Handmetric Verification Based on Feature-Level Fusion

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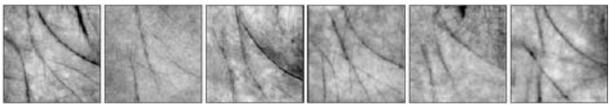
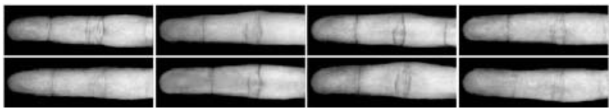
Summary
This paper presents a multimodal biometric system called “handmetric”, which is the fusion of hand based biometrics including palmprint, knuckleprint and hand shape. Moreover, a new framework of FLF (feature-level fusion) is put forward based on subspace analyzes. While verifies that existing feature concatenating methods are instances of the framework, a parameter optimized model using KPCA (kernel principal components analyze) is presented and applied to the verification system. The experiments testify the effectiveness of proposed method.
Key words:
Multimodal biometric, handmetric verification, feature-level fusion, kernel principal components analyze, palmprint

Introduction

Information fusion for multimodal biometrics is a hot topic recently. As one of the most reliable biometric traits, palmprint and have got widely attention in recent years [1]. While fusing with other kind of biometric, palmprint recognition could be more accurate and more ready to business use. By adding hand geometry information on palmprint, Kumar et al. [2] suggests that fusion in decision level using max rule could outperform traditional serial concatenate feature-level fusion (FLF) method and single palmprint system. Ribaric et al. [3] testifies weighted sum rule in a similar manner. Based on these works, we name the outline of the hand and cuticle in the inner surface of the hand as “handmetric”. As to low-resolution images, handmetric contains palmprint, hand geometry and knuckleprint [4] with their geometrical correlativity. Without loss of generality, we fuse the identity information of palmprint, middle finger shape and knuckleprint as shown in Fig.1 to represent handmetric features in this paper.



(a) palmprints from different persons



(b) finger shapes from different persons
Fig.1. Palmprint and finger images from different persons

Decision-level fusion and score-level fusion methods are most popular in the field of multimodal biometrics. According to Jain and Ross [5][6], FLF could keep the identity information to its most and is expected to perform better than at the above two levels, but the study on it is seldom reported. There are mainly two reasons of it [5]. First, the feature spaces of different biometric traits may not compatible. That is, different features may have different dimension and measurement, and their dynamic variation ranges lie in different complicated nonlinear spaces. Second, FLF may lead to the “curse of dimensionality” problem by concatenating two features as one. While solving these problems, we propose a new strategy for FLF based on the fusion of the relationship between samples but not the samples themselves.

Actually, the existing serial and parallel feature concatenating methods are special cases of the framework. While implementing the framework using nonlinear kernels, the performance of the system would be enhanced greatly. In this paper we apply polynomial kernel with principal components analyze (KPCA) method to the handmetric system, the result of the evaluation shows the power of the framework.

2. Idea and Algorithm

2.1 The framework

The traditional way of FLF can be sorted into two catalogues: serial concatenate and parallel concatenate, which are suffer from space incompatible and dimension curse greatly [5]. Lanckriet et al. [7] and Kuncheva et al. [8] suggest another way. By fusing different features using kernel matrix or template matrix, the problem of space incompatible is solved. However, dimension curse is still unfathomed. Based on these ideas, we employ KPCA with

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decision level fusion operators to construct a novel framework for FLF. As shown in Fig.2, three steps are needed:

- Step 1. Determine kernel matrixes. The kernel can be treated as nonlinear correlation between the samples. A more generalized operator $\mathcal{A}$ is defined to describe the transform from the original sample space to the relation measurement space.
- Step 2. Fusion of kernel matrixes using decision level fusion operator $\mathcal{B}$, the fused kernel space **O** is produced by it.
- Step 3. Feature extraction by operator $\mathcal{C}$ in **O**, then the fused feature space **F** is determined.

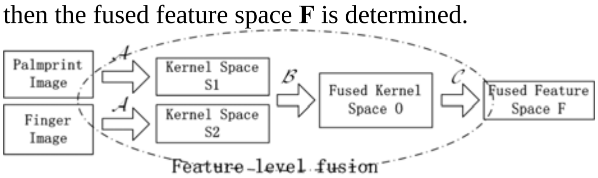


Fig.2. Three steps of the framework

2.2 Implementation

Given M zero-mean training samples of palmprint $\{p_i\}$ and finger samples $\{s_i\}$ (i=1,…,M), the corresponding new handmetric feature $\{h_i\}$ could be acquired using operators $\mathcal{A}$, $\mathcal{B}$, and $\mathcal{C}$.

