ADAPTIVE MULTIMODAL BIOMETRIC FUSION ALGORITHM USING PARTICLE SWARM OPTIMIZATION AND BELIEF FUNCTIONS

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ABSTRACT

In this paper, an adaptive multimodal biometric fusion algorithm is proposed. It is based on belief functions and Particle Swarm Optimization (PSO). The fusion is performed at the score level using belief functions such as Dempster Shafer, Yager, Proportional Conflict Redistribution and Dezert-Smarandache hybrid rules. A hybrid PSO is employed to select the best belief function and estimate its parameters. Several experiments have been conducted on BANCA dataset and a comparison between the well established methods has been performed. The preliminary results provide adequate motivation towards future research in the application of optimization techniques in the belief functions.

***Index Terms*—** Biometric fusion, score level fusion, belief functions, PSO

1. INTRODUCTION

Biometrics is a statistical measurement of human physiological/behavioural traits. It can be used as an alternative of the traditional security systems based on keys, cards, badges, passwords or PIN numbers. Unimodal biometric systems rely on a single modality, so they are limited against accuracy and vulnerability to spoofing. This is mainly due to many reasons such as imperfect sensor, noisy data, intra-class variation and non universality [1]. To overcome these limitations, the fusion of biometric systems has been proposed [1]. Multi biometric systems combine various biometric data at different levels like sensor level, feature extraction level, score level or decision level. The fusion at score level is widely used in biometric as it is simple and efficient. It is based on the combination of similarity scores of the biometric matchers. Fusion methods at score level are divided into three categories [2] statistical, learning and belief functions based methods. Statistical techniques combine the scores of the different unimodal matchers by using various basic statistical rules such as sum, product, Max and Min. Learning techniques classify multimodal scores into one of the two classes: genuine or impostor. The main techniques are support vector machine (SVM), Bayesian inference and neural networks (NN). Belief functions are used to convert the scores into beliefs assignments which are mixed by a combination rule based on Dempster Shafer and Dezert-Smarandache theories.

The main problem with statistical and learning fusion techniques appears when different unimodal biometric systems produce highly conflicting results. These methods are not able to handle this conflict and the fusion performance is not enhanced. In opposition, belief functions can manage the conflict between many unimodal biometric systems [2]. Many belief functions have been proposed in literature. Each function differs from another one and the most important problem is how to choose the belief function which gives the best performance. Motivated by this case, we propose to use a hybrid PSO to select the best belief function and estimate its parameters in order to obtain a higher accuracy. PSO is used because it is a powerful method for parameters estimation.

The remainder of this paper is divided into four sections. Related work is discussed in section 2, while section 3 describes the proposed method. Experimental results are presented in section 4. The paper is concluded in section 5.

2. RELATED WORK

Recently, the design and the development of a multimodal biometric system which automatically selects the best fusion rule and estimates its parameters has become one of the most active research area. In literature, some works have been proposed.

An adaptive multimodal biometric fusion algorithm has been proposed by Veeramachaneni et al. [3]. It is based on a Bayesian decision fusion and PSO. A Bayesian framework has been employed to combine the decisions of several biometric classifiers. PSO has been used to search the best decision fusion rule and the threshold at a desired security level. This algorithm has been tested only on simulated data to investigate its performance. The simulated data distribution is assumed to be Gaussian which is not true for several biometric systems.

A method for enhancing the performance of correlated biometric classifiers is suggested by Srinivas et al. [4]. It is based on the weighted sum rule and PSO. PSO has been used to compute the weight for each classifier. A Bayesian risk function is used as a fitness function. This approach has been tested on the NIST BSSR dataset and on synthetic scores which have been generated by a multivariate normal distribution. This method outperforms the classical weighted sum rule.

A Particle Swarm Optimization scheme in the weighted sum rule is proposed by Anzar et al. [5]. The d-prime statistics has been used to measure the separation between the genuine and the impostor score distribution. It is calculated for both of fingerprint and voice modalities. The weight of each modality is based on the ratio of these two statistics and it is estimated by PSO. This method has been studied under various noise conditions. It has decreased the FAR (False Acceptance Rate) even at low conditions. The recognition rate is enhanced above 0 dB SNR (Signal to Noise Ratio). However, this method presents poor results under noise conditions (for SNRs$<$0 dB).

