Manuscript received May 20, 2007; revised August 10, 2007

Iris Recognition Based on Multialgorithmic Fusion

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Abstract: Fusion of multiple algorithms for biometric verification performance improvement has received considerable attention. This paper proposes an iris recognition method based on multialgorithmic fusion. The proposed method combines the phase information based algorithm and zero-crossing representation based algorithm at the matching score level. The fusion rule based on support vector machine (SVM) 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 with any single algorithm, and the results also demonstrate that the fusion rule based on SVM can achieve better performance than conventional l fusion rules.

Key-Words: Biometrics**,** iris, multialgorithmic fusion, fusion rule, support vector machine, score level

1 Introduction

Biometric identification is gaining more popularity and more acceptance 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[1-5]. Daugman used multi-scale 2D Gabor filters to extract texture phase structure information of the iris and Hamming distance for classification[2]. Wildes represented the iris texture with a Laplacian pyramid constructed with four different resolution levels and used normalized correlation for verification[3]. Boles proposed an algorithm for iris feature extraction using zero-crossing representation of 1D wavelet transform[4]. In [5], Li Ma developed an algorithm based on iris texture analysis.

Although some algorithms can get high recognition rate in ideal conditions, any iris recognition algorithm has drawbacks and cannot warranty 100% identification rate , nor 0% False Acceptance and Rejection Ratios especially in nonideal conditions. To improve the identification performance, multibiometric fusion techniques are applied in some literatures[6][7]. 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, the multi-algorithmic 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 paper, an iris recognition method based on multialgorithmic fusion is proposed. For verification performance improvement, we combine two different iris recognition algorithms. The first is phase information based algorithm. The second algorithm is zero-crossing representation based recognition algorithm. Two algorithms are fused at the matching score level prior to making a specific identification decision, and a fusion rule based on support vector machine(SVM) is used. CASIA and UBIRIS are chosen as the testing databases to prove the effectivity of the proposed method[8][9].

The rest of the paper is structured as follows. The architecture of multialgorithmic fusion system is described in section 2. In section 3, we review the two recognition algorithms. Section 4 and section 5 introduce the score normalization method and fusion strategies respectively. The experimental procedure and experimental results are presented in section 6. Finally the main conclusions are in section 7.

2 Multialgorithmic Fusion System Overview

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 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.

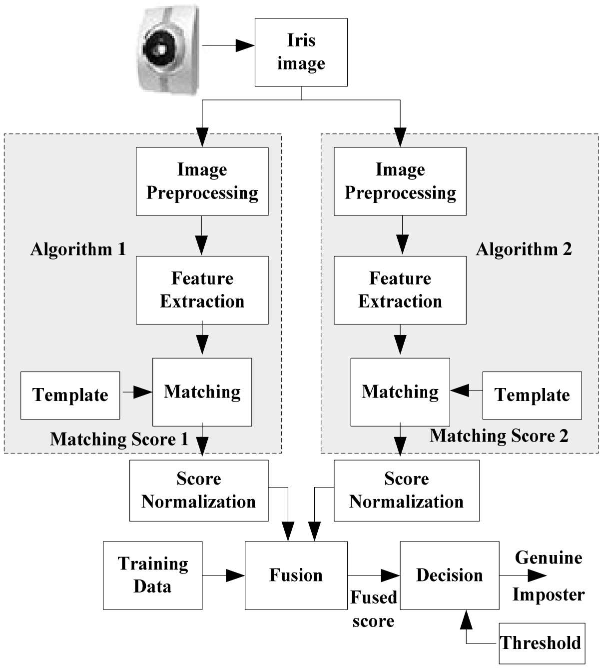

Fig.1 Multialgorithmic fusion block diagram

Fig.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 SVM-based fusion rule. A decision threshold is set to make a final decision. The decision threshold can be adjusted to meet demands of different application conditions.

