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Minimax Probability Machine Multialgorithmic Fusion for Iris Recognition

Fenghua Wang, Xianghua Yao and Jiuqiang Han
School of Electronics and Information Engineering,
Xi'an Jiaotong University, Xi'an 710049, China

Abstract: This study presents an iris recognition method based on multialgorithmic fusion. Fusion of multiple algorithms for biometric verification performance improvement has received considerable attention. The proposed method combines two kinds of iris recognition algorithms: one is based on phase information and the other is based on zero-crossing representation. Two algorithms are fused at the matching score level and a novel fusion strategy based on Minimax Probability Machine (MPM) is applied to generate a fused score which is used to make the final decision. The experimental results on CASIA and UBIRIS iris image databases show that the proposed multialgorithmic fusion method can bring obvious performance improvement compared to the individual recognition algorithm. The comparison among all fusion strategies also demonstrates that the fusion strategy based on MPM can achieve better performance than traditional fusion strategies.

Key words: Biometric verification, iris recognition, multialgorithmic fusion, minimax probability machine

INTRODUCTION

The increasing demand on enhanced security has led to an unprecedented interest in automated personal identification based on biometry. Biometry makes use of physiological or behavioral characteristics to identify individuals. 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 (Jain *et al*., 2004).

Much work has been done in iris recognition. Daugman (2004) used multi-scale 2D Gabor filters to extract texture phase structure information of the iris and hamming distance for classification. Boles and Baoshash (1998) proposed an algorithm for iris feature extraction using zero-crossing representation of 1D wavelet transform. Ma *et al*. (2003) developed an algorithm based on iris texture analysis.

However, any iris recognition algorithm has drawbacks and cannot warranty 100% identification rate, nor 0% false acceptance and rejection ratios especially in non-ideal conditions. To improve the identification performance, multibiometric fusion techniques are applied in some literatures (Ross and Jain, 2003; Hong and Jain, 1998). Multibiometric 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 multibiometric fusion techniques, multialgorithmic fusion is considered attractive, both from an application point of view and from a research point of view. From an application perspective, it appears to minimize sensor and sensing cost, since there is only one sensor and only one sample sensed in order to obtain a recognition result, so the integration of multiple algorithms is the cheapest way of technology improvement. From a research point of view, relatively little work has been done in this area.

In this study, an iris recognition method based on multialgorithmic fusion is proposed. For verification performance improvement, we combine two different recognition algorithms. The first is based on phase information. The second is based on zero-crossing representation. Two algorithms are fused at the matching score level prior to making a specific identification decision and a novel fusion strategy based on MPM is used. CASIA and UBIRIS are chosen as the testing databases to prove the affectivity of the proposed method (CASIA, 2003; Proenca and Alexandre, 2005).

ARCHITECTURE OF MULTIALGORITHMIC FUSION SYSTEM

Iris recognition involves image preprocessing, feature extraction, matching and decision making. Multialgorithmic fusion for iris recognition can be done at the feature extraction level, the matching score level and the decision level. Although feature sets usually contain more information about the iris data than the matching score, feature from different algorithms are usually

Corresponding Author: Fenghua Wang, School of Electronics and Information Engineering, Xi'an Jiaotong University, Xi'an 710049, China

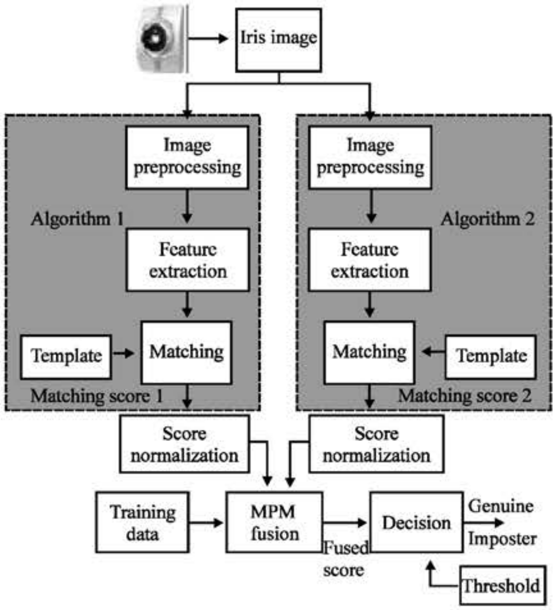


Fig. 1: Multialgorithmic fusion block diagram

incompatible. Fusion at the decision level is thought to lack flexibility (due to the limited information from each classifier, e.g., no information on confidence of decisions). Thus, fusion at the matching score level is the most popular and frequently used method because of its good performance, intuitiveness and simplicity.

