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Analysis of Different Techniques for Score Level Fusion in Multimodal Biometrics

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Abstract: Fusion in the multimodal biometric system is a very important part of the authentication process. Two modalities are combined to form a single authentication factor so selection of fusion method is also need very attention. As there are different level of fusion so in this work, score level fusion is used to analyze multimodal biometric system's performance. This work uses two data sets CASIA and IITD and firstly texture features of both iris and fingerprint will be extracted. Then theses texture feature will further used to calculate score for both modalities and fuse using SUM, PRODUCR and MAX methods. Performance of all three methods has been analyzed in terms of FAR, FRR and accuracy.

I. INTRODUCTION

Security is concerned with the assurance of availability, confidentiality, and integrity of data in all forms. A number of tools and techniques are there which supports the management of security systems based on biometrics. Biometric systems manage authentication, authorization, and non-repudiation. Biometrics Systems are automatic methods which are used to recognize a person based on their behavioural and physiological characteristics. This technology becomes very highly secure technology for identification and verification of persons. As frauds increases, this will also increase the need of highly secure authentication and authorization systems.

Biometric systems are of two different types: (i) Unimodal and (ii) Multimodal. Unimodal system is defines by a biometric system where only single biometric traits. This type of system have a very practical problems like errors, attacks, noise and lack of performance. Whereas Multimodal biometric system uses two or more biometric traits which solves the various issues. Different studies suggested that multimodal performs better than the unimodal biometric system in real world as well [2].

Fusion of the modalities is the one of the major part of the multimodal biometric system. So, there is a need of better fusion techniques which will fuse the information gathered from individual modalities. Fusion can be done at four different levels and these are: (i) Sensor, (ii) Feature Extraction, (iii) Matching, and (iv)Decision making. So, at these levels fusion can be done.

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Sensor-level fusion: In sensor level fusion, there a direct concatenation of data or information. This fusion method works on the compatibility among all the data sources.

Feature Level Fusion: In this, firstly raw data or information are sensed or processed from resources and then individually their features has been extracted. These features are then fused to get a new feature vector which is used for recognition purposes. Fusion at this level expected better results as compare to other levels.

Matching Score Level Fusion: After feature extraction this level calculates scores of the traits individually and then these scores are used for classification or for recognition [5]. This is also known as Confidence level fusion and number statistical of methods are used to combine the scores.

Decision Level Fusion: This level firstly pre-classified the traits individually and then on the basis of this classification fusion is done. This step involves data collection, feature extraction and then classification with the help of various learning classifiers.

The rest paper includes detailed information different sections. Section 2 provides detailed study of score level fusion and their techniques. Section 3 provides the information about the data set used and methods used for fusion process. Section 4 presents the results on the basis of experiments done.

II. SCORE LEVEL FUSION

Fusion in biometrics is done at various levels as discussed in previous section. In this paper, score level fusion is used to fuse biometric traits Iris and Fingerprint. Score level fusion is also known by match score method which measures the similarity of Input with feature vectors template. When final decision of the recognition is based on the match score output then this type of fusion is said to be fusion at match score level. Confidence level and measurement level is the other names of the match score level fusion. This level of fusion contains the information of input pattern which is different from feature vectors. Scores of the different biometric traits are very easy to combine and access. This approach is very commonly used in mulmodal biometric system. Various studies present a number of approaches for both Unimodal and Multimodal biometric systems. Unimodal biometrics faces some issues because of that Multimodal biometrics system has been proposed [3]. Many approaches were found by different researchers to measure the performance of multimodal biometrics which is combination of two or more traits like 'Iris and Fingerprint', 'Speech and Signatures', 'Face and Fingerprint' and many more combinations. Maryam et al. [4] proposed a robust biometric recognition system using Iris and face.

