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Original Article

Multimodal Biometric Identification system using Random Selection of Biometrics

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Abstract - *Biometric systems employ their biometric features to identify people. Identification systems that solely employ one biometric modality would not be able to meet the demands of demanding biometric applications in terms of performance, acceptance, and uniqueness. The majority of unimodal biometrics systems have problems with concentrated data noise, variances within and across classes, non-universality, etc. Multimodal biometric systems, which may establish identity from many sources of information, can bypass some of these restrictions. Identifying a person using multimodal biometric technology is more accurate and dependable. Early integration tactics are anticipated to perform better than late integration strategies. In this paper, feature-level fusion using the random selection of biometrics is presented. Block variance features and contourlet transform features are used to carry out the feature-level fusion. LDA is used to reduce the feature vector's dimensions. When compared to alternative integration approaches and their unimodal cousin, integrating the contourlet transform features of two independently determined biometric qualities delivers a consistent gain in performance accuracy. In this work, we use a random selection of biometric traits to guarantee the presence of a real human being at the time of data collection. Only fingerprints, palm prints, and faces will be included in the random selection.*

Keywords - *Hand geometry, Contourlet transform, Multimodal, Feature level fusion, Biometric.*

1. Introduction

Information transparency is a fundamental concern in the age of information technology. The information must be protected from unwanted access because its confidentiality and integrity are crucial. Security is the act of preventing unauthorized individuals from accessing sensitive information or priceless assets. Personal identification in various contexts (ATM cards, driver's licences, passports, citizen cards, mobile phones, voter ID cards, etc.) must be reliable and automated [1]. Furthermore, securing yourself and your belongings is essential. The traditional identification methods, including PINs and passwords, are unreliable because fraud is possible. Utilizing biometric identification provides a solution to this issue [2].

The term "biometric" refers to a person's physiological (such as fingerprints, the face, or the iris) and behavioral (such as speech) traits completely unique to him. Unlike traditional authorisation systems like smartcards, biometrics identifies a person based on who they are rather than what they have on them. You can never misplace, guess, or fake a biometric id. Regarding biometrics, the vast majority of real-world applications are single-modal [4]. When just one biometric identifier is employed, the process is said to be "unimodal." However, these systems have limitations that may be overcome by using additional sensors in a multimodal setup [5]. These limitations include noise in sensed data, intra-class variations, inter-class similarities, nonuniversality, and spoof assaults.

An attempt is made in this study to present a multimodal system that is flawless. Section 2 describes the materials and methods used to design the multimodal framework. Section 5 includes the results of the framed system, and finally, the conclusion highlights conclusive remarks of the resultant system.

2. Literature Survey

2.1. Multimodal Biometric System

Most existing biometric systems rely on what is known as a unimodal system, in which just a single biometric attribute is utilised to identify a person. Considering several different biometric characteristics, Multimodal biometric systems can circumvent some restrictions imposed by single-trait biometric methods. In theory, many biometric features make multimodal biometric systems more robust [7]. The lack of universality is solved by multimodal biometric systems, which include numerous characteristics that provide enough features for identification. As it is difficult for a fraudster to fake many biometric features at once, multimodal authentication systems effectively reduce the likelihood of identity theft.[3] In addition, a multimodal system may verify the presence of a 'live' user at the time of data collection by having the subject show a random subset of biometric features [8].

The following are five examples of integration possibilities for multimodal biometric systems: 1) a network of sensors whose results are averaged. There are four types of biometric identifiers: 2) multiple instances, 3) multiple samples, and 4) various biometric traits incorporate a number of biometric features (e.g., face and iris). Fifthly, several methods for recognising the same biometric—for instance, a fingerprint matcher that uses both texture and fine-grained features—are merged [6,9,10,18].