An evolutionary approach for adaptive combination of multiple biometric systems is presented by Kumar et al. [6]. This adaptive combination consists on finding an optimal fusion rule and estimating its parameters by using a hybrid PSO. The score level fusion rules used in this work are sum, product, exponential sum and tanh hyperbolic sum. This approach has been tested on real and simulated biometric data. Experiments have shown that this approach achieves good and stable performance over the fusion at the decision level based on PSO.

3. PROPOSED METHODOLOGY

In the previous mentioned works [3], [4], [5] and [6], the integration of PSO in a multi biometric system to choose the best fusion rule and estimate its parameters has given promising results. These works have only used combination rules such as: or, and, weighed sum, product, exponential sum and tan-hyperbolic sum rules. To our knowledge, there is no work which uses PSO combined to other fusion techniques such as learning and belief functions methods. Consequently, in this work, we propose the fusion of unimodal biometric systems for person verification using belief functions and evolutionary method. This choice is justified by the fact that the belief functions can deal with the conflict between the different classifiers and the evolutionary techniques like PSO allows the best parameters estimation.

The proposed method consists in the following steps as depicted on figure 1. First, the score of each biometric system is transformed into belief assignment by using the best parameters obtained by PSO. Next, the fusion is performed by the best belief function returned by PSO. Finally, in the decision step, a person is classified as a genuine or an impostor by using the best decision threshold calculated by PSO.

3.1. Transformation of the scores into masses

Typically, the classification step in a verification biometric system is formulated as a two class problem. The two classes are genuine θ_{gen} and impostor θ_{imp}. Consequently, $\Theta = \{\theta_{imp}, \theta_{imp}\}$ is used as a frame of discernment.

In this step, the score provided by each unimodal biometric system is transformed into three masses: the mass of genuine θ_{gen}, the mass of impostor θ_{imp} and the mass of the uncertainty $\theta_{imp} \cup \theta_{imp}$. This transformation is performed with Appriou [7] model. It is defined by:

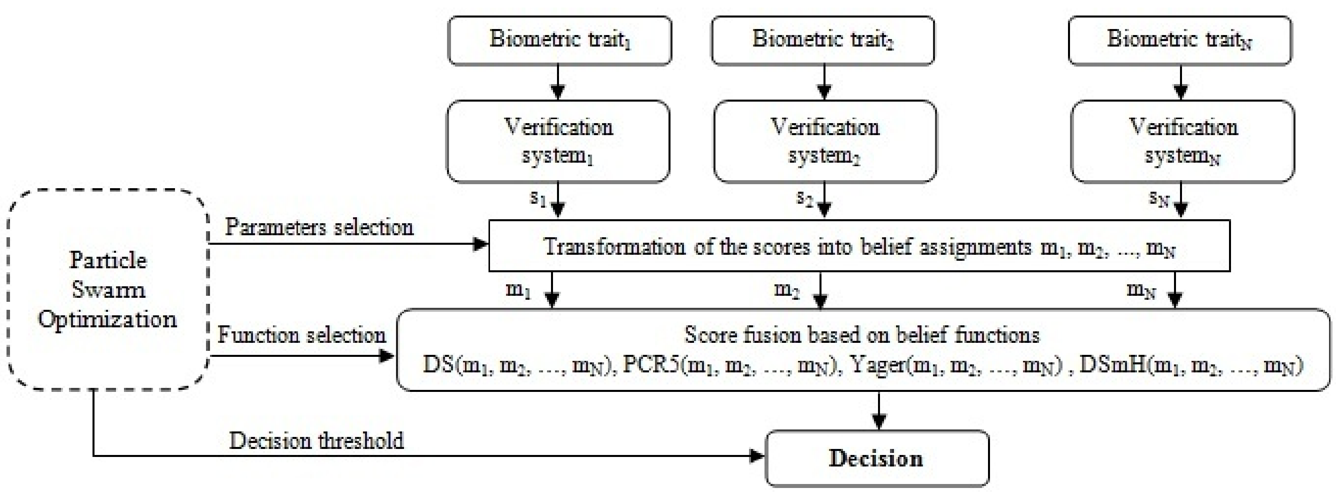


Fig. 1. Flow diagram of the proposed method.

$$\begin{cases} m_i(\theta_{gen}) & = & \alpha_i \times \psi(s_{ij}) \\ m_i(\theta_{imp}) & = & \alpha_i \times (1-\psi(s_{ij})) \\ m_i(\Theta) & = & 1-\alpha_i \end{cases} \quad (1)$$

Where

i corresponds to the i^{th} unimodal biometric system.