Figure 1 shows the block diagram of the iris recognition system based on Multialgorithmic fusion, with algorithm 1 and algorithm 2 corresponding to phase information based algorithm and zero-crossing representation based algorithm. The matching scores from two algorithms are normalized to transform into a common domain before fusion. Prior to decision, the normalized scores are fused using the MPM-based fusion strategy. A decision threshold is set to make a final decision.

DESCRIPTIONS OF TWO IRIS RECOGNITION ALGORITHMS

Iris recognition based on phase structure information: The iris recognition algorithm based on phase structure information was proposed by Daugman (2004). The process can be divided into three main stages: Iiris image preprocessing, feature encoding and matching.

Iris image preprocessing: An image of the iris contains information which is not of interest for iris recognition in the pupil, sclera and eyelid. In addition, the illumination is not uniform over different images. Thus, prior to feature extraction, the image needs to be preprocessed to eliminate these factors (Fig. 2).

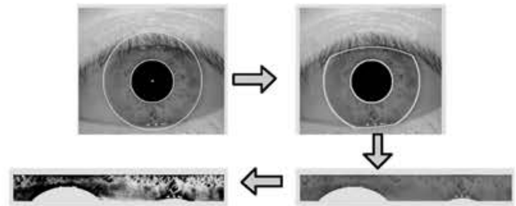


Fig. 2: Steps involved in iris preprocessing

The main preprocessing steps consist of localization of the inner and outer iris boundaries, localization of eyelid boundaries, transformation from polar coordinates to a fixed size rectangular image and image enhancement.

Feature encoding complex: 2D Gabor filters are employed to extract the phase information of the iris texture. During the phase extraction, the iris image is divided into m by n blocks. The phase information in each block is described by 2-bit codes and totally 2 mn bits to describe the whole iris (Fig. 2).

Matching: The difference between two iris images was measured by their hamming distance according to the following equations:

$$d_H = \frac{\sum[(\text{codeA} \otimes \text{codeB}) \bigcap (\text{maskA} \bigcap \text{maskB})]}{\sum(\text{maskA} \bigcap \text{maskB})} \quad (1)$$

Where, $\otimes$ denotes the Boolean Exclusive-OR operator(XOR), maskA and maskB denote two iris matching masks, respectively, 0 for the non-iris regions and 1 for the iris regions; $\cap$ denotes the and operator. The decision whether two irises are from the same eye is made by the predefined threshold.

In this algorithm, the matching score is obtained as the hamming distance.

Iris recognition based on zero-crossing representation: It is known that one can obtain the position of multi-scale sharp variations points from the zero-crossing of the signal convolved with the laplacian of a Gaussian (Mallat, 1991). Based on this theory, Boles *et al*. (1998) proposed the iris recognition algorithm using zero-crossing. In this work, a similar algorithm is adopted.

Iris signature from iris virtual circles: For obtaining the data set (iris signature I_s) from each isolated iris sample, the centroid of the detected pupil is chosen as the reference point. The iris signature will be the gray level values on the contour of the virtual circles which are centered at the centroid of the pupil. N virtual circles (each length is M) are selected and the total length of iris signature is M*N.