3 Descriptions of Two Iris Recognition Algorithms

3.1 Iris Recognition Based on Phase Structure Information

The iris recognition algorithm based on phase structure information was proposed by Daugman[2]. The process can be divided into three main stages: iris 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. The main preprocessing steps, as illustrated in Fig.2, 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.

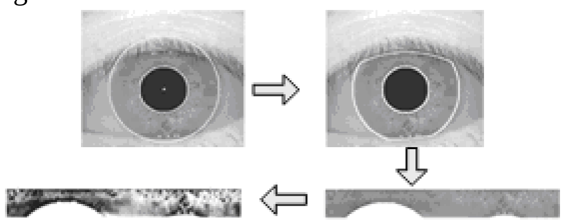

Fig.2 Steps involved in iris preprocessing

Feature encoding Complex 2D Gabor filters $g(x,y)$ are employed to extract the phase information of the iris texture[2]. The mathematical expression of $g(x,y)$ is shown in Eq.1.

$$g(x,y) = g^e(x,y) + jg^o(x,y) \quad (1)$$

Where $g^e(x,y)$ and $g^o(x,y)$ indicate the real and imaginary parts of the complex 2D Gabor filters respectively. They have the following forms:

$$g^e(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x_1^2}{\sigma_x^2}+\frac{y_1^2}{\sigma_y^2})]\cos(2\pi Fx_1) \quad (2)$$

$$g^o(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp[-\frac{1}{2}(\frac{x_1^2}{\sigma_x^2}+\frac{y_1^2}{\sigma_y^2})]\sin(2\pi Fx_1) \quad (3)$$

Where $x_1 = x\cos(\theta) + y\sin(\theta)$, $y_1 = -x\sin(\theta) + y\cos(\theta)$, F is the frequency of the sinusoidal plane wave, θ is the orientation of the Gabor filter, σ_x and σ_y are the standard deviations of Gaussian envelope along the x and y axes, respectively.

During the phase extraction, the iris image is divided into m by n blocks. Consequently, the local phase information in each block is encoded into 2-bit codes according to the following equations:

$$h_{\mathrm{Re}} = 0 \text{ if } \iint_{x,y} I(x,y) * g^e(x,y)dxdy \geq 0 \quad (4)$$

$$h_{\mathrm{Re}} = 1 \text{ if } \iint_{x,y} I(x,y) * g^e(x,y)dxdy < 0 \quad (5)$$

$$h_{\mathrm{Im}} = 0 \text{ if } \iint_{x,y} I(x,y) * g^{o}(x,y)dxdy \geq 0 \quad (6)$$

$$h_{\mathrm{Im}} = 1 \text{ if } \iint_{x,y} I(x,y) * g^{o}(x,y)dxdy < 0 \quad (7)$$

Where $*$ denotes convolution operator and $I(x,y)$ denotes the preprocessed iris image.

Thus the phase information in each block is described by 2-bit codes and totally $2mn$ bits to describe the whole iris.

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

$$d_H = \frac{\sum [(codeA \otimes codeB) \cap (maskA \cap maskB)]}{\sum (maskA \cap maskB)} \quad (8)$$

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.

3.2 Iris Recognition Based on Zero-crossing Representation

It is known that one can obtain the position of multiscale sharp variations points from the zero-crossing of the signal convolved with the laplacian of a Gaussian[10]. This procedure can be used in iris texture feature representation. So Boles proposed the iris recognition algorithm using zero-crossing representation of 1-D wavelet transform[4]. In this work, an algorithm similar to [4] is applied to multialgorithmic fusion system.

Iris signature from iris virtual circles The first step is to obtain a set of data (iris signature I_S) from each isolated iris sample which allows a suitable extraction of its features. For obtaining this data set, the centroid of the detected pupil is chosen as the reference point. Thus, 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, with radius r and considering angular increments of $2\pi/M$ (M is the length of each virtual circle). In this work, N virtual circles are selected. So the total length of iris signature is M*N.

