A New Multimodal Fusion Scheme Based on Heterogeneous Biometrics Data

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***Abstract*—**

Keywords*—*Ear Biometrics authentication, Genetic Algorithm, Feature Selection, Gabor feature, Principal Component Analysis.

I. INTRODUCTION

Biometric authentication allows the automatic recognition of an individual based on his physiological or behavioural characteristics.

Unimodal biometric systems are based on an unique biometrics trait such as face, finger print or iris. However, these systems suffer from some drawbacks such as noisy input data, limited degrees of freedom, intra-class variability, low distinctiveness, non-universality and unacceptable error rates [5], [14]. Alternatively, reliable and effective multibiometrics systems are used to overcome these limitations by combining more than one physiological (ear, fingerprint) or behavioral biometric traits (voice, gait). The accuracy of multimodal biometric systems depends on information fusion, which can be integrated in different levels which are sensor level, feature level, matching score level and decision level [12], [15].

At sensor level, the raw data acquired from multiple sensors can be processed and integrated to generate new data. For exemple constract the 3D model of face using two 2D face images. At the second level; Feature level fusion, the fusion takes place after having extracted the features from each biometric templates then concatenating them into one feature vector. The third case of fusion is the matching score level fusion, computes the score of each individual biometrics modality then combine them together. The last way of fusion data, the decision level fusion takes place at the later stage of authentication.

In literature, Ross [13] indicates that feature level fusion outperforms the others levels of fusion. Indeed ,it represents more and richer information at earlier stage of processing. However, these level fusion requires homogeneous data which can be a constraint in the choice of biometrics data.

In this paper, we present a new fusion scheme that combine two biometrics modalities which have different nature (image and signal). The first proposed method allows producing a new biometric data by combining ear biometric image and keystroke dynamics features using convolution. The second proposed technique present a new score level fusion scheme which combine ear biometrics, keystroke dynamics and the new biometric data produced using the first proposed method. Genetic Algorithm (GA) is used in the proposed score level fusion scheme in order to find the optimum weights associated to the modalities being fused.

The rest of the paper in organised as follow: A Literature review related to multibiomritrics is presented in Section 2. In Section 3, we present the two proposed techniques. First, the new biometric data produced by convolution using ear biometrics images and keystroke dynamics. Then, a new score level fusion scheme using GA. In Section 4, we present the experimental protocol used to validate the proposed approches . The results obtained from applying the proposed approach on a chimeric database of keystroke dynamics and ear biometrics and its comparison with the uni-modal systems and score level fusion of keystroke dynamics and ear biometrics are presented in Section 5. Finally, some conclusions and future research directions are drawn up in Section 6

II. RELATED WORK

Many works on multibiometrics have bee carried out by combining different biometrics traits at differents level, we can found the work of Ramya *et al* [10] who performed a fusion at feature level of iris and fingerprint. The proposed method is based on the decryption of features. Lin *et al* [6] present a new fusion scheme who combine fingerprint and finger vein at feature level. The proposed method uses a dynamic weighting matching algorithm based on quality evaluation of interest features. Raja *et al* [9] propose a multimodale secure authentication scenarios for smartphones who combine face periocular and iris caractheristics at score level fusion. Eskandari and Toygar [1] propose a multimodal biometric system based on score level fusion technique using face and iris. Mezai and hachouf [8] proposed a particale swarm optimisation method that weights the belief assignement of voice and face classifiers. Ghoualmi *et al* [2] have proposed a multimodal biometrics sytstem who combine ear and iris at feature level. Giot and Rosenberger [11] have proposed a

TABLE I. CONVOLUTION OF EAR BIOMETRICS USING KEYSTROKE DYNAMICS FEATURES

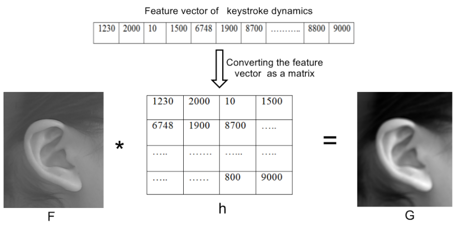
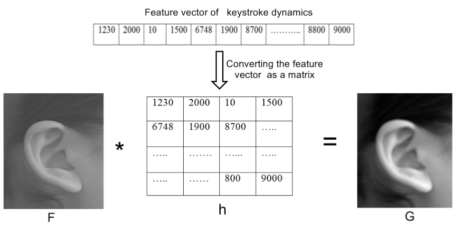


TABLE II. FUSION OF HETEROGENEOUS BIOMETRICS DATA USING CONVOLUTION



method who perform fusion at score level and use the genetic programming in order to generate a complex function rules.

