Particle Swarm Optimization based Iris Recognition System

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***Abstract*— Biometrics-based human authentication systems are becoming critical as governments and corporations worldwide use them in systems like access and border control, time and attendance, driving license registration, and national ID cards systems. The iris is a powerful contender alongside face and fingerprints for involvement in multimodal recognition systems. Regularly, the iris image has low contrast and non-uniform illumination; this is due to the position of the light source. All these factors could be compensated by the image enhancement algorithms. Feature extraction is the process of obtaining the iris features. In this paper we introduced an algorithm to select the most representative feature subset through the extracted features using Particle Swarm Optimization (PSO). The binary PSO algorithm's task is to look for the most representative feature subset through the extracted features. This paper aims for Improvement to Libor Masek Algorithm using PSO as a feature selection technique by applying the proposed algorithm to CASIA-IrisV4 data base and comparing its performance with various iris recognition algorithms found in the literature.**

***Keywords*—** *iris recognition; Particle Swarm Optimization; feature extraction; Feature selection; Receiver Operating Characteristic curve.*

I. INTRODUCTION

The iris, the colored part of the eye that circles the pupil, consists of unique patterns that can be distinguished under near-infrared lamination. These patterns are the same since childhood and never change; they bar trauma or diseases and allow precise identification with a very great standard of reliability. A recognition system based on the iris became important in the last decades and been used in multiple applications. This is because the iris is found to be more dependable because its structure is unique to every individual, doesn't change with age, iris pattern changeability between different individuals is huge and iris image is relatively insensitive to angle of illumination and is also comfortable to use due to the fact that the iris can be captured in a less invasive demeanor [1], [2].

Commercial iris systems are deployed in applications such as access to secure facilities or other resources; they are also deployed in criminal/terrorist identification. Enrolling an individual into a commercial iris system requires capturing one or more images from a video stream. In general, the database for such systems does not contain actual iris images, but instead it stores a binary file that represents each enrolled iris (the template). The created template is called an IrisCode. The template is stored as 512 bytes per eye. Once the template is created, the iris image is discarded.

Ophthalmologists were the first to recognize the fact that human iris patterns can be used for personal identification [2]. John Daugman [2] who devised an algorithm exploiting integro-differential operators and Gabor filters, developed the first iris recognition software. The inner and outer boundaries of the iris were detected by the differential operators and Gabor filters were used to extract unique binary vectors constituting the iris code from the local texture phase information [3, 4]. The average Hamming distance between two codes was considered for matching. Many other techniques as referred to in [6] were developed that attained similar performances. Most of these techniques consider single metric or criterion to identify an authentic person from an impostor.

Libor Masek [6] developed an algorithm to automatically segment the iris region from an eye image then an implementation of Daugman's polar representation [3] was used to normalize the iris region in order to counteract imaging inconsistencies such as pupil dilation. This normalized iris pattern was convolved with 2D Gabor wavelets in order to extract features.

PSO proposed in the year 1995 by Dr. Eberhart and Dr. Kennedy, is a computational paradigm based on the concept of collaborative behavior and swarming in biological populations inspired by the social behavior of fish schooling and also the social behavior of bird flocking [7-9]. Recently PSO has been applied as an effectual optimizer in a lot of domains like training artificial neural networks, linear constrained function optimization, wireless network optimization, and data clustering [10].

This paper addresses for Improvement to Libor Masek Algorithm using Particle Swarm Optimization (PSO) as a feature selection technique by applying the proposed algorithm to CASIA-IrisV4 data base and comparing its performance with various iris recognition algorithms found in the literature.

The paper is organized as follows; in section 2, we discuss previous work on iris recognition; section 3 motivates and gives a theoretical grounding to stages of iris recognition systems; in Section 4, we illustrate the particle swarm optimization (PSO) algorithm in detail; section 5 illustrates the improvements to Libor Masek Algorithm; in section 6 we illustrate the system evaluation and its results, and finally, section 7 discusses the results and concludes the paper.

