Comparing Feature and Matching Score Fusion Levels of Multimodal Biometrics Recognition System using Particle Swarm Optimization

Mohammed Safy Moussa, Ola Mohammed Ali

Egyptian Academy for Engineering & Advanced Technology, Egypt.

Abstract

Multimodal biometric systems which fuse information from a number of biometrics are most spreads lately because they are able to overcome problems in unimodal biometric systems. Most of the proposed multibiometric systems offer one level of fusion. In this paper, a comparison between two levels of fusion has been proposed: a proposed fusion system of three biometrics at the feature level based on Particle Swarm Optimization approach (PSO) is presented with a new multi objective fitness function for PSO has been used. Also the score level fusion rule is optimized using (PSO) Particle Swarm Optimization. Results shown that matching score fusion outperforms matching score fusion in one multimodal system (palmprint_Knuckle), while matching score fusion outperforms feature fusion in the other two systems.

Keywords: Multimodal biometric; feature level fusion; Matching score fusion; PSO; irsi; palmprint; finger-knuckle

I. INTRODUCTION

The unimodal biometric systems are faced with a variety of problems, noise in sensed data, non-universality, inter-class similarities, and spoof attacks. Multibiometrics overcomes these problems besides enhancing matching accuracy. The multibiometric systems have many advantages over traditional unibiometric systems. They address the issue of non-universality. It becomes increasingly difficult (if not impossible) for an impostor to spoof multiple biometric traits of an individual. A multibiometric system may also be viewed as a fault tolerant system [1].

Multibiometric systems are categorized into three system architectures according to the strategies used for information fusion [2]:

• Fusion at the feature extraction level: the information extracted from the different sensors are encoded into a joint feature vector, which is then compared to an enrollment template (which itself is a joint feature vector stored in a database) and assigned a matching score as in a single biometric system.

• Fusion at the matching scores level: feature vectors are created independently for each sensor and then compared to the enrollment templates, which are stored separately for each biometric trait. Based on the proximity of feature vector and template, each subsystem now computes its own matching score. These individual scores are finally combined into a total score, which is handed over to the decision module.

• Fusion at the decision level: a separate authentication decision is made for each biometric trait. These decisions are then combined into a final vote.

Fusion at the feature level is a challenging task due to a variety of reasons. Most feature sets gathered from multiple modalities may be incompatible. Moreover, concatenating several feature vectors may lead to construct a relatively large feature vector. This definitely increases the computational and storage resources demands and eventually requires more complex classifier design to operate on the concatenated data set at the feature level space [3].

The binary particle swarm optimization (PSO) algorithm proposed in [4] is applied to perform feature selection. Certainly PSO based feature selection has been shown to be very efficient in optimizing the feature selection process in large scale application problems [5]. PSO also used in other fusion levels like matching score level. The PSO is used to optimize the selection of score level combination rules, its corresponding parameters, and the decision threshold.

II. RELATED WORKS

Farmanbar & Toygar [6] employed a method that made use of various fusion schemes which were feature-level based also of match score level fusion in order to enable proving a robust system of recognition. They used face and palm-print systems of. A suitable and optimal subset which used palm- print and face extracted features was used for the purpose of selecting features by using backtracking search algorithm. This reduces a computation time minimizing of feature dimension meanwhile achieving a higher performance level. A performance of match score-level fusion was completed by making use of the sum rule method. The results of the experiment were later tested on a virtual multimodal database by a combination of PolyU palmprint databases and FERET face. A noticeable improvement was the result of the proposed approach and it outperformed to a significant level other palmprint and face multimodal systems that were used in the past with a level of 99.17% of accuracy of recognition. This method is rightly compared to other state-of-the-art methods.

Another multimodal biometric system for verification was proposed by Motamed et al [7] which was based on two different features, the ear and palm. They used a feature selection algorithms which was PSO based. Discrete Wavelet
Transform (DWT) and Discrete Cosine Transforms (DCT) were used in this as its two main features. The process of identification for this system was grouped into three phases: capturing of image followed by pre-processing which was followed by the extraction and normalization of the images of the ear and the palm. Then the features were extracted followed by matching fusion. The final step was to make a decision based on both the GA and the PSO classifiers. The results of this experiment showed that this PSO based algorithm for feature selection was able to generate a high degree of accurate recognition results by making use of minimum features that were selected.