They proposed new methods which uses Local binary pattern, local feature extractor and subspace linear discriminant analysis global feature extractor on both traits. Then their scores were normalized with 'tanh' method of normalization and after that fusion is done using weighted sum rule. Different datasets has been used to analyze the results and it then proofs that the performance of multimodal system is better than unimodal system. Yang and Fan [23] proposed a personal identity verification system using three biometric traits hand geometry, palmprint and fingerprint. Same image were used to take these traits. In this fusion is performed at score level and feature level both. Firstly fusion is done at feature level using palmprint and fingerprint and then match score fusion is done between the multimodal and hand geometry system. This multimodal biometric system performs better when tested on 98 subject database which is self constructed. Mohamed et al. [13] proposed a iris and fingerprint based multimodal biometric system. In this decision level fusion is used where result of each biometric is used for final decision. This work uses fuzzy logic for the combination of the individual results and achieved better accuracy as compare to unimodal system. Ajita and Massimo [1] proposed SIFT feature based approach for feature level fusion to fuse multi-modal and multi-unit sources of information. In this spatial sampling is perform to select the features extracted by SIFT and these features were combined to form a new feature vector which is further used for recognition. L.Latha and S.Thangasamy [15] proposed a score level fusion using weighted sum rule with iris and retinal features. They used database of CASIA and VARIA to perform experiments. The above study includes various score level fusion methods in multimodal biometric system. The other techniques or rules used for score level fusion are as follows:

Product Rule: It is an immediate ramifications of the suspicion of measurable autonomy between the m include portrayals x1… … xm. The item choice standard can be expressed as:

Assign $Z \rightarrow w_r$ if

$$P(w_r)\prod_{j=1}^{m} p(x_j|w_r) \geq P(w_n)\prod_{j=1}^{m} p(x_j|w_n),$$

where n = 1,..., Q. This rule can also be represented by using product of the posteriori probabilities of the individual classifiers as follows [19].

Assign $Z \rightarrow w_r$ if

$$\frac{\prod_{j=1}^{m} P(w_r|x_j)}{(P(w_r))^{(q-1)}} \geq \frac{\prod_{j=1}^{m} P(w_k|x_j)}{(P(w_k))^{(q-1)}}$$

where fc = 1,..., Q. Further, Equal Probabilities are assigned in most practical biometric systems.

Affectability to mistakes in the estimation of the posteriori probabilities is one of the primary impediments of the item rule. Regardless of whether one of the classifiers yields a likelihood near zero, the result of the R posteriori probabilities is fairly little and this regularly prompts an off base grouping choice.

Sum Rule: The entirety rule is more compelling than the item rule when the information Z will in general be boisterous, prompting blunders in the estimation of the posteriori probabilities. In such a situation, we can expect that the posteriori probabilities don't veer off drastically from the earlier probabilities for each class. This rule is defined as:

Assign $Z \rightarrow w_r$ if

$$\left\{(1-m)P(w_r) + \sum_{j=1}^{m} P(w_r|x_j)\right\} \geq \left\{(1-m)P(w_k) + \sum_{j=1}^{m} P(w_k|x_j)\right\}$$

Where k: = 1,..., M.

Max Rule: This rule is defined as [15] the maximum average values of the posteriori probabilities and it is defined as:

Assign Z→ w_r if

$$\left\{(1-m)P(w_r) + m \max_{j=1}^{m} P(w_r|x_j)\right\} \geq \left\{(1-m)P(w_k) + m \max_{j=1}^{m} P(w_k|x_j)\right\}$$

Where k: = 1,..., M.

Min Rule: This rule is one of the important rule where the minimum value of probability in the product is always greater than product of probabilities. It is defined as:

Assign $X \rightarrow w_r$ if

$$\frac{\min_{j=1}^{m} P(w_r|x_j)}{(P(w_r))^{m-1}} \geq \frac{\min_{j=1}^{m} P(w_k|x_j)}{(P(w_k))^{m-1}}$$

Where k: = 1,..., M.

III. DATABASE & EXPERIMENTAL DESIGN

This work is to analyze the performance of score level fusion using Iris and fingerprint as both modalities are unique identification of the person and are widely accepted. Number of methods was proposed for score level fusion. This work uses SUM, Product and MAX method for fusion at match score level.

