Multibiometric System Using Level Set Method and Particle Swarm Optimization

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Abstract. Multibiometric systems alleviate some of the drawbacks possessed by the single modal biometric trait and provide better recognition accuracy. This paper presents a multimodal system that integrates the iris, face, and gait features based on the fusion at feature level. The novelty of this research effort is that a feature subset selection scheme based on Particle Swarm Optimization (PSO) is proposed to select the optimal subset of features from the fused feature vector. In addition, we apply a Variational Level Set (VLS)-based curve evolution scheme to detect the silhouette shape structure. Experimental results indicate that the proposed approach increases biometric recognition accuracies compared to that produced by single modal biometrics.

Keywords: Multibiometrics, variational level set, active shape model, particle swarm optimization, feature subset selection.

1 Introduction

With the increasing concern of security, biometric-based authentication has been receiving extensive attention over the past decade. Biometric system based on single biometric trait generally suffers from different factors, including lack of uniqueness, nonuniversality and noisy data [1]. Multibiometric systems remove the drawbacks of the unibiometric systems by combining the multiple sources of information. The success of multimodal biometric system depends on information fusion, which is mainly performed at four different levels: sensor level, feature level, matching score level and decision level. It has been found from the literature review that the biometric authentication scheme that fuses the information at an earlier stage of processing provides better recognition accuracy than the systems that integrate information at a later stage [2]. The fusions at matching score, sensor and decision levels have been extensively studied in the literature. However, the biometric information fusion at feature level has been remained an understudied problem. In this research effort, we perform fusion at the feature level by considering three biometric modalities–iris, face and gait. Recent work [3] indicates that feature level fusion outperforms the match score fusion, because of the availability of more rich information. It is found that fusion at feature level is relatively difficult to achieve in practice because of the incompatible feature values across the multiple modalities and the correspondence among different feature spaces may be unknown [4]. Moreover, the concatenated feature set may lead to the problem of curse of dimensionality due to

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large size of the fused feature vector, thus leading to a decrease in the performance of the classifier [4]. Addressing the above problems, a feature selection scheme based on Particle Swarm Optimization (PSO) is deployed to reduce the dimensionality of the fused feature vector [5, 6]. For PSO-based feature subset selection, we apply a fitness function that minimizes the Recognition Error (RE) and False Accept Rate (FAR). Variational Level Set (VLS) methods have been extensively used in the field of medical image analysis [7, 8]. In this research effort, we demonstrate the significance of the VLS method in the context of gait recognition. We propose to apply the VLS-based curve evolution scheme to represent the silhouette shape data. The deployed active contour method in variational formulation uses a larger time step to solve the evolution *partial differential equation* (PDE) numerically, and thereby, resulting in a substantial speed up of the curve evolution [8]. The silhouette shape structure represented by the VLS may break and merge naturally during evolution, and thus, the topological changes are handled automatically. In addition, we apply the VLS method to localize the nonideal iris images that are acquired in an unconstrained situation and are affected by eyelid and eyelash occlusions, non uniform intensities, motion blurs, reflections, etc. The proposed variational model is robust against poor localization and blurred iris/sclera boundaries. Furthermore, an Active Shape Model (ASM) that is steered by optimal local features is deployed to track the facial feature points [9]. Fig.1shows the block diagram of the proposed multibiometric system.