Raghavendra & Dorizzi [8] further presented an effective feature scheme of selection with the authentication of biometrics for both multimodal and unimodal systems. AIPSO (Adaptive Inertia Particle Swarm Optimisation) was thereby used for the selection of features of Log Gabor for both the face as well as palmprint modalities both independently and also on fused Log Gabor space of both these modalities for fusion. In case of the final classification for the two schemes the space of projection for the features that are selected with the use of Kernel Direct Discriminant Analysis (KDDA) is considered. The results of the experiment show that the performance of AIPSO in comparison to other techniques likes Adaptive Boosting (AdaBoost), Sequential Floating Forward Selection (SFFS), Normal PSO, Genetic Algorithm (GA) an improvement of 5% and a reduction of 62% compared to the system that was used initially.

Kanhangad et al. [9] have presented a promising approach to the adaptive management of multimodal biometrics to adaptively ensure the desired performance. The authors have proposed an algorithm based on Particle Swarm Optimization (PSO) to optimally combine the individual biometric sensor decisions. The proposed algorithm selected the fusion rule and sensor operating points that minimize a given cost function.

Kumar et al. [10] have introduced an adaptive combination system of multiple biometrics to ensure the optimal performance for the desired level of security using PSO. They have used different biometric combinations (iris, palmprint), (face , speech) and (fingerprint , hand geometry). The experimental results showed that the proposed score-level approach generated fairly stable performance and required smaller number of iterations to generate better performance as compared to the decision level approach.

L. Mezai, F. Hachouf [11] proposed an adaptive multimodal biometric fusion algorithm based on belief functions and PSO. The fusion is performed at the score level, a hybrid PSO is employed to select the best belief function and estimate its parameters. The results provide adequate motivation towards future research in the application of optimization techniques in the belief functions.

Vijaykumar N, Irfan Ahmed M [12] further presented a feature selection algorithm also based on Particle Swarm Optimization (PSO). They used also Discrete Cosine Transform (DCT), PSO, Gabor Filter, correlation based selection of feature selection, feature fusion, PSO based feature selection as well as classification algorithms like that of K-nearest Neighbor and Naïve Bayes. Results have proved that this fusion of Naïve Bayes was able to improve the rate of recognition by 4.3% and 1.81% than when with the DCT-NB and Gabor-NB respectively. Likewise, the fusion that was proposed with KNN brought a great improvement in the rate of recognition by 3.05% and 2.42% than with that of DCTKNN and Gabor-KNN respectively.

Pedro H. Silva et al. [13] have recently propose a deep transfer learning optimized from a model trained for face recognition achieving outstanding representation for only iris modality. They have the proposed iris fine-tuned representation and a periculcar one from their previous work. They compare this approach for fusion in feature level against three basic function rules for matching at score level: sum, multi, and min. Results are reported for iris and periculcar region (NICE.II competition database) and also in an open-world scenario. The experiments in the NICE.II competition databases showed that transfer learning representation for iris modality achieved a new state-of-the-art, i.e., decidability of 22.2% and 14.56% of EER. They also yielded a new state-of-the-art result when the fusion at feature level by PSO is done on periculcar and iris modalities, i.e., decidability of 3.45 and 5.55% of EER.

III. APPROACH

In this paper, we present the proposed method aiming a comparison between two multimodal biometric fusion systems using different combinations of iris, palmprint and finger-knuckle based on feature and score level fusion.

1) Feature level: Usually, the fused feature vector is large in terms of dimensionality and may contain irrelevant or redundant information. Moreover, large feature vector also increase the storage cost and the consumed time in classification. From this point, the feature selection gains its absolute necessity in reducing execution time and improving recognition accuracy. We proposed a two proposed scenarios for the optimized Feature level fusion using (PSO).

In scheme 1, the features are extracted from each biometric iris, palmprint and finger-knuckle separately. The feature vectors then fused together. Finally the PSO was applied to the fused feature vector to select the most significant features. But as the fused feature values of vectors may exhibit significant variations both in their range and distribution, feature vector normalization is carried out. The objective behind feature normalization (also called range-normalization) is to modify the location (mean) and scale (variance) of the features values and to independently normalize each feature component to the range between 0 and 1 [24].

\[
S_i' = \frac{S_i - \mu}{\delta}
\]

Where:
- \(S_i'\) is the normalized matching scores
- \(S_i\) is the vector to be normalized, and \(i\) is the no of classes
- \(\mu\) and \(\delta\) are the mean and the variance of the fused feature respectively.
In scheme 2, the features are extracted from each biometric iris, palmprint and finger-knuckle separately. PSO then used to select optimized features from each biometric separately. The optimized feature vectors then normalized and fused together.