A. Dataset Used:

The experiments have been conducted on two different sets of database. The first set of data is of CASIA which have been used in various studies of multimodal biometrics. The second set of data is taken from IIT Delhi database. Total 200 samples where 100 samples were taken from each data set are used in this work. CASIA Iris and Fingerprint Image Database created by the exploration gathering and have been discharged to the global biometrics network. CASIA-Iris-Lamp was gathered utilizing a hand-held iris sensor delivered by OKI. A light was killed on/off near the subject to present more intra-class varieties when gathered CASIA-Iris-Lamp. The unique mark pictures of CASIA Version 1.0 were caught utilizing URU4000 finger impression sensor in one session. The volunteers of FP-TestV1 incorporate alumni understudies, specialists, servers, and so forth. The volunteers were approached to turn their fingers with different dimensions of strain to produce huge intra-class varieties. All unique mark pictures are 8 bit dark dimension BMP documents and the picture goals is 328 x 356. The IIT Delhi Iris Database for the most part comprises of the iris and unique finger impression pictures gathered from the understudies and staff at IIT Delhi, New Delhi, India.

This database has been gained in Biometrics Research Laboratory amid Jan - July 2007 (still in advancement) utilizing JIRIS, JPC1000, computerized CMOS camera [2]. The picture securing program was composed to gain and spare these pictures in bitmap position and is likewise unreservedly accessible on demand. The as of now accessible database is from 224 clients, every one of the pictures are in bitmap (*.bmp) design. Every one of the subjects in the database are in the age aggregate 14-55 years containing 176 guys and 48 females. The database of 1120 pictures is composed into 224 unique envelopes each related with the whole number recognizable proof/number. The goals of these pictures is 320x240 pixels and every one of these pictures were obtained in the indoor condition.

B. Experiment Design:

This work uses score level fusion with three different fusion rules that is sum, product and max rule method. These rules are discussed in the previous sections. In this work, firstly training data set is prepared by extracted their texture features and calculate the score by using all three methods. The basic design of this multimodal biometric system is as given in figure.

