ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

A Multimodal Biometric Recognition system using feature fusion based on PSO

Ola M. Aly [1], Hoda M. Onsi [2], Gouda I. Salama [3], Tarek A. Mahmoud [3]

Ministry of Military Production, Cairo, Egypt [1]

Faculty of Computers and Information, Cairo University, Cairo, Egypt [2]

Egyptian Armed Forces, Cairo, Egypt [3]

Abstract: **U**nimodal biometric systems that are based on utilising a single biometric trait often face limitations that influence their performances. In this paper, a proposed fusion system of three biometrics at the feature level based on Particle Swarm Optimization approach (PSO) is presented. A new multi objective fitness function for PSO has been used. This function has three main objectives, maximize the between-class scatter among the different classes, minimize the within-class scatter in the same class and improve the recognition rate of the system. Results shown how the optimized system fused at feature level can improve the recognition rate, reduce the number of features, reduce the total equal error rates and finally decrease the time consumed in recognition to the half.

Keywords: Multimodal biometric; feature level fusion; PSO; multi objective; irsi; palmprint; finger-knuckle

I. INTRODUCTION

Biometric identification provides authentication of a person based on unique characteristics produced by the individual. It has been developed based on various features, such as fingerprint, facial image, voice, hand geometry, handwriting, iris and retina. Unlike passwords and tokens, biometric traits cannot be lost, forgotten or manipulated. Biometric traits cannot be easily copied, shared, distributed or forgotten [1].

These unimodal biometric systems are faced with a variety of problems, noise in sensed data, non universality, inter-class similarities, and spoof attacks. Multibiometrics are a relatively new approach to overcome 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 [2].

A multibiometric system relies on the evidence presented by multiple sources of biometric information. Based on the nature of these sources, a multibiometric system can be classified into one of the following six categories [3]:

- Multi-sensor systems: They employ multiple sensors to capture a single biometric trait of an individual.
- Multi-algorithm systems: They invoke multiple feature extraction and/or matching algorithms on the same biometric data.
- Multi-instance systems: These systems use multiple instances of the same body trait and have also been referred to as multi-unit systems in the literature.
- Multi-sample systems: A single sensor may be used to acquire multiple samples of the same biometric trait in order to account the variations that can occur in the trait.
- Multimodal systems: These systems establish identity based on the evidence of multiple biometric traits, e.g. fingerprint and iris.
- Hybrid systems: The term hybrid is used to describe systems that integrate a subset of the five scenarios discussed above.

Multibiometric systems are categorized into three system architectures according to the strategies used for information fusion [4]:

- 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 score 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

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

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 an understudied problem. Fusion at this level can be applied to the extracted features from the same modality or different multimodalities. Since the feature set contains richer information about the raw biometric data, integration at this level is expected to act better in comparison with fusion at the score level and decision level [3]. Moreover, 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 [5].

In this paper, a proposed multimodal biometric system has been proposed. The aim of this system is to reduce the dimension of the fusion feature space and thus reduce the time consumed in classification, through an appropriate selection procedure, while keeping the same level of performance. The binary particle swarm optimization (PSO) algorithm proposed in [6] 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 [7]. PSO also used in other fusion levels like matching score level. As mentioned in our previous work [8], The PSO is used to optimize the selection of score level combination rules, its corresponding parameters, and the decision threshold.

The remainder of this paper is organized as follows: Section (II) describes the related works. Section (III) explores the unimodal systems used. Section (IV) introduces the proposed multimodal biometric system. Section (V) explains the feature selection using PSO. Section (VI) presents the experimental results and discussion. Finally the paper is concluded in section (VII).

II. RELATED WORKS

Raghavendra et al. [9] have presented an efficient feature level fusion scheme applied on face and palmprint images. The features for each modality were obtained using Log Gabor transform and concatenated to form a fused feature vector. Particle Swarm Optimization (PSO) approach was used to reduce the dimension of the vector. Two fitness functions were applied, one for verification process and other for the identification. Finally classification was performed on the projection space of the selected features using Kernel Direct Discriminant Analysis (KDDA). Results of the proposed feature fusion-PSO approach reduced the fused feature space dimension by a factor of 45% roughly.

Lin and Hanqi [10] have proposed a feature fusion method for the integration of voice and face biometrics. The task of feature fusion is accomplished by employing PSO. The objective of fusion using PSO was to obtain the optimal weights for each feature. The integrated feature vector is then fed to Probability Neural Network (PNN) for classification. The test results revealed that integrating information through the proposed method achieved much better performance and maintained much more robust results in comparison with any of the single modal systems from which it was derived.

