Measuring Biometric Feature Information in Palmprint Images

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Abstract. The measurement of biometric feature information is important for biometric technology, as for it can determine the uniqueness of biometric features, compare the performance of several feature extraction methods and quantify whether combination of features or biometric fusion offers any advantage. In this paper, we study the measurement of palmprint feature information using relative entropy between intra-person and inter-population. We compute the biometric feature information in which the feature extracted by three different methods, including: Principal Component Analysis (PCA), Linear Discriminant Analysis(LDA) and Locality Preserving Projections(LPP). The average biometric feature information is calculated to be approximately 280 bits for PCA, 246 bits for LDA features and 460 bits for LPP.

Keywords: Biometric, Palmprint images, Feature information, Relative entropy.

1 Introduction

Measuring the information in biometric, such as face, iris, fingerprint or palmprint, is an issue gradually gaining more attention because it can answer a number of questions related to security strength. First of all, there has always been an interest in finding out how unique different biometric types are, which ones are more reliable than others and under what conditions. Secondly, performance of different methods and technologies may be evaluated based on knowledge of information content of biometric samples and templates they produce. Finally, it becomes possible to say whether creating fusion biometric systems results in higher information.

Biometric information (BI) is defined as "the discriminating extra bits needed to represent an intraclass distribution with respect to the interclass feature distribution or, from the biometric recognition system point of the view, the decrease in uncertainty about the identity of a person due to a set of biometric

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measurements" [1]. In other words, initially, the person is a part of the population and can be anybody. However, after biometric measurements are acquired, the information for identification is available and the uncertainty decreases.

Compared with other biometrics technologies, palmprint has several advantages: low resolution, low cost, non-intrusiveness, stable structure features and high user acceptance[2]. It is for these reasons that palmprint has recently attracted an increasing amount of attention from researchers.

Several approaches were developed about biometric information. Daugman[3] suggested using discrimination entropy to calculate the information content of the iris by analyzing distributions of matching scores. Arakala et al. [4] proposed a preliminary theoretical model to predict the entropy of a retina template. Yagiz et al.[5] estimated the KL-Divergence as biometric information through nearest neighbor(NN) distance. The recently developed method by Adler[6] measuring the iris images of biometric information by using the concept of relative entropy, which is a measure of the distance between two probability distributions.

In this paper, we calculate the information through relative entropy in palmprint images. The database we use is from Palmprint Database of Beijing Jiaotong University.

2 Method

The diagram of our method is shown in Fig.1.

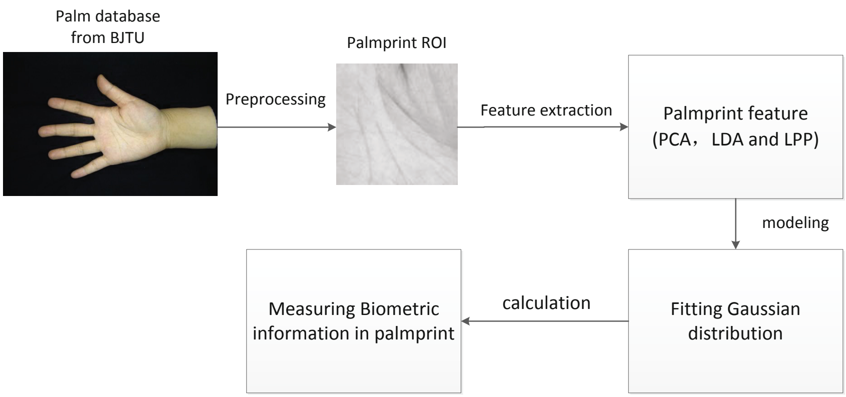

Fig. 1. Method diagram

Our effort contain four steps:

Step 1: Palmprint images preprocess: we transform original RGB mode images to grayscale mode, apply a Gaussian low-pass filter to the grayscale image, and then extract the hand contour by applying a contour following algorithm to a binarized image, locate the fingertips and the valleys between the fingers, finally palmprint ROI is normalized to 128 $\times$ 128 pixels [7].