Multiscale zero-crossing representation For extracting unique features from iris signatures and representing these features, discrete dyadic wavelet transform is used. Let $\{W_{2^j} I_S\}_{j\in\mathbb{Z}}$ 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 $(z_n)_{n\in\mathbb{Z}}$ can be represented by a piece-wise constant function:

$$Z_{2^j} I_S(x) = \frac{e_n}{z_n - z_{n-1}}, x \in [z_{n-1}, z_n] \quad (9)$$

In practical implementations, the iris signature I_S is measured with a finite resolution when computing the dyadic wavelet transform. In this work, four low resolution levels have been used; i.e., $3 \leq j \leq 6$. Therefore, the discrete zero-crossing representation of I_S is the set of signals $\{(Z_{2^j}(I_S))_{3\leq j\leq 6}\}$.

The dyadic wavelet used in this work is the quadratic spline of compact support defined in [11]. The advantage of using this function is that it has a finite support and it also has a smaller number of coefficients than those of the second derivative of a smoothing function[10].

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 $(|u_j|_p, |p_j|_p)$, whose imaginary $|p_j|_p$, and real $|u_j|_p$, parts indicate the zero-crossing position and magnitude of Z_{jp} between two adjacent zero-crossing points, respectively. Thus, the following dissimilarity is used to compare the unknown iris y and candidate model p at a particular resolution level j:

$$d_j(y,p) = \frac{\sum_{i=1}^{R_j} \{[u_j(r)]_y [p_j(r)]_y - \Gamma [u_j(r)]_p [p_j(r)]_p\}^2}{\Gamma \sum_{i=1}^{R_j} \left|[u_j(r)]_y [p_j(r)]_y\right| \left|[u_j(r)]_p [p_j(r)]_p\right|} \quad (10)$$

Where Γ is the scale factor and equals the ratio between the average radius of the candidate model and that of the unknown iris. 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:

$$d_Z(y,p)=\sum_{j=3}^{6}\frac{1}{4}d_j(y,p) \quad (11)$$

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

4 Score Normalization

The matching scores generated by different algorithms are heterogeneous. For example, the matching scores of two algorithms in this work are not on the same numerical range, which may negatively affect recognition performance. So normalization is required to transform these scores into a common domain before combining them to generate a single scalar score which is then used to make the final decision.

The normalization technique used in this work is the Min-max normalization. We first estimate the minimum and maximum value for a set of matching scores from the individual algorithm and then apply the min-max normalization. Given a set of matching scores d , the normalized scores are given by

$$x=\frac{d-\min}{\max-\min} \quad (12)$$

Min-max normalization can retain the original distribution of scores and transform all the scores into a common range $[0,1]$.

5 Fusion Rules

After score normalization, a score vector (x_1, x_2) can be obtained, with x_1 and x_2 corresponding to the normalized scores of a certain iris sample from the two different recognition algorithm. The next step is to combine the two-dimensional score vector to generate a single scalar score which is then used to make the final decision.

5.1 Traditional Fusion Rules

Simple-sum, weighted-sum, product, as well as fisher discriminant rule are traditional combination rules for matching score level fusion. Suppose x_1, x_2 is normalized scores of testing iris sample V . The fused score for sample V is denoted as $f(V)$.

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

Weighted-Sum(WS): $f(V)=w_1x_1+w_2x_2$, where w_1, w_2 is the weight assigned to the score of two different algorithms.

Product(PR): $f(V)=x_1x_2$.

Fisher discriminant: Fisher linear discriminant is to project data onto a one-dimensional subspace (a line) where within-class scatter matrix is maximized while the between-class matrix is minimized. Therefore, $f(V)=\mathrm{w}^T\mathrm{x}$, here $\mathrm{x}=[x_1,x_2]^T$, w is the optimal projection matrix by maximizing the fisher objective function.

SVM-based Fusion Rule

Support vector machine (SVM) is based on the principle of structural risk minimization[12][13]. In this work, we use SVM to provide a fused score.

