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PALMPRINT RECOGNITION USING FUSION OF LOCAL AND GLOBAL FEATURES

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ABSTRACT

Palmprint recognition is a rapidly developing biometrics technology over the last decade. However, there exist some typical problems when capturing palmprint images. First, the delta region in the center palm will raise the uneven light and brightness of the palmprint images varying with hand pressure, stretching and palm structure. Second, it is hard to align the palmprint images precisely to the same position, especially when the subjects are required to spread their hand on the scanner surface, even for the same palm. Either the global or the local features cannot satisfy the need for high recognition accuracy. Therefore, we propose a novel method using fusion of local and global features, extracted by non-negative factorization with sparseness constraint (NMFsc) and prominent component analysis (PCA), respectively, to improve the recognition performance. Experiments demonstrate the strong supplementary between local and global features for palmprint recognition.

Index Terms— Fusion, NMFsc, PCA, palmprint recognition

1. INTRODUCTION

A Palmprint contains distinctive and stable features: principle lines, wrinkles, delta and minutiae, etc [1]. Compared with face recognition, palmprint is hardly affected by age and accessories. Compared with fingerprint recognition, palmprint images contain more information and needs only low resolution image capturing devices, which reduces the cost of system. Compared with iris recognition, the palmprint images can be captured without intrusiveness. Hence, it has become an important and rapidly developing biometrics technology over the last decade.

The studies on Palmprint recognition mainly focus on feature extraction. The approaches to extract structures including dots and lines occurred in the earliest works [2]. But for online palmprint images with low resolution (less than 100 dpi), it is very hard to extract some minutiae. Zhang et al [3] applied Gabor filters to extract texture features. Also, texture features can be extracted by Fourier Transform and wavelet, etc [4,5]. Yet texture information depends on the orientation and scales, so it contains a large amount of features, whose expenses on storage and computation are very high. So Lu et al [6] attempted to extract "eigenpalms" by prominent component analysis (PCA), and in that followed, "fisherpalms"[7] and some other subspace methods are popular because of their stable performance, easy implementation for palmprint recognition. Basing on the multiple features, Fusion is becoming an important way to improve the recognition performance [8-11]. Some works fuse different kinds of palmprint features, such as lines, texture and appearance-based features [8].Some works fuse the obtained features to a new one for identification [9]. Some works fuse palmprint features and other hand features including fingers and palm shape [10, 11].

In this paper, we propose a novel method to fuse local and global features, extracted by non-negative matrix factorization with sparseness constraint (NMFsc) and PCA, respectively, for palmprint recognition. When capturing palmprint images, the center delta region of palm is shadowed and its area depends on the conditions of pressure, stretch and the palm structure, even for the same palm (see Fig. 1). In addition, the variations including translation and rotation are inevitable, especially when the subjects are required to spread their hand on the scanner surface freely. Therefore, it is reasonable to take the images locally to alleviate these interferences. Non-negative matrix factorization (NMF) [12] is a useful tool to decompose images into non-negative parts, which are intuitive and easy to understand. NMFsc [14], an improved extension of NMF, can explicitly controls the sparseness of the representation for more stable and desired local features. Meanwhile, global features extracted by PCA are very important and robust to palmprint recognition [6], which can reduce the

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effect raised by local noises. Taking local and global features together, which can supplement each other, will lead to a better recognition performance for palmprint recognition.

The paper is organized as follows. Section 2 presents the extraction of local and global features. Section 3 fused the two features for recognition. Section 4 provides the experimental results. And section 5 summarizes our conclusion.

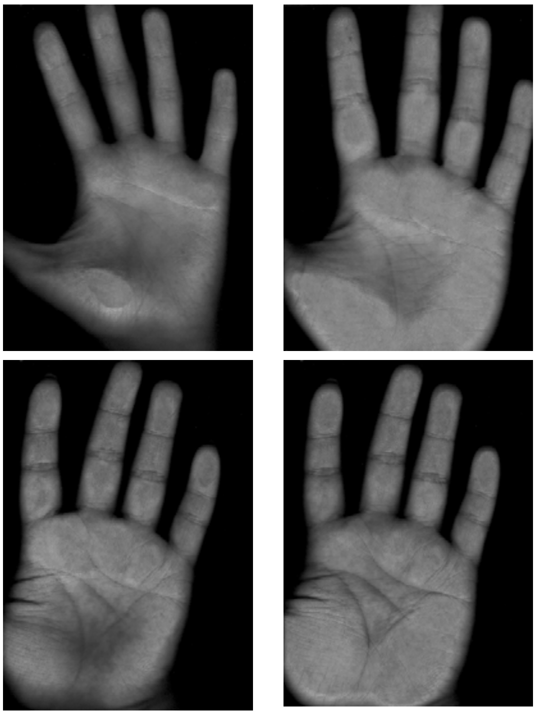

Fig1. Palm image examples captured by a scanner

2. LOCAL AND GLOBAL FEATURE FUSION

2.1 Local features extraction (NMFsc)

Nonnegative matrix factorization (NMF) is a part-based representation because of non-negative constraints, which allow only additive, not subtractive, combinations [12]. Given a training set containing m images of n pixels, then the training space can be represented as an n X m matrix V. The factorizations form is [12]

