Improving iris recognition performance via multi-instance fusion at the score level

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Fusion of multiple instances within a modality for biometric verification performance improvement has received considerable attention. In this letter, we present an iris recognition method based on multi-instance fusion, which combines the left and right irises of an individual at the matching score level. When fusing, a novel fusion strategy using minimax probability machine (MPM) is applied to generate a fused score for the final decision. The experimental results on CASIA and UBIRIS databases show that the proposed method can bring obvious performance improvement compared with the single-instance method. The comparison among different fusion strategies demonstrates the superiority of the fusion strategy based on MPM.

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Biometric identification is gaining more popularity and more acceptances in public as well as in private sectors. Among all biometric technologies, iris recognition is noted for its uniqueness, high reliability, and non-invasiveness, which make iris recognition a particularly promising solution to automated personal identification[1]. Much work has been done in iris recognition[2−5]. Although some methods can get high recognition rate in ideal conditions, any iris recognition method has drawbacks and cannot warranty 100% identification rate, nor 0% false acceptance and rejection ratios especially in nonideal conditions. To improve the identification performance, multi-biometric fusion techniques are often applied [6,7]. Multi-biometric is defined as the use of multiple biometric modalities, multiple instances within a modality, multiple sensors, or multiple algorithms prior to making a specific identification decision. As one of the multi-biometric fusion techniques, multi-instance fusion means combining the information of multiple instances within the same biometric modality (for example: iris (left) + iris (right), fingerprint (left index) + fingerprint (right index)). Multi-instance fusion is considered attractive from both points of view of application and research.

This letter focuses on the application of multi-instance fusion in iris recognition. An iris recognition method based on multi-instance fusion, which combines the information of the left and right irises of an individual, is proposed to improve verification performance. Iris recognition involves preprocessing, feature extraction, matching, and decision making. Multi-instance fusion for iris recognition can be done at the feature extraction level, the matching score level, and the decision level. Compared with the other two levels, fusion at the matching score level is the most popular and frequently used method because of its good performance, intuitiveness, and simplicity. So multi-instance fusion is carried out at the matching score level in this letter. When verifying, the left and right irises are respectively processed and matched with their corresponding templates. Then two matching scores from the two irises are fused using a novel fusion strategy based on minimax probability machine (MPM)[8] to generate a fused score for the final decision.

Figure 1 shows the block diagram of the iris recognition system based on multi-instance fusion. We can see that, before fusion at the matching score level, recognition algorithm based on phase information is applied to left iris and right iris[2]. Then the matching scores are obtained as the hamming distances.

After the left and right irises are matched respectively, a score vector (x_1, x_2) can be constructed with x_1 and x_2 corresponding to the matching scores from the left and right irises. The next step is fusion at the matching score level. This step can be approached in two distinct ways. In the first approach, the fusion is viewed as a classification problem, while in the second approach, it is viewed as a combination problem. In the classification approach, the score vector is classified into one of two

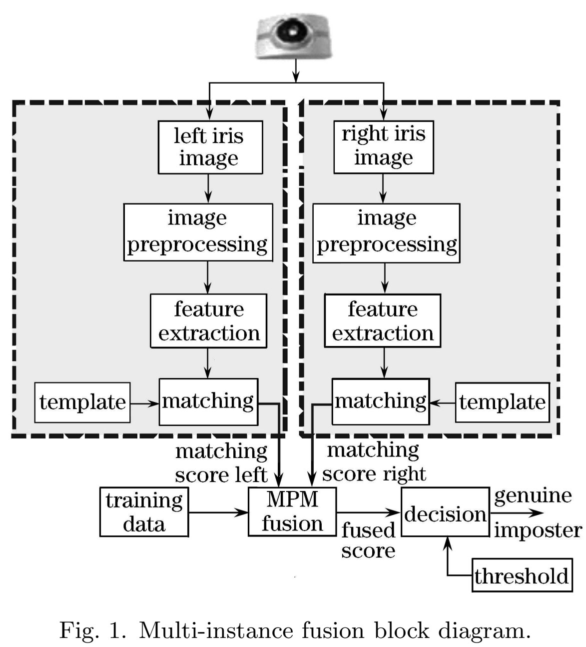

Fig. 1. Multi-instance fusion block diagram.