Let the matching scores, provided by the two different algorithms, be combined into a multimodal score vector $\mathrm{x}=[x_1,x_2]^T$, $x_1,x_2\in R$. The design of a trained fusion scheme consists in the estimation of a function $f: R^2\to R$ based on empirical data so as to maximize the separability of client $\{f(\mathrm{x})|$client attempt$\}$ and impostor $\{f(\mathrm{x})|$impostor attempt$\}$ fused score distributions.

Suppose that the training set is $X=(\mathrm{x}_i,y_i)_{i=1}^N$, where N is the number of multimodal score vectors in the training set, and $y_i\in\{-1,1\}=\{\mathrm{Impostor},\mathrm{Client}\}$. Via $\Phi: R^2\to Q$, X is mapped into a high dimension features space Q . The principle of SVM relies on a linear separation in the space Q . In order to achieve a good level of generalization capability, the margin between the separator hyperplane $\{\mathrm{h}\in Q|\langle\mathrm{w},\mathrm{h}\rangle_Q+w_0=0\}$ and the mapped data $\Phi(X)$ is maximized (where $\langle\cdot,\cdot\rangle_Q$ denotes inner product in space Q , and $(\mathrm{w}\in Q, w_0\in R)$ are the parameters of the hyperplane). According to the literature [12], the optimal hyperplane can be obtained as the solution of the following quadratic programming problem:

$$\min_{\mathrm{w},w_0,\xi_1,\ldots,\xi_N}\left(\tfrac{1}{2}\|\mathrm{w}\|^2+\sum_{i=1}^{N}C_i\xi_i\right) \quad (13)$$

Subject to

$$y_i(\langle\mathrm{w},\Phi(\mathrm{x}_i)\rangle_Q+w_0)\ge 1-\xi_i,\ i=1,\ldots,N \quad (14)$$

$$\xi_i\ge 0,\ i=1,\ldots,N \quad (15)$$

Where slack variables ξ_i are introduced to take into account the eventual non-linearities of $\Phi(X)$ into Q and parameter C_i is a positive constant that controls relative influence of two competing terms.

The optimization problem in (13), (14) and (15) is solved using the dual representation[12]:

$$\max_{\alpha_1,\ldots,\alpha_N}\left(\sum_{i=1}^{N}\alpha_i-\tfrac{1}{2}\sum_{i,j=1}^{N}\alpha_i\alpha_j y_i y_j K(\mathrm{x}_i,\mathrm{x}_j)\right) \quad (16)$$

Subject to $0\le\alpha_i\le C_i, i=1,\ldots,N$, $\sum_{i=1}^{N}\alpha_i y_i=0$ (17)

Where the introduction of the kernel function $K(\mathrm{x}_i,\mathrm{x}_j)=\langle\Phi(\mathrm{x}_i),\Phi(\mathrm{x}_j)\rangle_Q$ avoids direct manipulation of the elements of Q.

By using the Karush-Kuhn-Tucker(KKT) conditions to the problem in (16) and (17), the optimal hyperplane $H(\mathrm{w}^*,w_0^*)$ can be obtained.

So the fused score s_T of a test pattern x_T is defined as follow:

$$s_T = f(\mathrm{x}_T)=\langle\mathrm{w}^*,\Phi(\mathrm{x}_T)\rangle_Q + w_0^* \quad (18)$$

And it also can be shown to be equivalent to the following sparse expression:

$$s_T = f(\mathrm{x}_T)=\sum_{i\in SV}\alpha_i^* y_i K(\mathrm{x}_i,\mathrm{x}_T)+w_0^* \quad (19)$$

Where $(\alpha_1^*,...,\alpha_N^*)$ is the solution to the problem in (16) , (17) and $SV=\{i\,|\,\alpha_i^*>0\}$ indexes the set of support vectors. w_0^* is obtained from the solution to the problem in (16), (17) by using the KKT conditions. The kernel function $K(\mathrm{x}_i,\mathrm{x}_j)$ choose a radial basis function, defined by $K(\mathrm{x}_i,\mathrm{x}_j)=\exp(-\|\mathrm{x}_i-\mathrm{x}_j\|^2/2\sigma^2)$.

