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

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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 like 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 periocular 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 periocular 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 2.22 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 periocular 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].

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

Where:

S_i' is the 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.

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.
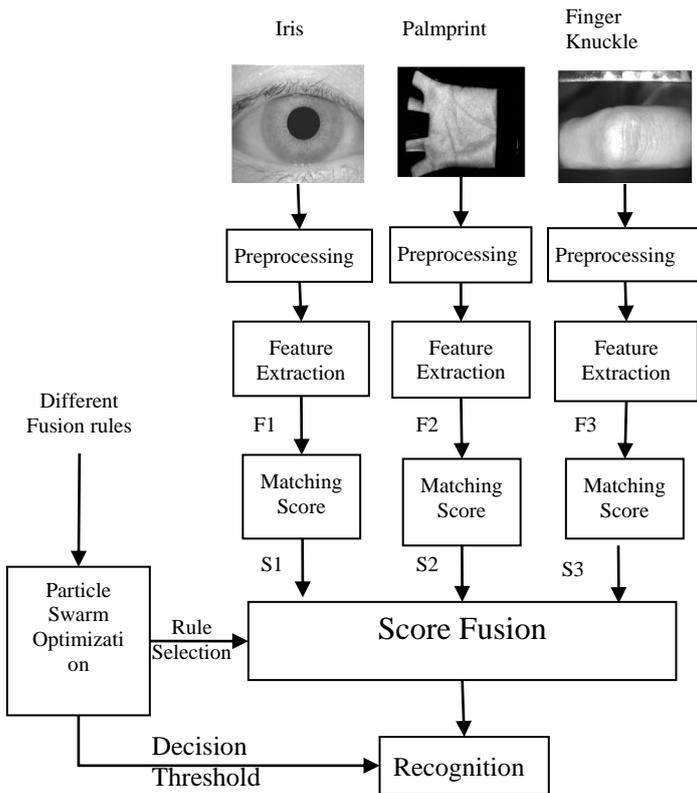
Fig. 1 The proposed optimized score level fusion

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.
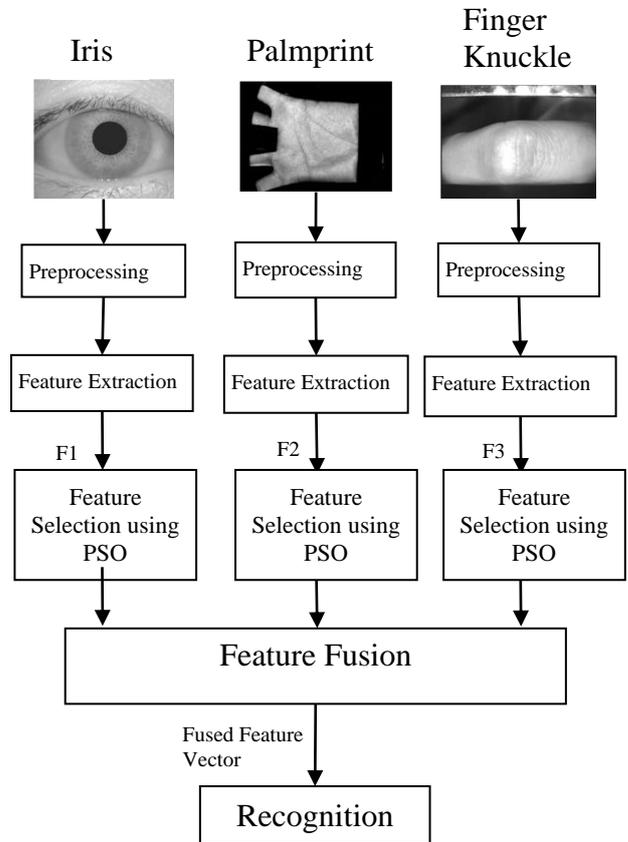
Fig. 2 The proposed optimized feature level fusion

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]:

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

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 [16] 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 $X_p = \{x_{p1}, x_{p2}, ..., x_{pd}\}$ 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]:

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

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

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 ith 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.

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

$$S_w = \sum_{i=1}^{c} \sum_{j=1}^{M_i} (y_i - \mu_i)(y_i - \mu_i)^T \qquad (6)$$

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

$$S_b = \sum_{i=1}^{c} (\mu_i - \mu)(\mu_i - \mu)^T \qquad (7)$$

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:

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

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]:

$$S_i' = \frac{S_i - S_{min}}{S_{max} - S_{min}} \qquad (8)$$

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:

$$Sum = \sum_{i=1}^{n} S_i \qquad (9)$$

$$Product = \prod_{i=1}^{n} S_i \qquad (10)$$

$$Weighted\_Sum = \sum_{i=1}^{n} w_i S_i \qquad (11)$$

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

Biometric Type	GAR %	FAR %	FRR %	TER %
Iris	**97**	7.14	3	**10.14**
Palmprint	**96.76**	0.00	3.24	**3.24**
Finger_Knuckle	**85.50**	0.00	14.50	**14.50**

Where EER_i is the unimodal biometric error.

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 corrosponding low FAR, FRR and Total Error Rate (TER) [18].