classes: "Accept" (genuine user) or "Reject" (impostor). In the combination approach, the score vector is combined to generate a single scalar score which is then used to make the final decision. Compared with the classification approach, the combination approach has more flexibility and can meet demand under more circumstances by adjusting the decision threshold, so the combination approach is used. Fusion strategy based on MPM is applied in this work. MPM is a new proposed classification technique[8]. The most attractive property of MPM, which makes it give competitive classification performance, is that it can explicitly provide a worst-case boundary on the probability of misclassification of future data when the mean and covariance matrix of the data are known.

Let the matching scores, provided by left iris and right iris, be combined into a multimodal score vector $\mathbf{z} = [x_1, x_2]^{\mathrm{T}}$ $(x_1, x_2 \in R)$. The design of a trained fusion scheme includes the estimation of a function $f : R^2 \to R$ based on empirical data so as to effectively separate the fused scores $f(\mathbf{z})$ of genuine user and impostor.

Suppose that $\mathbf{x}$ and $\mathbf{y}$ represent the genuine class and impostor class of data points with means and covariances as $\{\overline{\mathbf{x}}, \Sigma_{\mathbf{x}}\}$ and $\{\overline{\mathbf{y}}, \Sigma_{\mathbf{y}}\}$, respectively, where $\mathbf{x}$, $\mathbf{y}$, $\overline{\mathbf{x}}$, $\overline{\mathbf{y}} \in R^2$, and $\Sigma_{\mathbf{x}}$, $\Sigma_{\mathbf{y}} \in R^{2\times 2}$. Each data point is a multi-modal score vector, which is expressed as $[x_1, x_2]^{\mathrm{T}}$.

The training sets, which consist of genuine users and impostors, are given. With the reliable estimations of $\{\overline{\mathbf{x}}, \Sigma_{\mathbf{x}}\}$ and $\{\overline{\mathbf{y}}, \Sigma_{\mathbf{y}}\}$ for two classes of data obtained from the training data, MPM attempts to determine an optimal hyperplane

$$\mathbf{a}^{\mathrm{T}}\mathbf{z} = b \quad (\mathbf{a}, \mathbf{z} \in R^2, \mathbf{a} \neq 0, b \in R), \tag{1}$$

which separates the data into genuine users and impostors by minimizing the worst-case probability of misclassification of the future data. The mathematical formula of the original model can be written as[8]

$$\max_{a,b,\mathbf{a}\neq 0} a \;\text{ subject to :}\; \begin{array}{l} \inf P_r\{\mathbf{a}^{\mathrm{T}}\mathbf{x} \geq b\} \geq a, \\ \inf P_r\{\mathbf{a}^{\mathrm{T}}\mathbf{y} \leq b\} \geq a, \end{array} \tag{2}$$

where a represents the lower boundary of the accuracy for the classification of future data, namely, the worst-case accuracy.

After introducing the Lagrangian multiplier, the optimization problem becomes

$$\max_{k,\mathbf{a}} k \;\text{ subject to :}\; \begin{array}{l} \frac{1}{k} \geq \sqrt{\mathbf{a}^{\mathrm{T}}\Sigma_{\mathbf{x}}a} + \sqrt{\mathbf{a}^{\mathrm{T}}\Sigma_{\mathbf{y}}a}, \\ \mathbf{a}^{\mathrm{T}}(\overline{\mathbf{x}} - \overline{\mathbf{y}}) = 1. \end{array} \tag{3}$$

