Multimodal Biometrics Information Fusion for Efficient Recognition using Weighted Method

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Abstract— Biometrics do not provide unique identification. The matching process is probabilistic and is liable to measureable lapse error. A mistaken verfication or identification where the wrong person is matched against an enrolled user is termed a *False Acceptance* and the rate at which these occur is the *False Acceptance Rate (FAR)*. Conversely, an error that occurs where a legitimate user fails to be recognised is termed a *False Rejection* and the corresponding rate is the *False Rejection Rate (FRR).* These errors are dependent not only on the technology but also on the application and the environment of use.

Keywords— Multimodal biometrics, Fingerprint, Face, Iris, Fusion, Weighted Method

INTRODUCTION

"Biometrics" term refers to "life measurement", but the 'Biometric' term is typically related with the use of unique physiological or behavioural traits to recognise a single person. One of the applications which most people relate with biometrics is security. However, biometric identification or verification has eventually a much broader relevance as computer interface becomes more natural. Since the fraud has increases day by day there is the requirement for the highly secure identification system. In recent years, biometrics authentication has seen considerable enhancements in reliability and accuracy, with some of the traits offering great performance.

One way to overcome of unimodal biometrics (UB) problems with the use of multi-biometrics system (MBS). Driven by less equipment costs, a multi biometric system uses multiple sensors for information procurement[2]. This problem can be solved by installing multiple sensors that capture different biometric traits. These type of systems is, known as multimodal biometric systems. So, MBS to be more reliable due to the presence of multiple characteristics of proof these systems are also able to meet the stringent performance requirements imposed by different applications. This paper proposes an efficient multimodal biometric system which can be used to drecrease/reduce the limitations of unimodal biometrics systems. Next section presents an how to reduce limitation of UBS using multimodal biometric system. Finally, the individual characteristics are fused at matching score level using weighted sum method.

1. Limitation of unimodal biometrics: Limitations of unimodal biometrics are following as:

Non-universality: If every individual is able to present the biometric trait for recognition, then this charteristics is said to be universal. Non-universality leads to failure to enrollment error in a biometric system.

Intra-class variations: The biometric data acquired during variation will not be identical to the data used for generating template during enrollment for personal trait. This is known as intra-class variation. Large intra-class variation increases the false reject rate (FRR) of a biometric system.

Inter-class similarities: Inter –class similarity refers to the overlap of feature spaces corresponding to multiple individuals. Large Inter-class similarity increases the false acknowledgement rate (FAR) of a biometric system[3].

Susceptibility biometrics: Behavioral traits like signature and voice are more susceptible to such attack than physiological charteristics.

2.Multimodal Biometrics System: Multi modal biometric systems utilize more than one physiological or behavioural characteristic for enrolment, verification or identification for the improvement and accuracy of recognition. So, the reason to combine different charteristics is to improve the accuracy recognition rate. The aim of multi biometrics is to remove/reduce one or more of the following:

- False accept rate (FAR)

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- False reject rate (FRR)
- Failure to enroll rate (FTE)

Multi modal biometric systems take input from multiple or single sensors measuring two or more different modalties of biometric characteristics. For example, a system with face and fingerprint recognition would be considered “multimodal” even if the “OR” rule was being applied, allowing users to be verified using either of the modalities [4].

2.1. Multi algorithmic biometric systems: Multi algorithmic biometric systems take a single sample from a single sensor and proceed that sample with two or more than two different algorithms[5].

2.2. Multi-instance biometric systems: Multi-instance biometric systems use one sensor or possibly more sensors to capture samples of two or more different instances of the same biometric traits. Example is capturing images from multiple fingers.

2.3. Multi-sensorial biometric systems: Multi-sensorial biometric systems sample the same instance of a biometric trait with two or more distinctly different sensors[11]. Processing of the multiple samples can be done with one algorithm or combination of algorithms. Example face recognition application could use both a visible light camera and an infrared camera coupled with specific frequency[12].

3.Fusion in Multimodal Biometric System (MBS) system:

A technique that can combine the classification results from each biometric channel is called as biometric fusion. We need to design this fusion.

Multimodal biometric fusion combines measurements from different biometric traits to enhance the strengths. Fusion at matching score, rank and decision level has been extensively studied in the literature. Different levels of fusion are: Sensor level, feature level, matching score level and decision level[1].

