Differential Evolution Based Score Level Fusion For Multi-modal Biometric Systems

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***Abstract*—The purpose of a multimodal biometric system is to construct a robust classifier of genuine and imposter candidates by extracting useful information from several biometric sources which fail to perform well in identification or verification as individual biometric systems. Amongst different levels of information fusion, very few approaches exist in literature exploring score level fusion. In this paper, we propose a novel adaptive weight and exponent based function mapping the matching scores from different biometric sources into a single amalgamated matching score to be used by a classifier for further decision making. Differential Evolution (DE) has been employed to adjust these tunable parameters with the objective being the minimization of the overlapping area of the frequency distributions of genuine and imposter scores in the fused score space, which are estimated by Gaussian kernel density method to achieve higher level of accuracy. Experimental results show that, the proposed method outperforms the conventional score-level fusion rules (sum, product, tanh, exponential) when tested on two databases of 4 modalities (fingerprint, iris, left ear and right ear) of 200 and 516 users and thus confirms the effectiveness of score level fusion. The preliminary results provide adequate motivation towards future research in the line of the application of meta-heuristics in score level fusion.**

***Keywords*—multimodal biometric system, score-level fusion, Differential Evolution, ROC, kernel density estimation.**

I. Introduction

Over the last few years, the significance of biometric authentication has increased drastically and has been of paramount importance to various applications, like financial transactions and public network security, which strictly need authentic biometric information of the user personnel to verify his/her identity. Automatic personal authentication uses different biometric characteristics to attain robustness to noise, permanence, universality, distinctiveness, rotational invariance, translation or distortion, which in turn, ensures the prevention of spoofing. Since it is almost impossible to meet all these requisitions with a single biometric feature, the utility of multi-modal biometric system is firmly acknowledged in the field of automatic personal authentication. As multi-modal system consists of scores of different modalities (like face, palm print, iris, ear, speech etc.) for different individuals who are to be authenticated or classified, integration is recommended which guarantees speed and acceptability of the system. This integration or fusion can be done at several levels like sensor level, feature extraction level, score level and decision level.

A general rule for multimodal system design states that the integration at an early stage of biometric management i.e. at sensor level might be more accurate than those where the fusion is introduced at later stages. A feature extraction level fusion would be difficult as different features may be incompatible with the others. Hence due to the different natures of the biometric modalities, which might be hardly compatible (e.g., fingerprint and iris), fusion at sensor level is hard to obtain. Most commercial biometric systems do not provide access to the feature sets and hence exclude the possibility of fusion at feature level. Consequently, in most applications, fusions at sensor and feature levels are not performed. Fusion at matching level or at decision level does not require the creation of new databases or matching modules. Additionally, it is very difficult to fuse or integrate the scores of different attributes in a decision level methodology due to lack of information. This leaves us to score level fusion, which is indeed convenient where decent amount of information helps to differentiate the feature vectors obtained from the scores in two different classes: Genuine (Accept) and Impostor (Reject).

In context of verification, the fusion problem can be viewed in two ways: first as a classification problem; second as a combinational problem. Classification problem deals with different feature vectors obtained from individual matchers in order to classify the user as Genuine or Impostor. On contrary, a combinational problem can be approached by generating a single scalar score using different fusion algorithms in order to reach a final decision based on a discriminating threshold. Ross and Jain [1] showed the better performance of combinational approach than some classification approach like decision tree, linear discriminant analysis although no single classification or combination approach works well under all circumstances. Several efforts have been made in previous literature to apply different classifiers to fuse the matching scores. Wang *et al.*

[2] used Fisher Discriminant method and Neural network classifier with radial basis function using 2-D feature vectors. Meanwhile, Verlinde and Chollet [3] introduced three different classifiers on a bimodal system, consisting of face-recognition and speaker-recognition module, such as k-NN classifier that uses vector quantization, decision tree and logistic regression models.

