that of the LS-SVM network.

Table 2. Recognition speed of two methods

Testing samples	Recognition time (s)	
	FRIT & SVM	FRIT & LS-SVM
50	0.613	0.152
120	2.312	1.032
150	5.835	2.685
200	13.043	4.911

4. Conclusion

According to the relationship between image preprocessing, feature extraction and palmprint identification, a new method on palm classification which combines ridgelet and LS-SVM is proposed in this paper. In the proposed method, the method of gray variance standardized is used to guarantee that the normalized image has same mean and variance, reduce the influence of light on the palmprint image. Then FRIT was adopted to extract the line feature of palmprint image. Finally, the LS-SVM classifier is used and the recognizing speed has improved. Experimental results from PolyU palmprint database show that the efficiency of this method is high and the detection speed is improved greatly. This method could effectively overcome a low recognition speed by using SVM. According to the experimental results, there have similar classification accuracy between the two classifiers. We will extend the number of test sample to ensure the experimental result with abundant evidence, make full use of the algorithm to improve recognition rates. This is the work in the future.

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