Kaushik and Mohamed [11] have introduced a multimodal system for the integration of iris, face, and gait features based on the fusion at feature level. PSO is used to select the subset of informative features. This PSO-based dimensionality reduction method trimmed down the fused feature space dimension by a factor of 77% roughly while keeping same level of performance as that of the global system.

Waheeda et al. [12] have developed a multimodal biometric system using iris and online signature biometrics at feature level fusion. A binary particle swarm optimization (BPSO) procedure was used to significantly reduce the dimensionality of features while keeping the same level of performance. The objective of the used fitness function was maximizing the class separation term indicated by the scatter index among the different classes. The results proved that the implementation of a BPSO algorithm reduced the number of features while keeping the same level of performance.

III. UNIMODAL BIOMETRIC SYSTEMS

In this section, the three unimodal biometric systems used in the proposed system will be explored. Each system is briefly explained.

A. Iris Recognition System

Iris recognition is considered to be the most accurate biometric technology when compared to other technologies commercially in use today. This is because the false match and false non-match errors are very small, which implies a very high accuracy [13].

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

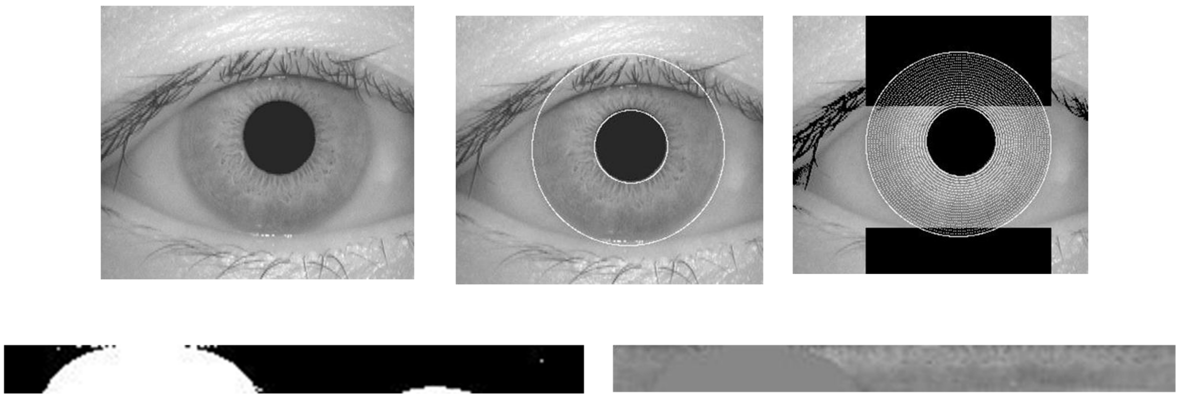

Fig. 1 A sample of Iris image with the corresponding segmented one and the normalized image

Iris recognition system consists of three stages; the first stage is the iris analysis which involves iris localization and iris normalization. The second stage is the feature extraction and encoding. The last stage is the recognition stage which involves identification or verification.

In this paper, Daugman's algorithm is used for performing iris localization which is based on applying an integro-differential operator to find the iris and pupil contours [14]. Only significant features of the iris are extracted and encoded in order to generate the iris code for the matching process. In the proposed system, log-Gabor filter [15] [16] is used for extracting the features from the iris image. Finally, matching is performed using the calculated Hamming distance (HD) which is a measure of the number of different bits between the two iris codes [17].

B. Palmprint Recognition System

Human beings are interested in the palm lines for fortune telling long time ago. The inner surface of the palm normally contains flexion creases, secondary creases and ridges.

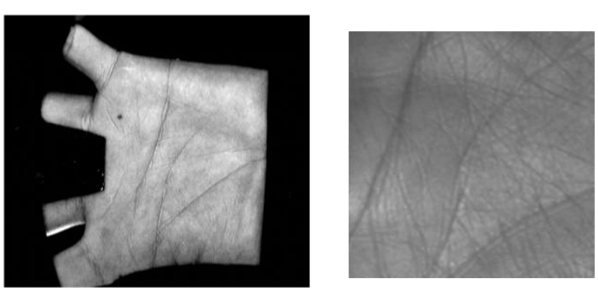

Fig. 2 A sample of palmprint image and the corresponding region of interest

The flexion and secondary creases are also called principal lines and wrinkles, respectively. The flexion creases and the main creases are formed between the 3rd and 5th months after conception and superficial lines appear after birth [18].

