IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 3, March 2018

Analysis of Different Fusion and Normalization Techniques

Komal[1], Dr. Chander Kant[2]

P.hd Scholar, Department of Computer Science and Application, KUK (Haryana) - India[1]

Assistant Professor, Department of Computer Science and Application, KUK (Haryana) - India [2]

Abstract: Multimodal biometric system fuses the data presented by multiple biometric sources, hence offering better performance than unimodal biometric system. In multimodal biometric systems, failure of any one trait may not seriously affect the person authentication as other trait can successfully work. Fusion of multiple modalities can take place at different levels i.e feature level, score level or decision level. But the data acquired from different modalities may be heterogeneous. So, there is a need to normalize the data into common domain. This paper presents the overview of various fusion and normalization techniques used in the biometric systems. Also, analyze the performance of different normalization techniques with various fusion techniques.

Keywords: - Fusion techniques, multimodal biometric, normalization techniques.

I. INTRODUCTION

Biometric is an automated recognition of an individual based on physiological and behavioral traits such as fingerprint, face, iris, voice, signature etc. Biometric system has been proven effective as compared to password based or token based systems. Unimodal biometric identification systems that explore only one modality, have some limitations: Noisy data, Non universality, Lack of individuality, Susceptibility to circumvention, Intra- class variations. These limitations can be overcome by multimodal biometric system. Multimodal biometric system is based on merging of more than one biometric trait. In multimodal biometric systems, failure of any one trait may not seriously affect the person authentication as other trait can successfully work. Reduction in failure to enrol rate is the major advantage of this system [1]. Multimodal biometric is basically subset of multi-biometric systems as shown in fig 1. Different types of multi-biometric systems are: -

- Multi sensor
- Multi instances
- Multi modal
- Multi unit
- Multi representations

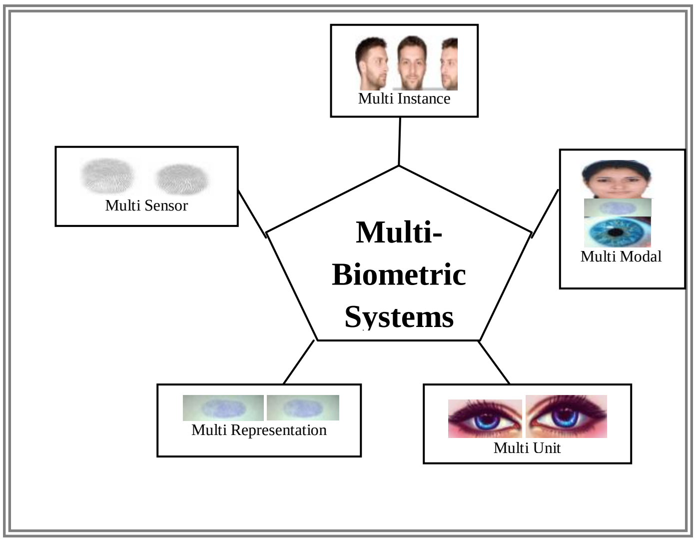

Fig 1: Multi-Biometric System

Information of different traits of an individual are taken and fused at different levels such as fusion at sensor level, fusion at feature extraction level, fusion at matching score level or fusion at decision level as shown in Fig 2 [2].