Chatzis et al. [4] introduced fuzzy k-means and fuzzy vector quantization with a median radial basis function neural network classifier. Also score level fusion of iris and fingerprint biometrics was implemented using Support Vector Machine [5]. Kittler et. al [6] proposed some classical combinational methods known as multiplication rules including sum rule, product rule, max rule, min rule, median rule, majority voting for the experiment to improve the performance of biometric management of real life data. Sim *et al.* [7] proposed an innovative approach to multi-modal biometrics ensuring higher security but the approach required continuous presence of user to be verified. A dynamic selection of matching scores in case of multi-modal problem has been proposed by Tronci *et al.* [8] but the latitude of the effectiveness of this method is insignificant. BioID system, which was developed by Frischholz *et al.* [9] associates different decision strategies for different biometric modalities but lacks from the automatic generation of adaptive strategies for desired performance. Some attempts in decision level fusion have also been made using k-NN (k-Nearest Neighbor) [10] [11], neural networks(NN) [12] [13], decisiontree(DT) [14] [15] [16] [17] , and support vector machine(SVM) [18] [19]. While considering the scaled independent contribution of input data to the output target vector, support vector machine (SVM), logistic regression and nearest neighbor methods produce satisfactory results. Decision Tree (DT), being a popular method in data mining, was applied in previous literature to fuse biometric information. The drawbacks and utilities of various DT-based algorithms can be discussed here. For example, C4.5 algorithm worsens palmprint recognition. A parallel method based on DT uses keystroke dynamics for authentication [14], whereas the application of DT as an indexing method in figure print authentication, is known for its drastic reduction of search space [15]. A DT based face recognition using local binary patterns (LBP) also exists in literature [20]. Component-based face detection integrating AdaBoost learning and DT [21], hybrid of SVM-DT for face recognition [22], also can be referred. Kumar et al.[23] proposed a new scheme using Fuzzy Binary Decision Tree (FBDT), which incorporated fuzzy gini index and fuzzy entropy for decision level fusion. Although there was an attempt using FDT and gini index in [24], its scope was limited. Mainly, this FDT and FBDT based methods were developed for classification of claimed identity into any two classes: Genuine and Imposter, hence are decision level fusion techniques.

Another promising approach was devised by Veeramachaneni et al. [25] which adaptively manages the decision rules for each individual modality to meet the desired performance. But as stated before, the decision level fusion deals with the least information and hence generates higher performance fluctuations and unstable results. Recently, Kumar *et al.* [26] successfully presented an automatic weight adaptation scheme while minimising the Bayesian cost function in order to reach the desired level of security. Still a skilful investigation over the proper threshold has been left undone. In our approach, we concentrate on minimizing the overlapping area of two distributions (Genuine and Imposter) to define a stringent threshold that can easily separate these two distributions and hence can be able to reflect the desired security guaranteed by a system. By the classical methods, once we obtain a combined or fused score, a proper threshold having proper tolerance can be defined to identify a test data as Genuine or Imposter. But for biometric attributes, the degree of importance may not be same for all, which in effect would not give the satisfactory result when fused by simple classical methods. Hence as Jain and Ross [1] proposed, it is customary to assign proper weight to individual attributes, thus in turn they can be fused to attain the minimum FAR and FRR. This user-specific parameter learning still is not adaptive until the process is optimized on the basis of an optimization function to minimize the overlapping area of two frequency distributions, one for Genuine and other for Imposter. Exponents on each score can improve the fusion characteristics, along with proper weights, assigned to every constituent matching score according to its degree of importance. Thus we can define a rule of score-level fusion as a weighted sum of individual scores (fingerprint, iris, left ear, right ear, etc.) with their corresponding exponents. These weights along with the exponents are the control parameters, the optimal values of which would render minimum overlap between the genuine and imposter distributions of the fused score. The novelty of our method lies in two aspects: 1) Firstly, we use kernel density estimation, a non-parametric measure to estimate the density functions of the genuine and imposters, the fused score being the random variable since the accuracy of the overlapping area calculation depends on the strategy of estimation which is heavily dependant on bin-size or interval in case of the naive histogram method of estimation. 2) Secondly,the overlapping area of such kernelized continuous fused genuine and imposter distributions is minimized by an efficient stochastic real-parameter optimization algorithm, Different Evolution (DE), which adaptively explores the problem space and then exploits it to find the optimum vector, consisting of the adaptive weights and exponents, in order to minimize the overlapping area between two frequency distributions of two different classes (genuine and imposter).