In the proposed palmprint recognition system a preprocessed image database is used, then log-Gabor filter is performed for extracting the features from the palmprint image and Hamming distance is calculated during the matching stage [19] [20].

C. Finger-Knuckle Print Recognition System

Among various kinds of biometric identifiers, hand-based biometrics has been attracting considerable attention over recent years. Fingerprint, palm print, hand geometry, hand vein, and inner-knuckle-print have been proposed and well investigated in the literature. Recently, it has been found that the image pattern in the outer finger knuckle surface is highly unique and thus can serve as a distinctive biometric identifier [21].

In the proposed finger-knuckle identification system, a preprocessed image database is used then the features are extracted from the finger-knuckle image. Linear Discriminant Analysis (LDA) is performed to extract the only significant features from the finger-knuckle image.

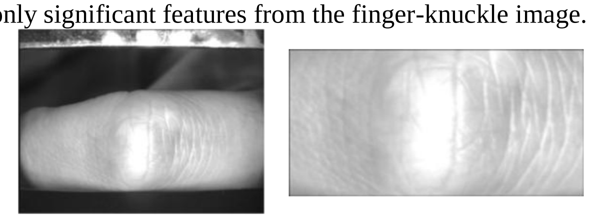

Fig. 3 A sample of Finger-Knuckle image and the corresponding region of interest

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

In the proposed system, the LDA is used to both reducing the dimensionality of the feature vector and performing the classification algorithm. [22] [23].

IV. THE PROPOSED MULTIMODAL BIOMETRIC SYSTEM

In this paper, a multimodal biometric system is proposed using different combinations of iris, palmprint and finger-knuckle based on feature level fusion. 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.

Figures 4 and 5 show the block diagrams of the 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].

$$S_i' = \frac{Si - \mu}{\delta} \qquad (1)$$

Where:

S_i' isthe normalized matching scores

S_i is the vector to be normalized, and i is the no of classes

μ and δ are the mean and the variance of the fused feature respectively.