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified

Vol. 7, Issue 3, March 2018

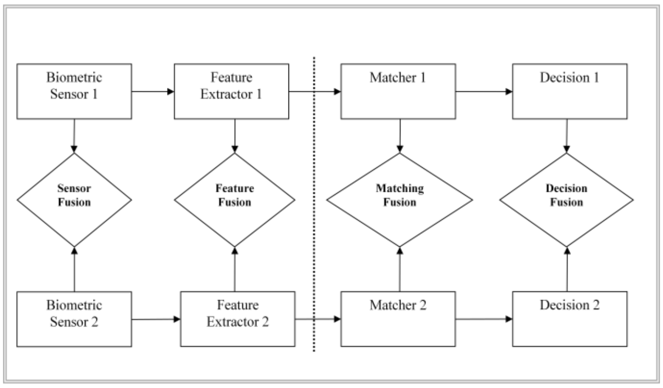

Fig 2: Fusion at Different Levels

- **Sensor Level Fusion:** Sensor level fusion involves combining raw information from two sensors. This type of fusion can be appropriate for multi sensor and multi sample systems.
- **Feature Level Fusion:** Feature level fusion includes combining different feature set from different modalities into single feature vector. If the feature sets are compatible with each other than it is reasonable to concatenate two feature set into one vector and if they are not compatible than several algorithms are used to making them compatible. New vector increases the discriminating power in the feature vector. Some significant feature selection techniques are used to extract the significant features from large set of features [3].
- **Match Score Level Fusion:** Match score fusion includes the combination of scores provided by the match score module for different input feature vectors in the database. This type of fusion is also called measurement level fusion. This type of fusion can be classified by two different approaches and these approaches are based on how the match score is processed. One is by classifying the feature vector and another is by combining the feature vector. One most significant feature in this type of fusion is the normalization of the match score. Normalization of the match score is necessary to maintain the compatibility between the match score generated by two different modalities.
- **Decision Level Fusion:** In this type of fusion, integration of the information occurs when each system makes the decision about the identity of the person based on the input data of the person. This is the simplest form of the fusion because this uses only the final output of the different modalities.
- Mainly three levels of fusion are possible in a multimodal biometric system. They are feature extraction level, matching score level and decision level [4]. Sensor level fusion is quite rare because fusion at this level requires that the data obtained from the different biometric sensors must be compatible, which is seldom the case with biometric sensors. Fusion at the feature extraction level is also not always possible because the feature sets used by various biometric modalities may either be inaccessible or incompatible. Fusion at the decision level is too rigid [5] since only a limited amount of information is available. Therefore, fusion at the matching score level is generally preferred due to the presence of enough information content and the ease in accessing and combining matching scores.

  Fig 3 shows the score level fusion of three different modalities [6]. First step is to normalize the matching scores of the modalities using various normalization techniques and convert them in a common domain. NS1, NS2, NS3 are the normalized scores. Next step is to fuse these normalized score using various fusion techniques and then take a final decision that the input modalities are genuine or imposter

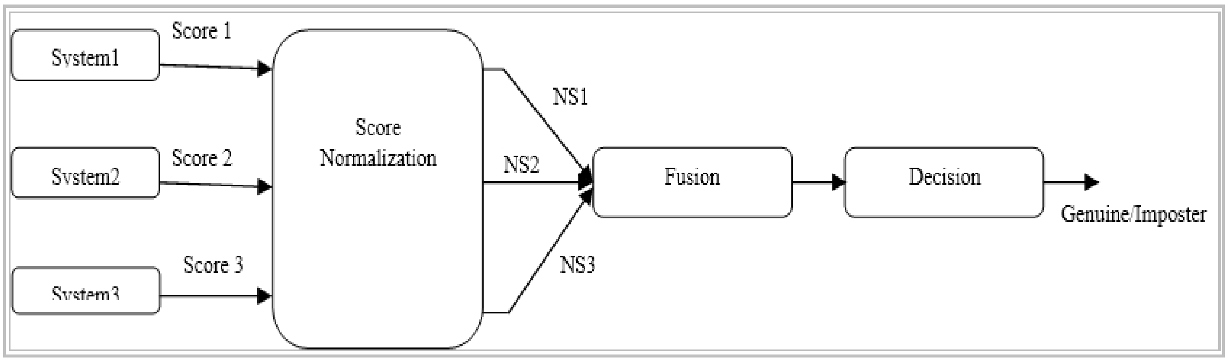

Fig 3: Score level Fusion (NS: Normalized Score)

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 3, March 2018

II. NORMALIZATION TECHNIQUES

Normalization is the technique of converting the matching scores with different scales into a common domain. Once the matching scores are normalized, they can be fused with each other. Various normalization techniques of the matching scores have been used in multimodal biometric systems [7]. These normalization techniques are as follows: -