Kernel matrixes of palmprint and finger are generated using $\mathcal{A}$. Fractional power polynomial model is evaluated in this paper, where the power is set to 0.7 and feature dimension d is set to 60 (which reaches the best performance in palmprint verification task). The kernel matrix of palmprint $\mathbf{K}_p$ and that of the finger $\mathbf{K}_s$ are:

$$[\mathbf{K}_p]_{ij} = (p_i \cdot p_j)^{0.7}, [\mathbf{K}_s]_{ij} = (s_i \cdot s_j)^{0.7} \tag{1}$$

For different biometrics, the same $\mathcal{A}$ is applied. Therefore, the kernel matrixes have the same kind of relation measurement. According to Kuncheva et al. [8], these matrixes could be fused reasonably. Operator $\mathcal{B}$ performs the fusion step. The four most popular rules in decision level fusion (sum, product, min and max) are adopted to evaluate the performance of our method. The new kernel matrix for handmetric $\mathbf{K}_h$ using different $\mathcal{B}$ could be:

$$\begin{aligned}
\mathcal{B}_1: &\quad [\mathbf{K}_{h-avg}]_{ij} = ([\mathbf{K}_p]_{ij} + [\mathbf{K}_s]_{ij})/2 \\
\mathcal{B}_2: &\quad [\mathbf{K}_{h-prd}]_{ij} = [\mathbf{K}_p]_{ij} \times [\mathbf{K}_s]_{ij} \\
\mathcal{B}_3: &\quad [\mathbf{K}_{h-\min}]_{ij} = \min([\mathbf{K}_p]_{ij}, [\mathbf{K}_s]_{ij}) \\
\mathcal{B}_4: &\quad [\mathbf{K}_{h-\min}]_{ij} = \max([\mathbf{K}_p]_{ij}, [\mathbf{K}_s]_{ij})
\end{aligned} \tag{2}$$

The function of operator $\mathcal{C}$ is to find handmetric feature space based on $\mathbf{K}_h$. KPCA can be regarded as PCA in nonlinear mapping space. That is, the principle components of $\mathbf{K}_h$ span the fused feature space **F**:

$$\mathbf{K}_h\mathbf{F} = M\mathbf{F}\mathbf{\Lambda} \tag{3}$$

where $\mathbf{F} = [a_1 a_2 \cdots a_M]$, $\mathbf{\Lambda} = diag\{\lambda_1, \lambda_2, \cdots, \lambda_M\}$. **F** is the nonlinear mapping matrix from original image sample to handmetric feature.

Handmetric feature of all the samples could be calculated for further classification. Suppose p_t, s_t to be a pair of testing palmprint and finger samples, their kernel projections are:

$$\begin{aligned}
k_p &= [(p_1 \cdot p_t)^{0.7} \; (p_2 \cdot p_t)^{0.7} \cdots (p_M \cdot p_t)^{0.7}]^T \\
k_s &= [(s_1 \cdot s_t)^{0.7} \; (s_2 \cdot s_t)^{0.7} \cdots (s_M \cdot s_t)^{0.7}]^T
\end{aligned} \tag{4}$$

The “relation” between the testing handmetric to trained handmetric is:

$$k_h = \mathcal{B}(k_p, k_s) \tag{5}$$

And the handmetric f_h could be calculated using the projection matrix **F**:

$$f_h = \mathbf{F}^T k_h . \tag{6}$$

2.3 Describe other FLF methods by the framework

Serial concatenate is the most popular FLF method and is a linear instance of the framework. By concatenating different features serially, the ith new sample y_i can be defined as:

$$y_i = [p_{i1}, p_{i2}, \cdots p_{id}, s_{i1}, s_{i2}, \cdots s_{id}]^T, i \in [1, M] \tag{7}$$

Because y always has high dimension, PCA (principle component analyze) should be carried out to get the new feature f_{sc}. The scatter matrix Σ of the samples is:

$$\Sigma = \frac{1}{M}\sum_{i=1}^{M} y_i y_i^T = \frac{1}{M}\mathbf{Y}\mathbf{Y}^T \quad (1) \tag{8}$$

According to *theorem SVD*, calculating the eigenvalues and eigenvectors of Σ can be converted to diagonalize the matrix $\mathbf{Y}^T\mathbf{Y}$. Moreover, it can be proved that:

$$\mathbf{Y}^T\mathbf{Y} = \mathbf{P}^T\mathbf{P} + \mathbf{S}^T\mathbf{S} \tag{9}$$

Thus, serial concatenate is a special case when $\mathcal{A}$ degrades to linear correlation operator and $\mathcal{B}$ is set to sum rule. And, the equitation (9) verifies that using PCA to the concatenated feature sets has the same effect as it works on each feature before the fusion procedure.

