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# FINGERPRINT-FACE FEATURE MATCHING USING MULTI-MODALITY SYSTEM BY AGGLOMERATIVE MULTI-CLUSTERING

[1]V.LATHA JOTHI, [2]Dr.S.ARUMUGAM
[1]Research Scholar & AP, Department of CSE, Velalar College of Engineering & Technology, Erode, Tamilnadu
[2]Principal, Nandha Educational Institutions, Perundurai, Erode, Tamilnadu
E-mail: [1]lathajothi.s@gmail.com,

**ABSTRACT**

The biometric authentication is an effective alternative for traditional authentication techniques. Because biometric data cannot be easily restored or revoked, it is significant that biometric templates used in biometric applications must be built and stored in a secure way, such that attackers could not be able to falsify biometric data easily even when the templates are negotiated. Researches in this area prove that multi-modal biometric systems perform better than single mode. The fundamental idea of multi-modal biometrics is the integration of the different biometric data. This paper presents a multi-modality system, which integrates a function of fingerprint features and face features. The template matching is done using agglomerative multi-clustering process. Presented Multi-Modality System (MMS) considers fingerprint features including pores, incipient ridges, dots, and ridge edge protrusions and face features including eyebrows, eyes, mouth, nose, ears and face border for matching with template. It consists two feature enrollment modules for acquiring the fingerprints and faces into the system and two feature extractors for obtaining the feature sets of fingerprint and face biometrics. The final identification is then performed using a agglomerative multi-clustering process (AMP) which is fast and effective. We evaluate the effectiveness of our system using real fingerprints and face images from publicly available sources. Experimental results demonstrate that Multi-Modality System proposed here have higher security and matching performance compared to Single-Modality System.

**Keywords:** *Fingerprint, Face, Multi-Cluster, Multi-modality, Agglomerative Multi clustering*

## 1. INTRODUCTION

Biometrics has turned to have more and more significant solutions to defeat vulnerabilities of the security systems for people, corporations, companies, institutions and governments. Person recognition systems based on biometrics was utilized in many applications due to their reliability, performance and correctness of detection and verification processes. Some of the applications are information security, surveillance, law enforcement, forensics, smart cards, access control, and so on.

Still there is some limitation in biometrics system which reduces the effectiveness of the security process. For illustration, some people could not register in a biometrics system because of their physical retardations. Likewise, errors sometimes take place during matching process due to bugs. Studies have showed that the poor quality of biometric samples leads to a considerable reduction in the accuracy of a single-modality system. As a result of these issues, multi modal biometric systems were developed. These systems merge the evidence presented by multiple biometric sources. Such systems are stronger to variations in the sample quality than single-modality systems because of presence of multiple pieces of evidence.

The multi-modality systems can be of two types:

a. Those that utilize multiple instance of the similar biometric trait - eg: multiple fingers of the same person.

b. Those that utilize different biometric traits eg: facial plus hand geometry.

All biometric models comprise four basic steps,

i.Data Acquisition Module: Gathering data from users,

ii.Feature Extraction Module: input data get processed to obtain key features,

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iii.Matching Module: key features of input data is compared with data stored in the database to check if they are same or not. Match score is calculated based on the matching algorithm used,

iv.Decision Module: based on some thresholds value, the decision is made to accept or not.

In order to acquire full benefit of the multimodal method, it is necessary to choose a good scheme for fusing different sources of biometric information. Numerous schemes have been proposed to develop the signal quality in fusing at the match score level and decision level. Feature level fusion is chosen because the feature set holds much richer information about the raw biometric data than the matching score or decision level. A better recognition outcome is expected from this technique as this provides us a better performance/processing time.

This paper presents a multi-modality system using two different traits of biometric, face and fingerprint. Initially, the function of fingerprint features and face features are acquired for template matching. Then an agglomerative multi clustering is used to organize the clustered features and the template is matched with those clustered parts of the images.

## 2. LITERATURE SURVEY

Feature level fusion using hand and face biometrics is proposed in [1]. This is a multimodal biometric system using two dissimilar traits of biometric such as face and hand. They performed the fusion at the feature level which integrated the normalization of the feature to build them compatible. Feature-level fusion in [2] concurrently protects numerous templates of a user as a single protected sketch. Realistic implementation of the feature-level fusion employed two famous biometric cryptosystems, to be exact, fuzzy vault and fuzzy commitment.