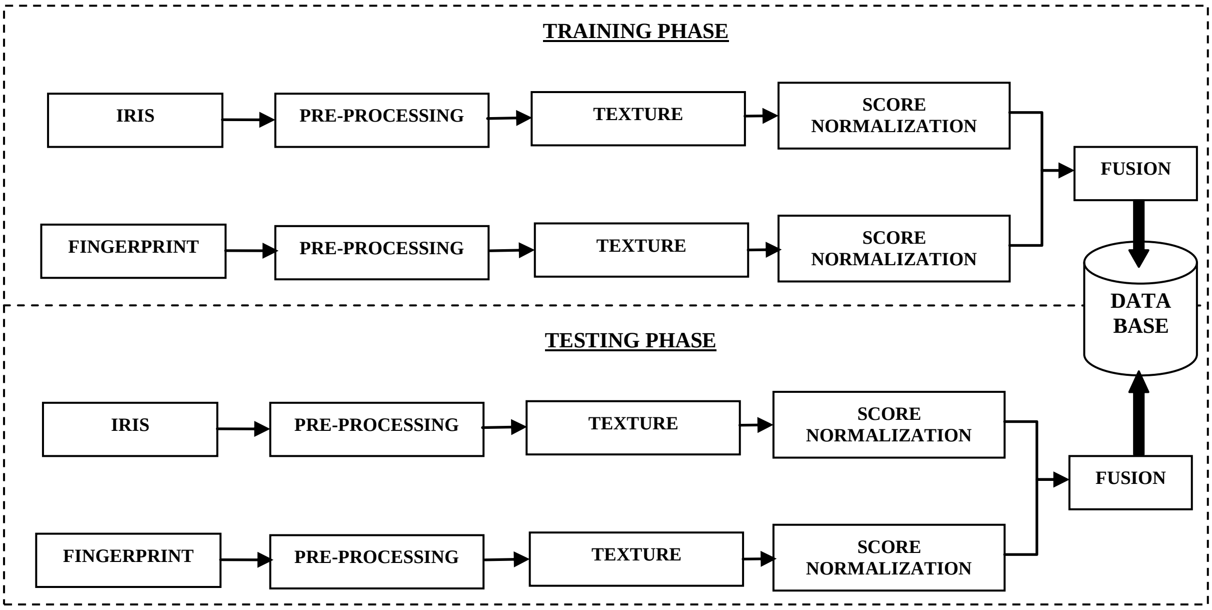

Fig 1: Basic design of the system

- ***Modality Used***

Fingerprints remain constant throughout life. In over 140 years of fingerprint comparison worldwide, no two fingerprints have ever been found to be alike, not even those of identical twins. An iris scan also provides unique biometric data that is very difficult to duplicate and remains the same for a lifetime. So because of these reasons these both modalities are used for authentication purposes in this work.

- ***Pre-processing***

In this work, Hybrid Wavelet is utilized to break down picture and 5-level deterioration is finished. The photos are believed to be systems with N lines and M fragments. At each dimension of crumbling the level data is filtered, and after that the gauge and focal points conveyed from this are isolated on segments. At each dimension, four sub pictures are gotten, askew details, estimation, even detail and vertical detail.

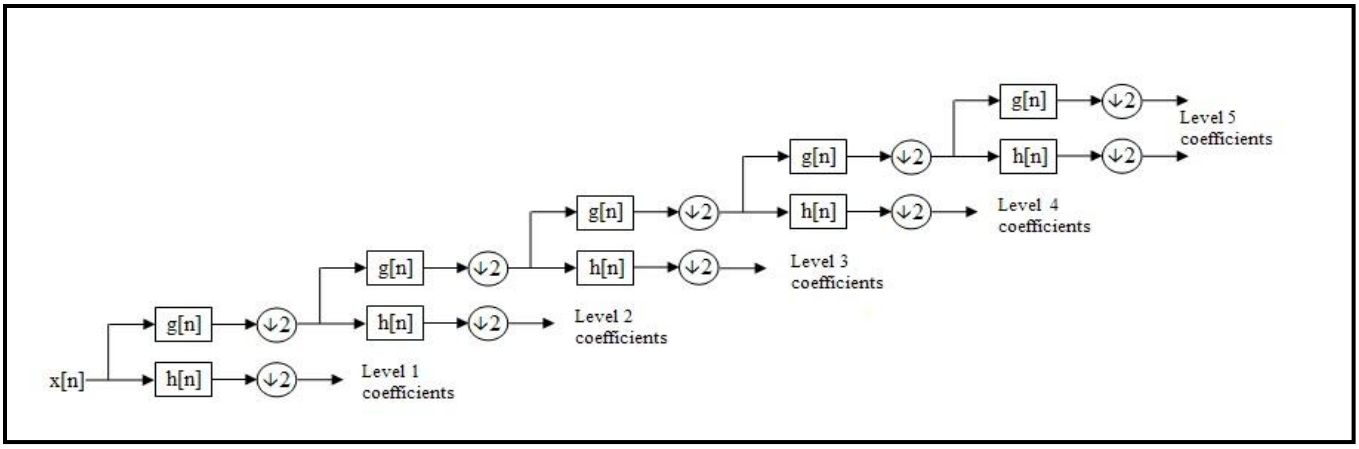

Fig 2: 5-Level Decomposition

- ***Texture Features***

Texture features has been extracted in this work after the decomposition of an image where wavelet is used to decompose. For Analysis Homogeneity, Directionality, Energy, Entropy, Contrast and C**oarseness texture features were extracted** [26] and these features are statistical features. Table 1 contains the extracted texture features of both the iris and fingerprint samples.