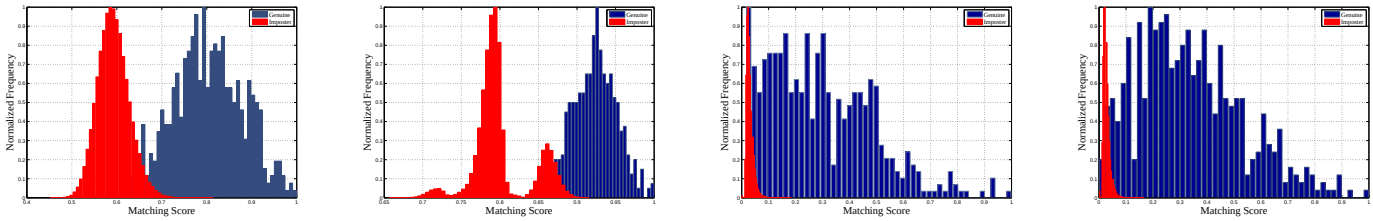
The organization of the paper is as follows: Section II provides the background required for proposing the new score-level fusion method. In Section III, the proposed algorithm, highlighting on the concepts of forming kernel-based continuous probability density distributions have been explained. Section IV presents the Experimental results while Section V concludes the proceedings.

II. Background

A. Differential Evolution

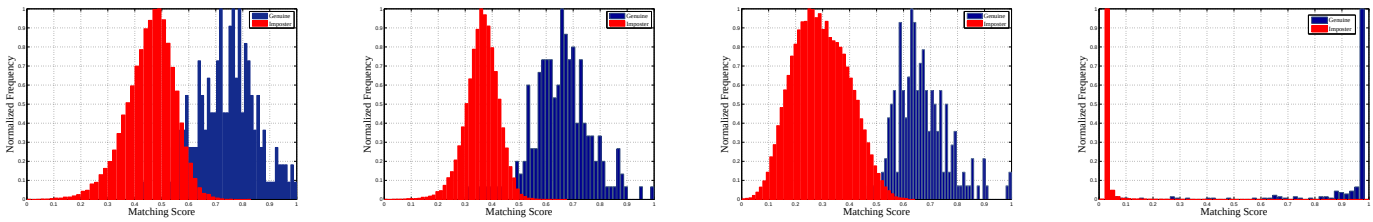
Differential evolution (DE) has emerged as one of the most competitive evolutionary algorithms. Invented by Storn and Price [27], DE is a stochastic direct search method using a population of multiple search points. Its variants have been successfully implemented in solving multi-objective, dynamic and constrained optimization problems and tackle many real world situations.

DE has a structure similar to genetic algorithm. It is equipped with a population which is a collection of trial solu-



(a) Fingerprint (b) Iris (c) Left Ear (d) Right Ear

Fig. 1: Matching score genuine and imposter distributions of the constituent modalities in Biometric_D database



(a) Fingerprint (b) Iris (c) Left Ear (d) Right Ear

Fig. 2: Matching score genuine and imposter distributions of the constituent modalities in XM2VTS database

tions. In case of real parameter optimization, the parameters to be optimized are encoded within a vector $\overrightarrow{x} = [x_1, x_2, ...x_n]$. These individual vectors (which constitute a population) are called parameter vectors or genomes. The population is then manipulated with three operations namely mutation, crossover and selection. However, unlike traditional Evolutionary Algorthms (EAs), DE employs difference of the parameter vectors to explore the objective function landscape. It perturbs the population members with the scaled differences of randomly selected and distinct population members. Therefore, there exists no separate probability distribution for generating the offspring.