- **Min-Max Normalization**
  It is the most common or simplest normalization technique. Let matching score S = (S_1, $S_{2 \dots\dots\dots}$ S_N) be a vector of N scores. The normalized scores S' are calculated as follows:
  $$S' = \frac{S - \mathrm{Min}(S)}{\mathrm{Max}(S) - \mathrm{Min}(S)}$$
  Where Max(S) and Min(S) are the maximum and minimum values of the matching scores. This technique transforms all the matching scores into common domain [0, 1]. This technique is very sensitive to the presence of the outliers.
- **Z-score Normalization**
  It is also most commonly used normalization technique. The normalized scores S' are calculated as follows:
  $$S' = \frac{S - \mu(S)}{\sigma(S)}$$
  where $\mu(S)$ and $\sigma(S)$ are the mean and standard deviation of the scores. This technique generates positive genuine scores and negative imposter scores. This method does not transform the scores into common interval but it keeps the original distribution if the distribution is Gaussian. Two parameters (μ and σ) are used in equation and these parameters are sensitive to outliers. The z-score normalization technique is not much robust technique.
- **Median-MAD Normalization**
  This technique is based on Median Absolute Deviation (MAD). The normalized scores S' are calculated as follows:
  $$S = \frac{S - \mathrm{Median}}{\mathrm{MAD}}$$
  Where MAD = Median(S - Median). This technique is insensitive to the presence of the outliers and does not transform the scores in to common interval. This technique also does not keep the original input distribution.
- **Tanh Normalization**
  In this technique, normalized scores S'are calculated as follows:
  $$S' = 0.5\{\tanh\left(0.01\left(\frac{S - \mu(S)}{\sigma(S)}\right)\right) + 1\}$$
  Where $\mu(S)$ and $\sigma(S)$ are mean and standard deviation of the user scores. This technique transforms the matching scores into common interval. Performance of this technique is better because it uses only genuine user scores while ignores the imposter scores.

Table 1: Summary of Normalization Techniques

Normalization Techniques	Formula
Min-Max	$S' = \frac{S - \mathrm{Min}(S)}{\mathrm{Max}(S) - \mathrm{Min}(S)}$
Z-Score	$S' = \frac{S - \mu(S)}{\sigma(S)}$
Median-MAD	$S = \frac{S - \mathrm{Median}}{\mathrm{MAD}}$
Tanh	$S' = 0.5\{\tanh\left(0.01\left(\frac{S - \mu(S)}{\sigma(S)}\right)\right) + 1\}$

After normalizing the matching scores, next step is to fuse the different normalized scores and then take the final decision based on fused score.

III. FUSION TECHNIQUES

Fusion is used to integrate the normalized scores obtained from different modalities [8]. Various techniques are used for the integration process. These techniques are as follows: -

IJARCCE
ISSN (Online) 2278-1021
ISSN (Print) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 3, March 2018

- **Simple Sum**
  Simple sum technique adds the scores of each modality to calculate the fused score [6]. The fused score S' are calculated as follows:
  $$S' = \sum_{i=1}^{N} S_i$$
  Where S_i is the score obtained from the i^{th} modality, and N is the total number of modalities.
- **Min Score**
  Min score technique selects that score having the minimum value of the modality. If there are N modalities used in the system then fused score S' is calculated as follows:
  $$S' = \min (S_1, S_2 \ldots\ldots S_N)$$
- **Max Score**
  Max score technique selects that score having the maximum value of the modality. If there are N modalities used in the system then fused score S' is calculated as follows:
  $$S' = \max (S_1, S_2 \ldots\ldots S_N)$$
- **Sum of Probabilities**
  Sum of probabilities uses the genuine posterior probability that represents the probability of a modality being genuine. Fused score S' is calculated by adding these probabilities for all modalities.
  $S' = \sum_{i=1}^{N} P(\text{genuine} \mid S_i)$
  $P(\text{genuine} \mid S) = P(S \mid \text{genuine}) / [P(S \mid \text{genuine}) + P(S \mid \text{imposter})]$

Where N is the total number of modalities used in the system. Probability density functions, P(S ∣ genuine) and P(S ∣ imposter), are used to evaluate the posterior probabilities of the genuineness.

Table 2: Summary of Fusion Techniques

Fusion Techniques	**Formula**
Simple Sum	$\sum_{i=1}^{N} S_i$
Min Score	$\min (S_1, S_2 \ldots S_N)$
Max Score	$\max (S_1, S_2 \ldots S_N)$
Sum of Probabilties	$\sum_{i=1}^{N} P(\text{genuine} \mid S_i)$

IV. ANALYSIS OF FUSION AND NORMALIZATION TECHNIQUES

For the analysis of fusion and normalization technique publicly available score set, obtained from NSIT (National Institute of Science and technology) in the U.S.A., have been used. In addition to these score set, we have created our own database of similarity scores. The database consists of small population of finger and face scores.