This allows us to eliminate k:

$$\min_{\mathbf{a}} \sqrt{\mathbf{a}^{\mathrm{T}}\Sigma_{\mathbf{x}}a} + \sqrt{\mathbf{a}^{\mathrm{T}}\Sigma_{\mathbf{y}}a} \text{ subject to } \mathbf{a}^{\mathrm{T}}(\overline{\mathbf{x}} - \overline{\mathbf{y}}) = 1 \tag{4}$$

or, equivalently:

$$\min_{\mathbf{a}} \left\|\Sigma_{\mathbf{x}}^{1/2}\mathbf{a}\right\|_2 + \left\|\Sigma_{\mathbf{y}}^{1/2}\mathbf{a}\right\|_2 \text{ subject to } \mathbf{a}^{\mathrm{T}}(\overline{\mathbf{x}} - \overline{\mathbf{y}}) = 1. \tag{5}$$

This is a second-order cone programming problem, and it can be solved using interior-point methods, which is described in Ref. [8].

At last, we can obtain $\mathbf{a}_*$ and b_* as the optimal values of $\mathbf{a}$ and b, and the optimal hyperplane $\mathbf{a}_*^{\mathrm{T}}\mathbf{z} = b_*$ also can be determined. Given a test multi-modal score vector $\mathbf{z}_{\text{new}}$, instead of the direct output of classification result, a fused score is generated using the optimal hyperplane. And the fused score s_{T} of the test pattern $\mathbf{z}_{\text{new}}$ is defined as

$$s_{\mathrm{T}} = f(\mathbf{z}_{\text{new}}) = \mathbf{a}_*^{\mathrm{T}}\mathbf{z}_{\text{new}} - b_*. \tag{6}$$

Moreover, taking into account the nonlinear classification problem, we map the two-dimensional (2D) space to a higher dimensional feature space Q^n via a mapping function $\Phi : R^2 \to Q^n$. So a nonlinear discriminant in the original space can be transformed into a linear discriminant in the feature space Q^n. The formula of the fused score is revised as

$$s_{\mathrm{T}} = f(\mathbf{z}_{\text{new}}) = \mathbf{a}_*^{\mathrm{T}}\Phi(\mathbf{z}_{\text{new}}) - b_*, \tag{7}$$

where Φ is also called the kernel function, and Gaussian kernel function is adopted in this work.

Unlike the original scores which are distributed in $[0, 1]$, the fused scores s_{T} are mainly distributed in $[-1, 1]$. Following the acquisition of s_{T}, the decision whether the test pattern belongs to a genuine user or an impostor is made by the predefined threshold. When determining the decision threshold, the initial threshold value can be set as 0. In this case, we can achieve the minimum total error rate. However, different performance demands including false acceptance rate (FAR) and false rejection rate (FRR) are often required in real applications, so the decision threshold can be adjusted to reach different working points. For example, we can increase the initial threshold to get less FRR or decrease the initial threshold to get less FAR.

In order to evaluate the performance of the proposed multi-instance fusion method, we have tested it on CASIA and UBIRIS iris databases[9,10].

CASIA1.0 iris image database consists of 756 iris images from 108 different subjects (seven iris images of each subject)[9]. Since each iris is unique and even the left iris and the right iris of the same person are quite different, in our experiment, 108 subjects are considered from 54 persons. 54 persons are divided into two sets: training set and testing set. Nine persons are selected as the training set to train and learn the parameters of MPM. The remaining 45 persons are used to simulate real authentication and test the performance of the trained MPM-based multi-instance fusion method. The performance of the method is represented by the receive operating characteristic (ROC) curves, which plots FAR versus FRR for different values of the decision threshold. To demonstrate the superiority of the proposed method, other methods such as the single-instance method (only using left iris or right iris) and the multi-instance fusion methods using the traditional fusion strategies are also carried out on the testing set. The experimental results on CASIA database are shown in Fig. 2, which gives the ROC curves and equal error rate (EER, for FAR=FRR) values of different methods.