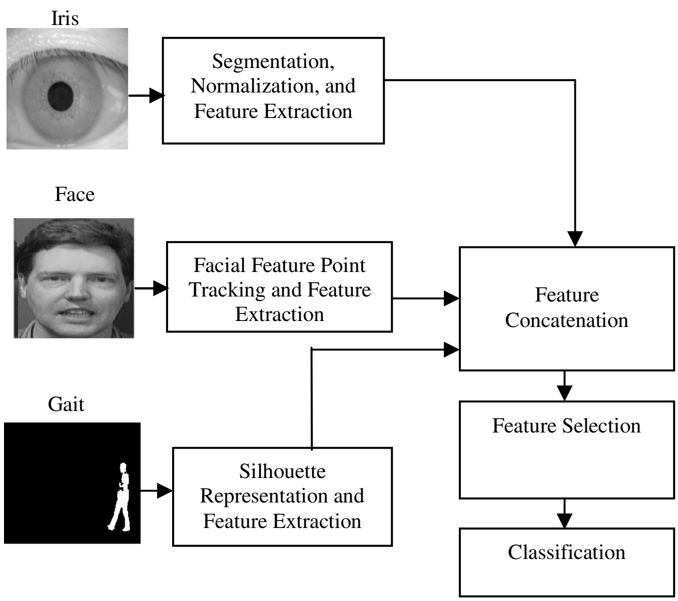

Fig. 1. Block diagram of the proposed multibiometric system

2 Preprocessing and Feature Extraction

In this section, we mainly focus on the preprocessing of three biometric modalities, distinctive feature extraction and fusion at feature level. In order to represent the moving silhouette of a walking figure, the curve is evolved by using the level set with a variational formulation technique [8]. In the following paragraphs, we briefly discuss outer contour detection of a moving silhouette using VLS method.

In the level set formulation, the active contours, denoted by C, can be represented by the zero level set $C(t) = \{(x, y)|\phi(t, x, y) = 0\}$ of a level set function $\phi(t, x, y)$. To evolve the curve towards the silhouette boundary, we define the following total energy functional [8]

$$\varepsilon(\phi) = \mu\rho(\phi) + \varepsilon_{g,\lambda,v}(\phi). \tag{1}$$

where $\varepsilon_{g,\lambda,v}(\phi)$ denotes the external energy, which depends on the image data and drives the zero level set toward the object boundaries, and $\mu\rho(\phi)$ $(\mu > 0)$ denotes the internal energy, which penalizes the deviation of ϕ from the Signed Distance Function (SDF) during evolution and is defined as [8]

$$\rho(\phi) = \int_\Omega \frac{1}{2}(|\nabla\phi| - 1)^2 dxdy. \tag{2}$$

where Ω is the image domain. In (1), g denotes the edge detector function and is defined by

$$g = \frac{1}{1+|\nabla G_{\sigma*I}|^2} \tag{3}$$

where G_σ is the Gaussian kernel with standard deviation σ, and I denotes a gait image. We can further define the external energy term $\varepsilon_{g,\lambda,v}(\phi)$ of (1) as [7]

$$\varepsilon_{g,\lambda,v}(\phi) = \lambda L_g(\phi) + vA_g(\phi) \tag{4}$$

where $\lambda > 0$ and v are constants, and the terms $L_g(\phi)$ and $A_g(\phi)$ in (4) are defined by

$$L_g(\phi) = \int_\Omega g\delta(\phi)|\nabla\phi|dxdy \tag{5}$$

and

$$A_g(\phi) = \int_\Omega gH(-\phi)dxdy \tag{6}$$

respectively, where δ is the univariate Dirac function, and H is the Heaviside function. The energy functional $L_g(\phi)$ measures the length of the zero level set curve of ϕ, and $A_g(\phi)$ is used to speed up curve evolution. From the calculus of variations, the Gateaux derivative of the functional ε in (1) can be written as

$$\frac{\partial\varepsilon}{\partial\phi} = -\mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] - \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) - vg\delta(\phi) \tag{7}$$

where Δ is the Laplacian operator. The function ϕ that minimizes this functional satisfies the Euler-Lagrange equation $\frac{\partial\varepsilon}{\partial\phi} = 0$. Now, the desired evolution equation of the level set function is defined as [7, 8]

$$\frac{\partial\phi}{\partial t} = \mu\left[\Delta\phi - div\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\right] + \lambda\delta(\phi)div\left(g\frac{\nabla\phi}{|\nabla\phi|}\right) + vg\delta(\phi) \tag{8}$$