It can also be verified that parallel concatenate is another instance of the framework in complex domain. Furthermore, the framework could be more generalized if the implementation of operator $\mathcal{A}$ is extends to more generic similarity measurement.

3. MAP Classifier for classification

The maximum a posteriori (MAP) classifier [9] is designed for handmetric verification. In the training stage, the feature difference should be calculated before classification. Every handmetric feature would minus all the other features to get the feature differences in the training set. If the difference is got form the same person, then it should be marked as "G (Genuine)" class. Otherwise, the difference is signed to "I (Impostor)" class. Classifier would build on the G and I classes in training samples.

In the testing stage, suppose a testing handmetric feature f_t has the identity statement Z, according to [8], the difference Δ between f_t and class center of Z is treated as a sample input to the classifier, that is:

$$\Delta = f_t - \overline{f_Z}, \quad \overline{f_Z} = \frac{1}{L}\left(\sum_{i=1}^{L} f_i\right), \; f_i \in Z \tag{10}$$

The likelihood of Δ to G and I are:

$$P(\Delta / G) = \frac{\exp\{-1/2(\Delta^T \Sigma_G^{-1} \Delta)\}}{(2\pi)^{D/2} \left|\Sigma_G\right|^{1/2}}$$
$$P(\Delta / I) = \frac{\exp\{-1/2(\Delta^T \Sigma_I^{-1} \Delta)\}}{(2\pi)^{D/2} \left|\Sigma_I\right|^{1/2}} \tag{11}$$

Under the assumption that the prior is $P(G)=P(I)=1/2$ [8], the posteriori probability $P(G/\Delta)$ should be:

$$P(G/\Delta) = \frac{P(\Delta/G)P(G)}{P(\Delta/G)P(G) + P(\Delta/I)P(I)} = \frac{P(\Delta/G)}{P(\Delta/G) + P(\Delta/I)} \tag{12}$$

Finally, comparing $P(G/\Delta)$ to similarity threshold T, we could draw the conclusion whether the identity statement is true.

4. Experiments

To evaluate the effectiveness of proposed method, a hand image database is set up. 1,853 right hand images from 98 individuals are captured using CCD camera based device. For each person, up to 28 images are captured in the period of 6 months for 4 times at most (the average is 2.7 times), 4 samples of each person are taken out to form a training set, while the remaining 1,481 images are taken as testing set. After preprocessing, palmprint database and finger database derived from the original database. For each biometric (including palmprint, finger and handmetric) in the verification test, a total of 145,138(1481 × 98) comparisons are performed for the testing images, in which 1,481(1481 × 1) are genuine matching.

4.1 Comparison of different fusion operators

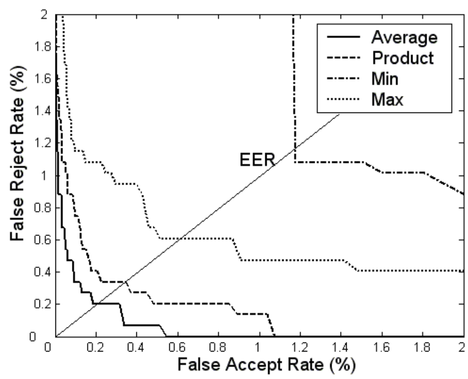


Fig. 3. ROCs using different kernel fusion operators

Different fusion operators affect the performance of handmetric greatly. A close-set test is carried out. That is, the training set contains training samples form all the classes. The experimental results of 3 samples for each class are plotted in Fig. 3. It is evidently that B_1 is better result than the other three. The EER (equal error rate) of it reach 0.20%, while that of palmprint and finger are 0.61% and 1.20% respectively.

4.2 Comparison of different fusion strategies

The widely used score-level fusion and feature concatenating method are tested and compared to given method. Both close-set test and open-set test are performed in this experiment. In the open-set test, samples from 62 classes are trained (to ensure the dimensionality of handmetric feature could be greater than 60). The other 36 classed are treated as new clients.

Together with proposed method, 5 biometric verification systems are setup and compared:

I. Palmprint verification system. The feature of palmprint is extracted using KPCA and proposed classifier is employed. Because palmprint contains most of identity information in handmetric, the system is optimized to determine the kernel parameters. Fractional power polynomial model with *degree*=0.7 and feature dimension 60 perform the best and are applied to all the other systems.