In the search population, each vector forms a candidate solution to the multidimensional optimization problem. We shall denote subsequent generations in DE by $G = 0, 1..., G_{max}$. Since the parameter vectors are likely to be changed over different generations, we may adopt the following notation for representing the ith vector of the population at the current generation $\overrightarrow{x}_{i,G} = [x_{1,i,G}, x_{2,i,G}, x_{3,i,G}, ..., x_{D,i,G}]$. Where $x_{j,i,0}$ is randomly initialized with in the search space constrained by the prescribed minimum and maximum bounds: $x_{j,min}$ and $x_{j,max} \forall j = 1, 2, ..., N$. Hence, we may initialize the jth component of the ith vector as,

$$x_{j,i,0} = x_{j,min} + rand \times (x_{j,max} - x_{j,min}), \qquad (1)$$

where $rand$ is a uniformly distributed random number lying between 0 and 1 and is instantiated independently for each component of the ith vector.

Mutation, in the paradigm of DE, signifies a random perturbation about a trail vector. In the simplest version of mutation, three non overlapping vectors $\overrightarrow{x}_{p_1,i,G}, \overrightarrow{x}_{p_2,i,G}, \overrightarrow{x}_{p_3,i,G}$ are randomly selected from the population (p_1, p_2, p_3) are three mutually exclusive random integers belonging to the range $[1, NP]$). The donor vector which is the outcome of mutation is generated as,

$$\overrightarrow{v}_{i,G} = \overrightarrow{x}_{p_1,i,G} + F \times (\overrightarrow{x}_{p_2,i,G} - \overrightarrow{x}_{p_3,i,G}) \qquad (2)$$

where F is the scaling factor and F $\in [0.4,\ 1]$.

After generating the donor vector, the cross over operation comes into play to enhance the potential diversity of the population. The genes of $\overrightarrow{u}_{i,G}$ and $\overrightarrow{x}_{i,G}$ are interchanged to form a trial vector $\overrightarrow{u}_{i,G} = [u_{1,i,G}, u_{2,i,G}, .., u_{D,i,G}]$. The scheme of binomial crossover is dictated by the following.

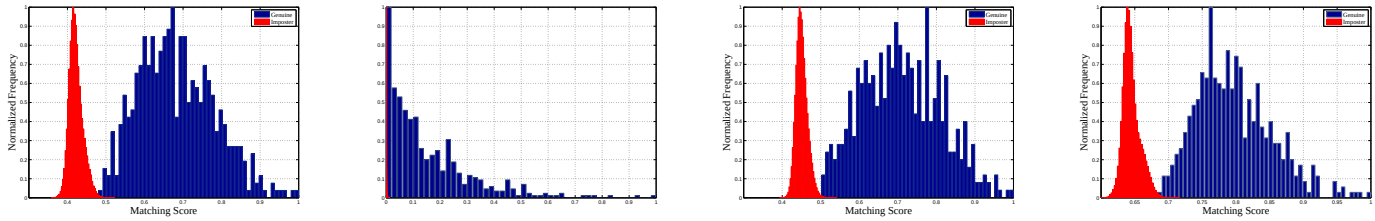
$$u_{j,i,G} = \left\{ \begin{array}{ll} v_{j,i,G}, & if\ rand \leq Cr\ or\ j = j_{rand} \\ x_{j,i,G}, & otherwise \end{array} \right\} \qquad (3)$$

where $j_{rand} \in [1, 2, ., NP]$ is a randomly chosen index ensuring that at least one component of $\overrightarrow{u}_{i,G}$ is selected from $\overrightarrow{v}_{i,G}$.

In the experiments conducted, the values Cr and F have been taken as 0.9 and 0.8. The size of the population has been kept at 20 for all the comparisons.