Framework for continuous user verification is proposed in [3] that primarily use soft biometric traits (for example, color of user's clothing and facial skin). It routinely registered (enrolls) soft biometric traits each time the user logs in and combines soft biometric matching with the traditional authentication schemes, that is password and face biometric.

Biometric recognition from three-dimensional (3-D) facial surface characteristics has turn out to be fashionable, particularly in high security applications. In [4], a fully automatic expression insensitive 3-D face recognition system is proposed. It deals with Surface deformations because of facial expressions in 3-D face recognition.

GEB techniques presented in [6] for multi-biometric fusion and multi-biometric feature selection and weighting. Fingerprint Matching Incorporating Ridge Features with Minutiae is presented in [9]. Fingerprint matching system using Level 3 features is proposed in [10]. Hierarchical matching system [7] utilizes features at all the three levels obtained from 1,000 ppi fingerprint scans.

Automatic Face Parts Prediction System from Fingerprints based on Artificial Neural Network is presented in [11]. For face recognition [8], a uniform local binary pattern (ULBP) is used, while minutiae extraction is used for fingerprint recognition.

Multi-Modal Biometric System based on neural network [5] utilizes the ear and face features. In order to guide exact set of classifiers, the subspace clustering technique has been used to conquer the problem of high dimensionality of the feature space.

## 3. FINGERPRINT-FACE FEATURE MATCHING USING MULTI-MODALITY SYSTEM BY AGGLOMERATIVE MULTI-CLUSTERING

Multi-modality system deals with the acquisition of fingerprint and face features either using sensor device or from a group of fingerprints and faces of same individual stored in the form of templates.

### 3.1 Feature Extraction

Preprocessing of the image is done by applying Gabor Filter to improve the quality of the image. The Gabor filter is given of the form:

$$F(a,b,\lambda,\Omega,\mu,\sigma,\rho) = \frac{\exp(a^{'2} + \rho^2 b^{'2})}{2\sigma^2} \otimes \frac{\exp(i(2\prod(a^{'} + \mu)))}{\lambda} \qquad (1)$$

where a & b represents the pixel value co-ordinates, λ represents the wavelength factor, Ω represents orientation format, μ represents phase offset value, σ represents sigma value and, ρ denotes spatial aspect.

Fingerprint (FPi) features are extracted from the preprocessed image which combines the process of extracting incipient ridges, scars, ridges and pores using Wavelet transform. Then the feature extraction of Face (Fi) is done which combines the process of extracting eyebrows, eyes, mouth, nose, ears and face border using Wavelet transform.

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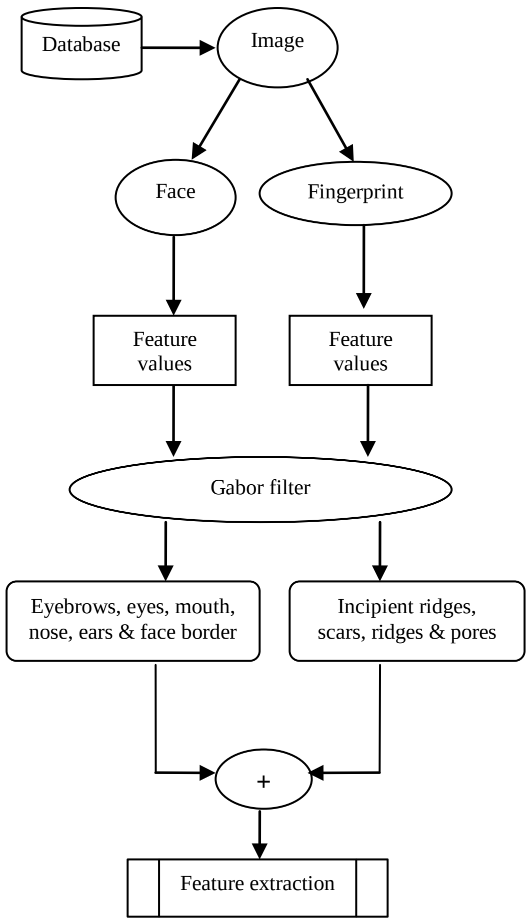


*Figure 1: Feature Extraction of Multi-Modality System*

Figure 1 shows the feature extraction of face and fingerprint features using multi-modality system. The extracted fingerprint and face features vectors FPi and Fi are computed by applying wavelet transformation to make sure that the feature values across the two modalities are compatible. The Combined feature vector Xi will be obtained by augmenting the feature vectors FPi and Fi. Feature selection is then performed on the concatenated vector.

