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Palmprint recognition based on the representation in the feature space

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ABSTRACT

In this paper, we propose a palmprint recognition method based on the representation in the feature space. The proposed method seeks to represent the test sample as a linear combination of all the training samples in the feature space and then exploits the obtained linear combination to perform palmprint recognition. We can implement the mapping from the original space to the feature space by using the kernel functions such as radial basis function (RBF). In this method, the selection of the parameter of the kernel function is important. We propose an automatic algorithm for selecting the parameter. The basic idea of the algorithm is to optimize the feature space such that the samples from the same class are well clustered while the samples from different classes are pushed far away. The proposed criterion measures the goodness of a feature space, and the optimal kernel parameter is obtained by minimizing this criterion. Experimental results on multispectral palmprint database show that the proposed method is more effective than 2DPCA, 2DLDA, AANNC, CRC_RLS, nearest neighbor method (NN) and competitive coding method in terms of the correct recognition rate.

1. Introduction

Biometrics is one of the most important and reliable methods [1,2]. Biometric is based on personal physiological characteristics such as iris pattern [3], palmprint [4], fingerprint [5], and face [6]. It is based on the biologic data and information technology, and has the advantages of safety, validity and ease of use. Many biometric systems have been developed successfully for various applications, including attendance, monitoring system and access control [1].

A palm is defined as the inner surface of a hand. Palmprint refers to principle lines, wrinkles and ridges on a palm [7]. All of these features could be used for palmprint recognition. Palm biometrics is represented by the information presented in a friction ridge impression. This information combines ridge flow, ridge characteristics, and ridge structure of the raised portion of the epidermis. The data represented by these friction ridge impressions allows a determination that corresponding areas of friction ridge impressions either originated from the same source or could not have been made by the same source [8]. The palmprint recognition techniques can be classified into four types: structure-based [7], statistic-based [9,10], subspace-based [11–13] and code-based [14].

Structure-based methods mainly refer to the direction and location information of the main line and fold in the palm. This kind of method always consists of two parts. The first is to extract the features of the ridge, and the second is the effective representation and matching. The effective representation of the line features is easy to match, and takes up minimal storage space. For feature extraction, it is more likely to use a variety of line detection operator [15] and edge detection operator [16]. For the representation of the features, it mainly uses straight line segment or feature points instead of the ridge. Hausdorff distance and Euclidean distance are always used for the matching.

Statistic-based methods refer to the mean, variance and center of gravity of the palm. They can be divided into local statistics-based methods and global statistics-based methods. For the local statistics-based methods, the image is divided into several small parts [17], the mean and variance of each part can be combined as the feature vector of the palm. While in global statistics-based methods, the torque, center of gravity and other statistical information are directly calculated as the features of the palm. Correlation coefficient, first-order norm and Euclidean distance are often used for the matching.

The palmprint images can be seen as high dimensional vectors or matrices which can be transformed into low dimensional vectors or matrices by using subspace-based method. Then the images can be represented and matched in this low dimensional space. Subspace-based methods can be divided into linear space methods and nonlinear space methods. Now some linear space methods are widely used, such as PCA [18–20], LDA [21–23], ICA [24,25], and LPP [26–28]. The optimal projection vector or matrix can be calculated in the training set of each class. The nearest neighbor method

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(NN) is often used to perform classification. Subspace-based methods have been applied in face recognition successfully, and make a good effect on the palmprint recognition.

The palmprint images can be filtered by filters and coded according to certain rules in code-based methods. The features are stored in forms of bits. The similarity between the palmprint images can be calculated by binary operators. These methods mainly include three core parts: the choice of the filter, coding rules and the way of matching. For example, Kong proposed to process the images by using Gabor filter with six directions, and then to code the direction whose corresponding value is minimum [14]. Although the existing palmprint recognition approaches have shown excellent results, better performance is still needed to meet the demand of some high security situation.

Personal recognition based on representation method has been used recently [29–31]. Ref. [31] shows the good performance of the representation-based kernel method. In this paper, we propose a palmprint recognition method based on the linear combination of all the training samples in the feature space. A similar method has shown good performance in face recognition [31]. The kernel function can help us to solve the mapping from the original space to the feature space [32–34]. But the parameter of the kernel function in the method in Ref. [31] must be manually set. It is known that different kernel parameters produce different mappings and different feature spaces. If the positive and negative image samples are severely overlapped in the feature space, it should not be expected that the negative ones can be pushed far away from the positives in a subspace. Hence, selecting the optimal kernel parameter can be viewed as selecting a good feature space in which the images from the same class have been well clustered, whereas the samples from different classes have been pushed far away. We know that the value of the parameter exercises a great influence on the recognition rate. So an automatic method for selecting the parameter of the kernel function is proposed in this paper. A criterion ($J(\sigma)=(1-\omega(\sigma)+b(\sigma))$) is developed to measure the goodness of a feature space, and the optimal kernel parameter is the one to minimize this criterion. From the definition of the RBF kernel function, we can know that the value of the kernel function of the samples from the same class (defined as $\omega(\sigma)$) should be close to 1. What's more, the value of the kernel function of the samples from different classes (defined as $b(\sigma)$) will be in the range [0,1]. If $\omega(\sigma)$ is close to 1 and $b(\sigma)$ is close to 0, then the possibility of the samples from the same class will be very great. So we can get proper σ by minimizing $(1-\omega(\sigma))$ and $b(\sigma)$. Experimental results on a large database show the effectiveness of the proposed method.