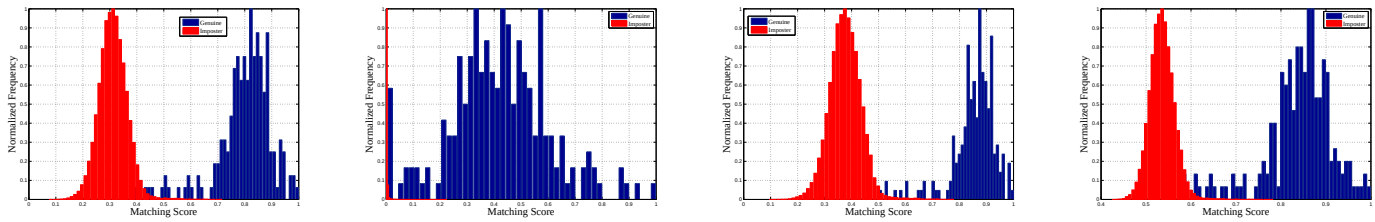
B. Performance Metric for biometric authentication system

The ultimate aim of the multimodal biometric score level fusion method is to separate the fused genuine and imposter distributions to a considerable extent so as to accurately partition the genuine and imposter classes by a threshold λ. A receiver operating characteristic (ROC), or simply the ROC curve, is a graphical plot that analyses the performance of such a binary classifier with varying discrimination thresholds denoted by λ. The ROC curve is created by plotting Genuine Acceptance Rates (GAR) with respect to False Acceptance Rates(FAR) at varying λ(s). In our approach, $ROC(\lambda) = FAR(\lambda), GAR(\lambda)$ will be mainly used to analyse the performance of competing score-level fusion algorithms in biometric authentication system. To define $FAR(\lambda)$ and $GAR(\lambda)$, let



(a) Sum (b) Product (c) Tanh (d) Exponential

Fig. 3: Matching score distributions of genuine and imposter of Biometric_D database using conventional fusion methods



(a) Sum (b) Product (c) Tanh (d) Exponential

Fig. 4: Matching score distributions of genuine and imposter of XM2VTS database using conventional fusion methods

us first assign names to the genuine and imposter probability density distributions as $\widehat{f}_g(x)$ and $\widehat{f}_i(x)$ respectively.

1) False Acceptance Rate (FAR):
FAR denotes the probability of accepting a user as genuine when, in reality, he or she is an imposter and is mathematically given as:

$$\int_{\lambda}^{\infty} \widehat{f}_i(x)\, dx \tag{4}$$

2) Genuine Acceptance Rate (GAR):
False Rejection Rate (FRR) denotes the probability of rejecting a genuine user and is related with GAR as $GAR = 1 - FRR$. Mathematically GAR is given as:

$$\int_{\lambda}^{\infty} \widehat{f}_g(x)\, dx \tag{5}$$

III. Proposed Algorithm

An ideal score enhancement will map the matching scores in such a way that there exists zero overlapping area between the frequency distributions of the genuine and imposters. Under the circumstances, the genuine and imposters can be classified with 100% accuracy based on the discriminating threshold defined. But, in practice, no matching score distribution based on a single biometric trait can ensure such a condition and hence comes the necessity of dealing with multiple traits. The primary objective of a score level fusion rule is to minimize the overlapping area of the fused genuine and imposter score distributions such that two classes are well separated. Another way to illustrate the objective of a mapping property required for fusion can be interpreted as follows. Suppose $f : (R^P) :\rightarrow (R)$ be the mapping function, P being the number of features to be fused and all component matching scores properly scaled to belong to the interval [0,1]. Let, g_j^p and i_k^p be the scores of jth genuine and k^{th} imposter for the pth feature. Let $d_{jk}^p = g_j^p - i_k^p$ denote the distance between the genuine and imposter candidate in the corresponding feature space assuming $g_j^p > i_k^p$. Then after fusion, the enhanced distance is given as: $D_{jk} = f(G_j) - f(I_k) > d_{jk}^p, \forall \quad p = 1, 2, ..., P$.