4.1 FAR and FRR

False Acceptance Rate (FAR) and the False Rejection Rate (FRR) are the two most general error rates that are used to rate the performance of the biometric system. FAR refers to the possibility where an unauthorized user is accepted by the authentication biometric system as an authenticated person. It measures the percentage of invalid inputs that are incorrectly accepted. FRR is the probability for an authorized person is rejected by the biometric machine as an unauthenticated person. It measures the percentage of incorrectly rejected valid users. False Accept Rate is also called False Match Rate, and False Reject Rate is sometimes referred to as False Non-Match Rate.

These error rates can be measured by mapping a series of genuine and imposter scores on a graph according to their scores. Overlap region of genuine and imposter score measures the error rates. If there is no overlapping in genuine and imposter score then system is called as 100% perfect or accurate system but no biometric system is 100% perfect in these days.

4.2 Genuine Acceptance Rate (GAR)

GAR is the overall performance measurement of the biometric system. Fig 4 shows how GAR, FRR and FAR are related to each other.

IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified
Vol. 7, Issue 3, March 2018

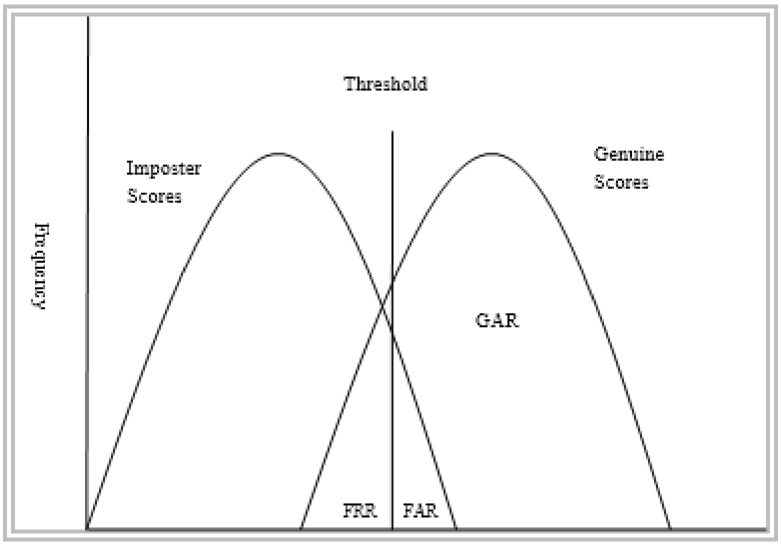

Fig 4: GAR, FRR and FAR

These metrics are generally mapped against each other on a graph known as ROC (Receiver Operating Characteristics) curve. These curves are also used to measure the accuracy of the biometric systems.

4.3 Simple Sum Fusion – ROC Curve

Fig 5 shows the ROC curve of simple sum fusion technique paired with different normalization techniques.

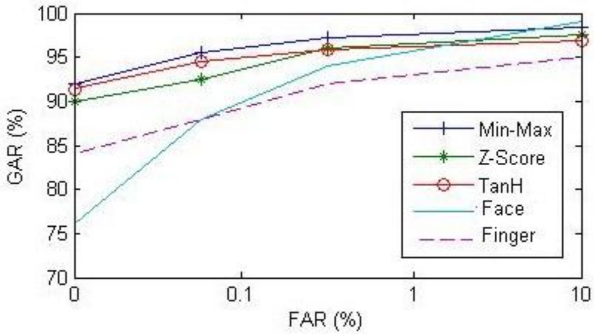

Fig 5: ROC Curve for Simple Sum Fusion with Different Normalization Techniques

It clearly shows that unimodal matchers (Face or finger) are outperformed with respect to the multimodal matchers. Min-Max technique performed consistently well across all FAR range.

4.4 Min-Max Normalization – ROC Curve

Fig 6 shows the ROC curve of Min- Max normalization paired with different fusion techniques.

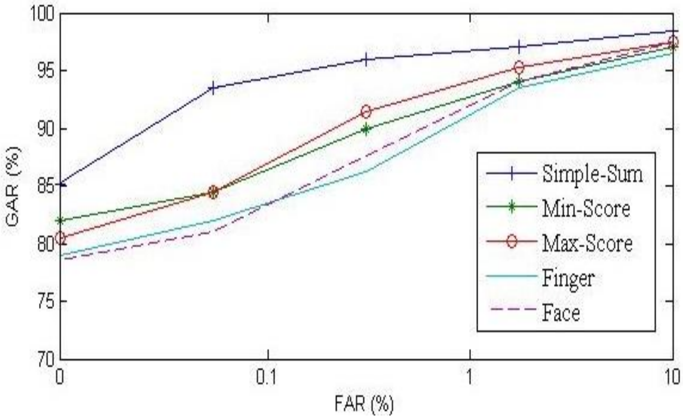

Fig 6: ROC Curve for Min-Max Normalization with Different Fusion Techniques

It clear from the graph that multimodal techniques are better than unimodal techniques. Simple Sum technique gives best result with Min-Max normalization.