### 3.2 Agglomerative Multi-clustering Algorithm

The Agglomerative multi-clustering algorithm forms clusters in a bottom-up way, as follows:

Step 1: Set every article in its individual cluster.
Step 2: Between all existing clusters, choose the two clusters with the minimum distance.
Step 3: Substitute these two clusters with a novel cluster, formed by integrating the two original ones.
Step 4: Repeat the above two steps until there is only one remaining cluster in the pool.

As a result, the agglomerative clustering algorithm will create the result in a binary cluster tree with distinct object clusters as its leaf nodes and a root node comprising all the articles.

### 3.3 MMS-AMP Technique

Once feature selection is made, the multi-clustering process is performed for clustering the given image (fingerprint and face) using agglomerative clustering. The architecture diagram of the proposed agglomerative multi-clustering process for matching the fingerprint-face features using multi-modality system is shown in Figure 2.

Initially the testing and training image (Fingerprint and face image of same individual) is taken out from database. After that, the images have to be preprocessed to remove the noise using Gabor filter. Then the feature extraction has been done by Wavelet transform to extract the features of the given fingerprint and face image. Then agglomerative clustering process (AMP) is applied to cluster the face and fingerprint features of the given image. Organize the images in template form. Then matching process is efficiently performed by comparing the input image with the clustered image present in the database.

## 4. EXPERIMENTAL EVALUATION

An extensive experimental study has been conducted to examine the proposed Multi-Modality System using Agglomerative Multi-clustering Process (MMS-AMP). The proposed MMS-AMP technique has been tested on a real multimodal database. The database consists of 100 people with four face and fingerprint images per person.

The first face and fingerprint combination is used for training and the rest three image pairs are used for testing, providing 100x3=300 client scores. Every individual is subject to imposter attack by ten arbitrary face and fingerprint pairs for a total of 100x10=1000 impostor scores

The proposed MMS-AMP technique successfully identified the matching pairs by clustering the features. The performance of the proposed MMS-AMP technique for fingerprint-face features matching is evaluated in terms of

i. False Positive rate
ii. False Negative rate
iii. Peak to Signal Noise Ratio (PSNR)
iv. Matching Accuracy

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## 5. RESULTS AND DISCUSSION

Since Multi-Modality System is used for Agglomerative Multi-clustering Process to combine the features, a user is considered as authentic if and only if both the face and fingerprint features match the template. Consequently, the proposed scheme is equal to a fusion scheme that takes the logical and of the two tests in terms of performance. For ease, we conduct experiments on the face and fingerprint data independently, and merge the results to obtain the performance of the resulting system. For each modality, we have a template and a few test samples for each one user. We describe False Positive rate as the ratio of the number of test samples that do not belong to a user however are considered as authentic by the scheme over the total number of test samples. False Negative rate is defined in a similar way. The performance results of Multi-Modality System using Agglomerative Multi-clustering Process (MMS-AMP) is compared with Single-Modality System using Agglomerative Multi-clustering Process (SMS-AMP) which uses Fingerprint as the biometric feature for recognition.

*Table 1: PSNR rate (%)*

| No. of users | PSNR rate (%) | |
|---|---|---|
| | Proposed MMS-AMP | Existing SMS-AMP |
| 1 | 53.35 | 28.73 |
| 2 | 47.64 | 45.83 |
| 3 | 56.77 | 50.04 |
| 4 | 79.03 | 67.94 |
| 5 | 84.18 | 70.45 |

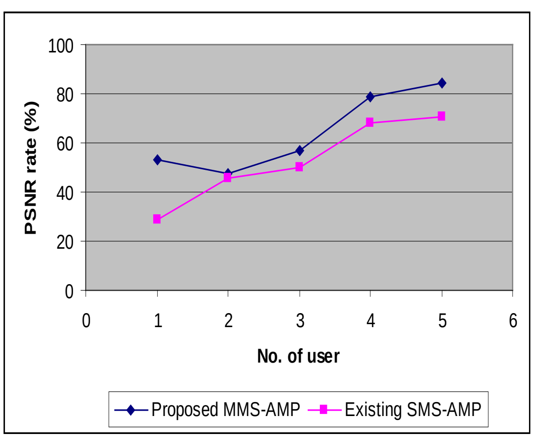


*Figure 3: The results of PSNR Rate when combining the Fingerprint and face biometrics of a user*

Table 1 and Figure 3 demonstrate the quality of image for the existing SMS-AMP and proposed MMS-AMP for Fingerprint-Face matching features. PSNR value is calculated in terms of decibels. PSNR ratio is used to measure the quality of image. Higher the PSNR rate better will be the quality of matched image. PSNR rate is plotted for different number of users. It is observed from the graph and table that PSNR rate (%) obtained for the proposed MMS-AMP for fingerprint-face matching features is higher (12%-17%) when compared to existing SMS-AMP.