II. RELATED WORK

There are various algorithms for matching available; they all basically depend on the shape, color and texture. Precise recognition of individuals can be done by extracting the most discriminating information present in an iris pattern. Only the significant features of the iris must be encoded so that comparisons between templates can be made. The template that is generated in the feature encoding procedure will also need an equivalent matching metric, which gives a measure of similarity between two iris templates [11]. The first one is the pioneer patent dealing with the general idea of the iris recognition process. It was developed by the ophthalmologists Flom and Safir (1987) [12] and it expired back in the year 2005. The second one, developed by the professor John Daugman (1994), was used to protect the iris-code approach and expired back in the year 2011. The iris recognition process begins with the segmentation of the iris ring, after that, data is transformed into a double dimensionless polar coordinate system, this is done through the Daugman's Rubber Sheet process. Regarding the feature extraction stage, existing approaches can be roughly divided into three variants: the phase-based variant [14], the zero-crossing variant [14] and the texture analysis methods [15] variant. Daugman [13] used multi-scale quadrature wavelets to extract texture phase-based information and obtain an iris signature with 2048 binary components.

Boles and Boashash [16] calculated a zero-crossing representation of one-dimensional (1-D) wavelet transform at different resolution levels of a concentric circle on an iris image to characterize the texture of the iris. Wildes et al. [17] represented the iris texture with a Laplacian pyramid constructed with four different resolution levels and used the normalized correlation to determine whether the input image and the model image are both from the same class. Tisse et al. [18] analyzed the iris's characteristics using the analytic image constructed by the original image and its Hilbert transform. Emergent frequency functions for feature extraction were in essence samples of the phase gradient fields of the analytic image's dominant components [19], [20]. Similar to the matching scheme of Daugman, they sampled binary emergent frequency functions to form a feature vector and used Hamming distance for matching. Park et al. [21] used a directional filter bank to decompose an iris image into eight directional subband outputs and extracted the normalized directional energy as features. Iris matching was done by computing Euclidean distance between the input and the template feature vectors.Kumar et al. [22] utilized correlation filters to measure the consistency of iris images from the same eye. The correlation filter of each class was designed using the two-dimensional. In [23], Hong and Smith proposed the octave band directional filter banks which are capable of both directional decomposition and an octave band radial decomposition.

For effectual storage and retrieval of eye image with iris, an effectual compression algorithm would have to be developed. Contourlet transform is one of the directional transforms which can efficiently extract the directionality features with multi resolution capability from images that have textures with smooth contours. The contourlet transform outperform the wavelet transform in terms of capturing the singularities found in images. In the conventional method used for contourlet transformation [24], a Laplacian pyramidal decomposition of images is implemented in the first stage [26]. The band pass output result at various levels of Laplacian pyramids are analyzed using Directional Filter Banks (DFB) for extracting the angular information [27] but, due to the redundancy nature of Laplacian pyramidal representation of images, the conventional contourlet transform will have redundancy as well. This redundancy of conventional contourlet representation limits the usage of contourlet transform for image compression applications [27], [28].

Kulkarni [29] addresses for improvement to Libor Masek algorithm of template matching method for iris recognition [6] .The proposed algorithm is an improvement over an existing algorithm in terms of its performance and efficiency over metric, template creation, is about 10%, matching time, is about 99% and the difference between the images (False Rejection), is about 10%. Algorithm is tested by using about 100 images of CASIA iris image database version 1.0 and version 3. The proposed algorithm shows an overall improvement over Libor Masek algorithm. This paper addresses for Improvement to Libor Masek Algorithm also using Particle Swarm Optimization as a feature selection technique by applying the proposed algorithm to CASIA-IrisV4 data base and comparing its performance with various iris recognition algorithms found in the literature.

III. STAGES OF IRIS RECOGNITION SYSTEM

Image processing techniques can be employed to extract the unique iris pattern from a digitized image of the eye, and encode it into a biometric template, which can be stored in a database. This biometric template contains an objective mathematical representation of the unique information stored in the iris, and allows comparisons to be made between templates. When a subject wishes to be identified by iris recognition system, their eye is first photographed, and then a template is created for their iris region. This template is then compared with the other templates stored in a database until either a matching template is found and the subject is identified, or no match is found and the subject remains unidentified [6]. There are four main stages of an iris recognition and compression system. They are: image preprocessing, feature extraction, feature selection, and template matching [29].

A. *Image preprocessing*

The iris image is to be preprocessed to get the useful iris region. Image preprocessing consists of two steps; the first is iris localization. Iris localization detects the inner and outer boundaries of iris [5], [31]. The second step is iris normalization; in this phase, the iris image is converted from Cartesian coordinates to Polar coordinates. Figure 1 demonstrates the output of the segmentation process using Masek algorithm.