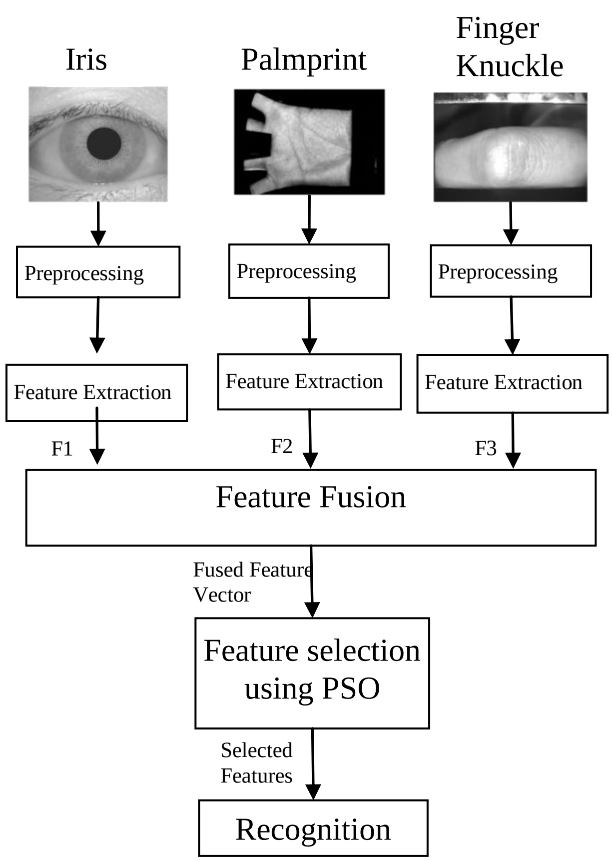

Fig. 4 The proposed optimized feature level fusion system using scheme 1

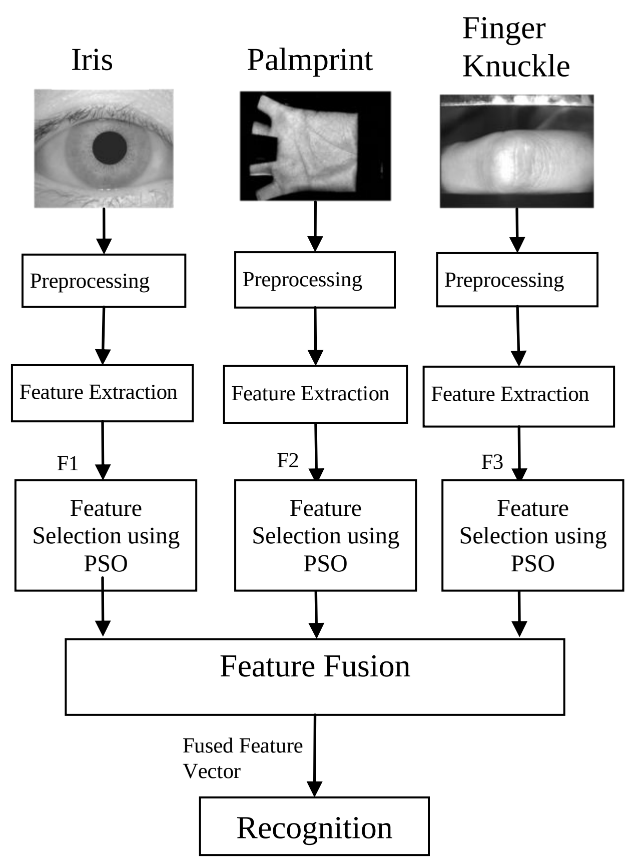

Fig. 5 The proposed optimized feature level fusion system using scheme 2

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

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.

V. FEATURE SELECTION USING PSO

A. Particle Swarm Optimization (PSO)

PSO is an evolutionary, stochastic, population-based optimization algorithm whose goal is to find a solution to an optimization problem in a search space. The PSO algorithm was developed by Kennedy and Eberhart in 1995 [25]. 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 [26]:

$$v_{pd}^{new} = \omega\, v_{pd}^{old} + c_1\, r_1 \left(pbest_{pd} - x_{pd}^{old}\right) + c_2 r_2 \left(gbest_{pd} - x_{pd}^{old}\right) \qquad (2)$$

Where

ω 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:

$$x_{pd}^{new} = x_{pd}^{old} + v_{pd}^{new} \qquad (3)$$

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 [27] presented a discrete binary version of PSO method (BPSO) for discrete optimization problems.

In BPSO, particles use binary string to represent thier position in form by $X_p = \{x_{p1}, x_{p2}, \ldots, x_{pd}\}$ 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 $V_p = \{v_{p1}, v_{p2}, \ldots, v_{pd}\}$, 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 [27]:

$$S\,(v_{pd}^{new} = \frac{1}{1+e^{-v_{pd}^{new}}}) \qquad (4)$$

$$x_{pd}^{new} = \begin{cases} 1 & if\ \left(r < S\left(v_{pd}^{new}\right)\right) \\ 0 & otherwise \end{cases} \qquad (5)$$

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, yi is the i^{th} vector, M_i the number of samples within class i , i = 1,2, ….. C. μ_i the mean vector of class I, and μ be the total mean vector of samples.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

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

$$\mu = {}^1/_C \sum_{i=1}^{c}\mu_i$$

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

$$maximize \frac{\det(S_b)}{\det(S_w)}$$

Where det () is the determinant of the matrix.

VI. EXPERIMENTAL RESULTS AND DISCCUSION

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 corrosponding low FAR, FRR and Total Error Rate (TER) [28].

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

$$FAR(\%) = \frac{false\ accep\tan ce\ numbers}{No\ of\ imposter\ test} X100\% \quad (8)$$

$$FRR(\%) = \frac{false\ rejection\ numbers}{No\ of\ client\ test} X100\% \quad (9)$$

$$GAR(\%) = 100 - FRR(\%) \quad (10)$$

$$TER(\%) = FRR(\%) + FAR(\%) \quad (11)$$

Firstly, the results for each unibiomtric system will be presented, and then the results of fusion of two or three biometrics at feature level using PSO will be introduced.

A. Unimodal Experimental Results

For iris images, CASIA iris Image Database is used [29], 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 [30], 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 [31] is used, collected from 600 volunteers (12 samples for each user). 200 persons have been selected, for each person 6 finger-knuckle images for training and 4 for testing.

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

B. Feature Level Fusion Experimental Results

The goal of this experiment is to evaluate the system performance when using a unimodal biometric system versus a multimodal biometric system using feature fusion by the aid of PSO as an optimizer.

As mentioned earlier, the first set of experiments (scheme 1) is based on applying BPSO after fusing the features of the iris, palmprint and finger-knuckle. Whereas, the second feature fusion experiments (scheme 2) is based on applying BPSO on each biometric separately, then fused the feature vectors together.