α_i is the confidence factor of the i^{th} unimodal biometric system such as $0 < \alpha_i < 1$.

s_{ij} is the match score of a person j provided by the i^{th} unimodal biometric system.

ψ is an increasing function which maps the scores in the range [0, 1]. The sigmoid function is used in the proposed method. It is defined by:

$$\psi(s_{ij}) = logsig(s_{ij}) = 1/(1+exp(-s_{ij})) \quad (2)$$

Computing (α_1, α_2, ..., α_N) is performed by PSO in section 3.4 where N is the number of unimodal biometric system.

3.2. Score level fusion by belief functions

Belief functions theory is a powerful tool for representing uncertain knowledge. It is a generalization of the probability theory. It includes many approaches. In this work, Dempster Shafer, Yager, Proportional Conflict Redistribution and Dezert-Smarandache hybrid combination rules are used.

The Dempster Shafer (DS) combination rule of two belief functions $m1(.)$ and $m2(.)$ over the power set of Θ (i.e. 2^Θ) is defined by [8]:

$$m_{DS}(A) = \frac{\sum_{X,Y\in 2^\Theta, X\cap Y=A} m_1(X)m_2(Y)}{1-k_{12}} \quad (3)$$

$$k_{12} = \sum_{X,Y\in 2^\Theta, X\cap Y=\emptyset} m_1(X)m_2(Y) \quad (4)$$

Where

$A \in 2^\Theta = \{\theta_{gen}, \theta_{imp}, \theta_{gen} \cup \theta_{imp}\}$.

$1-k_{12}$ is a normalizing factor, it consists on eliminating the conflict of information between the sources to combine.

$m_i(.)$ represents the belief assignment of the i^{th} unimodal biometric system.

The Yager combination rule admits that in the case of conflict the result is not reliable. In this case, the factor k_{12} is considered as an absolute discounting term added to the ignorance. This rule is given by [2]:

$$\begin{array}{l} m_{Yager}(\emptyset) = 0 \\ m_{Yager}(A) = \sum_{X,Y\in 2^\Theta, X\cap Y=A} m_1(X)m_2(Y) \\ m_{Yager}(\Theta) = m_1(\Theta)m_2(\Theta) + k_{12} \end{array} \quad (5)$$

The Proportional Conflict Redistribution (PCR) combination rule redistributes the partial conflicting mass to the elements involved in the partial conflict. It has five versions: PCR1 to PCR5. In [2], PCR5 is considered as the most accurate version. The PCR5 combination rule of two sources is given by [2]:

$$m_{PCR5}(A) = m_{12}(A) + \sum_{A,B\in 2^\Theta, A\cap B=\emptyset} \left[\frac{m_1(A)^2 m_2(B)}{m_1(A)+m_2(B)} + \frac{m_2(A)^2 m_1(B)}{m_2(A)+m_1(B)}\right] \quad (6)$$

Where $m_{12}(A)$ corresponds to the conjunctive consensus on A between the two sources. It is defined as:

$$m_{12}(A) = \sum_{X,Y\in 2^\Theta, X\cap Y=A} m_1(X)m_2(Y) \quad (7)$$

The basic idea of the Dezert-Smarandache hybrid combination rule (DSmH) is to define the belief assignments on hyper-power set $D^\Theta = \{\theta_{gen}, \theta_{imp}, \theta_{gen} \cap \theta_{imp}, \theta_{gen} \cup \theta_{imp}\}$. The DSmH combination rule of two independent sources of evidence is defined as follow [2]:

$$\begin{array}{l} m_{DSmH}(\emptyset) = 0 \\ m_{DSmH}(A) = \sum_{X,Y\in D^\Theta, X\cap Y=A} m_1(X)m_2(Y) + \\ \sum_{X,Y\in\emptyset,(A=U)\vee(U\in\emptyset\wedge A=I)} m_1(X)m_2(Y) + \\ \sum_{X,Y\in D^\Theta, X\cup Y=A, X\cap Y\in\emptyset} m_1(X)m_2(Y) \end{array} \quad (8)$$

Where

U is the disjunctive form of $X \cap Y$

I is the total ignorance.

