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An Algorithm for Feature Level Fusion in Multimodal Biometric System

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Abstract—**The increasing demand for high secure and reliable authentication schemes, led to improvement in unimodal biometric system and hence multimodal biometric system has emerged as a mean of more secure and reliable authentication scheme. Multimodal biometric fusion is very promising process to enhances the strengths and reduce the weaknesses of the individual measurements. In multimodal biometrics, the classification results obtained from each independent biometric channel is fused to obtain composite classification is known as biometric fusion. The appropriate fusion scheme combines the processed information, which can be further used for authentication. In this paper, I propose an ensemble algorithm for feature level fusion in multimodal biometric system. The proposed feature level fusion algorithm is accomplished by normalizing feature point sets extracted independently from two modalities of user and making the two point sets compatible for concatenation and then performing feature selection on the concatenated vector.**

Index Terms— **Multimodal Biometrics, Feature level fusion, Normalization**

I. INTRODUCTION

Biometrics is a fascinating and promising area, having opportunities for a more secure authentication mechanism for financial institutions. In recent years the impact of biometrics has grown enormously with a growing demand of security in accordance of unique identification of individuals in Banking. A biometric can be defined as any measurable, robust, distinctive physical characteristic or personal trait that can be used to identify, or verify the claimed identity of, an individual. Biometric authentication refers to automated methods of identifying, or verifying the identity of, a living person [1]. The main advantage of biometric authentication is that it reduces the risk of information (passwords) or tokens (keys or chip cards) being stolen or passed on to unauthorized people, intentionally or unintentionally [2]. The principle advantage of using biometric signals is its uniqueness. The unique physical feature or biological feature or attributes favors biometrics authentication over other type of authentication methods because it is difficult to forge that makes biometrics an attractive solution for enhancing security.

Most of the real life biometric applications are unimodal. But the unimodal biometric system has the limited reliability, accuracy and security. The increasing demand for high secure and reliable authentication schemes, led to improvement in unimodal biometric system and hence multimodal biometric system has emerged as a mean of more secure and reliable authentication scheme. A multimodal biometric system merges the results obtained from two or more distinct features of a person for robust biometric authentication tasks. In multimodal biometric system, the information of each biometric trait is processed independently. The appropriate fusion scheme is then used to combine the processed information, which can be further used for authentication.

In multimodal biometrics, the classification results obtained from each independent biometric channel is fused to obtain composite classification is known as biometric fusion. The Fusion process in biometric provides increased reliability, i.e. biometric system with fusion process gives improved results if compared with uni-modal biometric systems. Multimodal biometric fusion is very promising process to enhances the strengths and reduce the weaknesses of the individual measurements. Multimodal biometric fusions have four scenarios i.e. sensor level, feature level, matching score level and decision level.

Fusion levels can be generally classified into two groups: pre-classification (or fusion before matching) which includes sensor level and feature level and post-classification (or fusion after matching) which includes match score level and decision level. Amongst these, fusion at feature level is gaining much research interest.

It has been observed that, a biometric system that follows preprocessing scheme probably provide more accurate results than post-processing scheme, because of the availability of richer information. As the Feature set hold rich information on source biometric data as compared to the matching score or final decision, fusion at the feature level is relatively considered to provide improved recognition performance.

This paper is divided into five sections: first section is the introduction, second one is review of related works, third section discuss the advantages of using multimodal biometric system instead of conventional uni-modal biometric system, fourth section explain the feature level fusion in multimodal biometric system and fifth section propose an algorithm for feature level fusion.