Multiscale zero-crossing representation: Let $\{W_{2^j} I_s\}$ $j \in z$ be the dyadic wavelet transform of I_s. For any pair of consecutive zero-crossings of W_{2^j} whose abscissae are respectively (z_{n-1}, z_n), we record the value of the integral

$$e_n = \int_{z_{n-1}}^{z_n} W_{2^j} I_S(x)dx \; .$$

For the function $W_{2^j} I_s$, the position of the zero-crossings $(z_n)_{n \in Z}$ can be represented by a piece-wise constant function:

$$Z_{2^j} I_S(x) = \frac{e_n}{z_n - z_{n-1}}, x \in [z_{n-1}, z_n] \qquad (2)$$

In practical implementations, I_s is measured with four low resolution levels when computing the dyadic wavelet transform; i.e., $3 \le j \le 6$. Therefore, the discrete zero-crossing representation of I_s is the set of the signals $\{(Z_{2^j}(I_s))_{3 \le j \le 6}\}$.

Matching: Let us denote the zero-crossing representation of an iris p at a particular resolution level j by Z_{jp}. Also, let $X_j = \{x_j(r); r = 1,....R_j\}$ be a set containing the locations of zero-crossing points at level j, where, R_j is the number of zero-crossings at this level. Then the representation Z_{jp} can be uniquely expressed in the form of a set of complex numbers which can be written as a set of ordered pairs $(|u_j|_p, |p_j|_p)$. Thus, the following dissimilarity is used to compare the unknown iris y and candidate model p at a particular resolution level j:

$$d_j(y,p) = \frac{\sum_{i=1}^{R_j} \{[u_j(r)]_y [p_j(r)]_y - \Gamma[u_j(r)]_p [p_j(r)]_p\}^2}{\Gamma \sum_{i=1}^{R_j} \left|[u_j(r)]_y [p_j(r)]_y\right| \left|[u_j(r)]_p [p_j(r)]_p\right|} \qquad (3)$$

Where, Γ is the scale factor. The overall dissimilarity value of the unknown iris and the candidate model over the resolution interval [3, 6] will be the average of the dissimilarity functions calculated at each resolution level in this interval:

$$d_Z(y,p) = \sum_{j=3}^{6} \frac{1}{4} d_j(y,p) \qquad (4)$$

Therefore, the matching score of this algorithm is obtained as the value of the dissimilarity function.

SCORE NORMALIZATION

The matching scores generated by different algorithms are heterogeneous. For example, the matching scores of two algorithms in this study are not on the same numerical range, which may negatively affect fusion performance. So normalization is required to transform these scores into a common domain before fusion at the matching score level.

A double sigmoid function is used for score normalization (Cappelli *et al.*, 2000). Given a set of matching scores d, the normalized score x is calculated by:

$$x = \begin{cases} \dfrac{1}{1 + \exp(-2((d - t)/t_1))} & d < t \\ \dfrac{1}{1 + \exp(-2((d - t)/t_2))} & \text{otherwise} \end{cases} \qquad (5)$$

Where, t is the reference operating point and t_1 and t_2 denote the left and right edges of the region (i.e., the interval $(t-t_1, t-t_2)$) in which the function is near-linear. By using appropriate parameters, the scores can be mapped to the [0,1] range.

Because the matching scores of the phase-based algorithm are all in the [0,1] interval, score normalization is mainly applied to the matching scores of the zero-crossing based algorithm. The scores of the zero-crossing based algorithm are mapped to the common range [0,1] using $t = 43$, $t_1 = 10$ and $t_2 = 20$.

FUSION STRATEGIES

After score normalization, a score vector (x_1, x_2) can be constructed, with x_1 and x_2 corresponding to the normalized scores of a certain iris sample from two recognition algorithms. 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 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 to the classification approach, the combination approach can get more flexibility by adjusting the decision threshold. So the combination approach is used in this research.

Traditional fusion strategies: Sum, fisher, as well as Support Vector Machine (SVM) are traditional combination strategies in the combination approach at the matching score level. Suppose (x_1, x_2) is normalized scores of an iris sample V from two algorithms. The fused score for the sample V is denoted as f (V).

Sum: $f(V) = x_1+x_2$.

Fisher discriminant: $f(V) = w^T x$, here $x = [x_1, x_2]^T$, w is the optimal projection matrix by maximizing the fisher objective function.