The second and third terms on the right hand side of (8) represent the gradient flows of the energy functional and are responsible of driving the zero level set curve towards the outer boundary of the silhouette. The Dirac function $\delta(x)$ in (8) is defined by

$$\delta_\epsilon(x) = \begin{cases} 0, & |x|>\epsilon \\ \frac{1}{2\epsilon}\left[1+\cos\left(\frac{\pi x}{\epsilon}\right)\right], & |x|\leq\epsilon \end{cases} \tag{9}$$

In order to estimate the exact boundary of the moving silhouette quickly, a narrowband implementation of VLS method is adopted [8]. Fig. 2 shows the silhouette representation process. Next, we measure the shape centroid (x_c, y_c) of the detected outer boundary. We compute all distances $dist_i$ between each boundary point (x_i, y_i) and the centroid (x_c, y_c). Therefore, the 2D silhouette shape can be represented by a 1D distance signal, $S_i = (dist_1, dist_2, \dots\dots, dist_i, \dots\dots, dist_{nb})$. To avoid the effect of spatial scale and signal length, first, we normalize 1D signal magnitude by using L_1-norm [10]. Then, we use equally spaced re-sampling to normalize the signal size into a fixed length (300 in our experiments) and thus, form a feature vector, $\hat{x}_{gait}$ of size 300.

The segmentation of the nonideal iris image is a difficult task because of the noncircular shape of the pupil and the iris, and the shape differs depending on the image acquisition techniques [7]. We divide the iris segmentation process into three steps. In the first step, we remove the specular reflection spots that are found inside the pupillary region using the method proposed in our early work [7]. The white spots may cause a false inner boundary detection and may also halt the active contour-based propagation prematurely. In the second step, we use an elliptical model to approximate the inner (pupil) and outer (iris) boundaries of the iris. Finally, we apply the VLS curve evolution scheme described before for accurate segmentation of the pupil and iris regions [7, 8] based on the approximation of the inner and outer boundaries. In order to estimate the exact boundary of the pupil, we initialize the active contour φ to the approximated pupil boundary, and evolve the curve in the narrow band of ± 10 pixels. We evolve the curve from outside the approximated inner boundary to remove the effect of reflections. Similarly, for computing outer boundary, the active contour φ is initialized to the estimated iris boundary, and the optimal estimation of the iris boundary is computed by evolving the curve in a narrow band of ± 20 pixels. In this case, the curve is evolved from inside the approximated iris boundary to reduce the effects of the eyelids and the eyelashes. Fig. 3 (a) shows the segmentation results. Besides reflections, eyelid occlusion, and camera noise, the iris image data may be corrupted by the occlusion of the eyelashes [7]. We deploy one dimensional Gabor filters and variance of intensity to isolate the eyelashes [7]. We unwrap the iris region to a normalized rectangular block with a fixed dimension of size 20×240 by adopting the circle fitting strategy proposed in [7]. Since the normalized iris image has relatively low contrast and may have non- uniform intensity values due to the position of the light sources, a local intensity-based histogram equalization technique is applied to enhance the contrast of the