A. Proposed Adaptive Weight-Exponent Fusion ($AWEF$)

In this paper, we propose a matching score fusion function to yield the fused score vector $\mathbf{x}$ in the form:

$$F(\mathbf{x}) = a_0[(\sum_{p=1}^{P} a_p \mathbf{x}_p^{b_p}) + c_0]^{b_0}; \tag{6}$$

where a_p and b_p, respectively, denote the weight and exponent associated with the constituent p-th feature score vector i.e $\mathbf{x}_p$. c_0 is an additional offset term while a_0 and b_0 are incorporated as additional weight and exponent respectively for increased flexibility in guiding the optimization procedure. These parameters explore the proper degree of combination of the individual scores by giving adaptive weights to them and introducing powers or exponents to incorporate non-linear combination possibilities subject to the optimization criterion. Thus for P features, there are $2p + 3$ terms to be optimized for attaining minimum overlapping area between the fused genuine and imposter distributions. The two databases that we have worked with, use 4 features (fingerprint, iris, left ear and right ear) and thus have 11 parameters which require optimization. The databases will be formally introduced in Section IV. These parameters are tuned by a meta-heuristic optimization algorithm(DE, in our case) in order to minimize the overlapping area of the resulting frequency distributions of the genuine and imposter classes in the fused feature space.

B. Minimizing Overlap Area after Kernel mapping

Definitely, minimizing the overlapping area will shift the distributions further apart by minimizing the FAR and FRR.

Now, the frequency distribution of the resulting matching scores being unknown, accuracy of the overlapping area calculation depends on the strategy of estimation. In histogram technique, the most naive estimation strategy, the domain is divided into equal intervals and the number of data points belonging to each intervals is tallied. The problem of this approach is that the choice of interval or histogram bin-size leads to severe changes in the shape of the probability distribution. Instead, we have used kernel density estimation, a non-parametric measure to estimate the density functions of the genuine and imposters, the fused score being the random variable. Let, x_1, x_2, ..., x_n be n fused scores for any of the two classes(genuine/ imposter) sampled from an unknown distribution f. Then, the estimation of f i.e. $\widehat{f}$ may be obtained as,

$$\widehat{f(x)} = (1/(nh)) \sum_{i=1}^{n} K((x - x_i)/h); \tag{7}$$

where $K(.)$ is the kernel function and h is the bandwidth or smoothing parameter. Among different kernels, we have used the most-widely used variant, i.e. the Gaussian kernel given by $K(\tau) = 1/2\pi e^{-\tau^2/2}$. As for the bandwidth of the kernel h, it has been set to the value of the optimal bandwidth for univariate Gaussian kernel, i.e., $h = (4\widehat{\sigma}^5/3n)^0.2$, where $\widehat{sigma}$ denotes the standard deviation of the sample scores.

Once the densities of the fused scores, i.e. $\widehat{f}_g(x)$ and $\widehat{f}_i(x)$ have been calculated, the overlapping area may be obtained by the following equation,

$$A = \int_{-\infty}^{\infty} min(\widehat{f}_g(x), \widehat{f}_i(x))\, dx \tag{8}$$

Let us now formally set up the objective of the optimization heuristic. Let $\overrightarrow{x}_{i,G}$ denote an i-th population member of the DE-metaheuristic whose dimensions are the $2p+3$ parameters defined before. The fused scores are obtained using 6 and thus we get the fused score distribution, $F(\mathbf{x})$. Since the scores are actually represented in the form a score matrix, the diagonal elements of $F(\mathbf{x})$ yield the fused genuine distribution, $\widehat{f}_g(x)$ and the non-diagonal elements yield the imposter distribution $\widehat{f}_i(x)$. The overlapping area between these two distributions is calculated in accordance with 8 to yield A. Thus the optimization function of the DE-metaheuristic can be set up as:

$$minimize \quad A = \int_{-\infty}^{\infty} min(\widehat{f}_g(x), \widehat{f}_i(x))\, dx \tag{9}$$

IV. Experimental Discussions

A. Experimental Setup

For testing the utility of our algorithm for biometric score-level fusion, we have used matching score matrices, where the diagonal elements correspond to the genuine scores and the non-diagonal elements correspond to the imposter scores. The four individual matrices in the databases used for the score-level fusion method contain biometric scores for fingerprint, palmprint, left ear and right ear identification.