$$V \approx WH = \sum_{a=1}^{r} W_{ia} H_{a\mu} \tag{1}$$

where W and H are non-negative factorization matrix. W is the projection matrix and H is the coefficients matrix. These two matrices can be obtained by iteration converging to a local maximum of the objective function [12]

$$F = \sum_{i=1}^{n} \sum_{\mu=1}^{m} [V_{i\mu} \log(WH)_{i\mu} - (WH)_{i\mu}] \tag{2}$$

Although NMF can decompose the images into intuitive parts, NMF does not always represent images locally, especially when they are not well aligned [13]. To solve the problem, P.O. Hoyer solves the problem by proposing NMF with sparseness constraints, which explicitly controls the sparseness of the representation , and leads to parts-based decomposition and match the intuitive features of the data [14]. The sparseness measure can be defined [14]

$$sparseness(x) = \frac{\sqrt{n} - (\sum |x_i|) \Big/ \sqrt{\sum x_i^2}}{\sqrt{n} - 1} \tag{3}$$

Where n is the dimensionality of x. And the projection matrix can be obtained by iteration

$$W = W - \mu_w (WH - X) H^T \tag{4}$$

In our work, local features are extracted by NMFsc [14]. (The Matlab code is available at http://www.cs. helsinki. fi/patrik.hoyer.) Project the training set and testing set onto the basic matrix W, and we can get the local features y_{local}.

2.2 Global features extraction (PCA)

PCA is a classic appearance-based technique to extract global features in many applications. By maximizing the trace of feature variance, it can effectively find the optimum linear feature representation for appearance in an unsupervised mode to obtain the minimum variance. The covariance matrix can be evaluated by

$$G = \frac{1}{N} \sum_{i=1}^{N} (X_i - \overline{X})^T (X_i - \overline{X}) \tag{5}$$

where $\overline{X}$ is the average vector. The orthonormal eigenvectors of G corresponding to the d largest optimal value is proven to be optimal projection matrix. Project the training set and testing set onto the projection matrix, and we can get the global features y_{global}..

3. FUSION PROCEDURES

Basing on the global and local features, the fusion procedure can be realized as follows:

Step 1: Compute the Euclidean Distance metric

$$L_2 = \| y_{test} - y_{traini} \| = \sqrt{\sum_j (y_{test}^j - y_{traini}^j)^2} \tag{6}$$

Where y_{test}^j and y_{traini}^j respectively represent the jth component of feature vector to be classified and that of ith class.

Step 2: Normalize the distance with Min-Max mapping

$$norL = \frac{l - \min(L)}{\max(L) - \min(L)} \quad (7)$$

Step 3: Select fusion rules

Let $norL_{local}$ and $norL_{global}$ denote the matching distance of local and global features, the combined matching score L_{com} can be obtained by the fusion rules: simple-sum, max-score, min-score [16].

Simple-sum: $$L_{com} = \frac{1}{2}(L_{lcoal} + L_{global}) \quad (8)$$

Max-score: $$L_{com} = \max(L_{lcoal}, L_{global}) \quad (9)$$

Min-score: $$L_{com} = \min(L_{lcoal}, L_{global}) \quad (10)$$

Step 4: Classification by nearest neighbor (NN) classifier

The unknown sample will be determined to the class with which it has the minimum combined matching score L_{com}.