Four fusion stages are present in multimodal systems (sensor, feature, matching, and decision) [11]. It is generally accepted that the device and feature levels are where pre-mapping fusion takes place, while post-mapping fusion is assumed to take place at the corresponding score and determination levels. In premapping fusion, the biometric information is combined before classification; however, in postmapping fusion, the biometric information is patterned separately before being structured into a corresponding score/decision space and fused. Premapping fusion is contrasted with postmapping fusion, described in the following sentence. After each stage of a biometric system's processing, the quantity of data accessible for fusion decreases [13]. In this context, "fusion" at the classification stage refers to the process of merging feature sets that correlate to numerous modalities. When contrasted to the match score or the option, the feature set connects to more data about only the basic biometric information. This finding suggests that integrating at this stage might result in recognition results that are more accurate [14].

2.2. Feature Level Fusion

Features are derived from all biometric characteristics in feature-level fusion. By combining the retrieved features, a final output vector of increased dimension may be generated. Integration at the classification stage produces better identification results than score level or decision level fusion because the feature set contains more detail about the input information [16]. As shown in Fig.1, feature-level fusion involves pre-processing a feature set from two different sensors (such as a face and a palm print) before extracting features separately from each sensor to construct a trait vector [17]. Characteristics are then combined into a single new vector via composition. In this paper, to select biometric traits logistic regression method is used. So weights to the four biometric traits have been assigned depending upon the accuracy of biometric traits [19]. Weights assigned to fingerprint, palmprint, face and Hand geometry are 0.3, 0.25, 0.25 and 0.2, respectively. A higher value of weight assigns to the more accurate biometric trait.

Let's assume F_p and F_s are two feature vectors obtained by applying the contourlet transform to any two multimodal biometrics at random. Each trait's dimension will be denoted by f_p and f_s. Two-trait feature vectors are denoted by, $F_p = \{P_1, P_2, \ldots\ldots f_p\} and\ F_s = \{S_1, S_2, \ldots\ldots f_s\}$

In order to create a new different feature F_c= [F_p.... F_s], we join together two existing feature vectors. According to Fig.2, Fc has a size proportional to (fp + fs). Dimension 128 is achieved by concatenating the estimated correlation Characteristics of dimension 64 taken from each characteristic [20]. Fc is added to the database as a new template for finding a good match.

3. Feature Level Fusion using Block Variance Feature

The extracted features of 128 features are generated by concatenating the features of 64 different modalities into a single vector. The first modality contributes 64 features, and the second modality contributes 64 features [22]. The size of the picture being input is 256 by 256. The image is then cut into windows that are 32 pixels by 32 pixels, which results in eight blocks across and eight blocks down, as illustrated in Figure 3. Because of this, 64 features are taken from the first set of possibilities and 64 features are taken from the second set of paradigms [23]. The overall size of the feature vector is 128 when the characteristics of both modalities are concatenated together.