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

$$FAR(\%) = \frac{false\ accep\tan ce\ numbers}{No\ of\ imposter\ test} X100\% \tag{13}$$

$$FRR(\%) = \frac{false\ rejection\ numbers}{No\ of\ client\ test} X100\% \tag{14}$$

$$GAR(\%) = 100 - FRR(\%) \tag{15}$$

$$TER(\%) = FRR(\%) + FAR(\%) \tag{16}$$

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 I Recognition rates for proposed multimodal systems using PSO

Biometric System	Feature Fusion Scheme 1				Feature Fusion Scheme 2				Matching Score Fusion			
	GAR %	FAR %	FRR %	TER %	GAR %	FAR %	FRR %	TER %	GAR %	FAR %	FRR %	TER %
Iris_knuckle	97.83	0	2.16	**2.16**	97.12	0	2.83	**2.83**	98	0.00	2	**2**
Palmprint_iris	97.25	1	2.75	**3.75**	98.33	1	1.66	**2.66**	98.40	1	1.60	**2.60**
palmprint_Knuckle	98.83	0	1.16	**1.16**	98.58	0	1.41	**1.41**	97.25	0	2.75	**2.75**

TABLE III Results comparing with literature methods

Methods	Modalities	Database	Fusion level	GAR %
A Mayya (2017) [25]	Iris, Palmprint		Score fusion	98.54
M. Madane (2016) [22]	Iris, Palmprint	IIT Delhi	Score fusion	76.58
Proposed method	Iris, Palmprint	CASIA, PolyU	Score fusion	98.40
S. Singh (2015) [23]	Finger-knuckle, Iris	PolyU, CASIA	Score fusion	97.5
Proposed method	Finger-knuckle, Iris	PolyU, CASIA	Score fusion	98
A.Meraoumia1(2011) [24]	Finger-knuckle, Palmprint	PolyU	Score fusion	98.663
Proposed method	Finger-knuckle, Palmprint	PolyU	Score fusion	97.25

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

[1] A. Ross,” An Introduction to Multibiometrics”,appeared in proc.of the 15th European Signal Processing Conference(EUSIPCO),September 2007.

[2] A. Ross, and A. K. Jain, "Information Fusion in Biometrics". Pattern Recognition Letters, 2003,

[3] M. Faundez-Zanuy, "Data fusion in biometrics". IEEE Aerospace and Electronic Systems Magazine, vol. 20, pp. 34-38 2005.

[4] 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).

[5] 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).

[6] Farmanbar, M., & Toygar, Ö. (2015). Feature selection for the fusion of face and palmprint biometrics. Signal, Image and Video Processing, 1-8.

[7] Motamed, S., Broumandnia, A., & Nourbakhsh, A. (2013). Multimodal Biometric Recognition Using Particle Swarm Optimization-Based Selected Features.

[8] Raghavendra, R., & Dorizzi, B. (2011, November). A novel adaptive inertia particle swarm optimization (AIPSO) algorithm for improving multimodal biometric recognition. In Hand-Based Biometrics (ICHB), 2011 International Conference on (pp. 1-6). IEEE.

[9] V. Kanhangad, A. Kumar, and D. Zhang, "Comments on an adaptive multimodal biometric management algorithm," IEEE Trans. Sys. Man & Cybern., Part-C , vol. 38, no. 5, pp. 438-440, 2008.

[10] A. Kumar, V. Kanhangad and D. Zhang, " A new framework for adaptive multimodal biometrics managemen", IEEE Transactions on Information Forensics and Security, vol. 5, pp. 92-102, Mar. 2010

[11] Mezai, Lamia, and Fella Hachouf. "Adaptive multimodal biometric fusion algorithm using particle swarm optimization and belief functions." 2016 4th International Conference on Biometrics and Forensics (IWBF). IEEE, 2016.

[12] Vijaykumar, N., and MS Irfan Ahmed. "Multimodal biometric system using particle swarm based feature selection." 2017 International Conference on Algorithms, Methodology, Models and Applications in Emerging Technologies (ICAMMAET). IEEE, 2017.

[13] Silva, Pedro H., et al. "Multimodal Feature Level Fusion based on Particle Swarm Optimization with Deep Transfer Learning." 2018 IEEE Congress on Evolutionary Computation (CEC). IEEE, 2018.

[14] J. Kennedy and R. Eberhart, "Particle swarm optimization". IEEE Int. Joint Conf. on Neural Networks, Perth, Australia. (1995).

[15] 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.

[16] 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.

[17] A. Pour, K. Faez, and R. Amirfattahi "Multimodal biometric system using face, ear and gait biometrics", 10th International Conference on Information Science, Signal Processing and their Applications (ISSPA 2010).

[18] T. Sabareeswari and S. Stuwart," Identification of a person using multimodal biometric system", International Journal of Computer Applications vol. 3, no.9, 2010.

[19] Chinese Academy of Science Institute of Automation, Database of the Eye Grayscale Images. http://www.sinobiometrics.com

[20] PolyU Palmprint Database, http://www.comp.polyu.edu.hk/~biometrics/

[21] L. Zhang, "Finger-Knuckle-Print: A new Biometric Identifier", ICIP, Cairo, Egypt, 2009.

[22] Madane, M., & Thepade, S. (2016). Score Level Fusion Based Bimodal Biometric Identification Using Thepade's Sorted n-ary Block Truncation Coding with Variod Proportions of Iris and Palmprint Traits. Procedia Computer Science, 79, 466-473.

[23] Singh, V., Kant, C., & tech Scholar, M. An Efficient Multi-Modal Biometric Authentication System Using Face, Iris and Finger Knuckle Print.(2015)

[24] Meraoumia, A., Chitroub, S., & Bouridane, A. (2011, June). Fusion of finger-knuckle-print and palmprint for an efficient multi-biometric system of person recognition. In 2011 IEEE International Conference on Communications (ICC) (pp. 1-5). IEEE.

[25] Mayya, A., & Saii, M. Iris and Palmprint Decision Fusion to Enhance Human Recognition. International Journal of Computer Science Trends and Technology (IJCST), 5, 42-46. (2017)