2) Score level: Matching score level fusion is the most popular fusion method in the literature. Figure 3 shows the block diagram of the proposed system for optimized matching scores level fusion using Particle Swarm Optimization (PSO). The feature vectors are extracted from each biometric separately. Then the matching score for each biometric sample is calculated according to the corresponding templates.

IV. FEATURE SELECTION USING PSO

A. Particle Swarm Optimization (PSO)

The PSO algorithm was developed by Kennedy and Eberhart in 1995 [14]. The main idea of PSO is inspired from the social behavior of organisms, such as birds in a flock. The PSO algorithm imitates the behavior of flying birds and their means of information exchange to solve optimization problems. Each particle (representing a bird in the flock), characterized by its position and velocity, represents the possible solution in search space. Behavior of the particles in the PSO imitates the way in which birds communicate with each other, while flying. During this communication, each bird reviews its new position in the space with respect to the best position it has covered so far. The birds in the flock also identify the bird that has reached the best position/environment. Upon knowing this information, others in the flock update their velocity (that depends on a bird’s local best position as well as the position of the best bird in the flock) and fly towards the best bird. The process of regular communication and updating the velocity repeats until reaching a favorable position.

In a similar manner, the particle in the PSO moves to a new position in the multidimensional solution space depending upon the particle’s best position (also referred to as local best position ($P_{ak}$) and global best position ($P_{gk}$). The $P_{ak}$ and $P_{gk}$ are updated after each iteration whenever a suitable solution is located by the particle (lower cost). The velocity vector of each particle represents/determines the forthcoming motion details. The velocity updates equation of a particle of the PSO, for instance (t+1), can be represented as follows [15]:

$$v_{pd}^{new} = \omega v_{pd}^{old} + c_1 r_1 (p_{best_{pd}} - x_{pd}^{old}) + c_2 r_2 (g_{best_{pd}} - x_{pd}^{old})$$

(2)

Where

$\omega$ is the inertia weight between 0-1 and provide a balance between global and local search abilities of the algorithm. The accelerator coefficients $c_1$ and $c_2$ are positive constants, and $r_1$ and $r_2$ are two random numbers in 0-1 range.
The corresponding position vector is updated by:

\[ x_{pd}^{new} = x_{pd}^{old} + v_{pd}^{new} \quad (3) \]

Equation (2) indicates that the new velocity of a particle in each of its dimensions depends on the previous velocity and the distances from the previously observed best solutions (positions of the particle).

B. Binary PSO

PSO was initially developed for a space of continuous values and it consequently, faced several problems for spaces of discrete values. Kennedy and Eberhart [16] presented a discrete binary version of PSO method (BPSO) for discrete optimization problems.

In BPSO, particles use binary string to represent their position in form by \( x_p = \{ x_{p1}, x_{p2}, ..., x_{pd} \} \) which is randomly generated. As each bit in the string represents a feature, value =1 means that the corresponding feature is selected while =0 means that it is not selected. The velocity of each particle is represented by \( v_p = \{ v_{p1}, v_{p2}, ..., v_{pd} \} \), where \( p \) is the number of particles, and \( d \) is the number of features of a given dataset. The initial velocities in particles are probabilities constrained to the interval [0.0 – 1.0]. Each particle is updated according to the following equations [16]:

\[ S( v_{pd}^{new} ) = \frac{1}{1 + e^{-v_{pd}^{new}}} \quad (4) \]

\[ x_{pd}^{new} = \begin{cases} 1 & \text{if } (r < S( v_{pd}^{new} )) \\ 0 & \text{otherwise} \end{cases} \quad (5) \]

Where \( v_{pd}^{new} \) denotes the particle velocity obtained from equation 2, function \( S( v_{pd}^{new} ) \) is a sigmoid transformation, \( x_{pd}^{new} \) is the new particle position and \( r \) is a random number selected from a uniform distribution \( U(0, 1) \).

