Identification System Based on Iris-Palmprint Fusion

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Summary
Unimodal biometrics systems face a diversity of problems. Multimodal biometric systems are proposed to solve these problems such as background noise and distortion. It used to enhance accuracy of the Identification system. This paper introduces a bimodal biometric recognition system. In this system, two traits are combined such as plamprint and iris. An approach for feature extraction of each modality is proposed by using texture based descriptor the Scale Invariant Feature Transform (SIFT). Different fusion techniques were tested at different levels. In feature fusion level, many feature vectors are used to compose a single feature vector, these features will be concatenated then to reduce the dimensionality of the feature, particle swarm optimization (PSO) is used as a feature selection technique. The proposed algorithm will be applied to the IITD database. By running the voting technique, the proposed system generates excellent recognition results with less selected features.
Key words:
Algorithm, extraction; feature; identification, swarm; voting.

1. Introduction

The iris is a circular, thin construction in the eye, liable for monitoring the size and diameter of the pupil and the quantity of light reaching the retina, contains a unique pattern that can be different under near-infrared lamination. At 10 months of age, the distinctive pattern in the human iris is shaped, and its residues unchanged throughout the lifetime of the human. The iris recognition system becomes significant in the last decades and been used in several applications. This is because the changeability of the iris between different individuals is huge and iris image is somewhat insensitive to angle of illumination and is easy to use due to the circumstance that the iris can be captured in a less invasive manner, Jain et al. [1], Rakshit et al. [2].
In daily life, the most natural tool for the human being is hand to reconstruct and perceive environments. The biometric of palmprint is relatively a new technology that is used to recognize people by their palm features. In fact, the data may be obtained from palmprint with low cost devices and a nominal support from subjects. The palmprint image has many features that can be extracted to recognize a person, such as ridges, principal lines, texture, wrinkles, minutiae points may be cited, Charfi [3].
There are many algorithms for matching available; they all depend on the shape, color, and texture. Exact recognition of individuals can be done by extracting the most discriminating data existing in an iris pattern. The template that is created in the feature encoding procedure will require that an equivalent matching metric, which provides a measure of match between two templates of iris , Masek [4]. The first one was dealing with the idea of the iris recognition. It was established by Flom and Safir [5]. In 1994, the professor John Daugman developed protecting the iris-code approach. The procedure of iris recognition begins with the iris segmentation then the transformation of the data to a 2-D polar coordinate system through the Rubber Sheet process, which is proposed by the Daugman. The feature extraction process can be divided into three variants: the zero-crossing variant, the phase-based variant, Daugman [6], and the texture analysis methods variant, Daugman [7]. Daugman [8] extracted texture phase-based information by using multi-scale quadrature wavelets to get the signature of the iris with 2048 binary components, Daugman [9].
Boles and Boashash [10], the researchers used a zero-crossing technique, which represent the one-dimensional wavelet transform at diverse levels of resolution to describe the texture of the iris. Wildes [11], used Laplacian pyramid to represent the iris texture which is constructed with four dissimilar resolution levels, and to decide whether the input image and the model image are both from the same class, they used the normalized correlation. Tisse et al. [12] analyzed the iris's characteristics using the Hilbert transform to construct analytic image using the original image and its transform. Tangsukson and Havlicek [13] and Havlicek et al. [14] sampled binary emergent frequency functions to form a feature vector and used Hamming distance for matching. Park et al. [15] used eight directional sub band that obtained by using a directional filter bank to decompose the iris image and extracted the normalized directional energy as features. To measure the consistency of iris images from the same eye, Kumar et al. [16] utilized correlation filters. Hong and Smith [17], Hong and Smith suggested the octave band directional filter banks which are capable of both an octave band radial decomposition and directional decomposition.
Contourlet transform is used to extract the directionality features from iris images that have textures with smooth contours. The contourlet transform achieves better performance than the wavelet transform by capturing the image singularities. Lowe [18] and Bicego et al. [19], Laplacian pyramidal decomposition of images is applied, Bicego et al. [19]. For extracting the angular information, the band pass output result at several levels of Laplacian

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pyramids are analyzed using Directional Filter Banks (DFB), Walha et al. [20]. The conventional contourlet transform will have redundancy due to the redundancy nature of Laplacian pyramidal representation of images that bounds the usage of contourlet transform for image compression Walha et al. [20], Chen and Moon [21].