III. THE PROPOSED APPROACHES

In this section we present the two proposed architectures of multibiometrics based on two modalities who have different nature (image and signal) which are ear biometrics and keystroke dynamics.

A. Fusion of heterogeneous biometrics data

The aim of the proposed methods is to combine biometrics data which have different nature such as image and signal using convolution. Convolution is a simple mathematical operation which is fundamental to many common image processing operators. Convolution provides a way of multiplying together two matrix of numbers, generally of different sizes, but of the same dimensionality, to produce a third matrix of numbers of the same dimensionality. In this work, convolution is used in order to combine the ear biometrics images and keystroke dynamics features.

Figure I presents the proposed method for combining heterogeneous data using convolution. Where keystroke dynamics features represent the kernel which will be sliding over the ear image. To perfom convolution using these two heterogeneous biometrics data. First, the features of keystroke dynamics which are presented by a vector will be converted to a matrix which had a dimension of $n*m$. Where m is equal to 4 and n is varied according to the feature size of keystroke dynamics. If the size of features is not sufficient to build the kernel, zeros will be added to complete the kernel.

Figure II present the proposed architecture of biometrics system who combine ear biometrics images and keystroke dynamics features using convolution.

Let F an image of ear biometrics caracterisez by gray-level f, h is the kernel with size of $n*m$ and G is the resulting ear image obtained from sliding the kernel h over the ear image. The convolution is calculated as described in formula 1.

$$g(m,n) = f*h|_{m,n} = \sum_{(i,j)\in voisinage} \sum f(m-i,n-j)*h(i,j) \tag{1}$$

B. Score level fusion scheme using genetic algorithm

In order to get more accurate results, we present in this section a new score level fusion scheme which combine 3 biometrics modalities: ear biometric, keystroke dynamics and the new biometric data produced by convolution. We have used the sum weighted rule function in order to combine the 3 biometrics modalities which is described in formula **??**. Where w_I presents the wight assign to each score of a biometric system and S_i^m presents the score m of user i. Figure 1 present the propose score level fusion where genetic algorithm is used in order to find the optimum weights associated to the modalities being fused.

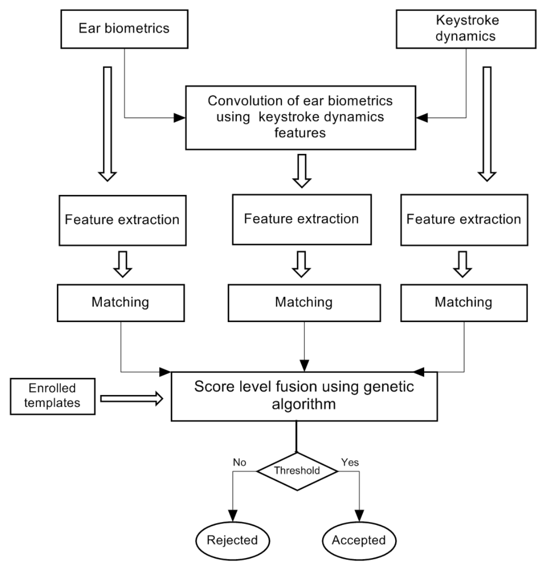


Fig. 1. Scheme 2: Score level fusion using genetic algorithm

IV. EXPERIMENTAL PROTOCOLE

in this section, we present the experimental protocol in order to validate our proposed approaches.

A. Databases

We constructed chimeric databases based on biometrics databases of ear biometrics and Keystroke dynamics. For ear biometrics, The database of the University of Science and Technology Beijing collection 1 and 2 (USTB) is used. The USTB colection 1 contains 180 images taken from 60 subjects in three sessions between July and August 2002. The database contains only images of the right ear from each subject. The USTB colection 2 contains right ear images from students and teachers from USTB. This time, the number of subjects is 77 and there were four different sessions between November 2003 and January 2004. The database contains 308 images taken under different lighting conditions. For Keystroke dynamics the GREYC [4] which contain 110 persons originaire of 24 different countries. We have used 3 passwords written by the right hand. From theses two databases, we have construct 6 chimeric databases. Each password of Keystroke dynamics is assigned to the two ear biometrics.

B. Methodologies

To validate our approach, we have compared it with. First, the uni-modal biometric systems ear and keystroke dynamics. Then, the score level fusion method using sum weighted rule which is the most common method used in multibiometrics.