4.5 Performance Table

Table 2 shows the combined scores of all tested normalization and fusion techniques. Average fusion and Average normalization are also calculated in the table. Table 3 shows the performance of all the methods at the FAR = 0.1%. At FAR = 0.1%, simple sum fusion is the most accurate and very simple to use technique as compared to others and TanH normalization technique gives the highest average normalization score.

Table 3: GAR performance at FAR of 0.1%

	Normalization Methods			
Fusion Methods	**Min-Max**	**Z-Score**	**TanH**	**Average Fusion**
Simple Sum	95.5	92.5	94.5	94.16
Min Score	84.5	84.1	83.3	84.26
Max Score	84.4	86	87.5	86.30
Average Normalization	88.1	87.5	88.4	

But Min-Max is the simplest and easy to use normalization technique and performs consistently well across all range of FAR. For TanH and Z-Score normalization techniques, we have to calculate the mean and standard deviation from the scores. And these calculations make the TanH and Z-Score techniques quite difficult to use.

4.5 Observations on Normalization techniques

- **Min-Max:** It is very easy to use technique and performs well across all FAR range.
- **Z-Score:** It is quite simple to use but difficult than min-max. It does not perform well if input matching scores are outside the range of training scores.
- **TanH:** It is difficult to use but gives best performance in practical tests. It adapts well if input matching scores are outside the range of training scores.

4.6 Observations on Fusion techniques

- **Simple-Sum:** It is quite easy to use and gives best or accurate results in practical tests.
- **Min-Score:** It is simple to use but performs poorly.
- **Max-Score:** It is also simple to use but performs better than min-score.

V. CONCLUSION

The results shows that choosing right fusion technique and pairing it with right normalization technique, makes a considerable impact on the performance of the multimodal biometric system. Because there is no single normalization or fusion technique that would performs well in all conditions. But in most of the cases, simple sum fusion and min-max normalization techniques are the easy to use and give better results as compared to others. We have also shown that multimodal biometric system performs better than unimodal system. By using multimodal biometrics, we can improve the accuracy and security of the system as it is harder for an intruder to spoof more than one modalities.

REFERENCES

[1] Mishra, "Multimodal Biometrics it is: Need for Future System," International Journals of Computer Application, vol 3, no 4, pp. 28-33, ISSN: 0975-8887, 2010.

[2] M. Gudavalli,A. V. Babu and D.S. Kumar, "Multimodal Biometrics–Sources, Architecture and Fusion Techniques: An Overview," IEEE: International Symposium on Biometrics and Security Technologies, pp. 27-34, ISBN: 978-0-7695-4696-4/12, DOI: 10.1109/ISBAST.

[3] Joshi SC, Kumar A., "Design of multimodal biometrics system based on feature level fusion," 10th International Conference on Intelligent Systems and Control (ISCO), pp. 1-6, 2016.

[4] X. Zhou, "Template Protection and its Implementation in 3D Face Recognition Systems," In: Proceedings of SPIE Conference on Biometric Technology for Human Identification, Orlando, USA, 6539, pp. 214-225.

[5] Y.K. Lee, K. Bae,S. J. Lee, K. R. Park and J. Kim, "Biometric Key Binding: Fuzzy Vault based on Iris Images," In: Proceedings of Second International Conference on Biometrics, South Korea, pp. 800-808, 2013.

[6] Rzouga, A. BenKhalifa, and N. Essoukri BenAmara, "Authentification multimodale d'un individu par le visage, l'empreinte digitale et la paume de la main," Le Colloque de Recherche Appliquee et de Transfert de Technologie, pp. 1 – 6, 2012.

[7] L.Latha, and S.Thangasamy, "Efficient approach to Normalization of Multimodal Biometric Scores," International Journal of Computer Applications, Vol 32, no. 10, October 2011.

[8] Ghayoumi M., "A review of multimodal biometric systems: Fusion methods and their applications," IEEE/ACIS 14th International Conference on Computer and Information Science (ICIS), p. 131–6, 2015