4. EXPERIMENTS AND RESULTS

4.1 Palmprint database description

We have collected 1000 different palmprint images of 292×413 pixels with a small-scale scanner in our lab (see Fig.1) from 100 palms, and each palm has 10 samples. The volunteers spread their hands on the surface of the scanner, which has a fixation on the thumb. The freely stretching of four fingers leads to the rotation and translation of palm. In addition, the changes in palm pressure and structures individually bring forth the uneven brightness and light. The central part of 128×128 pixels extracted from original palms constitutes a palmprint database. To simplify the calculation, we resize the image matrix into 64×64 pixels. Fig. 2 gives some examples in our palmprint database. All the experim-

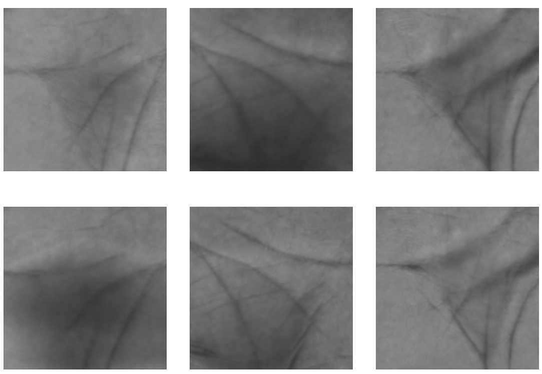

Fig. 2 some examples in the palmprint database
(images in the same column are from the same palm)

ents are executed on the computer system of PIV 2.67GHz and 256MB RAM with Matlab 7.3.

4.2 Experiments and results

In our experiments, we compare the recognition accuracy by PCA, NMFsc and their fusion abiding by simple-sum, max and min rules. Five images per palm are chosen randomly as the training samples and the remaining are used for testing. Both the training set and testing set contain 500 images. Fig. 4 plots the correct recognition rate of these methods under different feature dimension. It is can be seen that NMFsc is better than PCA when taking Euclidean distance as the metric. The highest correction rate of PCA and NMFsc are 92.8% and 96.6% with 150 and 130 features, respectively. Fusions of local and global features with single-sum and max rules improve the recognition performance, and the highest recognition rate can reach 97.8% and 97.6% when feature dimension is 190, 2% or more over that of NMFsc (95.6%) and PCA(94.4%) at 180 feature dimension. Whereas, when we take min rule to fuse global and local futures, the recognition accuracy is not as good as that of NMFsc.

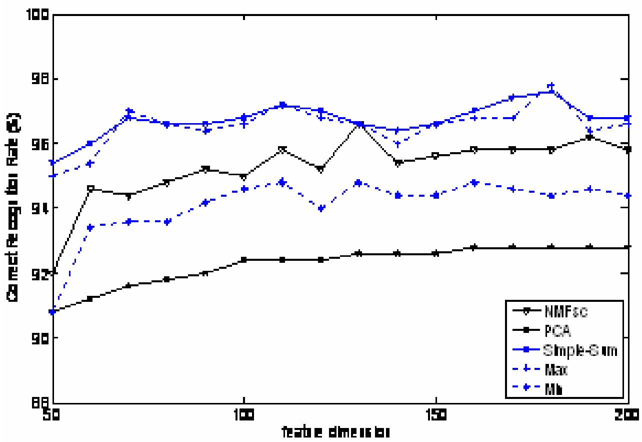

Fig.3 The recognition accuracy at different feature dimensions.

In order to further investigate the effect of training samples on recognition accuracy when using fusion of global and local features, we also choose 1 to 4 training samples per class for experiments, and the testing samples are still 500 altogether. Table 1 lists the top recognition results by different methods. It can be seen that the recognition performance is enhanced with the increase of training samples. The local features extracted by NMFsc have a better recognition performance than global features extracted by PCA for palmprint recognition. It proves that extracting effective local features is promising in palmprint recognition. The fusion of local features and global features by simple-sum rule improves the recognition performance stably. Max-rule can also improve the recognition rate, too, not as much as simple-sum. However, Min-score cannot reach the accuracy as that of NMFsc. It is fusion of local and global features by simple-sum rule that can effectively improve the recognition accuracy for palmprint recognition.

Table 1 Comparison of the top recognition accuracy (%) and the corresponding dimensions with different training samples per class

Training samples per class	1	2	3	4
NMFsc	72.4	86.4	90.2	94.0
PCA	59.8	77.0	83.8	89.4
Simple sum	73.6	88.4	91.6	95.0
Max-rule	72.0	87.4	91.2	94.2
Min-rule	67.8	80.8	87.6	92.6
Dimension	100	180	180	200

5. CONCLUSION

In this paper, we proposed a method using fusion of local and global features for palmprint recognition. The local and global features are extracted by NMFsc and PCA, respectively, using simple-sum as the fusion rule. The method, taking the local and global features together, can alleviate the effect of uneven brightness and lightness caused by delta structure in the center of palm and the variations of rotation and translation of palm. By comparing the recognition performance of single features and their fusion with different rules, our proposed method is proved to improve the recognition performance with different training samples and feature dimension. Using fusion of local and global features, the top recognition rate reaches 97.6% when using five samples per palm, at least 2% more than the single extraction method.

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