Step 2: Palmprint feature extraction: we make use of three palmprint feature extraction algorithms, i.e. Principal Component Analysis (PCA), Linear Discriminant Analysis(LDA) and Locality Preserving Projections(LPP) algorithms, we extract three different set of the palmprint features.

Step 3: Gaussian modelling of palmprint feature: as Gaussian distribution is the most widely used model and it is a good reflection of the real world distributions, we modeled the features as Gaussian distributions.

Step 4: Calculation of Palmprint biometric information: we measure the palmprint image information based on an information theoretic concept of relative entropy. We calculate the biometric feature information three algorithms and find the difference and analysis.

2.1 Relative Entropy

The relative entropy, (also called information divergence, information gain, or Kullback-Leibler divergence), D(p‖q) is a measure of distance from a true probability distribution p to an assumed distribution q, it defined as:

$$D(p \parallel q) = \int_{\chi} p(x) \log_2 \frac{p(x)}{q(x)} dx \tag{1}$$

where χ is a set of all feature dimensions, p(x) is the feature distribution for one individual, or intra-person distribution, and q(x) is the feature distribution in the whole population, or inter-person distribution. In the above definition,relative entropy is always nonnegative and is zero if and only if p = q. It is often useful to think of relative entropy as a "distance" between distributions [8].

The relative entropy D(p‖q) was preferred over the shannon entropy H(p) since it allows to determine the amount of information distinguishing one person, discribed by the distribution p(x) based on the assume total population distribution q(x).

2.2 Feature Extraction

There are numerous approaches proposed for palmprint feature extraction. Principal component analysis (PCA) [9], also known as "eigenpalm", as the most fundamental dimensionality reduction methods, has been widely used in face recognition and palmprint identification[10]. The key idea is to project the high dimensional features to an orthogonal subspace for their compact representations.

PCA seeks a projection that best represents the data in a least-squares sense. The matrix ww^T is a projection onto the principal component space spanned by w which minimizes the following objective function,

$$min \sum_{i=1}^{n} \left| x_i - ww^T x_i \right|^2 \tag{2}$$

The second method we use to extract palmprint features is Linear Discriminant Analysis (LDA), also known as Fisherpalms [11]. In this method, LDA is used to project palmprints from this high-dimensional original palmprint space to a significantly lower dimensional feature space (Fisherpalm space), seeks the projection directions that are advantageous for discrimination. In other words, the ratio of the determinant of the between-class scatter to that of the within-class scatter is maximized. Suppose we have a set of n-dimensional samples x_1, x_2,x_3,...,x_n, belonging to l classes of palms. The objective function is as follows,

$$max \frac{w^T S_B w}{w^T S_W w} \tag{3}$$

$$S_B = \sum_{i=1}^{l} |C_i| \, (m^i - m)(m^i - m)^T \tag{4}$$

$$S_W = \sum_{i=1}^{l} |C_i| \, E\left[(x^i - m^i)(x^i - m^i)^T\right]^T \tag{5}$$

where m is the total sample mean vector, $|C_i|$ is the number of samples in class C_i, m^i are the average vectors of C_i, x^i are the sample vectors associated to C_i, S_W is the within-class scatter matrix and S_B the between-class scatter matrix.

However, both of them effectively only the Euclidean structure of feature space. LPP [12] has been proposed in palmprint recently, which takes into account the space structure of the samples, and in the process of dimension reduction, it can thus find a good linear embedding that preserves local structural information and intrisinc geometry of the data space. In this way, the unwanted variations resulting from changes in lighting, expression, and pose may be eliminated or reduced. [13] The objective function of LPP is as follows:

$$min \sum (y_i - y_j)^2 S_{ij} \tag{6}$$

The objective function with our choice of symmetric weights $S_{ij}(S_{ij} = S_{ji})$ incurs a heavy penalty if neighboring points x_i and x_j are mapped far apart. Therefore, minimizing it is an attempt to ensure that if x_i and x_j are close then y_i and y_j are close as well. S_{ij} can be thought of as a similarity measure between objects.