Following the obtainment of the fused score s_T, the decision threshold can be adjusted to reach different working points.

6 Experimental Results

In order to evaluate the recognition performance, we have tested the proposed multialgorithmic fusion method on the CASIA iris database and UBIRIS iris database which are widely used.

6.1 Experiments on CASIA Iris Database

Chinese Academy of Sciences-Institute of Automation (CASIA1.0) iris image database consists of 756 iris images from 108 different subjects (7 iris images of each subject)[8]. The database is divided into two sets: training set and test set. The training set is used to estimate the parameters of SVM. The test set is used to simulate real authentication tests. For maintaining the independence, the training set and the test set select different subjects. 15 subjects from CASIA1.0 are selected as the training set, and the remaining 93 subjects are the test set. In the training set, each iris image is compared with all the other iris images using two algorithms described in section 3, which can yield 315 clients and 5145 impostors multimodal score vectors. In order to reduce the computational complexity of the SVM, not all yielded multimodal score vectors, but 100 clients and 150 impostors multimodal score vectors are selected as the training data to learn the parameters of SVM. Then the multialgorithmic fusion method with the trained SVM fusion strategy is carried out on the test set. Similar to the training set, each iris in the test set need to be compared with all the other irises in the test set using the multialgorithmic fusion method.

The false acceptance rate (FAR) and the false rejection rate (FRR) are two widely used error measures in a verification system. When the decision threshold is different, FAR and FRR are also different, so FAR and FRR are the function 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), 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.

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

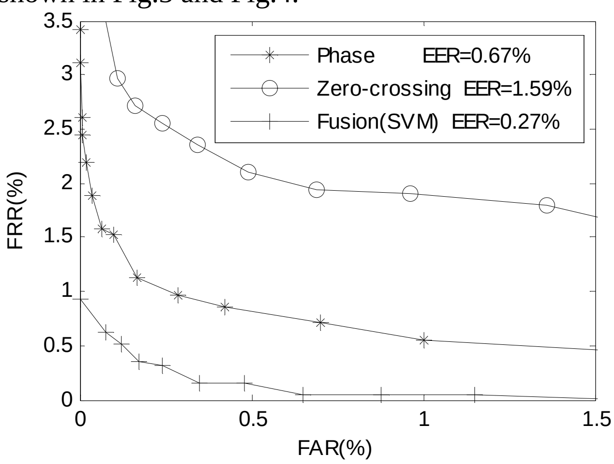

Fig.3 ROC curves of single algorithms and SVM-based multialgorithmic fusion on CASIA

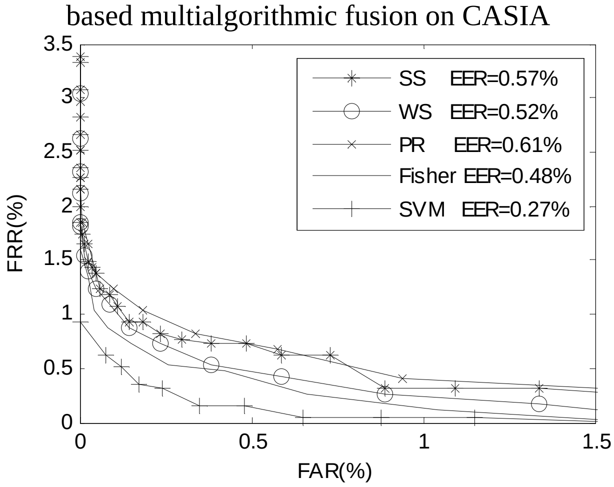

Fig.4 ROC curves of different fusion strategies on CASIA

Fig.3 represents the ROC curves of the following systems: phase based algorithm, zero-crossing based algorithm and multialgorithmic fusion method based on SVM. Fig.4 represents the ROC curves for the multialgorithmic fusion systems with different fusion rules: simple-sum (SS), weighted-sum (WS), product(Pr), fisher discriminant (Fisher) and SVM-based fusion. As can be seen from Fig.3, multialgorithmic fusion method obtains a performance of 0.27% EER, and brings obvious performance improvement compared with any single recognition algorithm. Fig.4 shows that multialgorithmic fusion method based on SVM fusion rule gets the best performance among all fusion rules.