II. REVIEW OF RELATED RESEARCHES

Several researchers [3-6] have proposed the usage of multimodal biometric traits for achieving user authentication. Vijay M. Mane et al [7] describe the various applications, challenges, issues and research areas related to multimodal biometrics. K. Sasidhar et al [8] examined relatively large face and fingerprint data sets over a spectrum of normalization and fusion techniques and the results of this study shows multimodal biometric systems better perform than uni-modal biometric systems. Farhat Anwar et al [9] proposed a new multi-biometric based verification system using hand geometry and finger stripe geometry. It has been demonstrated that this method is efficient due to its high success rate. A. Mishra [10] discusses different types of multimodal biometric systems, different decision fusion techniques, feasibility and advantage of multimodal biometric system over unimodal biometric systems & some of the future directions of biometrics system. A. Ross et al [11] discusses the various scenarios that are possible in multimodal biometric systems, the levels of fusion that are plausible and the integration strategies that can be adopted to consolidate information. A. Rattani et al [12] study the fusion at feature extraction level for face and fingerprint biometrics. Ross and Jain [13] have presented an overview of Multimodal Biometrics with various levels of fusion, namely, sensor level, feature level, matching score level and decision level. Ross and Govindarajan [14] proposed a method for the fusion of hand and face biometrics at feature extraction level. Ziou and Bhanu [15] proposed a multibiometric system based on the fusion of face features with gait features at feature level.

III. WHY MULTIMODAL BIOMETRIC SYSTEM?

Multimodal Biometrics system employ the combination of more than one physiological characteristics (Fingerprint, Iris, Retina, Facial, Hand Geometry, Palm geometry, Signature, Voice etc) or behavioral characteristic (Keystroke or speaker identification) for enrollment, verification or identification. Multimodal biometric system has emerged as a mean of more secure and reliable authentication scheme. The advantages of using multimodal biometric system instead of conventional unimodal biometric system are as follows:

a) Multimodal biometric system is capable to maintain a high threshold recognition setting, which results in reduced False Accept Rate (FAR) significantly.
b) Reduce the risk of admitting an impostor.
c) Multimodal biometric system effectively deters spoofing because it is not possible for an impostor to spoof more than one biometric trait.
d) The combination of more than one modality causing reduced inter-class similarities and intra-class variations in individuals.
e) Multimodal system provides flexibility to authentication system because if one biometric trait temporarily changes due to any reason, the other traits compensate nicely.
f) More than one biometric trait helps in improving the identification accuracy and hence results in considerable improvement in reliability and accuracy of overall system.
g) The multimodal-based authentication system increase the accuracy, efficiency and security as compared to unimodal biometric authentication, as it is very difficult for an impostor to spoof the system because of two distinct biometrics traits.
h) Different biometric trait used by systems can be operated (enrolment and verification) independently and their decisions may be combined.
i) The availability of complementary person-specific information among different biometric features emphasis on adoption of Multimodal biometrics based authentication system. For instance, a noisy modality can be complement by some another reliable modality in a multimodal framework in providing robustness.

IV. FEATURE LEVEL FUSION IN MULTIMODAL BIOMETRIC SYSTEM

In feature level fusion, the data obtained from each biometric modality or sensor is utilized to compute a multimodal feature vector. The feature vector obtained from different biometric modality can be concatenated to produce a new feature vector. The result new feature vector is high dimensional vector having more feature information of decision requirement.