Support Vector Machine (SVM): SVM is based on the principle of structural risk minimization. In some literatures, it has been used for multibiometric fusion. (Jiang and Su, 2004).

MPM-based fusion strategy: In some cases, the traditional fusion strategies are effective, but they also have some disadvantages. For example, sum and fisher rule are often less effective in case of nonlinear separation problem. Although SVM can solve nonlinear separation problem, its performance is directly affected by the kernel function and its complexity is highly dependent on the size of training data, which make SVM not provide robust performance. So this study adopts a new fusion strategy based on minimax probability machine which can not only effectively solve the nonlinear separation problem but also provide robust performance.

MPM is a new proposed classification technique (Lanckriet *et al*., 2002a, b). The most attractive property of MPM is that it can explicitly provide a worst-case bound 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 two algorithms, be combined into a multimodal score vector $d = [x_1, x_2)^T$ ($x_1, x_2 \in R$). The design of a trained fusion scheme consists in the estimation of a function f: $R^2 \rightarrow R$ based on empirical data so as to effectively separate the fused scores f (d) of genuines and impostors.

Suppose that two random vectors x and y represent two classes of data points with means and covariance matrices as $\{\bar{x}, \Sigma_x\}$ and $\{\bar{y}, \Sigma_y\}$, respectively, where x, y, $\bar{x}$, $\bar{y} \in R^2$ and Σ_x, $\Sigma_y \in R^{2\times 2}$. Let x and y denote genuines and impostor, respectively.

The training sets, which consist of genuines and impostors, are already given. With the reliable estimations of $\{\bar{x}, \Sigma_x\}$ and $\{\bar{y}, \Sigma_y\}$ for two classes of data obtained from the training data, MPM attempts to determine an optimal hyperplane

$$a^T z = b \quad a, z \in R^2, a \neq 0, b \in R \tag{6}$$

which separates the data into genuines and impostors by minimizing the worst-case probability of misclassification. The mathematical formulation of the original model can be written as follows (Lanckriet *et al*., 2002a, b):

$$\max_{a,b,a\neq 0} a \text{ subject to: } \inf P_r\{a^T x \geq b\} \geq a \quad \inf P_r\{a^T y \leq b\} \geq a \tag{7}$$

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

After introducing the Lagrangian Multiplier, the optimization problem then becomes:

$$\max_{k,a} k \text{ subject to: } \tfrac{1}{k} \geq \sqrt{a^T \Sigma_x a} + \sqrt{a^T \Sigma_y a} \quad a^T(\bar{x} - \bar{y}) = 1 \tag{8}$$

Which allows us to eliminate k and the problem can be transformed into:

$$\min_a \left\|\Sigma_x^{1/2} a\right\|_2 + \left\|\Sigma_y^{1/2} a\right\|_2 \text{ subject to } a^T(\bar{x} - \bar{y}) = 1 \tag{9}$$

This is a second order cone programming problem which can be solved using interior-point methods (Lanckriet *et al*., 2002a). Then we can obtain a_* and b_*, where, a_* and b_* are the optimal values of a and b and the optimal hyperplane $a_*^T z = b_*$ also can be determined.

Given a new iris score vector z_{new}, a fused score s_T can be generated using the optimal hyperplane. s_T is defined as follow:

$$s_T = f(z_{new}) = a_*^T z_{new} - b_* \tag{10}$$

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

$$s_T = f(z_{new}) = a_*^T \Phi(z_{new}) - b_* \tag{11}$$

Where, Φ is called the kernel function and Gaussian kernel function is adopted in this research.

Following the obtainment of the fused score s_T, the final decision can be made by the predefined threshold. In practical implementations, the decision threshold can be adjusted to reach different working points.

RESULTS AND DISCUSSION

In order to evaluate the recognition performance, we have tested the proposed multialgorithmic fusion method on CASIA and UBIRIS iris databases.