Lowe [18] proposed Scale Invariant Feature Transform (SIFT) as a feature extraction technique. Lowe used it to extract local feature points from an image. It became well appeared for pattern recognition process, Charfi et al. [22], and object detection. Charfi et al. [23] merged palm print and hand shape features extracted using the Scale Invariant Feature Transform (SIFT) and used it in a new approach for personal verification. These experiments on IITD hand database establish promising outcomes by fusing at matching level score. To extract palm print features, Chen et al. [24] fused Symbolic Aggregate Approximation (SAX) features and Scale Invariant Feature Transform (SIFT) descriptors. To improve precisions, combining SIFT and competitive code cores for palm print verification exposed the strength of local invariant features fusion, Zhao et al. [25].

Sparse representation method is proposed in Charfi et al [23], which is applied to a touch less palm print images. Using Scale Invariant Feature Transform (SIFT) descriptors and Sparse representation to excerpt palm print features. The fusion scheme at rank level is established to produce the final identity of an individual using Support Vector Machines (SVM) classifier and probability distribution. Experiments evaluated on CASIA palm print database and a proposed touch less REST (REgim Sfax Tunisia) hand database. The results are competitive with other palm print identification methods. In Charfi et al. [22] SIFT are concern with the localization of key points on the contour of the hand in order to describe the shape of the hand. To enhance as much as possible the number of matched key points and reduce false matches. Two levels of SIFT matching refinement of hand shape process and one level for palm print process were used. The experiments were assessed on 1150 hand images of IITD hand database [26], acquired from 230 subjects. The gained results are promising and competitive to other biometric systems based on hand images. In Charfi et al. [3], to represent images with high discrimination, a local sparse representation method was implemented. Fusion at feature and decision levels was performed to generate the identification rate of the bimodal system. Two hand databases: Indian Institute of Technology of Delhi (IITD) hand database and Bosphorus hand database are used in the experiments. The correct identification rate reaches 99.57% that is competitive compared to current systems.

Jain and Ross [27] fuse the evidence of three different fingerprint matchers to determine the resemblance between two particulars sets using the Hough transform. Han used the palm print image to extract the seven indicated line profiles and three fingers as well and used wavelets to calculate low-frequency information, Han [28]. In a multi-biometric system, fusion is carried out at the abstract or decision level when the decisions obtained by the separate biometric matchers are available in Dong et al. [29]. Methods for decision level fusion using "AND" and "OR" rules in Fogel and Sagi [30], majority voting in Jaswal et al [31], weighted majority voting in Kekre et al. [32], Bayesian decision fusion and behavior knowledge space in Jain and Ross [1].

In this research, we introduce a new bimodal biometric system in which iris and palm print biometric modalities are merged. SIFT descriptor was extracted from both iris and palm print images for personal recognition. Since SIFT method is invariant to image transformations in Charfi et al. [3], preprocessing task is not essential to extract features. The comparison score between training and testing images from IITD database is calculated.

Kennedy and Eberhart [33, 34, 35] proposed PSO that is a computational model established on the theory of cooperative performance and swarming which inspired by the fish schooling behavior and the behavior of bird flocking. In recent times, PSO has been applied as an effective optimizer in a lot of fields like wireless network optimization, artificial neural networks, linear constrained function optimization, and data clustering, Ramadan and Abdel-Kader [36]. In this paper, Particle Swarm Optimization (PSO) is addressed for reduction the number of features by using it as a feature selection technique. The proposed algorithm is applied to IIT Delhi Database [37] and its performance will be compared with iris recognition algorithms found in the literature.

2. Methodology

The block diagram of the proposed system is shown in figure 1. The left hand segmented ROI palm print of IITD database is used in this paper. This database contains 230 subjects, five images for each with size 150x150 pixels in grayscale. For iris images, IIT Delhi Iris Database [37] (Version 1.0) is used.

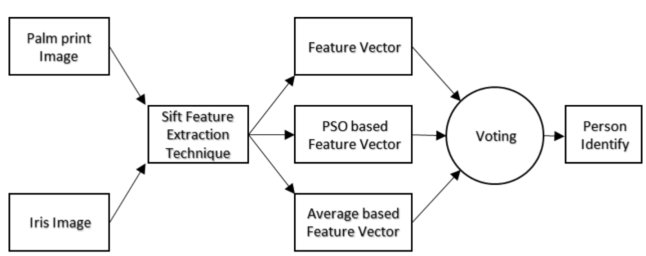

Fig. 1 Block diagram of the proposed system.