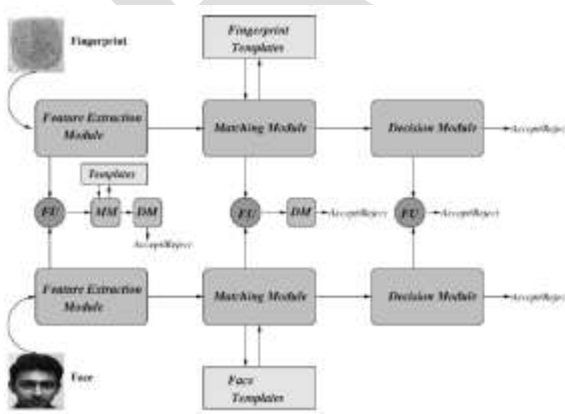

Figure 1 Multimodal System using three levels of Fusion (taken from Ross & Jain, 2003)

From the architecture of MBS system:
1. Fusion at sensor level
2. Fusion at feature level
3. Fusion at matching score level
4. Fusion at decision level

Fusion at the matching scores level: [1] and our work deals with fusion at the matching score level. Each system (Fingerprint, Face, Iris) provides a matching score indicating the proximity of a feature vector with a template vector. These scores are normalized and then combined using same weight and different weight techniques which are described in the later sections.

4.Algorithm For Designing MBS System:

Step 1: To generate the scores for Fingerprint, Face and Iris
Step 2: Normalizing scores
The max scores are :
FP max = 37.4775
Face max = 3.7372e+017
Iris max = 1.6199
Step 3: Generating the vector data. And after normalizing each triplate looks like

$X = (X_{Fingerprint}, X_{Face}, X_{Iris})$
Step 4: fusion using Weighted Method: Same weight and Weighted Method
Step 5: plot the ROC curve

5.Matchers to generate respective scores:

5.1 Fingerprint: A few matchers to generate Fingerprint scores were available on the internet. One such matcher was a work done in MATLAB by Chonbuk National University[6]. This matcher preprocessed a fingerprint image to enhance the image by Short Time Fourier Transform analysis[7]. Then, three sets of invariant moment features for traits, as a kind of texture features, are extracted from three different sizes of Region of Interest (ROI) areas based on the reference point from the enhanced fingerprint image. Every set of invariant moments contain five different moments. Fingerprint verification is acknowledged by Euclidean distance between the two corresponding features of the test fingerprint image and template fingerprint image in the database.
5.2 Face: A few matchers to generate Face distances using the standard PCA based method, 'eigenface' were available[8,15]. We used one such matcher implemented in MATLAB to generate the 'distance' scores.
5.3 Iris: A matcher for Iris recognition was available as a MATLAB code. The system basically inputs an eye Image, and outputs a binary biometric template. The scores are calculated as Hamming distance between the templates.

6. Experiment: Datasets:

6.1 Preparing the individual Dataset: Data for each trait: We had dataset(per trait) for 50 users with 5 samples per user. We followed the author's approach[1] to generate the Genuine and Imposter Scores. Genuine Score: For every user, we have combinations of sample pairs(which doesn't include the pairing of a sample with itself). We have ${}^5C_2$ combination i.e. 50 and we obtained 50*10 i.e 500 genuine score. Hence we have 10 genuine scores per user, therefore a total of 500 genuine scores per trait.

Imposter Score: For every user, we picked a random sample, and generated the respective score with every sample of every other user. Hence, we obtained 49 * 5 i.e. 245 scores for every random sample. The total number of imposter scores obtained per trait was 50 * 245 i.e. 12250 scores.

6.2 Combining the Datasets: Data pertaining to all three modalities were not available for a single set of users. The mutual no dependence of the biometric indicators(traits) allows to assign the biometric data of one user to another. Each user from respective traits were randomly paired(triplets) with one user from the other traits.

Normalizing scores: Suppose that for each trait, the maximum distance obtained is Max. The minimum distance is 0. Max maps to 0 as a similarity score and 0 distance maps to a score of 100[10]. Hence, the normalized score for every respective distance score was obtained from the following equation:
Max × normalized Score = (100 × Max) **-** (100 × obtained Distance)[13,14].