Experiments on CASIA iris database: Chinese Academy of Sciences Institute of Automation (CASIA 1.0) iris image database consists of 756 iris images from 108 different subjects (7 iris images of each subject) (CASIA, 2003). The database is divided into two sets: training set and testing set. The training set is used to train and learn the parameters of MPM. The testing set is used to simulate real authentication. For maintaining the independence, the training set and the testing set select different subjects. Fifteen subjects from CASIA are selected as the training set and the remaining 93 subjects are the testing set. In the training set, each iris image is matched with all the other iris images using two algorithms described in previous section, which can yield 315 genuines and 5145 impostors multimodal score vectors. These multimodal score vectors are used as the training data to train MPM. When the optimal MPM has been obtained, the multialgorithmic fusion method with the MPM fusion strategy is carried out on the testing set. Similar to the training set, each iris in the testing set need to be matched with all the other irises using the multialgorithmic fusion method and a final decision is made upon whether a claim is genuine or impostor.

The False Acceptance Rate (FAR) and the False Rejection Rate (FRR) are two widely used error measures in a verification system. FAR and FRR are the functions of the decision threshold that can control the tradeoff between the two error rates. The performance of the verification system can be represented by the ROC (Receive Operating Characteristic) curves, which plots probability of FAR versus probability of FRR for different values of the decision threshold. The point on the ROC defined by FAR=FRR is the EER point.

In this experiment, we compare the proposed method with the single algorithm and the approaches using the traditional fusion strategies. Different approaches are evaluated by plotting their ROC curves and comparing their EER values.

The experiment results on CASIA database are shown in Fig. 3 and 4.

Figure 3 shows the ROC curves of the following systems: single algorithm based on phase information, single algorithm based on zero-crossing and multialgorithmic fusion method based on MPM. ROC curves for the multialgorithmic fusion systems with different fusion strategies: sum, fisher, SVM and MPM. The EER values of the different approaches are also given in Fig. 3 and 4.

Far better overall performance has been achieved when the two algorithms (phase based algorithm and zero-crossing based algorithm) are combined, which proves that multialgorithmic fusion can bring obvious performance improvement (Fig. 3). Some iris images, which the single algorithm fails to recognize, can be correctly recognized using the multialgorithmic fusion method. For example, the irises in Fig. 5a and b are, respectively uncorrectly recognized by the algorithm based on phase information and based on zero-crossing, but they both can be correctly recognized using the proposed method.

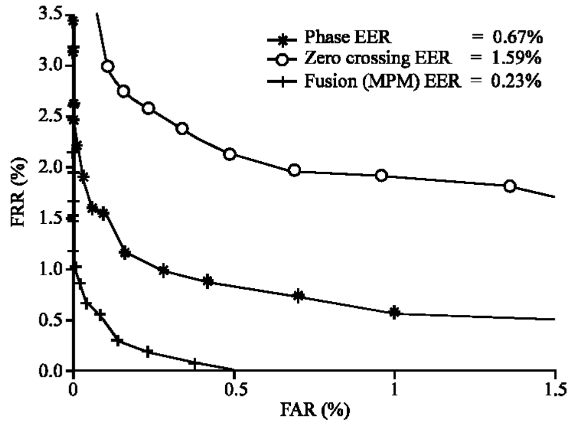


Fig. 3: ROC curves of single algorithms and MPM- based multialgorithmic fusion on CASIA

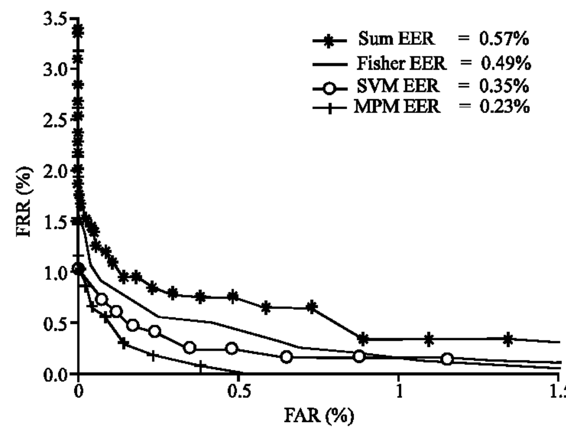
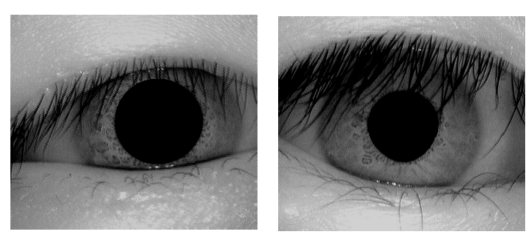