The rest of the paper is organized as follows: Section 2 presents the proposed method. Section 3 reports experimental results and Section 4 gives some conclusions.

2. Proposed method

In this section, we will present the proposed method in detail. Fig. 1 shows the flowchart of the proposed method. We assume that there are c classes and n training samples in the original space: $x_i (i=1,2,\ldots,n)$. If a training sample is from the kth class ($k=1,2,\ldots,c$), k will be taken as the class label of the training sample. Let y be a test sample in the original space.

(A) The mapping from the original space to the feature space and parameter selection

In this section, we describe how to map the original space to the feature space and how to perform parameter selection for the kernel function to conduct the mapping. The dimension will be the biggest obstacle when we classify the test sample in the original space. So to map the original space to the feature space is helpful. We know that the kernel function can help us to realize the mapping. We assume that $x, z (x, z \in X, X \in R^m)$ are the samples in the original space and the nonlinear function ϕ is the mapping from the original space X to the feature space $F (F \in R^n, n \ll m)$. The kernel function is defined as follows:

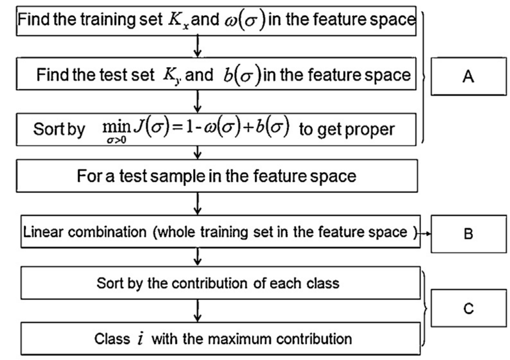

Fig. 1. Flowchart of the proposed method.

$$k(x, z) = \langle \phi(x), \phi(z) \rangle \tag{1}$$

where $\langle , \rangle$ is the inner product computation, and $k(x,z)$ is the kernel function. We can change the inner product computation in the high dimensional space R^m to the computation of the kernel function in the low dimensional space R^n by Eq. (1). Then we can solve the problem in the high dimensional space easily.

The Gaussian radial basis function (RBF) kernel $k(x, z, \sigma) = \exp(-(\|x-z\|^2)/(2\sigma^2))x, \quad z \in R^m$ is one of the most popular kernel function. $\sigma \in (0, \infty)$ is the parameter [35,36]. Different value of σ indicates the different corresponding mapping ϕ and leads to different recognition results. So we should find an automatic way to determine the value of σ.

For any training samples $\phi(x_i)$ and $\phi(x_j)$ in feature space, the cosine of the angle between them is $\cos\theta = (\phi(x_i)\cdot\phi(x_j))/(\left\|\phi(x_i)\right\|\cdot\left\|\phi(x_j)\right\|) = k(x_i, x_j)/\sqrt{k(x_i, x_i)k(x_j, x_j)}$. From the definition of the RBF kernel function, we can know that the values of $k(x_i,x_i)$ and $k(x_j,x_j)$ are 1. What's more, we also can get $k(x_i, x_j)=\cos\theta \geq 0$. Suppose that w_i is the training sample set of class i, $i=1,2,\ldots,c$. The RBF kernel function [37] has the following two important properties:

(1) $k(x_i, x_i, \sigma) = 1, \quad \forall i = 1, 2, \ldots, c$
(2) $0 \leq k\left(x_i, x_j, \sigma\right) \leq 1, \quad \forall i, j = 1, 2, \ldots, n$

Based on the above two properties, the following constraints can be obtained. (1) The cosine of the angle between the samples in the same class should be 1. (2) The cosine of the angle between the samples in the different class should approximate zero. We know that the optimal σ should satisfy:

(1) $k(x, z, \sigma) \approx 1, \quad \text{if } x, z \in w_i, \quad i = 1, 2, \ldots c$
(2) $k(x, z, \sigma) \approx 0, \quad \text{if } x \in w_i, \quad z \in w_j, \quad i \neq j$

In this paper, two indexes are proposed for exploiting the above two constraints [37]. The first one is:

$$\omega(\sigma) = \frac{1}{\sum_{i=1}^{c}\left|w_i\right|^2}\sum_{i=1}^{c}\sum_{x\in w_i}\sum_{z\in w_i} k(x, z, \sigma) \tag{2}$$

where $|w_i|$ is the number of training samples in class i. The second one is:

$$b(\sigma) = \frac{1}{\sum_{i=1}^{c}\sum_{j=1, j\neq i}^{c}\left|w_i\right|\left|w_j\right|}\sum_{i=1}^{c}\sum_{j=1, j\neq i}^{c}\sum_{x\in w_i}\sum_{z\in w_j} k(x, z, \sigma) \tag{3}$$

Here σ should be determined such that $\omega(\sigma)$ is close to 1 and $b(\sigma)$ is close to 0.