Table II shows the results of the classification rate including FAR, FRR, TER and GAR for the proposed multimodal biometric fusion approach by the aid of PSO as an optimizer (scheme 1), And the number of features before and after using PSO. It is clear that the performance of the proposed multimodal biometric system outperforms the unimodal systems and strongly reduces the TER, and the number of features to the half. The proposed system achieves significant results with best GAR 98.83 and TER 1.16%.

TABLE I

UNIMODAL BIOMETRIC RECOGNITION RATE RESULTS

Biometric Type	No of Features	GAR %	FAR %	FRR %	TER %
Iris	4800	**97**	7.14	3	**10.14**
Palmprint	4096	**96.76**	0.00	3.24	**3.24**
Finger_Knuckle	4096	**85.50**	0.00	14.50	**14.50**

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

TABLE II
RECOGNITION RATES FOR PROPOSED MULTIMODAL SYSTEM USING PSO (SCHEME 1)

Biometric Type	No of features before PSO	No of features after PSO	GAR %	FAR %	FRR %	TER %
Iris_knuckle	8896	4526	**97.83**	0	2.16	**2.16**
Palmprint_iris	8896	4355	**97.25**	1	2.75	**3.75**
palmprint_Knuckle	8192	3991	**98.83**	0	1.16	**1.16**

TABLE III
RECOGNITION RATES FOR PROPOSED MULTIMODAL SYSTEM USING PSO (SCHEME 2)

Biometric Type	No of features before PSO	No of features after PSO	GAR %	FAR %	FRR %	TER %
Iris_knuckle	8896	4395	**97.12**	0	2.83	**2.83**
Palmprint_iris	8896	4382	**98.33**	1	1.66	**2.66**
palmprint_Knuckle	8192	4047	**98.58**	0	1.41	**1.41**

Table III shows the result of the classification rate including FAR, FRR, TER and GAR for the proposed multimodal biometric fusion approach by the aid of PSO as an optimizer (scheme 2), and the number of features before and after using PSO. It is clear that the performance of the proposed multimodal biometric system outperforms the unimodal systems and strongly reduces the TER, and the number of features to the half. The proposed system achieves significant results with best GAR 98.58% and TER 1.41%.

From tables II and III, it's clear that the results of 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.

TABLE IV
ELAPSED TIME IN (SEC) FOR CLASSIFICATION PER SAMPLE

Fusion without using PSO			Fusion using PSO		
Iris_Knuckle	Iris_palm	Palm_knuckle	Iris_Knuckle	Iris_palm	Palm_knuckle
0.11441	0.1080	0.10054	0.0558	0.0514	0.0490

Table IV show the time consuming in classification without and with using PSO optimization. It's clear that the time consumed decreases to half as the features reduced by 50%.

VII. CONCLUSION

In this paper, the problem of feature level fusion has been tackled in the context of multimodal biometrics. A new multimodal biometric recognition system is proposed using three modalities including iris, palmprint and finger-knuckle based on PSO approach. The main objective of this work is to prove that it could be possible to reduce the dimension of the fusion feature space and thus reduce the time consumed in classification, through an appropriate selection procedure, while keeping the same level of performance.

PSO is used to optimize the selection of features based on a new multi objective fitness function. The experimental results show that we can obtain a considerable improvement in terms of recognition performance while reducing the number of features and decreasing the time consumed to half. The results show that the proposed multimodal biometric system outperforms the unimodal biometric systems using different biometric combinations. Moreover, the TER is strongly decreases to 1.16% at 98.83% recognition rate.

REFERENCES

[1] A. K. Jain, R. Bolle, and S. Pankanti, editors. *Biometrics: Personal Identification in Networked Society*. Kluwer Academic Publishers, 1999.
[2] A. Ross," An Introduction to Multibiometrics",appeared in proc.of the 15th European Signal Processing Conference(EUSIPCO),September 2007.
[3] A. Ross, K. Nandakumar, and A. K. Jain. Handbook of Multibiometrics. Springer, New York, USA, 1st edition, 2006.
[4] A. Ross, and A. K. Jain, "Information Fusion in Biometrics". Pattern Recognition Letters, 2003,
[5] M. Faundez-Zanuy, "Data fusion in biometrics". IEEE Aerospace and Electronic Systems Magazine, vol. 20, pp. 34-38 2005.
[6] J. Kennedy, R. C Eberhart "A discrete binary version of the particle swarm algorithm". In Proceedings of the IEEE International Conference on Computational Cybernetics and Simulation, pp. 4104 – 4108. (1997).
[7] X. Wang, J. Yang, X. Teng, W. Xia and B. Jensen, "Feature selection based on rough sets and particle swarm optimization". Pattern Recognition Letters, vol. 28. pp. 459–471. (2007).
[8] O. M. Aly, T. A. Mohamed, G. I. Salama, H. M. Onsi, "An Adaptive Multimodal Biometrics System using PSO". International Journal of Advanced Computer Science and Applications, vol. 4, no. 7, 2013.
[9] R. Raghavendra, D. Bernadette, R. Asok and G. Hemantha "PSO versus AdaBoost for Feature Selection in Multimodal Biometrics". Biometrics: Theory, Applications, and Systems, 2009. BTAS '09. IEEE 3rd International Conference on.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