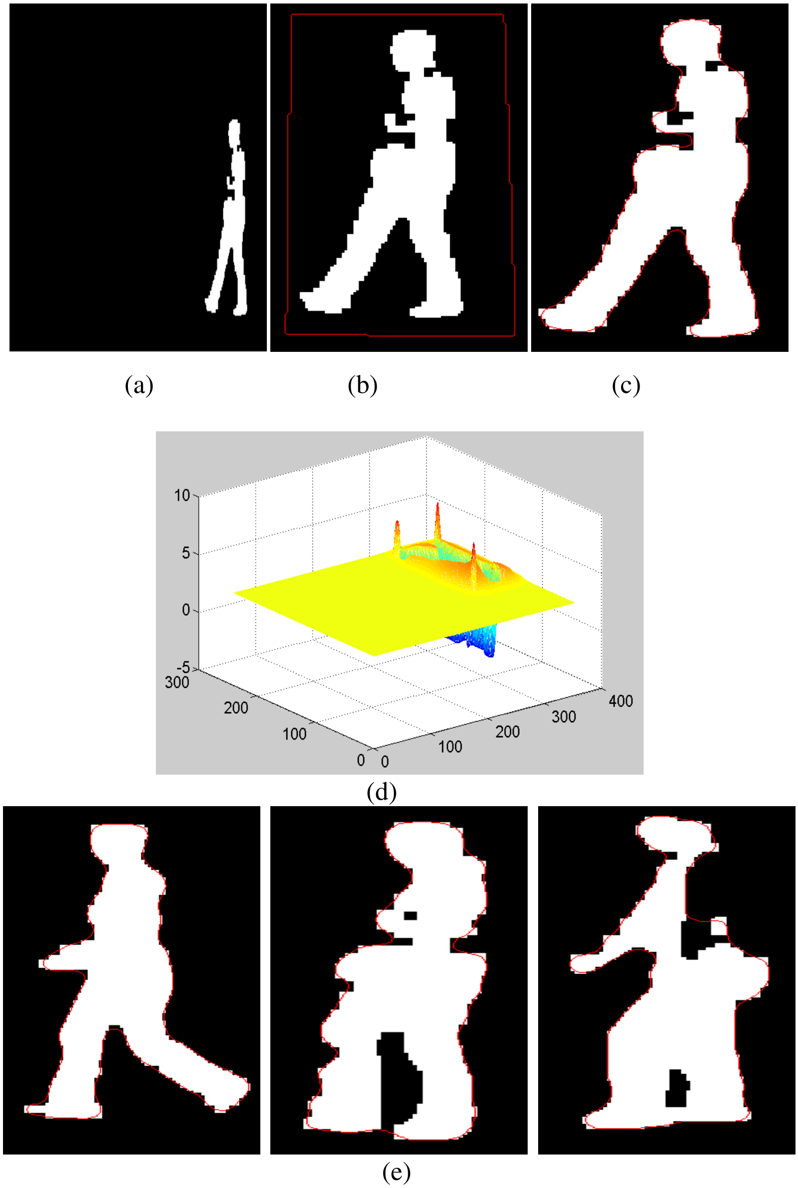

Fig. 2. Silhouette structure representation (a) Original image, (b) Initial contour, (c) Final contour, (d) Final level set function of (c), and (e) Silhouette shape representation of three gait images

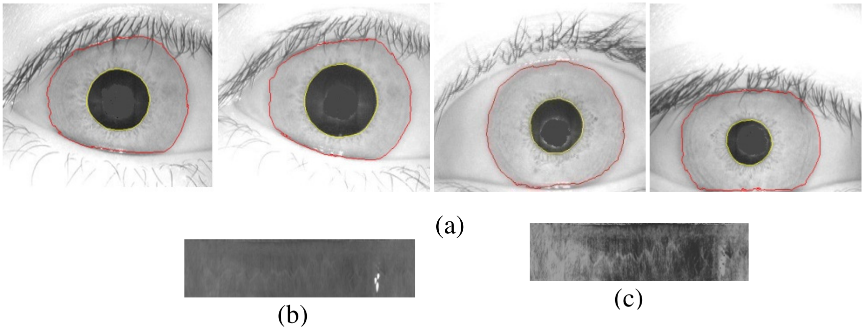

Fig. 3. (a) VLS-based iris/pupil segmentation, (b) Normalized image, and (c) Enhanced image

normalized iris image within a small image block of size 20×20. Fig. 3(b, c) shows the unwrapped image and the effect of contrast enhancement, respectively. In this paper, log-Gabor filters were used to extract a set of 4800 features from normalized and enhanced iris image [7] and thus, a feature vector, $\hat{x}_{iris}$ of size 4800 is formed.