6.2 Experiments on UBIRIS Iris Database

We also test the proposed multialgorithmic fusion method on UBIRIS iris database[9]. 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 test set. The experimental procedure is similar to CASIA and the experimental results are shown in Fig.5 and Fig.6. Fig.5 represents the ROC curves for the multialgorithic fusion system and the individual algorithm systems, and Fig.6 represents the ROC curves for different fusion strategies.

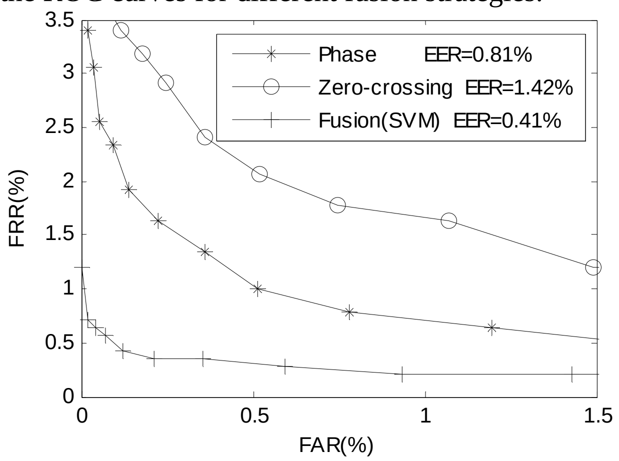

Fig.5 ROC curves of single algorithm and SVM based multialgorithmic fusion on UBIRIS

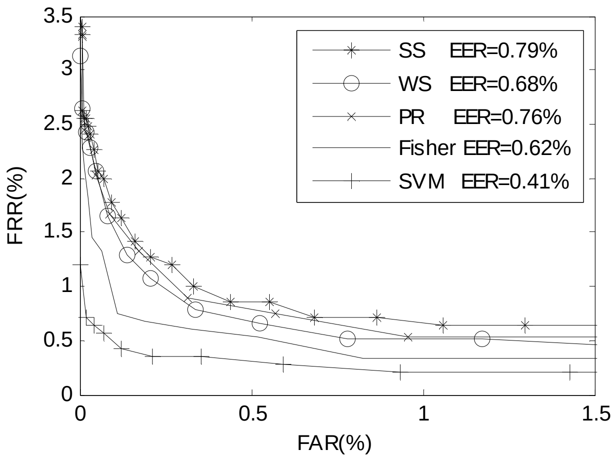

Fig.6 ROC curves of different fusion strategies on UBIRIS

From Fig.5 and Fig.6, we can see that multialgorithmic fusion method also gives the better recognition performance than any single recognition algorithm and SVM based fusion rule gets the maximum performance improvement compared with the traditional fusion rules.

7 Conclusion

We presented a multialgorithmic fusion approach for iris recognition, which combines phase based algorithm and zero-crossing based algorithm. The two algorithm are fused at the matching score level using SVM fusion strategy. The experimental results on CASIA and UBIRIS iris database show that the proposed approach can improve the recognition performance compared with the individual recognition algorithm and SVM based fusion strategy can give the better performance than the traditional fusion strategies.

8 Acknowledgements

Thanks to the creators of the CASIA and the UBIRIS iris image databases. This work is funded by research grants from the National Natural Science Foundation of China (No. 60502021) and the Ph.D. Programs Foundation of Ministry of Education of China (No. 20050698025).

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