2.1 Scale Invariant Feature Transform (SIFT)

Feature extraction is the procedure of extracting the iris features; this process was employed by Scale Invariant Feature Transform in Charfi et al. [3] to extract constant local feature points from the input image. This is reached by selecting key locations in scale space using local minima and maxima of a difference of Gaussian function. Matching each pixel to its neighbors is used to conclude maxima and minima of this scale space function in Elgallad et al. [38] as in (1), (2), and (3).

$$L(a, b, \sigma) = G(a, b, \sigma) * I(a, b) \quad (1)$$

Where I (a, b) is the original image, L(a, b, σ) is the scale space, and G(a, b, σ) is a variable scale function which is defined as:

$$G(a, b, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(a^2+b^2)/2\sigma^2} \quad (2)$$

In addition, the Gaussian difference scale space is defined as:

$$\begin{aligned} D(a, b, \sigma) &= (G(a, b, k\sigma) - G(a, b, \sigma)) * I(a, b) \\ &= L(a, b, k\sigma) - L(a, b, \sigma). \end{aligned} \quad (3)$$

When extreme point locations are identified, the key points that are insensitive to noise and invariant to affine transformations must be considered.
The direction can be calculated in that section as in (4), (5).

$$m(a, b) = \sqrt{\left(L(a+1, b) - L(a-1, b)\right)^2 + \left(L(a, b+1) - L(a, b-1)\right)^2} \quad (4)$$

$$\theta(a, b) = \tan^{-1}\left(\frac{L(a,b+1)-L(a,b-1)}{L(a+1,b)-L(a-1,b)}\right) \quad (5)$$

Where θ (a, b) is the orientation of the key point.

2.2 Particle Swarm Optimization (PSO)

PSO is implemented to answer an optimization problem. For an optimum solution, a swarm of elements, called particles, is used to discover the solution space, Kennedy and Eberhart [33, 34, 35]. Each computation element, or particle, denotes a candidate solution that identified with coordinates in the M-dimensional search space. The position of the jth particle is represented as Yj = (yj1, xj2,…..,xjM). Vj = (vj1, vj2,…,vjM) represented the velocity of an element. The calculation of the fitness function is performed and is matched to the fitness of the finest preceding result for that similar particle and is compared to the fitness of the finest particle. Then, the two best values are determined and the particles are evolved by upgrading their positions and velocities as in (6).

$$V_i^{t+1} = \omega * V_i^t + C_1 * rand_1 * \left(p_{i_{pest}} - y_i^t\right) + C_2 * rand_2 * (g_{best} - Y_i^t) \quad (6)$$

$$Y_i^{t+1} = Y_i^t + V_i^{t+1}$$

Where the size of the swarm is N ; the particle best reached solution is pi _best is and i = (1, 2 …N) and gbest is considered the global best solution. c1 and c2 are Cognitive and social parameters bounded between 0 and 2. rand1 and rand2 are two uniform distribution random numbers U(0,1).

$$-V_{max} \le V_i^{t+1} \le V_{max}$$

Where Vmax is the maximum velocity.
To control the stability of the search algorithm between exploration and exploitation, the inertia weight ω is used. To reach the termination condition (maximum number of iterations K), the recursive levels will continue.

2.3 Feature Selection Using Binary PSO

In Kennedy and Eberhart [35] and Daugman [9], a binary PSO algorithm has been established. In the binary version of the algorithm, the location of the particle is coded in the formula of a binary string that emulates the chromosome. The probability distribution for the position equation is the velocity of the particle. The updates equation becomes as in (7).

$$\begin{aligned} &If \;\; rand_{3<\frac{1}{1+e^{-v_i^{t+1}}}} \;\; then\; Y_i^{t+1} = 1; \\ &else\; Y_i^{t+1} = 0 \end{aligned} \quad (7)$$

When the bit value is 1 in the position vector shows that this feature is selected to be an essential feature for the new generation, Kennedy and Eberhart [35].
A binary PSO algorithm will be deployed for feature selection to select the most demonstrative features subset in the extracted features.

2.4 Fusion in Feature Level

In order to improve the efficiency of unimodal biometric systems, multimodal methodologies for personal recognition have developed rather than using a single biometric feature, Alsaade et al. [39], Chang et al. [40], Shu and Zhang [41]. In feature fusion level, many feature vectors are used to compose a single feature vector, Shu and Zhang [41]. In feature level fusion, the evidence of two biometric feature sets of the same individual are fused. Kumar [42]. A simple method would be to compute the average of the feature vectors and use the average feature vector as the new template. In this paper, we introduced a new technique for feature fusion level using PSO to select the most representative feature subset through the extracted feature vectors.