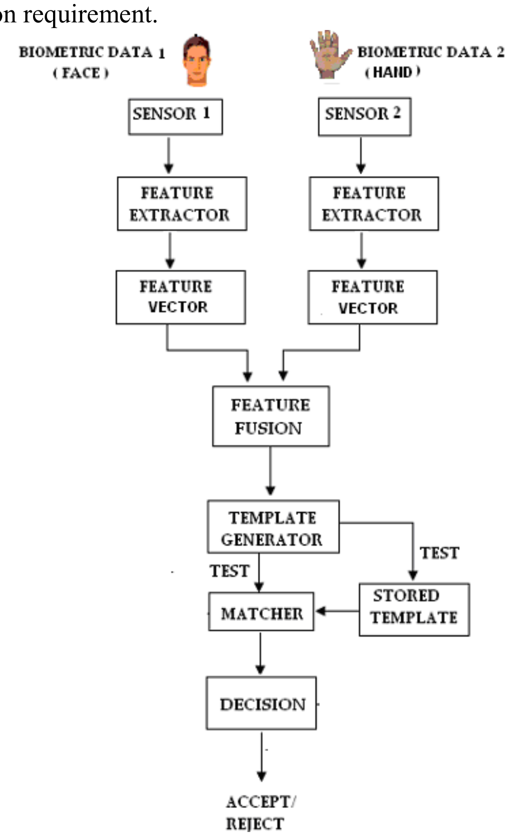

Fig. 1 Feature Level Fusion

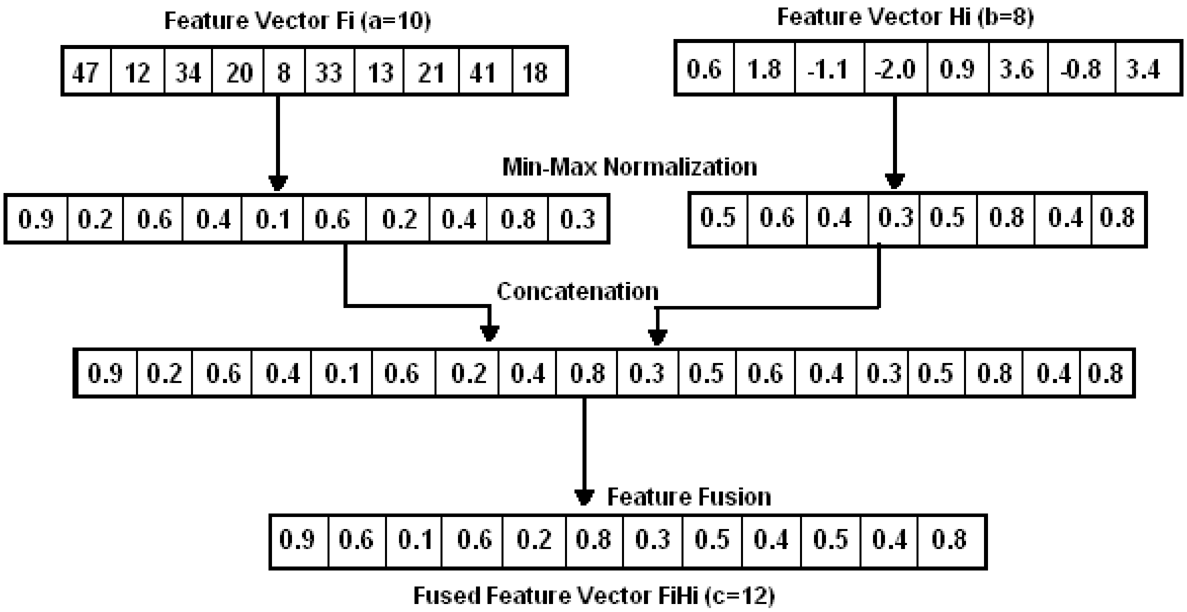

Fig. 2 Example on Feature Level Fusion of two Heterogeneous Feature Vectors

In feature level fusion as shown in Fig 1.1, the feature set originating from two different sensors (face and hand) are initially pre-processed and then features are extracted independently from each sensor, form a feature vector. These features are then concatenated to form a single new vector. Feature level fusion employs some feature selection technique to perform feature selection on the concatenated feature vector.

A simple feature level fusion scheme shown in Fig 1.2 involves the fusion of two heterogeneous feature vectors obtained from face and hand modalities of user. The lengths of these feature vectors are fixed across all users. In this scheme, min-max normalization is adopted to transform each value between 0 and 1. It is assumed that the ranges of feature values of face and hand modalities are [0, 50] and [-5, 5] respectively.

The face and hand modality contains its feature vector. Since these feature vectors contain heterogeneous features, some normalizing technique is employed on features vectors for both modalities before concatenate them to form a single one.

The main purpose of feature normalization is to modify the location and scale parameters of individual feature values to transform the value into a common domain. The feature can be normalized via various normalization schemes like min-max, z-score, tanh and median absolute. In our example, we used the Min-max normalization scheme due to its robustness to outliers. The implementation of min-max normalization technique results in modified feature vectors. Let x and x^{1} denote a feature value before and after normalization. The min-max technique computes x^{1} as