3.3. Decision

In this step, the fused beliefs are transformed into a probability measure by using the pignistic transformation [2] in the case of DS, Yager and PCR5 rules and the generalized pignistic transformation [2] in the case of DSmH rule. These two transformations are defined by (9) and (10). Then, a statistical classification approach such as the likelihood ratio test is used to compute the final decision (see (11) and (12)).

$$betP(X) = \sum_{X\in\Theta, Y\in 2^\Theta, Y\neq\emptyset} \frac{|X\cap Y|}{|Y|} \frac{m_{fusion}(Y)}{1-m_{fusion}(\emptyset)} \quad (9)$$

Where $|Y|$ denotes the cardinality of Y.

$$GPT(X) = \sum_{X\in\Theta, Y\in D^\Theta} \frac{C_M(X\cap Y)}{C_M(Y)} \frac{m_{fusion}(Y)}{1-m_{fusion}(\emptyset)} \quad (10)$$

Where $C_M(Y)$ is the DSm cardinality corresponding to the number of parts of Y.

$$Decision_{DS,Yager,PCR5} = \begin{cases} genuine\ if \dfrac{betP(\theta_{gen})}{betP(\theta_{imp})} \geq \Delta \\ impostor\ otherwise \end{cases} \quad (11)$$

$$Decision_{DSmH} = \begin{cases} genuine\ if \dfrac{GPT(\theta_{gen})}{GPT(\theta_{imp})} \geq \Delta \\ impostor\ otherwise \end{cases} \quad (12)$$

Where Δ is the decision threshold that minimizes the weighted error rate (WER) on a development set.

3.4. Belief function and confidence factor optimization

PSO is a population optimization method. It was proposed by Kennedy and Eberhart in 1995 [9]. A particle in the search space is considered as an individual bird. It has an initial position and velocity. To find the best solution, all particles and their velocities are replaced by the best previous position of the current particle $Pbest_i$ and the best previous position of all particles $Gbest$ using (13) and (14). A fitness function is used to evaluate the position of the particles. After a limited number of iterations, the particle that satisfies the global best fitness is chosen as the optimal result.

$$v_i(t+1) = w \times v_i(t) + c_1 \times r_1 \times (Pbest_i - p_i(t)) + c_2 \times r_2 \times (Gbest - p_i(t)) \tag{13}$$

$$p_i(t+1) = p_i(t) + v_i(t+1) \tag{14}$$

Where

v_i is the velocity of the i^{th} particle.

p_i is the position of the i^{th} particle.

w is the inertial weight.

c_1 and c_2 are the acceleration constants used to pull each particle towards $Pbest$ and $Gbest$.

r_1 and r_2 are random numbers generated between [0, 1].

Equation (14) operates on continuous space. However, there exist optimization problems where the particles are represented in a discrete space. The concept of PSO in a discrete domain is proposed in [10]. It is named binary PSO (BPSO). In BPSO, (14) is rewritten as follows:

$$p_i(t+1) = \begin{cases} 1 & if \quad r_3 < S(v_i(t+1)) \\ 0 & otherwise \end{cases} \tag{15}$$

Where r_3 is a random number generated between [0, 1] and S is the sigmoid function.

In our implementation, BPSO is employed to select the best belief function among the following functions: DS, Yager, PCR5 and DSmH. Each particle is composed of $log_2 K$ binary values, where K is the number of belief functions. However, PSO is used to estimate the confidence factors (α_1, α_2, ..., α_N) with the constraint $0 < \alpha_i < 1$, for $i = 1, 2, .., N$ where N is the number of modalities. The flow diagram of this step is explained in figure 2.

At the initial step, the particles population is set to 10 and the maximum number of iterations to 100. After randomly initializing the position and velocity of all particles, all training scores are transformed into belief assignments. Then, they are multiplied by the position of PSO particles. After that, the belief assignments are fused by the function which exists in BPSO particles. The weighted error rate (WER) is used as a fitness function. It is defined by [11]:

$$WER(\Delta) = C_{FA} \times FAR(\Delta) + (1 - C_{FA}) \times FRR(\Delta) \tag{16}$$

Where C_{FA} varies from 0 to 1, it balances between the costs of FAR and FRR. FAR is the false acceptance rate and FRR is the false rejection rate.

At the end of iterations, $Gbest$ contains the best belief function and its parameters (confidence factors).