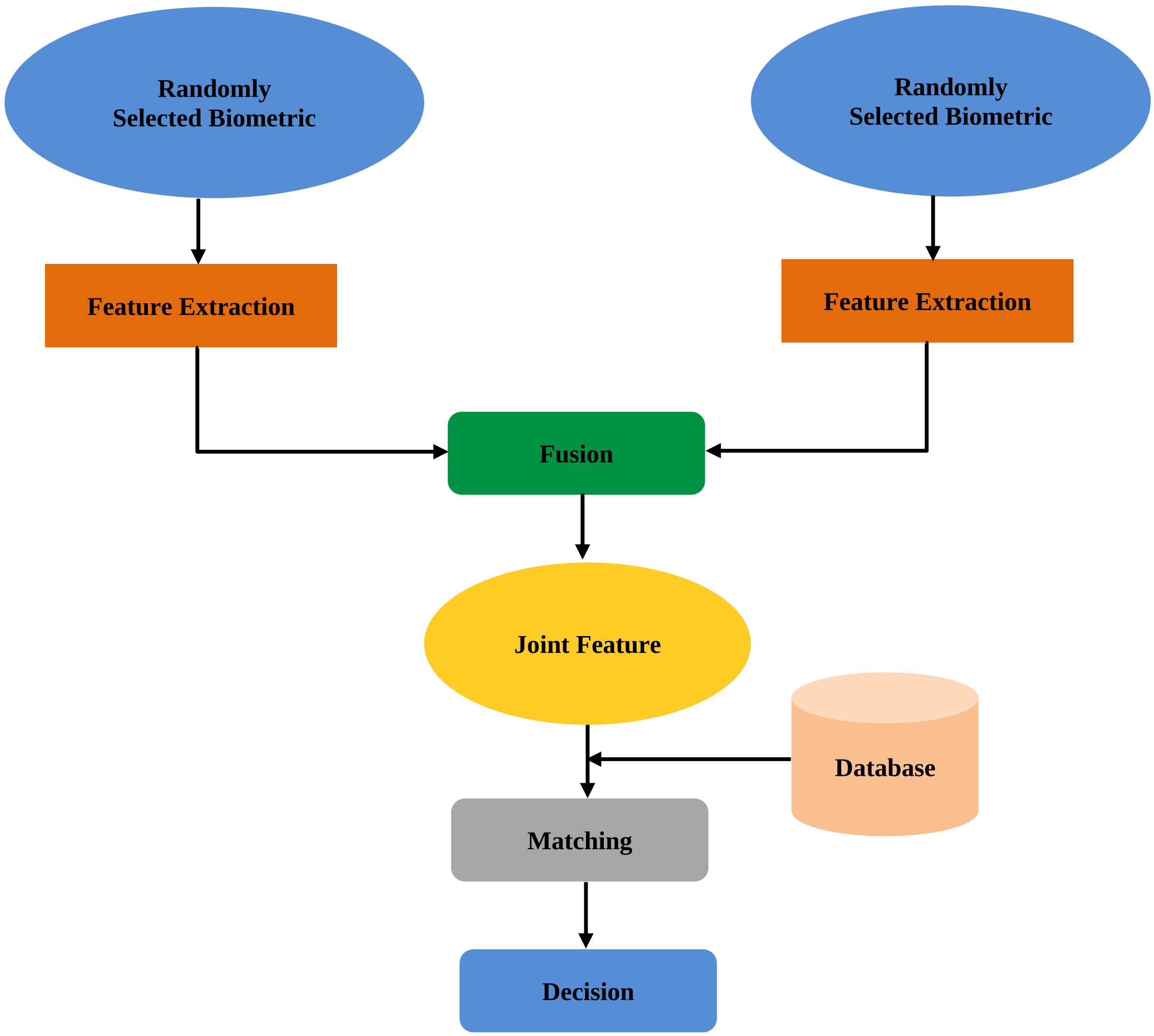

Fig. 1 Block Diagram of Feature Level fusion

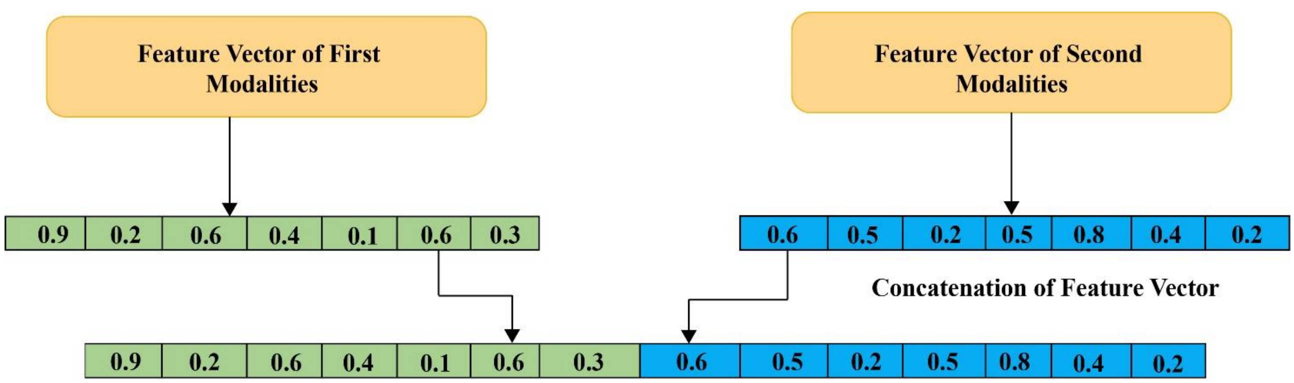

Fig. 2 Combining of two distinct characteristic vectors