Fig. 4: ROC curves of different fusion strategies on CASIA



(a) (b)

Fig. 5: Typical iris images

From Fig. 4, multialgorithmic fusion using different fusion strategies demonstrate different recognition performance. MPM based fusion strategy can achieve the best performance among all fusion strategies, which shows the superiority of the fusion strategy proposed in this study.

Experiments on UBIRIS iris database: We also test the proposed multialgorithmic fusion method on UBIRIS iris database (Proenca and Alexandre, 2005). UBIRIS consists of 1877 iris images from 246 subjects. It is a noisy database and it contains many poor quality images which are unsuitable for iris recognition. We select 780 clear iris images from 156 subjects (5 images of each subject) for our experiments. The selected iris images are divided into two sets: 15 subjects as the training set and the remaining 141 subjects as the testing set. The procedure of the experiment is similar to CASIA and the experimental results are shown in Fig. 6 and 7.

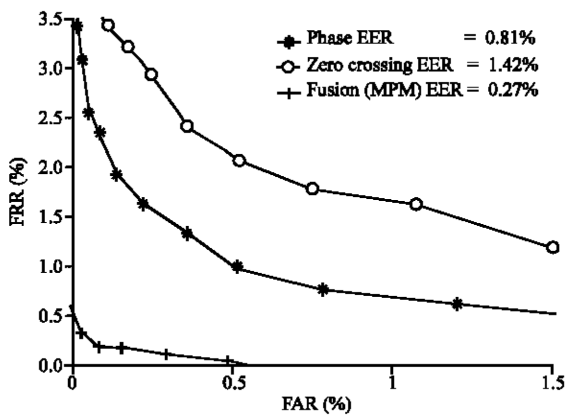


Fig. 6: ROC curves of single algorithm and MPM based multialgorithmic fusion on UBIRIS

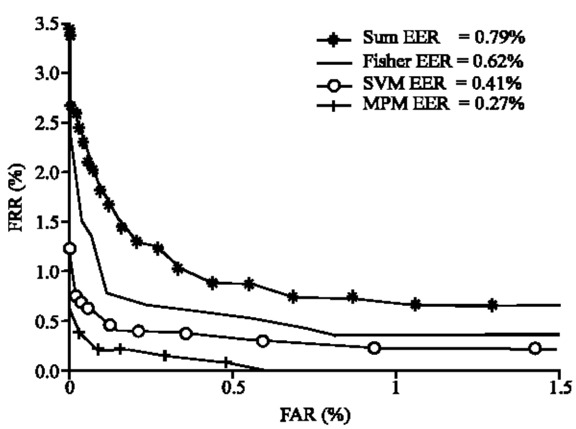


Fig. 7: ROC curves of different fusion strategies on UBIRIS

The proposed multialgorithmic fusion method based on MPM shows the best ROC performance and gets the lowest EER value, which also proves that multialgorithmic fusion method can achieve the better recognition performance than any single recognition algorithm and MPM based fusion strategy proposed in this research gets the maximum performance improvement compared to the traditional fusion strategies (Fig. 6 and 7).

CONCLUSIONS

This study introduces an effective method based on multialgorithmic fusion for improving iris recognition performance. The proposed method, which combines phase based algorithm and zero-crossing based algorithm at the matching score level, can bring obvious performance improvement compared to the single recognition algorithm. When fusing at the matching score level, a novel fusion strategy using (MPM) is adopted. The adopted fusion strategy can get the maximum performance improvement compared to the traditional fusion strategies. The experimental results on CASIA and UBIRIS iris database prove our conclusions.

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