An Active Shape Model with Local Features (ASMLF) [9] is applied to find a set of 60 facial feature points from the face image. In this paper, ASM is guided by optimal local features for detecting the facial feature points. The Support Vector Machines (SVMs) are deployed to find the optimal displacements of landmarks [11]. For each of the landmarks, an optimal set of features is selected by taking into account each resolution level. For the purpose of the optimal feature selection, sequential forward and backward elimination methods are used. Fig. 4 shows the facial point tracking results. For feature extraction, a discrete set of log-Gabor kernels is used that contains 4 spatial frequencies and 6 different orientations from 0° to 180°, differing in 30 steps that makes a filter bank of 24 different Gabor filters. These log-Gabor filters are deployed to each of the images and filter responses are obtained only at the selected fiducial points. Therefore, the facial feature points in an input image are represented by a feature vector, $\hat{x}_{face}$ of length 1440 elements (60 fiducial points, 24 filter responses per point). We concatenate $\hat{x}_{gait}$, $\hat{x}_{face}$, and $\hat{x}_{iris}$ and get the fused feature vector, $\hat{x}_{gait\_face\_iris}$ of size 6540×1. The z-score normalization technique is then deployed on $\hat{x}_{gait\_face\_iris}$ to ensure that the feature values across three modalities are compatible [4].

3 Feature Ranking Using Particle Swarm Optimization (PSO)

The main objective of PSO is to optimize a given fitness function [5]. A swarm of computational elements, called particles, is used to explore the search space for an optimum solution. Each particle represents a point in the n-dimensional feature space. The i-th particle can be represented as $X_i = (x_{i1}, x_{i2}, \cdots\cdots, x_{in})$. At each iteration, each particle is updated by two best values called *pbest* and *gbest*. The *pbest* corresponds to the position that provides the best fitness values and is represented as

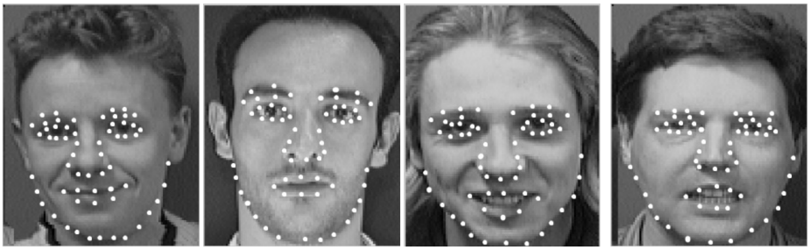

Fig. 4. Facial fiducial point tracking using ASMLF

$P_i = (p_{i1}, p_{i2}, \cdots\cdots, p_{in})$, where P is the population. The *gbest* provides the best position among all the particles in the swarm. The velocity of particle `$i$` is represented as $V_i = (v_{i1}, v_{i2}, \cdots\cdots, v_{in})$. The particles are updated according to following equations

$$v_{id} = w * v_{id} + c1 * rand\,()(p_{id} - x_{id}) \\ +c2 * rand()(p_{gd} - x_{id}) \tag{10}$$

$$X_{id} = \begin{cases} 1, & if\ \frac{1}{1+e^{-vid}} > rand() \\ 0, & 0therwise \end{cases} \tag{11}$$

where $d = 1, 2, \dots\dots\dots., n$. The inertia weight, w is set to 1 and both the acceleration constants, c_1 and c_2, are set to 2. $rand()$ is the random number between $(0, 1)$. Particles' velocities on each dimension are set to a maximum velocity, $Vmax$, and minimum velocity, *Vmin*. The (10) is used to measure the particle's new velocity according to its previous velocity and the distances of its current position from its own best experience (position) and from the group's best experience. The experience is evaluated using the fitness function. Based on the nature of our problem, we propose the following fitness function that minimizes the RE and FAR

$$u(F) = W_1.RE + W_2.FAR \tag{12}$$

where, W_1 and W_2 are constant weighting parameters which reflect the relative importance between *RE* and *FAR.*