For feature extraction method, we have used SIFT [7] features from the ear and the new biometrics modality produced by convolution. For keystroke dynamics we have calculated the scores using the method proposed in [3].

We have used the following configuration for the genetic algorithm where the probability of crossover and mutation is set to 0.6 and 0.1 respectively. We have made 10 run and 100 iterations with population of 50 chromosomes

V. Experimental results

In this section, we present the experimental results of the two proposed approaches and their comparison with the unimodal biometrics systems and the traditional score level fusion method of ear and keystroke dynamics.

We have chosen the dynamics keystroke as kernel because the latter has a small feature vector compared to the size of ear biometrics image .

Table III presents the results of applying the two proposed approaches on 6 chimeric databases. The fusion of ear biometrics and keystroke dynamics using convolution (Scheme 1) gives a good results compared to the unimodal biometrics systemes of ear and keystroke dynamics in the databases 1,2 and 4. However, in the databases 3,5 and 6 the ear unimodal biometrics system is better than the proposed method. Also, the quality of the acquired image (acquisition conditions) is an important factor to be considered in biometrics systems.

The proposed score level fusion method using GA outperforms the unimodal biometrics systems of ear and keystroke dynamics and the score level fusion method of the state of the art in the databases 1,2,3 and 6. However, in the database 5 our proposed approach and the score level fusion method of the state of the art work similar. However, in the database 4 the state of the art work better than our proposed approach.

VI. Conclusion

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TABLE III. Performance evaluation of the two proposed approach and their comparsion with the state of the art

chimeric database 1	
Approaches	EER (%)
Password 1	21.56
USTB 1 database	4.2
Scheme 1	3.79
Score level fusion	2.28
Scheme 2	**1.64**

chimeric database 2	
Approaches	EER (%)
Password 2	16.40
USTB 1 database	4.2
Scheme 1	3.47
Score level fusion	2
Scheme 2	**1.38**

chimeric database 3	
Approaches	EER (%)
Password 3	20.82
USTB 1 database	4.2
Scheme 1	4.28
Score level fusion	2.92
Scheme 2	**2.10**

chimeric database 4	
Approaches	EER (%)
Password 1	21.56
USTB 2	11.76
Scheme 1	9.80
Score level fusion	**3.92**
Scheme 2	4.31

chimeric database 5	
Approaches	EER (%)
Password 2	16.40
USTB 2	11.76
Scheme 1	13.73
Score level fusion	**6.86**
Scheme 2	**6.86**

chimeric database 6	
Approaches	EER (%)
Password 3	20.82
USTB 2	11.76
Scheme 1	12.75
Score level fusion	9.80
Scheme 2	**9.41**

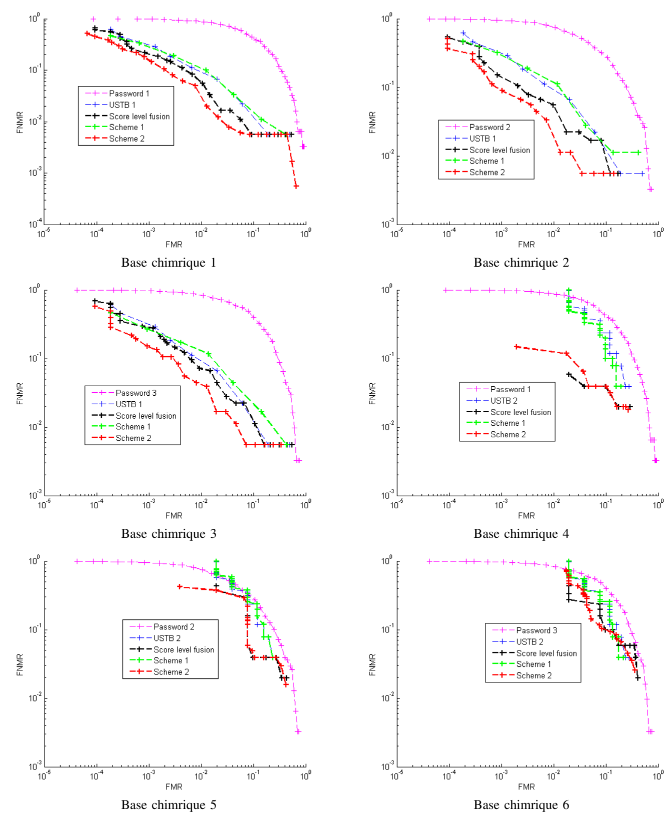

Fig. 2. Courbes ROC des 6 bases chimriques. Notre proposition 2 est au moins gale la fusion de base par somme pondre des scores mono-modaux

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