2.3 Distribution Modeling

Considering of the Gaussian model is the most common and good reflection of the real world distributions[6], we can write person distribution as:

$$p(x) = \frac{1}{\sqrt{|2\pi \Sigma_p|}} exp(-\frac{1}{2}(x - \mu_p)^t \Sigma_p^{-1}(x - \mu_p)) \tag{7}$$

whereas the population distribution q(x) is defined similarily, replacing q by p. The number of samples of all the palm images in the system is denoted as

N_q. Defining the samples of the palmprint images be x_1, x_2,x_3,...,x_N, then the population feature mean value is defined as a vector:

$$\mu_q = E(x) = \frac{1}{N_q}\sum_{i=1}^{N_q} x_i \tag{8}$$

the individual person mean is replacing q by p. The population feature covariance is defined:

$$\Sigma_q = E[(X-\mu_q)^t(X-\mu_q)] = \frac{1}{N_q-1}\sum_{i=1}^{N_q}(X-\mu_q)^t(X-\mu_q) \tag{9}$$

also, the person feature covariance, Σ_p, is defined analogously. μ_q and μ_p are feature vector with the size of $N \times 1$, feature covariances are matrices of size $N \times N$.

Based on the Gaussian distribution, the relative entropy will be easy to caculate, $D(p \parallel q)$ as follows [1]:

$$D\left(P \parallel Q\right) = K\left(\ln\frac{|2\pi\Sigma_q|}{|2\pi\Sigma_p|} + trace\left(\left(\Sigma_p + T\right)\Sigma_1^{-1}\right) - I\right) \tag{10}$$

where $T = \left(\mu_p - \mu_q\right)^t\left(\mu_p - \mu_q\right)$, and $k = log_2\sqrt{e}$

Generate a mapping form the biometric features to the new space. According to the Singular Value Decomposition (SVD), within the feature covariance matrix,

$$US_qV^t = svd(\Sigma_q) = svd\left(cov\left(x\right)\right) \tag{11}$$

So the individual's is

$$S_p = V^t\Sigma_pU \tag{12}$$

$$S_t = V^t(U_p - U_q)^t(U_p - U_q)U \tag{13}$$

The Σ_p in the most occation is singular and it may lead some troubles. $|\Sigma_p|$ will decrease to zero and the relative entropy we measured will turn to infinity. To solve this problem,multiplying the mask M [1] ,

$$M\begin{cases} 1, \text{ if } i = j \; or \; (i < L \bigcup j < L) \\ 0, \text{ if } otherwise \end{cases} \tag{14}$$

which we choose L=4 for the recommended of L is better when $L = \frac{3}{4}N_q$ this will regularizes the Σ_p, then D(p‖q) will not diverge.

Based on above, the equation (5) can be written as:

$$D\left(P \parallel Q\right) = K\left(\ln(\frac{|S_q|}{|S_p|}) + trace\left(\left(S_p + S_t\right)S_q^{-1} - I\right)V^t\right) \tag{15}$$

3 Experiments and Results

To evaluate the effectiveness of proposed method, a hand image database is set up. 980 right hand images from 98 individuals are captured using CCD camera based device, 10 images for each individuals.

After preprocessing, palmprint derived from the original database. palm database normalized to 128×128 pixels . The image in the palmprint database were also cropped in 64×64 pixels for the contrast test.

3.1 The Effect of Dimensions on Biometric Information

The biometric information were calculated using the features extracted by the methods of PCA(eigenpalm) features, LDA features(fisherpalm) and LPP features(Laplacianpalm).

As we expect, the dimension we choose has effect on the PCA feature information. We changed the dimension from 50 to 200 to observe the changes of relative entropy. The results shown in Table 1.