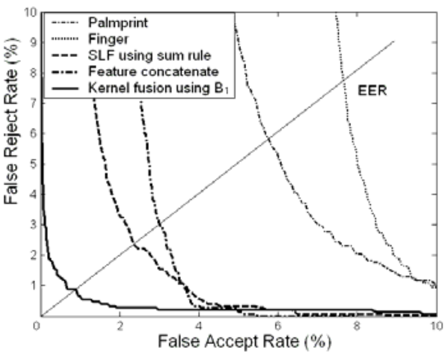
II. Finger (contains knuckleprint and hand shape) verification system.

III. FC based handmetric verification system. FC combines the palmprint and finger features got in I and II serially to get corresponding handmetric feature.

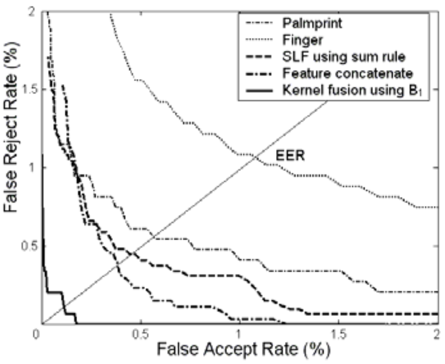
IV. SLF based handmetric verification system. The output of classifiers of I and II are normalized and fused to implement the system. According with Ribaric [5] and Ross [2], sum rule performs the best in SLF method in our test, and employed in the final comparisons.

V. KPCA based handmetric verification system. B_1 is used to extract handmetric feature. While system III and IV depend on I and II greatly, proposed method has the lowest computational complexity.

The experimental results using 4 training samples for each class are shown in Fig. 4 and Table. 1. First, it is testified that all the handmetric system are better than single biometric ones while KPCA based fusion method performs the best in all the systems. The HTER (half total error rate) of kernel fusion reaches 0.087% in the close-set test, which could meet the requirements of high security applications. Second, the performance of FC and SLF are at the same level. SLF better than FC mostly, but FC may reach lower HTER in the tests. Finally, it is evidently that the system performance degrades dramatically when turning close-set into open-set. Kernel fusion method may be the best solution of the problem through our test.



(a) open-set test



(b) close-set test

Fig. 4. ROCs of different verification systems

Table. 1. HTER of different systems.

HTER(%)	I	II	III	IV	**V**
Open-set	5.74	7.59	2.10	2.28	**0.78**
Close-set	0.56	1.04	0.35	0.43	**0.087**

4.3 Real time identification evaluation

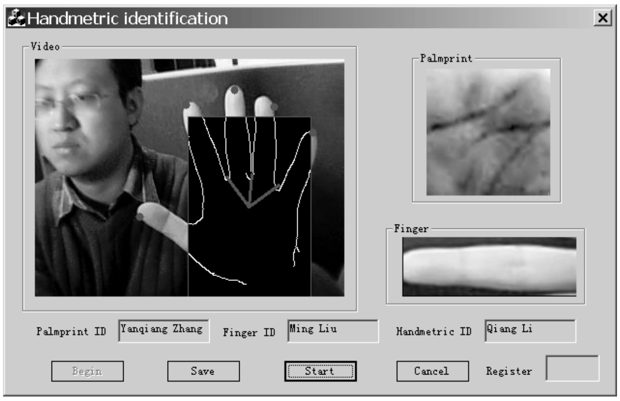


Fig. 5. Demo of real time identification

A real time handmetric identification system is implemented based on proposed method. 100 samples from 10 persons are trained for identification. The speed is about 22fps using P4 2.6G and 512M RAM. Though it uses low resolution images, the result is inspiring. While the fusion method could identify above 80% frames in the testing video correctly, that of palmprint and finger only achieve 54% and 32% respectively. Fig.5 shows a frame that fusion result is right while both of the stand-along systems get wrong result.

5. Conclusion

FLF based on KPCA outperforms the traditional FC (feature concatenate) and SLF schemes, and could improve the system performance greatly. It keeps more identity information than SLF method and more reasonable theoretically than traditional FLF method. Four most popular rules of SLF are employed and evaluated to fuse different kernel matrixes, and the sum rule gives the best result in the handmetric verification system. Further study includes normalization method of kernel matrix, fusion using ranks or decision results in kernel space, and more generalized subspace methods for FLF.

Acknowledgments

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