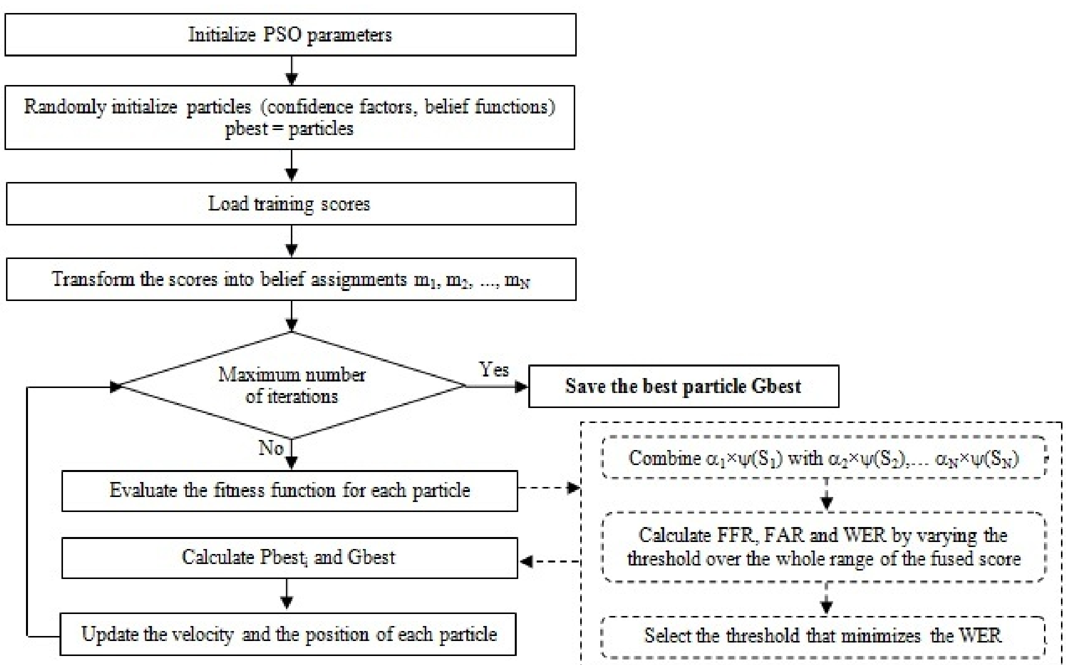


Fig. 2. Flow diagram of particle swarm optimization step.

4. RESULT

The experiments have been conducted on the scores of the BANCA multimodal base [12]. It contains real bimodal face and speech data. The English subset [11] contains 52 subjects. It is divided into two sets, called g1 and g2. Each set contains 13 males and 13 females. g1 is used as a development set and g2 is used as an evaluation set. In the BANCA database, there are 7 different protocols [11] matched controlled (Mc), matched degraded (Md), matched adverse (Ma), unmatched degraded (Ud), unmatched adverse (Ua), pooled test (P) and grant test (G).

The PSO parameters c_1, c_2 and w are computed by the formula cited in [13] and [14] respectively. The PSO algorithm is running 10 times. In each run, the HTER (Half Total Error Rate) is computed for each combination of the different classifiers on a test set (g2). The HTER is defined as [11]:

$$HTER_(\Delta^*) = (FAR(\Delta^*) + FRR(\Delta^*))/2 \tag{17}$$

Where $\Delta^* = argminWER(\Delta)$.

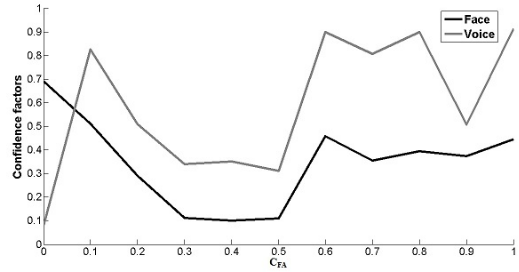
The HTER achieved by the proposed approach and the individual classifiers is presented in Table 1. The proposed approach achieves better HTER than the individual classifiers. Also, it is seen that the proposed approach reaches a high accuracy when compared to the fusion based on belief functions without using PSO over all the BANCA protocols.

Table 1 presents also the most selected function by BPSO. This selection differs from one protocol to another. For example, Yager rule is the most selected function in Ua and Ma protocols. However, PCR5 rule is the best function in Ud protocol. So, we confirm that using BPSO to select the best fusion rule is very important to improve the verification accuracy.