C. Fitness function

The PSO implementation relies on the appropriate formulation of the fitness function. In the proposed work, a multi objective fitness function has been used. The main objectives of the fitness function are

- Maximize the between-class scatter among the different classes.
- Minimize the within-class scatter in the same class.
- Improve the recognition rate of the system.

Suppose there are \( C \) classes, \( y_i \) is the \( i^{th} \) vector, \( M_i \) the number of samples within class \( i \), \( i = 1,2, ..., C \), \( \mu_i \) the mean vector of class \( i \), and \( \mu \) be the total mean vector of samples.

Within-class scatter matrix is represented by equation (6)

\[ S_w = \sum_{i=1}^{C} \sum_{j=1}^{M_i} (y_i - \mu_i)(y_i - \mu_i)^T \quad (6) \]

Between-class scatter matrix is represented by equation (7)

\[ S_b = \sum_{i=1}^{C} (\mu_i - \mu)(\mu_i - \mu)^T \quad (7) \]

Where

\[ \mu = \frac{1}{C} \sum_{i=1}^{C} \mu_i \]

Finally, we compute a transformation that maximizes the between-class scatter while minimizing the within-class scatter and this is performed by:

\[ \text{maximize} \quad \frac{\det(S_b)}{\det(S_w)} \]

Where \( \det() \) is the determinant of the matrix.

V. SCORE LEVEL FUSION USING PSO

Score level fusion refers to the combination of matching scores provided by the unimodal classifiers in the system. This is the most widely used fusion approach, as evidenced by the experts in the field. But before the fusion step, these matching score should be normalized. In this paper Min-max method is applied which transforms scores into a common range \([0, 1]\). The normalized scores are given by [17]:

\[ S_{i}' = \frac{S_i - S_{min}}{S_{max} - S_{min}} \quad (8) \]

Where

- \( S_{i}' \): the normalized matching scores
- \( S_i \): the matching scores,
- \( i= 1,2, ..., n \) and \( n \): number of matching scores
- \( S_{min} \) \& \( S_{max} \): the min and max match scores

In order to combine the scores reported by the three matchers, different score level combinations could be applied, such as sum, product, weighted sum rule and min rules:

\[ \text{Sum} = \sum_{i=1}^{n} S_i \quad (9) \]

\[ \text{Product} = \prod_{i=1}^{n} S_i \quad (10) \]

\[ \text{Weighted Sum} = \sum_{i=1}^{n} w_i S_i \quad (11) \]

Where:

- \( N \): number of match scores wanted to be fused
- \( S \): the matching score
- \( w_i \): The weight for each score which calculated as follow

\[ (12) \]
TABLE I. COMPARISON OF UNIMODAL BIOMETRIC RESULTS

<table>
<thead>
<tr>
<th>Biometric Type</th>
<th>GAR %</th>
<th>FAR %</th>
<th>FRR %</th>
<th>TER %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Iris</td>
<td>97</td>
<td>7.1</td>
<td>4</td>
<td>10.14</td>
</tr>
<tr>
<td>Palmprint</td>
<td>96.76</td>
<td>0.00</td>
<td>3.24</td>
<td>3.24</td>
</tr>
<tr>
<td>Finger_Knuckle</td>
<td>85.50</td>
<td>0.00</td>
<td>14.50</td>
<td>14.50</td>
</tr>
</tbody>
</table>

Where $EER_i$ is the unimodal biometric error.

$\text{m}$: the number of biometrics.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

Generally, the performance of any biometric recognition system is measured by False Acceptance Rate (FAR) and False Rejection Rate (FRR) or Genuine Acceptance Rate (GAR). The system should have a high GAR with a corresponding low FRR, FAR and Total Error Rate (TER) [18].

FRR, FAR, GAR and TER are determined as follow:

$$\text{FAR}(\%) = \frac{\text{false acceptance numbers}}{\text{No. of imposter test}} \times 100\%$$  \hspace{1cm} (13)

$$\text{FRR}(\%) = \frac{\text{false rejection numbers}}{\text{No. of client test}} \times 100\%$$  \hspace{1cm} (14)

$$\text{GAR}(\%) = 100 - \text{FRR}(\%)$$  \hspace{1cm} (15)

$$\text{TER}(\%) = \text{FRR}(\%) + \text{FAR}(\%)$$  \hspace{1cm} (16)

A. Unimodal Experimental Results

For iris images, CASIA iris Image Database is used [19], includes 2500 iris images from 250 eyes for each eye. 200 persons have been selected, for each person 6 Iris images are used for training and 4 for testing.