Table 1. PCA Feature Information and Dimensions

Dimensions / BI(bits)	50	100	150	200
Average BI	186.42	285.26	386.85	474.91

With the increase of dimension, a trend showing a steady growth of the biometric feature information. But we also can conclude that the relative entropy grow faster in low dimensional feature than high dimensional feature. Although the high-dimensional feature contains more biometric information , it also related to the increase of computational complexity. High dimensionality is critical to high performance, we should trade off the biometric information and computational complexity.

3.2 The Effect of Palmprint Image Size on Biometric Information

The size of the palmprint image also have influence in the information. So we cropped the pixels from 128×128 pixels to 64×64 pixels, and experiment them both in PCA,LDA and LPP features.

Table 2. Three methods' average biometric information and image size

Methods / Size	PCA	LDA	LPP
128 × 128	280.05	246.35	460.54
64 × 64	186.56	129.21	209.90

With the size of 128×128 pixels, the mean of PCA, LDA, LPP feature biomtric information is 280, 246, 460 respectively. When the size change to 64×64 pixels, PCA, LDA, LPP feature calculate the relative entropy is 186, 129 and 209 for each. The detailed data presented in the following.

3.3 BI of different Feature Extraction Methods

The following Figure 2,3 illustrate the biometric information calculated for each PCA, LDA and LPP features, respectively.

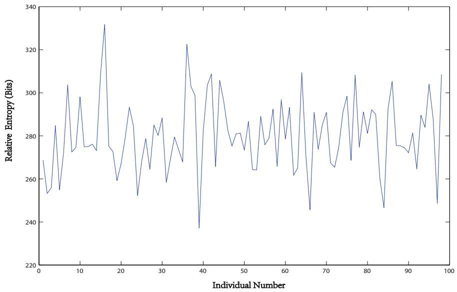

Fig. 2. PCA features biometric information, x axis present the individual's number and the y axis is relative entropy in bits

From Fig.2, we find that PCA features were measure the relative entropy with the dimension of 97, for the sake of the same dimension with LDA. From the experiment result, the mean of overall features is 280.0449 bits with the size of 128×128 pixels, higher than the LDA features

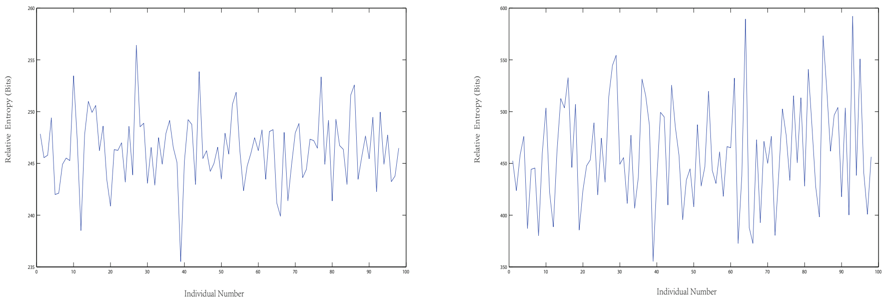

Fig. 3. The left side is LDA features biometric information,the right side LPP features biometric information. X axis present the individual's number, y axis is relative entropy in bits.

Fig.3. Left side shows that the detail information of the LDA feature. The avearage information is 246.3485 bits, with the size of 128×128 pixels.

The right one illustrates that comapare all the three experiments, the LPP approach provides a best representation and it contains the highest information. It may because the palm images probably reside on a nonlinear manifold, the unwanted variations resulting from changes in lighting and pose may be eliminated or reduced.

4 Conclusions

In this paper, we measure biometric feature information in the palmprint image using relative entropy. Based on three different feature extraction methods, contains: Principal Component Analysis (PCA), Linear Discriminant Analysis(LDA) and Locality Preserving Projections(LPP), we fitted the features to the Gussian distributions and calculated the biometric feature information. The effect of dimensions and image size on biometric information in PCA is presented, we also analysis the average information of the three kinds of feature extraction methods.

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