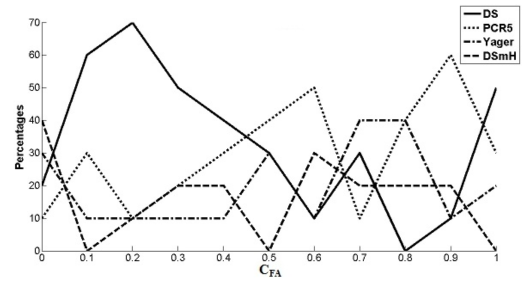
Table 2 summarizes a comparative study between the proposed method, the methods cited in [3] and the SVM based fusion using RBF kernel. The proposed approach surpasses the SVM based fusion on all the protocols because the belief functions deal the conflict between the classifiers but the SVM did not handle such conflict. Also, it is noticed that the proposed method outperforms the fusion at decision level using PSO [3] on all the protocols because the fusion at the score level has more significant information compared to the fusion at the decision level.

Figure 3.a presents the confidence factors calculated by the proposed approach by varying C_{FA}. We notice that the confidence factors values change by varying C_{FA}. This proves that the proposed approach find the best confidence factors that achieve the best performance.

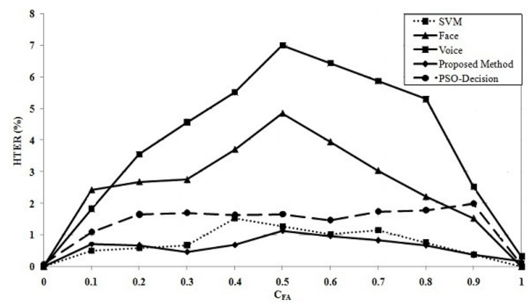
Figure 3.b presents the probability of selecting belief function by varying C_{FA}. It is noticed that DS rule is the best function for $0.1 \leq C_{FA} \leq 0.4$. However, PCR5 rule is most selected rule for $0.5 \leq C_{FA} \leq 0.6$ and $0.8 \leq C_{FA} \leq 0.9$. Moreover, Yager rule is the best one for $0.7 \leq C_{FA} \leq 0.8$.



(a)



(b)



(c)

Fig. 3. (a) Confidence factors achieved by the proposed approach, (b) Probability of selecting belief function, (c) HTER computed by varying C_{FA} using G Protocol.

Figure 3.c presents the HTER computed by the different methods against C_{FA} variations. It is noticed that SVM based fusion is the best method for $0 \leq C_{FA} \leq 0.2$ and $0.9 \leq C_{FA} \leq 1$. However, the proposed approach yields the minimum values of HTER for $0.2 \leq C_{FA} \leq 0.9$.

5. CONCLUSION

In this study, a new adaptive multi biometric fusion algorithm is proposed. It is based on belief functions and particle swarm optimization. The contribution of this research consists on selecting the best belief function rule among DS, Yager, PCR5 and DSmH by a binary PSO and estimating its parameters by PSO.

The comparison of the proposed approach with the fusion at decision level using PSO and the SVM has shown that the proposed method outperforms these methods on all the

Protocol	Face	Voice	DS	PCR5	Yager	DSmH	The proposed method	The most selected function
G	7.146	4.082	1.447	1.727	1.720	1.718	**1.181**	DSmH
P	18.480	8.412	6.779	7.548	7.573	7.543	**6.100**	DS
Ua	28.171	15.159	12.704	14.336	14.377	14.302	**11.549**	Yager
Ud	16.564	3.876	3.744	4.643	4.675	4.633	**2.285**	PCR5
Ma	12.706	11.785	6.498	6.481	6.462	6.459	**6.249**	Yager
Mc	3.835	2.962	1.101	1.241	1.252	1.270	**1.100**	DS
Md	8.459	6.244	**2.125**	2.744	2.738	2.752	2.676	DS

Table 1. Average HTER of the individual classifiers, DS, PCR5, Yager, DSmH and the proposed method (C_{FA} = 0.5).

Protocol	The proposed method	Fusion at decision level based on PSO	SVM (RBF kernel)
G	**1.181**	2.402	1.325
P	**6.100**	7.637	6.266
Ua	**11.549**	14.235	12.104
Ud	**2.285**	4.119	3.095
Ma	**6.249**	8.888	6.459
Mc	**1.100**	1.785	1.334
Md	**2.676**	3.797	2.960

Table 2. Average HTER of the proposed method, fusion at decision level based on PSO and SVM based fusion (C_{FA} = 0.5).

BANCA protocols.

In future work, we propose to integrate other fusion techniques in the proposed framework in order to select the fusion technique which gives the best performance.

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