*Table 2: FPR & FNR for Fingerprint and Face Features*

| False Positive rate (FPR) | False Negative rate (FNR) | |
|---|---|---|
| | FingerPrint | Face |
| 0 | 0.05 | 0.03 |
| 0.01 | 0.04 | 0.023 |
| 0.02 | 0.015 | 0.018 |
| 0.03 | 0.013 | 0.01 |
| 0.04 | 0.012 | 0.005 |
| 0.05 | 0.012 | 0.005 |

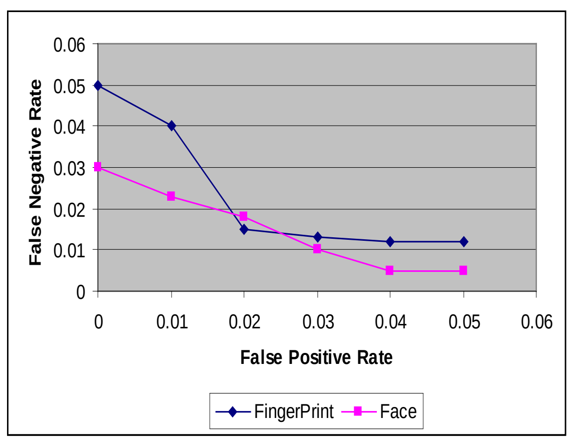


*Figure 4: ROC Curve for Fingerprint and Face Features*

Table 2 & Figure 4 illustrate the ROC curves of the fingerprint and face features. Since we assume that fingerprints and face features are independent, overall performance of the combined system can be obtained by examining relevant points from the ROC's of the individual modalities. When false positive rate gets increased, False Negative rate of both fingerprint and face gets decreased.

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*Table 3: Matching Accuracy (%)*

| No. of user | Matching Accuracy (%) | |
|---|---|---|
| | Proposed MMS-AMP | Existing SMS-AMP |
| 1 | 43.67 | 15.33 |
| 2 | 56.23 | 24.76 |
| 3 | 77.93 | 54.09 |
| 4 | 82.76 | 48.49 |
| 5 | 86.28 | 60.83 |

Table 3 and Figure 5 demonstrates results of matching accuracy when combining the Fingerprint and face biometrics of a user. The performance of general matching work is done for the proposed MMS-AMP and existing SMS-AMP. In order to display effectiveness of the proposed MMS-AMP, we have matching accuracy. The general matching curve for proposed MMS-AMP is plotted for number of user versus matching (%) for different users. It is observed from the graph that matching (%) obtained for MMS-AMP is higher (18% to 24%) when compared to SMS-AMP.

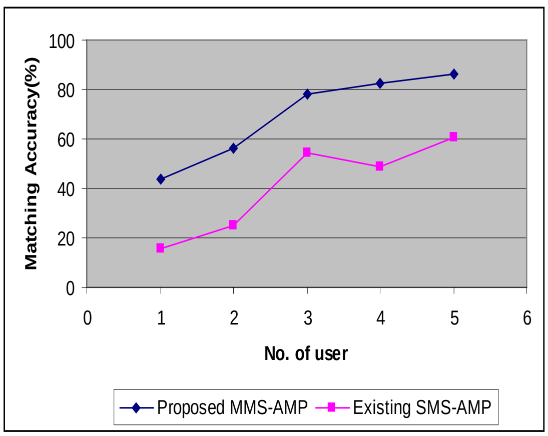


*Figure 5: Matching Accuracy*

## 6. CONCLUSION

In this paper, Multi-Modality System using Agglomerative Multi-clustering Process (MMS-AMP) for fingerprint-face features matching is presented. In order to improve the multimodal matching performance, MMS-AMP technique has been proposed. The study mainly concentrates on the integration of fingerprint and face biometrics in feature level. Although the MMS-AMP technique is relatively simple, comparable to logical and independent tests of fingerprint and face biometrics, it however shows possibilities for much more difficult operations that will be performed over the joint biometric features before performing clustering process. The experimental result shows that MMS-AMP achieves 86.28% of matching accuracy over the existing Single-Modality System which achieves only 60.83%. PSNR rate for MMS-AMP achieves 12% to 17% increase when compared to the existing Single-Modality System.