Table 1: Texture Features

	Coarseness	**Entropy**	**Contrast**	**Homogeneity**	**Directionality**	**Energy**
Finger_1	50.1166	6.2267	68.8937	0.102872	1.81E-09	4.74E-05
Finger_2	51.098	5.6711	59.6598	0.105445	0.10855	3.48E-05
Finger_3	50.7744	3.3996	55.9497	0.089383	0.062914	2.62E-05
Finger_4	51.131	4.7685	38.0714	0.105137	0.193313	4.29E-05
Finger_5	50.655	5.2559	56.0646	0.103091	0.174633	4.46E-05
	Coarseness	**Entropy**	**Contrast**	**Homogeneity**	**Directionality**	**Energy**
Iris_1	49.3697	8.0025	51.4723	0.043667	0.89187	2.57E-05
Iris_2	48.4234	8.0808	62.1753	0.042116	0.89187	2.82E-05
Iris_3	50.3055	7.9263	42.1728	0.043305	1.22498	2.53E-05
Iris_4	49.0232	7.7704	52.1553	0.043864	1.0675	2.77E-05
Iris_5	48.1678	8.1821	52.7022	0.043319	1.03037	2.64E-05

- ***Score Normalization***

Using these Texture Features, scores are calculated for all samples and then these score are then fused in the next level.

For score normalization, three different methods have been used that are MAX Rule, SUM Rule and PRODUCT Rule. The range of match scores is assumed to be [0, 100] for the both iris and fingerprint matchers.The calculated score are as given in table 2.

Table 2: Score Values

	Finger1	Finger2	Finger3	Finger4	Finger5
MAX	89	89	98	79	82
SUM	79	86	98	63	72
PRODUCT	30	63	83	28	29
	Iris1	**Iris2**	**Iris3**	**Iris4**	**Iris5**
MAX	57	65	48	53	79
SUM	49	52	57	44	66
PRODUCT	30	39	38	49	49

- ***Fusion at Score Level***

At this level, it is conceivable to join scores acquired from the same biometric trademark or distinctive ones. Such scores are gotten, for instance, on the premise of the vicinity of highlight vectors to their relating reference material. The general score is then sent to the choice module [4]. Presently, this gives off an impression of being the most valuable combination level due to its great execution and straightforwardness [11, 12]

This combination level can be partitioned into two classes: mix and arrangement. In the previous methodology, a scalar melded score is gotten by normalizing the information coordinating scores into the same reach and after that joining such standardized scores.

In the last approach, the information coordinating scores are considered as info components for a brief moment level example grouping issue between the two classes of customer and the Impostor [13].

IV. EXPERIMENTAL RESULTS

To evaluate the efficiency of this multimodal biometrics system, a database containing Iris and Fingerprint are required. To build the virtual modal for this biometric system samples are adopted from IITD and CASIA database for both iris and fingerprints. For the research work, 100 individual fingerprint images and iris images are selected; every person has 2 samples and totalling up to 200. MATLAB is used as a simulation to perform experimentation. For the analysis of performance of multimodal biometric systems [28], FRR and FAR is calculated.

Total Number of Samples in the database=200

4.1 False Acceptance Rate or False Match Rate (FAR or FMR):It is the likelihood that the system wrongly matches the input pattern to a non-matching template in the database list. Fig 3 demonstrates the determined false acceptance rate utilizing the embraced tests which results that score level combination utilizing MAX strategy accomplishes least false acknowledgment rate as contrast with others. It implies utilizing MAX strategy for score level combination a couple of manufactured examples were erroneously procured.

$$FAR = \frac{Number\ of\ Samples\ that\ Falsely\ accepted}{Total\ Number\ of\ Samples - Number\ of\ Samples\ that\ Falsely\ accepted} x\ 100 \quad (vi)$$