1) Experiment 1: The first experiment was conducted on the matching-score database, `Biometric_D`, which contains the four genuine and imposter matching score matrices corresponding to 516 test subjects.

2) Experiment 2: The second experiment was conducted on the publicly available matching-score database, `XM2VTS`, which contains the four genuine and imposter matching score matrices corresponding to 200 test subjects.

The courtesy of both these databases goes to Biometrics Lab, Indian Institute of Technology, Delhi (IITD).

B. Experimental Results

Databases → Fusion Algorithm ↓	Biometric_D	XM2VTS
Sum	$(1.355 \times 10^{-4}, 0.99835)$	$(2.328 \times 10^{-3}, 0.99431)$
Product	$(4.495 \times 10^{-3}, 0.99921)$	$(1.350 \times 10^{-3}, 0.99827)$
Tanh	$(1.349 \times 10^{-4}, 0.99956)$	$(2.108 \times 10^{-3}, 0.99152)$
Exponential	$(1.341 \times 10^{-4}, 0.99882)$	$(1.228 \times 10^{-3}, 0.98836)$
AWEF	$(\mathbf{5.128 \times 10^{-5}, 0.99987})$	$(\mathbf{7.430 \times 10^{-5}, 0.99981})$

TABLE I: Performance comparison of different algorithms w.r.t. (overlapping area, area under ROC curve)

1) Qualitative Analysis:

1) *Experiment 1:*
The genuine and imposter distributions for the matching scores of the individual fingerprint, iris, left ear and right ear matrices of the `Biometric_D` database are shown in Fig. 1. Fig. 3 shows the fused score distributions corresponding to the sum, product, tanh and exponential while Fig. 5 that corresponding to our proposed algorithm ($AWEF$). A closer look at the distribution plot corresponding to $AWEF$ in Fig. 5 shows that the proposed method has managed to minimize the over-lapping area to a much more acceptable extent when compared to the other score-level fusion techniques.
2) *Experiment 2:*
The genuine and imposter distributions for the matching scores of the individual fingerprint, iris, left ear and right ear matrices of the `XM2VTS` database are shown in Fig.2. Fig. 4 shows the fused score distributions corresponding to the sum, product, tanh and exponential while Fig. 6 shows that corresponding to our proposed algorithm ($AWEF$). A closer look at the distribution plot corresponding to $AWEF$ in Fig. 6 shows that the proposed method has managed to minimize the over-lapping area to a much more acceptable extent when compared to the other score-level fusion techniques.

2) Quantitative Analysis:

1) *Overlapping Area:*
Table. I reports the over-lapping area of the genuine and imposter distributions, obtained by the competing score-level fusion methods for both Experiments 1 and 2 and also the area under the ROC curves. Evidently $AWEF$ achieves the lowest overlapping area and highest area under its ROC curve with respect to the competing score-level fusion techniques.
2) *ROC curves:*