For palmprint images, PolyU palmprint database is used [20], contains 7752 grayscale images corresponding to 386 different palms (10 samples for each hand). 200 persons have been selected, for each person we have 6 palmprint images for training and 4 for testing.

For finger-knuckle images, database images introduced in [21] is used, collected from 165 volunteers (12 samples for each user), including 125 males and 40 females. 200 persons have been selected, for each person 8 finger-knuckle images for training and 4 for testing.

Table 1 shows the results of iris, palmprint and finger-knuckle identification systems. It could be noticed that the TER is too much to be suitable for high security applications.

B. Fusion Experimental Results

The goal of this experiment is to compare the system performance when using a feature fusion multimodal biometric system by the aid of PSO as an optimizer and a matching score fusion multimodal biometric system.

Table II shows the results of the classification rate including FAR, FRR, TER and GAR for the proposed multimodal biometric feature fusion approach (scheme 1), feature fusion approach (scheme 2) and the proposed multimodal biometric score fusion approach by the aid of PSO as an optimizer.

The results shown that feature fusion system approach (scheme 1) achieve significant results with best GAR 98.83% and TER 1.16%. While the feature fusion system approach (scheme 2) achieves significant results with best GAR 98.58% and TER 1.41%. Finally, The proposed score fusion system achieves significant results with best GAR 98.40% and TER 2.60%.

It’s clear that the results of feature fusion scheme 1 outperform that of scheme 2 in terms of recognition rates and total equal error rates. But scheme 2 achieves better results in only one case (palmprint_iris). This is because here the recognition rate and error basically depends on the rates of each biometric separately. But It is clear that the performance of the matching score fusion multimodal biometric system outperforms the two schemes of feature fusion systems and strongly reduces the TER. The proposed system achieves significant results with best GAR 98.40% and TER 2%.

As shown in Table III, we surpass the result presented by M. Madane [22] and S. Singh [23] both using score level fusion. We couldn’t make a comparison with systems using feature fusion level and the same biometric traits.
TABLE III Results comparing with literature methods

<table>
<thead>
<tr>
<th>Methods</th>
<th>Modalities</th>
<th>Database</th>
<th>Fusion level</th>
<th>GAR %</th>
</tr>
</thead>
<tbody>
<tr>
<td>A Mayya (2017)</td>
<td>Iris, Palmprint</td>
<td>IIT Delhi</td>
<td>Score fusion</td>
<td>98.54</td>
</tr>
<tr>
<td>M. Madane (2016)</td>
<td>Iris, Palmprint</td>
<td>CASIA, PolyU</td>
<td>Score fusion</td>
<td>76.58</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Iris, Palmprint</td>
<td>CASIA, PolyU</td>
<td>Score fusion</td>
<td>98.40</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Finger-knuckle, Iris</td>
<td>PolyU, CASIA</td>
<td>Score fusion</td>
<td>98</td>
</tr>
<tr>
<td>A. Meraoumia (2011)</td>
<td>Finger-knuckle, Palmprint</td>
<td>PolyU</td>
<td>Score fusion</td>
<td>98.663</td>
</tr>
<tr>
<td>Proposed method</td>
<td>Finger-knuckle, Palmprint</td>
<td>PolyU</td>
<td>Score fusion</td>
<td>97.25</td>
</tr>
</tbody>
</table>

VII. CONCLUSION

In this paper two levels of fusion (feature level fusion and matching score level fusion) based on Particle Swarm Optimization approach (PSO) are experimented in multimodal biometric identification systems with Iris, Palmprint and Finger-knuckle biometric traits.

From the results obtained we can conclude that superior any fusion system of them on another depend on number and type of biometrics used.

Although fusion at the feature level is a challenging task due to a variety of reasons, but it foretells promising results Outperforms score fusion with more experiments along with the PSO (or any optimization algorithm with the same principle) to reduce the high dimensional features vectors and to enhance the quality of the final features vector.

REFERENCES