UBIRIS is a noisy database and it contains many poor quality images which are unsuitable for iris recognition[10]. We select 780 clear iris images from 156

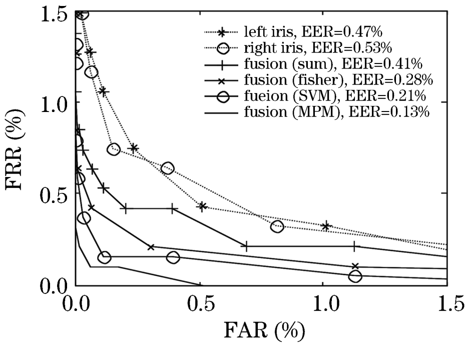

Fig. 2. ROC curves of different methods on CASIA iris data.

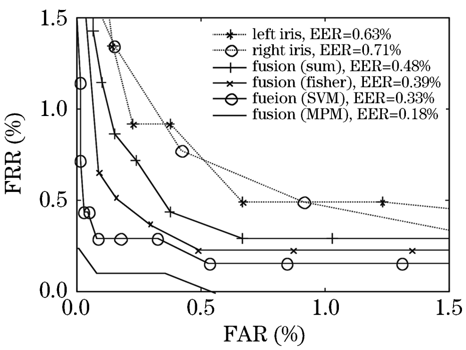

Fig. 3. ROC curves of different methods on UBIRIS iris data.

subjects (five images of each subject) for our experiments. 156 subjects are considered from 78 persons. 78 persons are divided into two sets: 12 persons as the training set; the remaining 66 persons as the testing set. The experimental results of different methods on UBIRIS database are shown in Fig. 3.

From Figs. 2 and 3, far better overall performance has been achieved when the information of left iris and right iris are fused for recognition, which proves that the proposed multi-instance fusion can bring obvious performance improvement. The experimental results also represent that multi-instance fusion using different fusion strategies demonstrate different recognition performance and the MPM-based fusion strategy can get the maximum performance improvement compared with the traditional fusion strategies, which shows the superiority of the fusion strategy proposed in this letter.

In case that one iris is identified as genuine user and the other iris is identified as impostor, the solutions are different due to various working circumstances. In some circumstances requiring top safety, the above cases are considered as an impostor attempt to achieve less FAR. By contrast, in some ordinary circumstances, the above cases can be considered as a genuine attempt to achieve less FRR. To arrive at different purposes, we should set these cases in different classes in the training stage.

In conclusion, we introduced an effective method based on multi-instance fusion for improving iris recognition performance. The proposed method, which combines the information of left and right irises at the matching score level, can bring obvious performance improvement compared with the single-instance method. When fusing at the matching score level, a novel fusion strategy using MPM is adopted. This fusion strategy can get the maximum performance improvement compared with the traditional fusion strategies. The experimental results on CASIA and UBIRIS iris database prove the superiority of this method.

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References

1. A. K. Jain, A. Ross, and S. Prabhakar, IEEE Trans. Circ. Syst. Video Technol. **14,** 4 (2004).
2. J. Daugman, IEEE Trans. Circ. Syst. Video Technol. **14,** 21 (2004).
3. W. W. Boles and B. Boashash, IEEE Trans. Signal Process. **46,** 1185 (1998).
4. X. Ye, Z. He, and Z. Zhao, Chin. Opt. Lett. **6,** 487 (2008).
5. W. Yuan, L. Xu, and Z. Lin, Acta Opt. Sin. (in Chinese) **27,** 2047 (2007).
6. A. Ross and A. Jain, Pattern Recogn. Lett. **24,** 2115 (2003).
7. L. Hong and A. Jain, IEEE Trans. Pattern Anal. Machine Intell. **20,** 1295 (1998).
8. G. R. G. Lanckriet, L. El Ghaoui, C. Bhattacharyya, and M. I. Jordan, J. Machine Learning Res. **3,** 552 (2002).
9. CASIA iris image database, http://www.sinobiometrics.com (March, 2006).
10. H. Proença and L. A. Alexandre, UBIRIS iris image database, http://iris.di.ubi.pt (December, 2006).