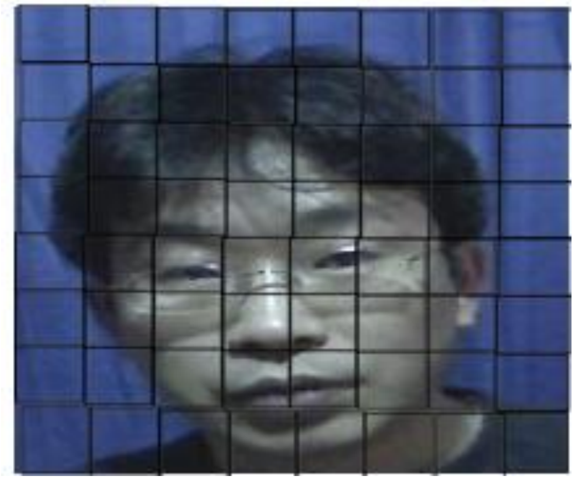

Fig. 3 Dividing Input Image into 64 blocks

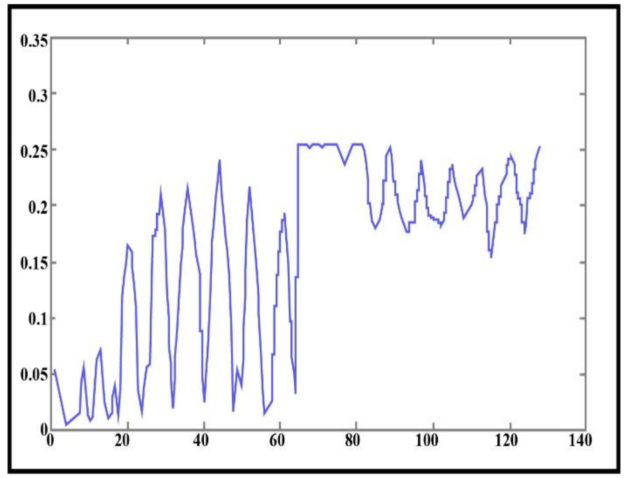

Fig.4. The combined face and fingerprint feature vector has 128 components.