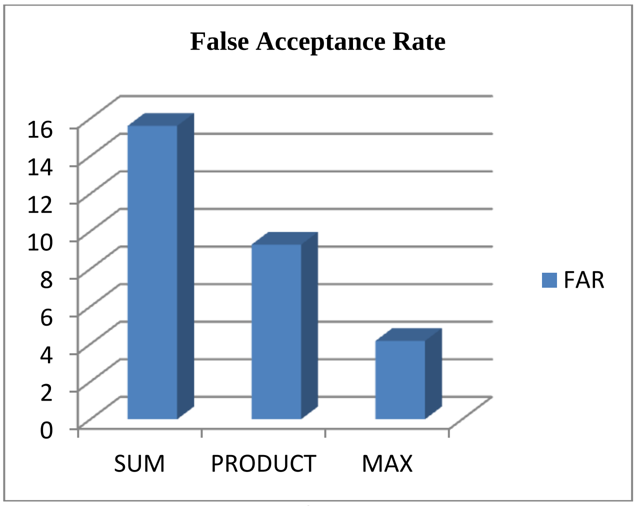

Fig 3: Comparison of False Acceptance Rate

4.2 False Non-Match Rate or False Rejection Rate (FNMR or FRR): The likelihood that the framework neglects to review a match between the matching template in the database rundown and information design. It processes the percent of substantial data sources which are erroneously dismissed. Fig. 4 demonstrates the determined false dismissal rate utilizing the received examples which results that Score level combination utilizing SUM Method accomplishes least false dismissal rate as contrast with others. It implies utilizing SUM technique a couple of tests were falsely refused.

$$FRR = \frac{Number\ of\ Samples\ that\ Falsely\ rejected}{Total\ Number\ of\ Samples - Number\ of\ Samples\ that\ Falsely\ rejected} x\ 100 \quad (vii)$$

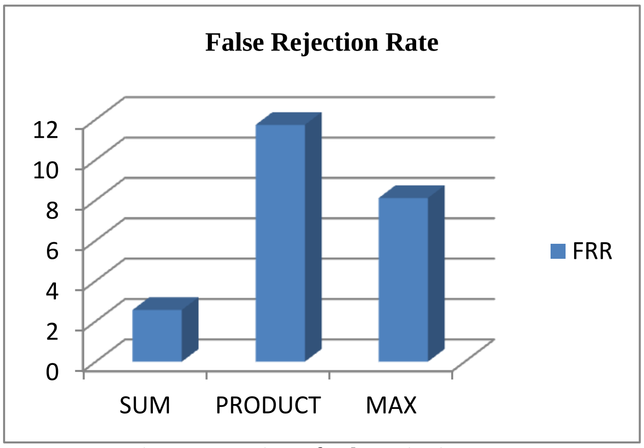

Fig 4: Comparison of False Rejection Rate

4.3 Recognition Accuracy

The FAR and FRR are figured with various strategies as appeared in the Fig. 3 and 4. On the dataset of 100 clients the test is finished. Feature vector are made for both authentic clients and gatecrasher, after this component vectors are intertwined utilizing diverse procedures depicted in table given. Yields are given as FRR and FAR which are found for various techniques. Precision is figured for every one of the techniques.

$$\boldsymbol{Recognition\ Accuracy} = \mathbf{100} - \frac{(\boldsymbol{FAR} + \boldsymbol{FRR})}{\mathbf{2}} \quad (viii)$$

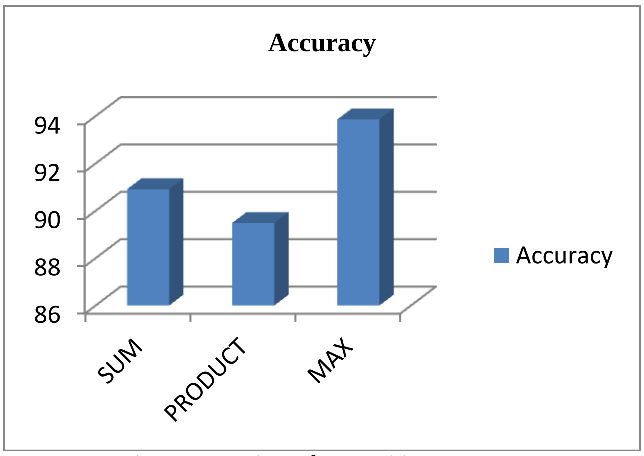

Fig 5: Comparison of Recognition Accuracy

V.CONCLUSION

This work concludes that there is a need of robust authentication system which provides high accuracy. In this work three methods of score level fusion named as SUM, PRODUCT and MAX has been analyzed and analysis shows that in terms of least false rejection rate SUM method works better than other methods whereas in terms of false acceptance rate MAX methods works better. Overall recognition accuracy of MAX method is more so, this method is the best method as compare to other methods for score level fusion in multimodal biometric system.

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