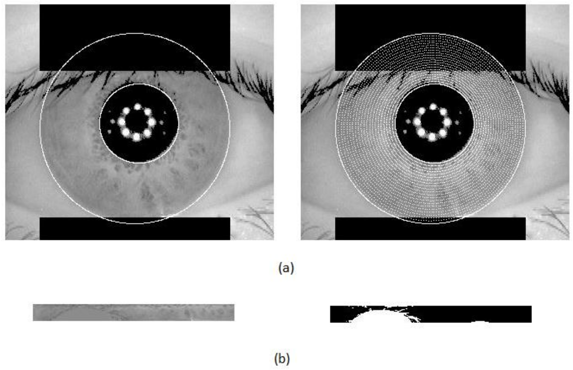

Fig. 1. *Example the output of the segmentation process using Masek algorithm. (a) Automatic segmentation of an iris image from the CASIA database. Black regions denote detected eyelid and eyelash regions. (b) Illustration of the normalization process (polar array – noise array)*

B. Feature Extraction

Feature extraction is the process of getting the iris features, this process was implemented by convolving the normalized iris pattern with 1D Log-Gobor wavelets [6].

C. Feature Selection using PARTICLE SWARM OPTIMIZATION (PSO)

PSO proposed by Dr. Eberhart and Dr. Kennedy back in the year 1995 is a computational paradigm based on the concept of collaborative behavior and swarming in biological populations inspired by the social behavior of fish schooling and also the social behavior of bird flocking [7-9]. Recently PSO has been applied as an effectual optimizer in a lot of different domains like training artificial neural networks, linear constrained function optimization, wireless network optimization, and data clustering.

D. Template Matching using Hamming Distance

Template matching compares the user template with templates found in the database by using a matching algorithm. The matching metric will provide a measure of similarity between the two iris templates. Finally, a decision with a great confidence level is made through matching methods to check whether the user is an authentic or a pretender. The Hamming distance gives a measure of how many bits are similar between two bit patterns. Using the Hamming distance of two bit patterns, a decision can be made as to whether the two patterns were produced from the same iris or from different ones. Two iris codes produced from the same iris will be highly correlated, that means bit patterns will be interrelated. If bit patterns are generated from two different iris, and not the same one, then each iris produces a completely different bit pattern. Hence, for such a bit pattern the Hamming distance should equal 0.5. This occurs due to the fact that independence implies that the two bit patterns will be totally random, so there is fifty percent chance of setting any bit to 1, and vice versa. Therefore, half of the bits will agree and half will not agree between the two patterns. If the two patterns are derived from the same iris, the Hamming distance between them will be close to 0.0, since they are highly interrelated and all the bits should agree between the two iris codes [32], [33], [6].

Let X and Y be the bit patterns to compare the Hamming distance, HD, is defined as the sum of disagreeing in the bit pattern.

$$HD = \frac{1}{N\sum_{j=1}^{N} x_j (XOR) y_j} \quad (1)$$

IV. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

When PSO is applied to answer an optimization problem, a swarm of computational elements, called particles, is used to explore the solution space for an optimum solution. Each computation element, or particle, represents a candidate solution and is identified with explicit coordinates in the D-dimensional search space. The position of the i–th particle is represented as Xi = (xi1, xi2,…..,xiD). The velocity of a particle (the rate of the change in position between the current position and the next) is denoted as Vi = (vi1, vi2, ……..,viD). The fitness function is then evaluated for each particle in the swarm and is then compared to the fitness of the best prior result for that same particle and is also compared to the fitness of the best particle between all particles in the swarm. After finding the two best values, the particles are evolved by updating their velocities and positions according to the following equations:

$$V_i^{t+1} = \omega * V_i^t + C_1 * rand_1 * \left(p_{i_{pest}} - X_i^t\right) + C_2 * rand_2 * (g_{best} - X_i^t)$$
$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (2)$$

Where i = (1, 2,… N) and N is the size of the swarm; p i_best is the particle best reached solution and gbest is the global best solution in the swarm c1 and c2 are cognitive and social parameters that are bounded between 0 and 2. $rand_1$ and $rand_2$ are two random numbers, with uniform distribution U(0,1).

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

(Vmax is the maximum velocity). The inertia weight ω, is a factor used to control the balance of the search algorithm between exploration and exploitation. The recursive steps will go on until we reach the termination condition (maximum number of iterations K).