2.5 Cross Validation

In the proposed system, SVM is used as a classifier. SVM is founded on cross-validation technique. Predictive models are estimated by distributing the original sample as two sets, a training set and a testing set.
The Structural Risk Minimization (SRM) is considered the base of SVM that depends on constructing a maximal separating hyperplane. This process maps the input vector to a higher dimensional space. In this research, the suggested system has 230 classes and SVM classifier as multi-class linear classifier is used as in Elgallad et al. [38].

$$\begin{aligned} \min_{w,\xi_n} &= \frac{1}{2} w^T w + C \sum_{n=1}^{N} \xi_n \\ s.t. \quad & w^T x_n t_n \geq 1 - \xi_n \qquad \forall_n \\ & \xi_n \geq 0 \qquad \forall_n \end{aligned} \tag{8}$$

where the slack variables are ξn , the vector of coefficients is w , and the capacity constant is C.
The unconstrained optimization problem as in (9)

$$min_w = \frac{1}{2}\, w^T\, w + C\, \sum_{n=1}^{N} \max(1 - w^T\, x_n\, t_n\, , 0) \tag{9}$$

L2-SVM minimized the squared hinge loss Because of the non-differentiability of L1-SVM as in (10):

$$min_w = \frac{1}{2}\, w^T\, w + C\, \sum_{n=1}^{N} \max(1 - w^T\, x_n\, t_n\, , 0)^2 \tag{10}$$

The class label of a test data x can be predicted as following:

$$arg_t \max(w^T x)\, t \tag{11}$$

For multiclass problem, SVMs is extended which is used in Elgallad et al. [38]. Representing the output of the k-th SVM as in (12)

$$a_k(x) = w^T x \tag{12}$$

2.6 Score Fusion

The voting process, Elgallad et al. [38], be influenced by the membership probability array of the class that was obtained from SVM classifier. In this approach, the index of the maximum value of each column of this array is extracted. This value is used to identify human identity for each feature vector.

$$Y_{k,i} = arg_i \max_{i=1}^{n} (X_{q,i}) \tag{13}$$

Where Y is a matrix that contains the labels of the test images, X is the class membership probability matrix. The Y matrix has n images with q features for each one that extracted during the fusion process.
By running the voting technique, the most frequent values in the output array Y are found.

$$K = mode(Y_{q,i}) \tag{14}$$

Where K is the class number matrix of the test images.

3. Results and Discussion

The fusion in the feature level proposed in this paper is based on using binary PSO algorithm that has been developed in Kennedy and Eberhart [34]. The task of PSO is to look for the most descriptive subset of features by applying the proposed algorithm. The fitness function is used to guide the search heuristics in PSO defined in terms of maximizing class separation.
The Database used in this paper is the IIT Delhi Database version 1.0 for both palm print images and iris image. The touchless palmprint images were saved in bitmap format and contains both left and right-hand images for 230 subjects. Automatically segmented and normalized palm print regions are also made available, in addition to the acquired whole hand images. IITD database contains ROI which is segmented is used in this paper. The number of classes is 230 with five images in each one with size 150x150 pixels in grayscale. The currently available database for iris images is from 224 users, in bitmap format. This database consists of 176 males and 48 females' images that arranged into 224 folders each have an integer identification.
The proposed system generates excellent recognition results with less selected features (1010 features). The features number has been reduced by 50% from its original number in feature level fusion without PSO (2048) as shown in table 1. While computing the difference between the images, the new feature vector, with the less selected features, will decrease the computation time and increase its performance. The proposed algorithm achieves 99.55 % recognition rate. After applying fusion at score level (voting process), the overall recognition rate is 99.78%

Table 1: Comparison of recognition rates and number of features for various fusion levels

Descriptor	DB	Features	RR SVM	Voting
SIFT	Iris IITD	1024	98.44%	99.78%
SIFT	Palm IITD	1024	97.32%	
fusion		2048	100.00%	
fusion ave.		1024	99.78%	
fusion PSO		1010	99.55%	

4. Conclusions

In this paper, Scale Invariant Feature Transform (SIFT) is used to extract features for both iris and palm print images. For fusion in feature level, the PSO-based feature selection algorithm is used. It searches within the feature space for the optimal feature subset. The proposed algorithm was found to produce comparable recognition results of 99.55% with less number of selected features and its performance is compared with the performance of average feature vector method. The use of fusion in feature level is hereby recommended for all firms and industries where security and personal identification is favorite. Using voting at decision level improves the recognition rate to 99.78%. Our experimental results show the efficiency of the recommended system.

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