$$x' = \frac{x - \min(F_x)}{\max(F_x) - \min(F_x)}$$

where F_x represent the function that generates x, and $\min(F_x)$ and max (F_x) represents the minimum and maximum values respectively for all possible x. This technique is used when the minimum and the maximum values of the trait feature values are beforehand. For example, we have considered -5 and 5 as minimum and maximum value respectively for feature values of hand. A simplified C code of implementing min-max normalization on two heterogeneous feature vectors shown in Fig 1.2 is given below:

```
#include<stdio.h>
#include<conio.h>
void main()
{
float frec[10]={47,12,34,20,8,33,13,21,41,18},fnorm[10],i;
float hrec[8]={0.6,1.8,-1.1,-2.0,0.9,3.6,-0.8,3.4,}
float j, k,hnorm[8], fusion[18];
  for(i=0;i<10;i++)
        fnorm[i]=(frec[i]-0)/(50-0);
        for(j=0;j<8;j++)
            hnorm[j]=(hrec[j]-(-5))/(5-(-5));
        for(k=0;k<18;k++)
        {
            if(k<10)
                fusion[k]=fnorm[k];
            else
```



```
            fusion[k]=hnorm[k-10];
        }
        for (i=0;i<18;i++)
          printf("\n\n%f\t",fusion[i]);
          }
```

The two normalized feature vector is then concatenated. The concatenation may yield a very large dimensional feature vector due to presence of noisy or redundant data, thus leading to a decrease in the performance. In order to avoid this problem, some feature selection process is employed. The feature selection process chooses a optimal subset of features from a large feature set. This process relies on some appropriate formulated criterion function. In our example, SFS (Sequential Forward Selection) is used as feature selection technique to reduce the dimensionality of both modalities' feature vectors.

V. PROPOSED ENSEMBLE ALGORITHM FOR FEATURE LEVEL FUSION

In this work, feature level fusion is accomplished by augmenting the normalized feature vectors obtained from face and hand modalities of user and performing feature selection on the concatenated vector. Let $F_i = \{ f_1, f_2, f_3, f_4, \ldots\ldots\ldots, f_n \}$ represent the feature vector of the face modalities of user and $H_i = \{ h_1, h_2, h_3, h_4, \ldots\ldots\ldots, h_n \}$ represent the feature vector of the hand modalities of user.

The purpose is to combine F_i and H_i feature sets in order to yield a new feature vector called F_iH_i, that would better represent the individual. The vector F_iH_i is generated by first normalizing the feature vectors F_i and H_i and then concatenating the resultant feature vectors. Then, feature selection is performed on the combined feature vector FH_i. In this paper, the fusion of feature level data from two biometric sources such as face and hand would follow an algorithm shown below. The different stages in this algorithm are described below.

Inputs:

F[ ] = {x1, x2,...., xn}; //*feature vector of face*
H[ ] = {y1, y2,...., yn}; //*feature vector of hand*

Outputs:

FH_aug[ ]; // *augmented vector of face and hand*
Y_K [ ]; //*fused feature vector of face and hand*

Numbers:

a =10; //*Length of feature vector of face*
b = 8; //*Length of feature vector of hand*
c = 12; // *Length of fused feature vector*
F_norm [ ]; //*Normalized feature vector of face*
H_norm [ ]; //*Normalized feature vector of hand*
F_min = 0; //*Minimum range for feature vector of face*
F_max = 50; //*Maximum range for feature vector of face*
H_min = -2; //*Minimum range for feature vector of hand*
H_max = 2; //*Maximum range for feature vector of hand*

1. begin
2. For i = 1 to a do
3. F_norm [i]= (Face[i]- F_min)/(F_max – F_min);
4. end;
5. For i= 1 to b do
6. H_norm [i]= (Hand[i]- H_min)/(H_max – H_min);
7. end;
8. For i= 1 to a do
9. FH_norm [i]= Face[i];
10. end;
11. For i= 1 to b do
12. FH_norm [a+i]= Hand[i];
13. end;

//*Sequential Forward Selection*

14. Y_0 [ ]={Φ} // *Empty Set*
15. For i=1 to c do
16. X^+=argmax[J(Y_k+X)]; // *Select the next best feature*
17. Update Y_{k+1}=Y_k+ X^+; //*Sequentially add the feature x+*
18. end;

VI. CONCLUSION

This paper outlined the possibility to enhance the person identification system by integrating multiple biometric traits at feature level. This paper presents an algorithm for feature level fusion of face and hand biometrics. It uses min-max normalization technique to normalize the features values obtained from face and hand. These features are fused to get one feature vector. To obtain the more discriminative reduced set of feature vector, Sequential Forward Selection (SFS) approach is applied to the concatenated feature set.

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