A. Binary PSO and Feature Selection

A binary PSO algorithm has been developed in [34]. In the binary version, the particle's position is coded in the form of a binary string that mimics the chromosome in a genetic algorithm. The particle velocity function is used as the probability distribution for the position equation. The equation that updates the particle position becomes the following:

$$If\ rand_3 < \frac{1}{1+e^{-v_i^{t+1}}}\ then\ X_i^{t+1} = 1\ ; else\ X_i^{t+1} = 0 \quad (3)$$

A bit value of {1} in any dimension in the position vector indicates that this feature is selected as a required feature for the next generation, whereas a bit value of {0} indicates that this feature is not selected[8]

A binary PSO algorithm will be deployed for feature selection. The task of the binary PSO algorithm is to look for the most representative feature subset in the extracted features by applying the proposed algorithm to the selected database and comparing its performance with various iris recognition algorithms found in the literature.

V. LIBOR MASEK ALGORITHM

Libor Masek algorithm is an open-source iris recognition system in order to confirm both the uniqueness of the human iris and to also confirm its performance as a biometric [6]. In his paper [6], a technique uses the extension of Hamming distance, since bit-wise comparison is essential, Hamming distance and Libor Masek algorithms are used for matching. The Hamming distance algorithm used also includes noise masking, this means that only significant bits are used in calculating the Hamming distance between two iris templates. In Hamming distance, the only bits that will be used in the calculation are those bits in the iris pattern that correspond to '0' bits in noise masking of both iris patterns. Only the bits generated from the true iris region will be used to calculate the Hamming distance, and the modified Hamming distance formula is given by Libor Masek [6], [29].

$$HD = \frac{1}{N-\sum_{k=1}^{N} X_{n_k}\ (OR) Y_{n_k}} \sum_{j=1}^{N} X_j\ (XOR)\, Y_j\ (AND) X'_{n_j}\ (AND) Y'_{n_j} \quad (4)$$

Where X_j and Y_j are the two bit-wise templates to compare, Xn'_j and Yn'_j are the corresponding noise masks for X with logical negation and N is the number of bits represented by each template. And Xn_k and Yn_k are noise mask bits. To address for rotational inconsistencies, bit-wise shift is incorporated, when the Hamming distance of two templates is calculated, one template is shifted left and right bit-wise and a number of Hamming distance values are calculated from successive shifts. This bit-wise shifting in the horizontal direction corresponds to rotation of the original iris region by an angle. If an angular resolution of 180 is used, each shift will correspond to a rotation of 2 degrees in the iris region. This method is suggested by Daugman, and corrects for misalignments in the normalized iris pattern caused by rotational differences during imaging [6].For the matching of templates, only the lowermost values of Hamming distance values is taken, this is because this corresponds to the best match between two templates [6], [29].

A. *Improvement to Libor Masek Algorithm*

Even though, in theory, two iris templates produced from the same iris will have a Hamming distance of 0.0, in practice this will not be the case. Normalizations are not perfect, and also there will be some noise present in the iris which will be undetected, so some difference will be present when comparing two intra-class iris templates [31]. Kulkarni et al. [29] states that, the comparison of Libor Masek algorithm and their algorithm is grounded on a number of significant bits and non-significant bits. Significant bits are represented by 1's and non-significant bits are represented by 0's. While computing the difference between the images, if only the significant bits are taken into account, then the size of the bits will decrease thereby decreasing the computation time and increasing its performance. The proposed algorithm in [31] was evaluated using CASIA iris image.

$$HD = \frac{1}{N-\sum_{k=1}^{N} X_{n_k}\ (AND) Y_{n_k}} \sum_{j=1}^{N} X_j\ (XOR)\, Y_j\ (AND) X'_{n_j}\ (AND) Y'_{n_j} \quad (5)$$

VI. EXPERIMENTAL RESULTS

The comparison of Libor Masek algorithm and the proposed algorithm is based on using binary PSO algorithm that has been developed in [10] . The binary PSO algorithm's task is to look for the most representative feature subset through the extracted features by applying the proposed algorithm to the selected feature vectors extracted. The search heuristics in PSO is iteratively adjusted guided by a fitness function defined in terms of maximizing class separation.