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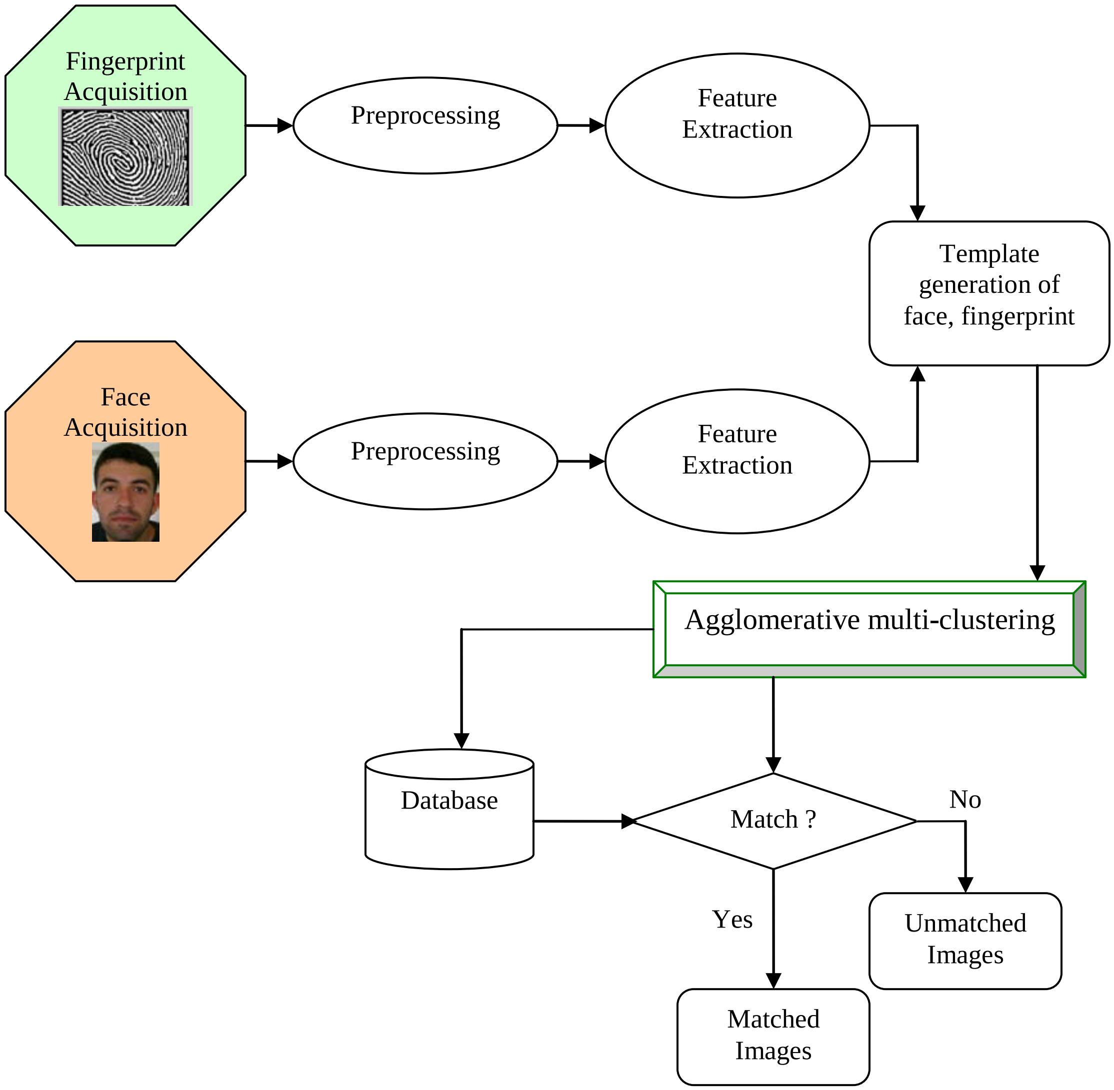


*Figure 2: Architecture diagram of Multi-Modality System*