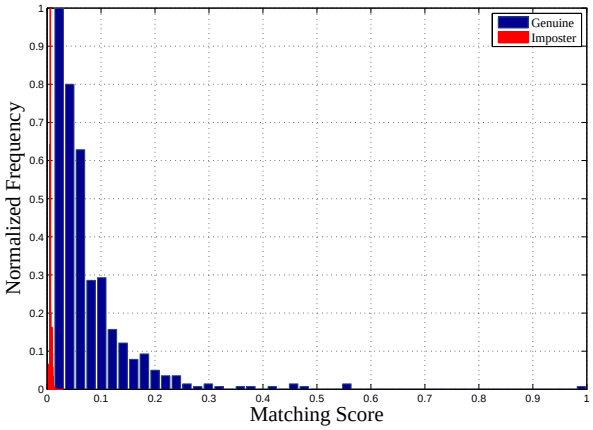


Fig. 5: Performance of AWEF in Biometric_D

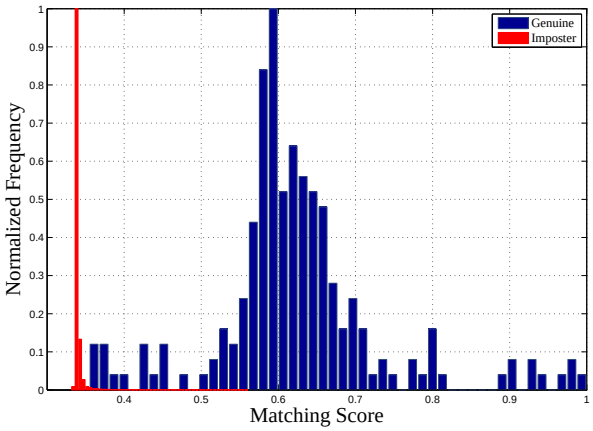


Fig. 6: Performance of AWEF in XM2VTS

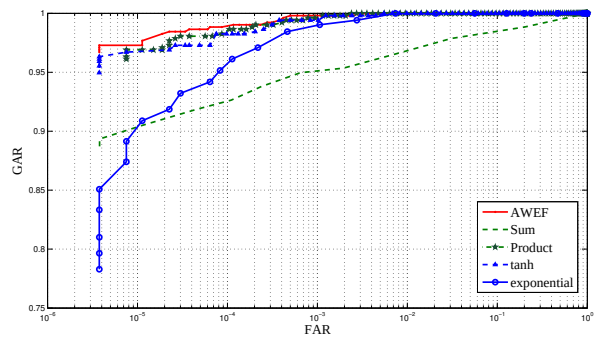


Fig. 7: ROC curve in Biometric_D

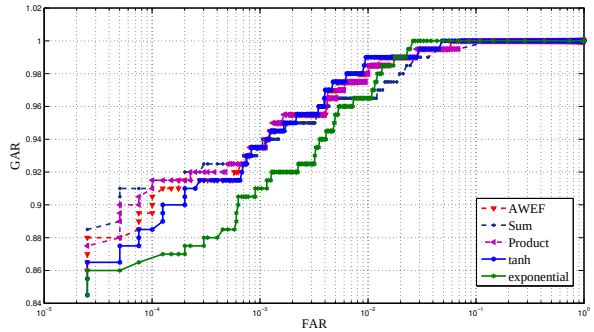


Fig. 8: ROC curve in XM2VTS

The ROC curve plotting involves the computation of False-Acceptance-Rates (FAR) and Genuine-Acceptance-Rates (GAR) at threshold intervals of 0.001. Figs. 7, 8 show that $AWEF$ achieves the most consistent ROC curve for both experimental test cases indicated by its highest area under the ROC curve in Table I. The best solution to a score-level fusion methodology has been attained by $AWEF$ reflected by its ROC curve, thereby pointing at the utility of such adaptive weight and exponent control coupled with kernelized mapping.

3) *Quantitative comparison with a few decision level algorithms*

V. Conclusion

This paper introduces a novel score level fusion strategy employing DE to minimize the overlapping area of the resultant frequency distributions of the resulting fused genuine and imposter scores. To the best of our knowledge, no such metaheuristic optimizer based parameter tuned mapping function has been deployed for blending individual scores in a multimodal biometric authentication system. However, the experimental results show that our approach significantly outperforms existing standard strategies in literature as far as ROC curves are concerned, which is the most standard metric for comparing score-level fusion algorithms. The fused scores can be used as input of a binary classifier to yield robust distinction between genuine and imposter classes. One of the notable future works of current study includes integration of such metaheuristic based fusion strategy with advanced classifiers to achieve more sophisticated decision level fusion with higher robustness and lesser computational complexity.

Acknowledgements

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