The CASIA-IrisV4 database was used to evaluate the performance of the proposed system. CASIA- IrisV4 is said to be an extension of CASIA-IrisV3 and contains six subsets. It contains a total of 54,601 iris images from more than 1,800 genuine subject and 1,000 virtual subjects. All iris images are 8 bit gray-level JPEG files. The proposed algorithm was evaluated using CASIA-Iris-Interval. There are 792 iris images from 198 different irises. For each eye, 7 images are captured. The proposed algorithm is also evaluated by comparing the result with the improvement to Libor Masek Algorithm of the template matching method proposed by Kulkarni [29]

The proposed algorithm was found to generate excellent recognition results with less selected features (4778 features) than Libor Masek algorithm (9600 features), the features number has been reduced by 50% from its original number 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.

To measure the effectiveness of the proposed feature selection technique and to assess its impact on the system's verification and identification performance, a biometric system can work in two modes, which must be distinguished during evaluation: verification and identification. In the verification mode, a user presents his identity and the biometric device verifies that the identity matches. In the identification mode, no assumption of identity is made in the beginning and comparison to all templates has to be made. It is therefore necessary to distinguish between these two situations, because identification is generally more demanding.

TABLE I. COMPARISON OF RECOGNITION RATES AND NUMBER OF FEATURES FOR VARIOUS IRIS RECOGNITION ALGORITHMS

Method	Recogniti on Rate	Number of feature
Libor Masek algorithm	99.6%	9600
Improvement to Libor Masek Algorithm of template matching method proposed by S.B.Kulkarni	97.9%	9600
Proposed Algorithm using PSO	96.7%	4778

Let's assume that you are evaluating a verification mode of a biometric system which assigns all authentication attempts a score from interval [0, 1]. 0 means no match and 1 means full match. Obviously, if you set your threshold to 0, all genuine users are admitted, but all impostors are admitted also. On the other hand, if you set your threshold to 1, no one is admitted. So for real usage, you usually set the threshold somewhere between. This might cause, that not all genuine users are admitted and some impostors are admitted. As you can see, there are two error rates: FAR (False Accept Rate) and FRR (False Reject Rate). FAR is calculated as a fraction of impostor scores exceeding your threshold. FRR is calculated as a fraction of genuine scores falling below your threshold.

Receiver Operating Characteristic (ROC) or Neyman-Pearson curve is used to test distance measure. From Figure 2, it is clear that the distance measure for the system with PSO is performed better than without PSO.

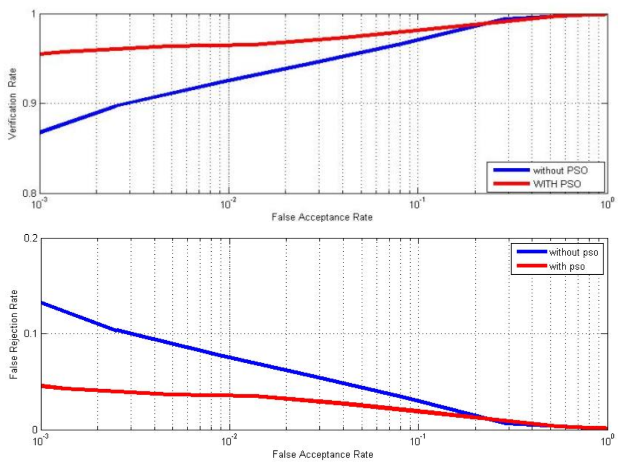

Fig. 2. *ROC curves of the PSO feature selection method for distance measure*

VII. CONCLUSIONS AND RECOMMENDATIONS

The accuracy of iris recognition is dependent on the performance of the iris segmentation and matching method [7]. In this paper, PSO-based feature selection algorithm for iris recognition is used. The algorithm is applied to feature vectors extracted by 1D Log-Gobor wave. The algorithm searches within the feature space for the optimal feature subset. Evolution is driven by a fitness function defined in terms of class separation.

The classifier performance and the length of the selected feature vector were considered for performance evaluation using the CASIA-IrisV4 data base. Experimental results show the superiority of the PSO-based feature selection algorithm in generating excellent recognition accuracy with the minimal set of selected features.The performance of the proposed algorithm is compared with the performance of Libor Masek algorithm [6] and to the improvement to Libor Masek Algorithm of template masking method proposed by S.B.Kulkarni [29] and was found to yield comparable recognition results with less number of selected features. In view of the aforementioned in this paper, the use of iris recognition is hereby recommended for all firms and industries where security and personal identification is desired. However, to improve on iris recognition, the algorithms that were used in feature extraction and feature selection may be deployed to achieve an improvement over existing algorithms in terms of its performance and efficiency.

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