[10] Lin H "Automated Biometrics of Audio-Visual Multiple Modals". PhD Thesis, University of Florida Atlantic, USA, 2010.
[11] R. Kaushik and S. Mohamed "Multibiometric System using level Set method and Particle Swarm Optimization", A. Campilho and M. Kamel (Eds.): ICIAR 2012, Part II, pp. 20–29, 2012. © Springer-Verlag Berlin Heidelberg 2012.
[12] A. Waheeda "A Multimodal Biometric fusion approach based on Binary Particle Optimization", Research and Development in Intelligent Systems *XXVIII*, Springer-Verlag London Limited 2011.
[13] J. Daugman "How iris recognition works", IEEE Trans. on Circuits and Systems for Video Technology. vol. 14, no. 1, pp. 21-30. 2004.
[14] J. Daugman, "High confidence visual recognition of persons by a test of statistical independence," IEEE Trans. Pattern Anal. Machine Intell, vol. 15, pp. 1148-1161, 1993
[15] D.Gabor, "Theory of communication ", J. Inst. Elect. Eng. London, vol. 93, no. 3, 1946.
[16] A. Kumar and A. Passi, "Comparison and combination of iris matchers for reliable personal authentication," Pattern Recogniion., vol. 23, no. 3, pp. 1016–1026, March 2010.
[17] L. Ma, T. Tan, Y. Wang and D. Zhang, "Efficient iris recognition by characterizing key local variations", IEEE Transactions on Image Processing, Vol. 13, No. 6, pp739-750, June 2004.
[18] A. Kong, D. Zhang and G. Lu, "A study of identical twins palmprint for personal verification", Pattern Recognition, vol. 39, no, 11, pp. 2149-2156, 2006.
[19] R. Chu, Z. Lei, Y. Han and S. Li," Learning Gabor magnitude features for palmprint recognition", ACCV, pp. 22–31, 2007.
[20] A. Kong, "Palmprint Identification Based on Generalization of Iris Code", PhD Thesis, University of Waterloo, Canada, 2007.
[21] A. Jain, L. Hong, and S. Pankanti. "Biometric Identification," Communications of the ACM, 2000.
[22] H. Yu and J. Yang, "A direct LDA algorithm for high dimensional data with application to face recognition," Pattern Recognition, September 2001.
[23] P. Navarrete and J. Ruiz-del-Solar, "Analysis and comparison of Eigenspace-Based face recognition approaches," International Journal of Pattern Recognition and Artificial Intelligence, vol. 16, no. 7, November 2002.
[24] k. Nandakumar Integration of Multiple Cues in Biometric Systems. M.S. Thesis: Michigan State University USA 2005.
[25] J. Kennedy and R. Eberhart, "Particle swarm optimization". IEEE Int. Joint Conf. on Neural Networks, Perth, Australia. (1995).
[26] M. Clerc and J. Kennedy, "The Particle Swarm-explosion, stability, and convergence in a multidimensional somplex space," IEEE Trans. Evolutionary Comp. , vol. 6, p. 58-73, 2002.
[27] J. Kennedy, R. Eberhart. "A discrete binary version of the particle swarm algorithm". Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics, Vol.5, pp. 4104–4108, 1997.
[28] T. Sabareeswari and S. Stuwart," Identification of a person using multimodal biometric system", International Journal of Computer Applications vol. 3, no.9, 2010.
[29] Chinese Academy of Science Institute of Automation, Database of the Eye Grayscale Images. http://www.sinobiometrics.com
[30] PolyU Palmprint Database, http://www.comp.polyu.edu.hk/~biometrics/
[31] L. Zhang, "Finger-Knuckle-Print: A new Biometric Identifier", ICIP, Cairo, Egypt, 2009.