4 Results and Analysis

Extensive experiments are conducted on CASIA Version 3 Interval Iris dataset [12], AT&T Face dataset [13], and CASIA Version A Gait dataset [14]. For the single sample recognition, we draw out the sample subsets of same size from these three databases. We select 20 classes from each of the databases, and each of these selected classes contains 10 samples. The first 4 samples of each class are used for training and the remaining samples are used for testing. In this paper, we use SVM for iris-face-gait pattern classification [11]. An extensive set of experiments are conducted using VLS for silhouette shape detection, and the selected parameter values are set to

$\mu = 0.04, v = -3.0, \lambda = 5.0$ and time step $\nabla t = 3.0$. For iris/pupil segmentation using VLS, the parameter values are set to $\mu = 0.05, v = -2.0, \lambda = 5.0$ and time step $\nabla t = 3.0$. The proposed PSO-based feature selection approach is used to reduce the feature dimension without compromising the recognition rate. For the combined dataset, we use a 5-fold crossvalidation to obtain the validation accuracy. Fig. 5 shows the crossvalidation accuracies of the selected feature subsets for the PSO approach. The values of two weighting parameters, W_1, and W_2 are set at 2000 and 150, respectively. From Fig. 5, we can see that the reasonable accuracy is obtained using the PSO scheme when the number of selected features is 1460 with an accuracy of 96.43%. The performance increases with the number of features selected with PSO up to 1450 and stabilizes afterwards. To demonstrate the effectiveness of the proposed feature selection scheme, we compare PSO-based scheme with Genetic Algorithms (GAs) [15] by deploying the same fitness function used in (12), and also, with Mutual Information (MI) [16]. GA achieves an accuracy of 96.21% when the selected feature subset size is 2200. Also, from Fig. 5, we can find that the performance curve of the MI-based approach starts to level off at 2550 feature elements with an accuracy of 95.10%. Therefore, we can find that the PSO-based feature reduction method outperforms the other two feature selection schemes and reduces the fused feature space by roughly 77%. From the ROC curve of Fig. 6 and Table 1, we can observe that the performance of the iris recognition scheme alone outperforms the face and gait recognition approaches with a Genuine Accept Rate (GAR) of 95.10% at the fixed FAR of 0.001%, while the achieved GARs of face and gait recognition schemes are 83.30% and 75.00%, respectively, at the same FAR of 0.001%. Furthermore, we apply the match score fusion strategy using a weighted SUM rule and compare with