7. Experiment and Results:

Combining the three modalities.We used three different approaches to combine(fuse) the scores of the three modalities. The results for each approach are listed in the corresponding section below.

7.1 Weighted Method: For each score vector $X = (X_{Fingerprint}, X_{Face}, X_{Iris})$, the weighted sum was calculated as
$\mathbf{X_{weightedSum}} = \sum_{i=Face;Fingerprint;Iris} weight_i \times X_i$
where $\sum_{i=Face;Fingerprint;Iris} Weight_i = 1$

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The weights were also calculated using two different approaches.
1. The 1st approach was the same as the author's approach. All the weights were equal i.e. 1/3.
Since the dataset was itself random, we paired $user_{(Face;i)}$, $user_{(Fingerprint;i)}$ and $user_{(Iris;i)}$.

Pairing of samples: For every triplet formed, say $user_i$ we followed the author's approach and paired the k^{th} score of face with k^{th} score of fingerprint and k^{th} score of iris. Hence now we had 500 triplets of genuine score and 12250 triplets of imposter scores. This pairing was done after normalizing the scores to matching scores of the same domain[0,100].
The values of Max obtained for each trait was:

1. $Fingerprint_{Max}$ = 37:4775
2. $Face_{Max}$ = 3:7372e + 017
3. $Iris_{Max}$ = 1:6199

After normalizing, each triplet looks like : $X = (X_{Fingerprint}\, ' X_{Face}\, ' X_{Iris})$
There was 500 such genuine vectors and 12250 such imposter vectors.
2. In this approach, we calculated the approximate area under the TAR(True Accept Rate) v/s TRR(True Reject Rate) graph for each of the trait. The weights assigned were
$Weight_i = Area_i / \sum_{k=Face;Fingerprint;Iris} Area_j$
where i = Face; Fingerprint; Iris
The ROC curves follow after the tabulation of the FAR, FRR values for Fingerprint alone, Face alone and Iris alone, Weighted sum with equal weights and Weighted sum with different weights for a few threshold values ranging from 1 to 99 for the range of scores 0 to 100. To get the tables corresponding to each threshold value. Please go through threshold table 1 and table 2.

Threshold	$^{FAR}Face$	$^{FRR}Face$	FAR_{FP}	FRR_{FP}	$^{FAR}Iris$	$^{FRR}Iris$
1	99.9918	0	99.9918	0	99.9918	0
4	99.9836	0	99.9836	0	99.9755	0
8	99.9755	0	99.8857	0	99.6897	0
11	99.9673	0	99.8204	0	97.5510	0
12	99.9673	0	99.7795	0	96.0489	0
17	99.9591	0	99.2163	0	78.6612	0
19	99.9591	0	99.0938	0	75.0857	0
20	99.9510	0	98.9551	0	71.8938	0
25	99.8693	0	97.9183	0	60.0326	0
30	99.7714	0	96.1632	0	53.6408	0
35	99.5673	0	92.8163	0	51.4857	0
40	99.3714	0	87.5346	0	51.4285	0
43	99.2326	0	84.8489	0.2	51.4285	0
45	98.8408	0	80.7428	0.2	51.4285	0
47	98.5795	0	77.7959	0.4	49.2816	1.8
50	98.0326	0	73.3877	0.6	49.2816	1.8
56	96.8489	0	64.2040	2.4	49.2816	1.8
60	95.6163	0	56.5469	4.6	49.2816	1.8
65	93.1346	0	44.2448	7.6	49.2489	1.8
71	89.7142	0	28.0979	15.6	48.3918	2.8
75	86.6448	0	18.0081	23.4	42.9306	7.6
80	80.5387	0	8.4571	36.4	27.1428	25.2
85	72.4979	0	1.9591	53.6	12.8816	49.4
86	70.2775	0.2	1.2653	57.8	10.4897	55.2
88	65.5673	0.6	0.4326	67	6.6204	68.4
90	59.6163	0.8	0.0734	77.6	3.6979	77
92	52.4571	0.8	0.0081	88.4	1.5755	88.2
94	43.2163	1.2	0	95.2	0.4653	94.8
97	19.0040	4	0	100	0.0244	99.2
99	1.8530	11.4	0	100	0	99.8