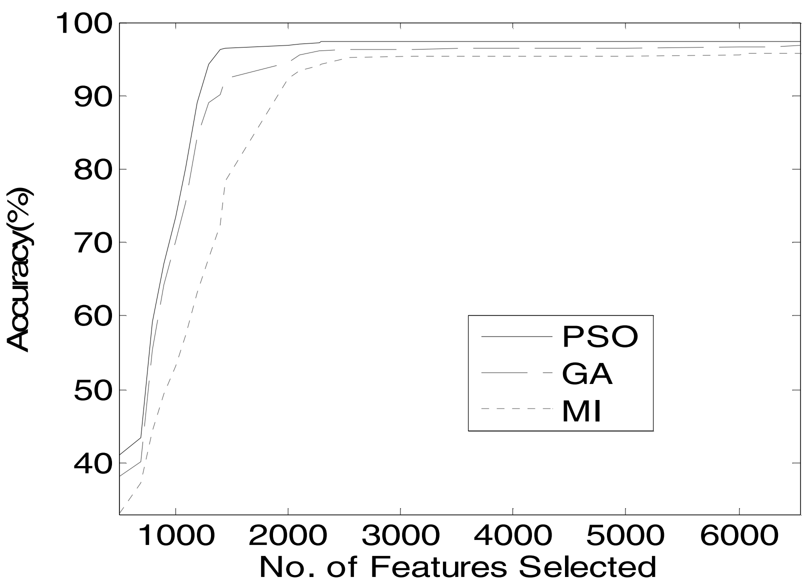

Fig. 5. Comparison of different feature selection schemes

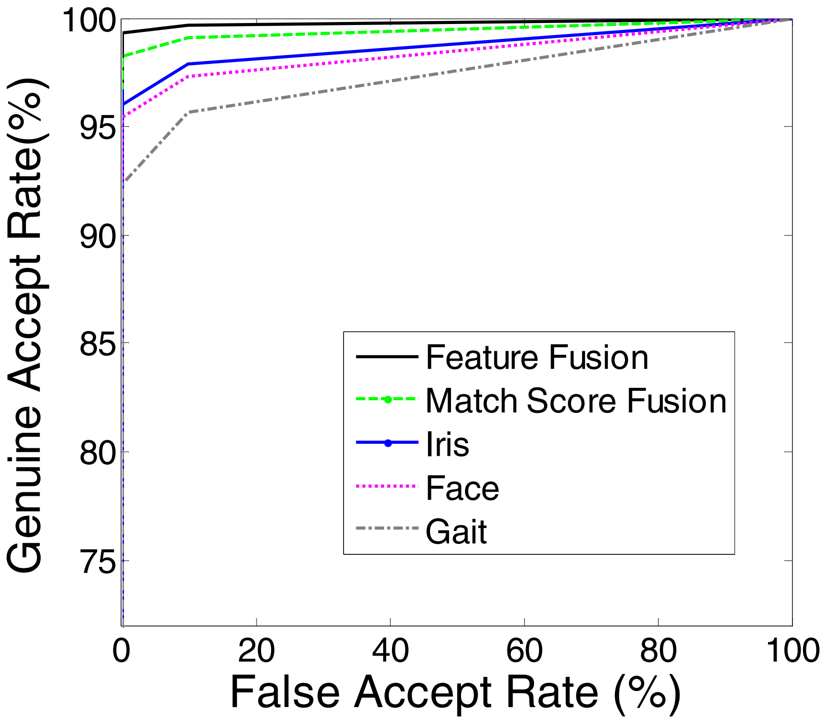

Fig. 6. ROC curve shows the comparison of different biometric traits

Table 1. Comparison of different biometrics modalities

Methods	GAR (%) at FAR of 0.001%
Iris Alone	95.13
Face Alone	83.30
Gait Alone	75.00
Match Score Fusion	95.25
Feature Level Fusion	96.40

the proposed feature level fusion scheme. We can observe that feature level fusion of three modalities shows a significant improvement in performance as compared with that of match score level fusion and also with that of individual biometrics with a GAR of 96.40% at FAR=0.001%.

5 Conclusions

In this research effort, we have achieved two performance goals. First, PSO is used to select the subset of informative features. The proposed PSO-based dimensionality reduction method trims down the fused feature space dimension by a factor of roughly 77% while keeping same level of performance as that of the global system. Second, a VLS-based scheme is deployed to enhance the performance of silhouette shape detection method. The proposed VLS method uses significantly larger time step to solve the evolution PDE equation, and therefore, speeds up the curve evolution process drastically. Therefore, the proposed scheme can be deployed in real time applications. In addition, the proposed VLS algorithm performs the accurate localization of the iris regions from degraded eye images, which may be affected by diffusion, non linear deformation, low intensity, poor acquisition process, eyelid and eyelash occlusions and small opening of the eyes. We validate the multimodal system on a virtual multibiometric database and obtain an encouraging performance. It is also found from the experimental results that the fusion of iris, face and gait feature elements at the feature level improves recognition accuracy over the match score level fusion and also, outperforms each of the single biometric traits discussed in this paper.

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