Table 1: FAR and FRR values in percentage for individual traits

Threshold	FAR EqualWt	FRR EqualWt	FAR DiffWt	FRR DiffWt
1	100	0	100	0
4	100	0	100	0
8	100	0	100	0
11	100	0	99.9918	0
12	99.9918	0	99.9918	0
17	99.9826	0	99.9826	0
19	99.9755	0	99.9836	0
20	99.9755	0	99.9755	0
25	99.9591	0	99.9591	0
30	99.8285	0	99.8530	0
35	99.4938	0	99.5673	0
40	98.4326	0	98.7020	0
43	97.6897	0	98.1387	0
45	95.8693	0	96.8571	0
47	94.2367	0	95.5428	0
50	90.3428	0	92.6530	0
56	76.6612	0	80.9387	0
60	64.6775	0	69.4612	0
65	51.2000	0	54.3102	0
71	40.3183	0	41.3632	0
75	30.9877	0.4	31.8775	0
80	16.3836	4.6	17.2897	3.4
85	4.4816	18.8	4.9224	17
86	3.1020	24.8	3.5346	22.6
88	1.1918	39.6	1.3877	36
90	0.2367	61.2	0.2938	55.6
92	0.0163	82	0.0244	79
94	0	94.8	0	92.6
97	0	99.8	0	99.8
99	0	100	0	100

TABLE 2: FAR AND FRR VALUES IN PERCENTAGE FOR WEIGHTED METHOD

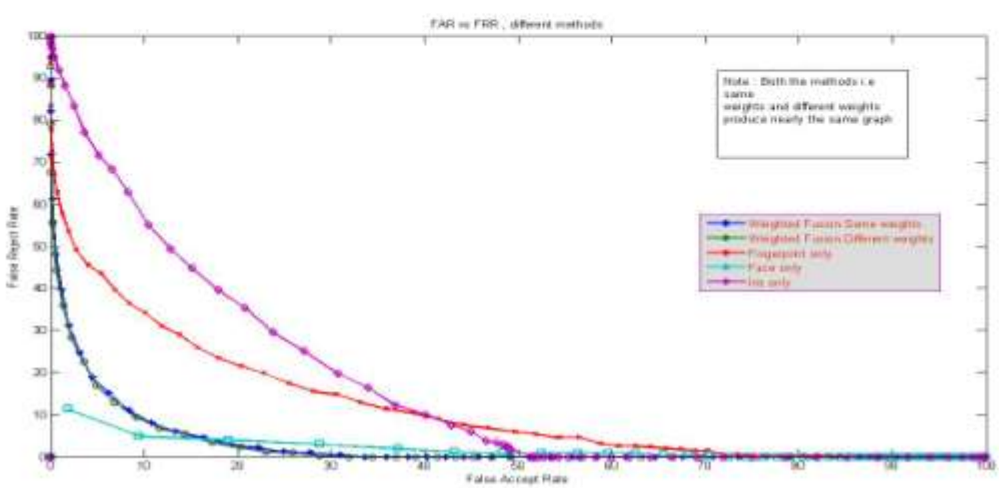

Figure 2 : ROC curve for individual trait, same weight and different weight fusion technique

Figure 2 represents the results of Min-Max normalization for a spectrum of fusion methods. The simple same and different weight sum fusion method yields the best performance over the range of FARs. Fusion techniques at FARs of 1% and 0.1% respectively. At 1% FAR, the total of probabilities fusion works the best. However, results of same weight and different weight fusion technique do not hold true at a FAR of 0.1%. The simple sum rule generally performs all over the range of normalization techniques. These results of MBS system demonstrate the utility of using multimodal biometric systems for achieving better reliable matching performance. These systems shows also that the method chosen for fusion has a significant impact on the resulting performance. In operational biometric systems, the selection of tolerable error rates are drive by the application requirement and in both unimodal and multimodal biometric systems, implementers are compelled to make a trade-off between security and usability.

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9.CONCLUSION:

As we can see from the figure 2 of FAR versus FRR graph, the IRIS curve deviates a lot. The weighted methods help nullifying this anomaly. From the results, these methods also minimize the FRR for a given FAR. As we are improve the performance of multi-biometric system as compared to the unimodal biometrics using the weighted method in the term of reliability, security ,accuracy and usability.

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