Fig. 5 Dividing Input Image into 16 blocks

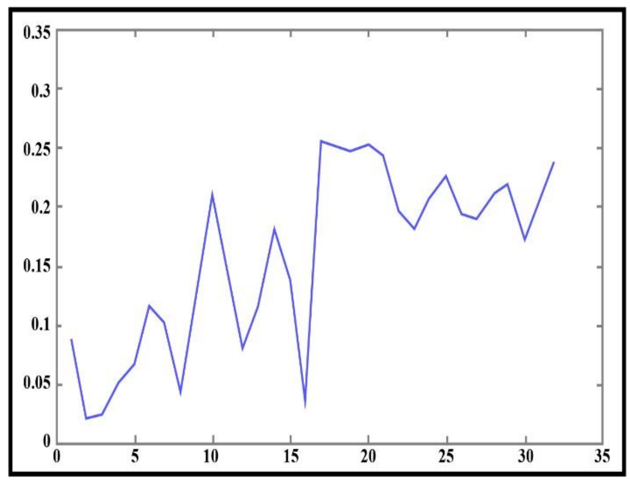

Fig. 6 Face and fingerprint features concatenated into a 32-feature vector

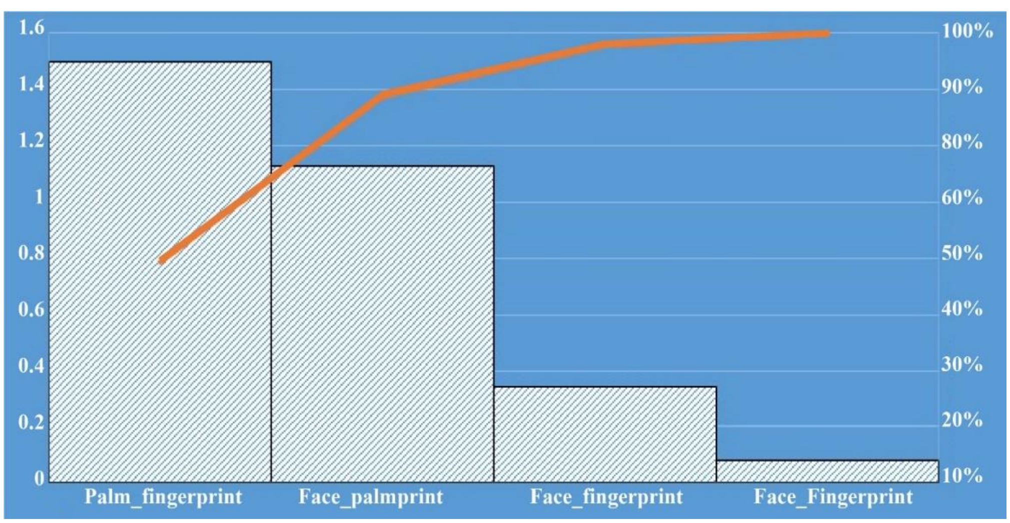

Fig. 7 Comparison Level Fusion with different concatenated biometric features modality for Casia database

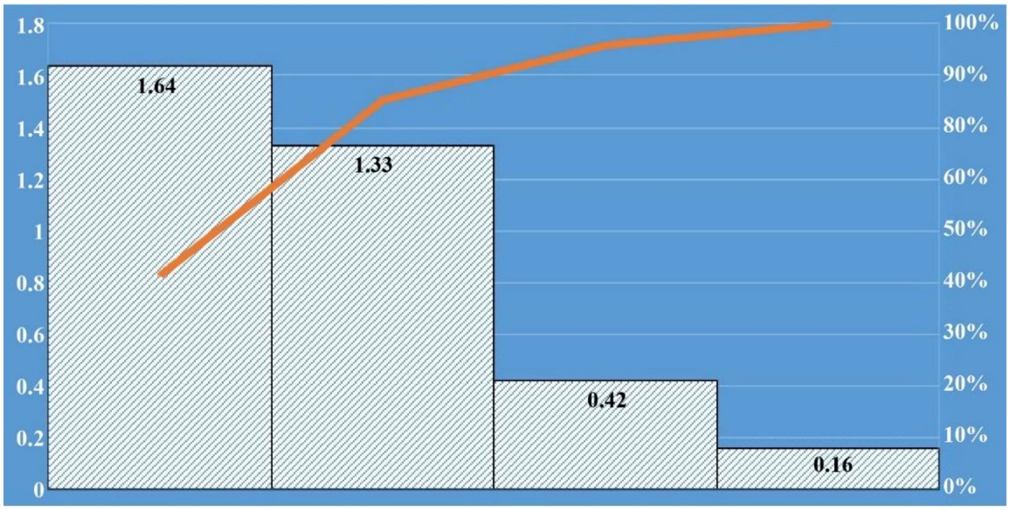

Fig. 8 Comparison level fusion of different with concatenated biometric features Modality for Local Database

Figure 4 depicts the integrated face and fingerprint feature vector. This figure exhibits a total of 128 features, consisting of the first 64 characteristics of the face biometric and the following 64 features of the fingerprint biometric, making the total number of features 128—a fusion of 32 feature vectors at the feature level [25].

Together, the 16 features from the first modality and the 16 features from the second modality make up the 32 features that make up the feature vector [26]. A 256x256 input picture is expected. As shown in Fig.5, the image is partitioned into 64x64-pixel windows, creating four blocks across and four down. It allows the extraction of 16 features from the first modality and 16 features from the second. Combining the feature vectors from the two modalities into one yield 32 features in total.

The first 16 characteristics of the face biometric and the following 16 features of the fingerprint biometric are shown concatenated in Fig.6.

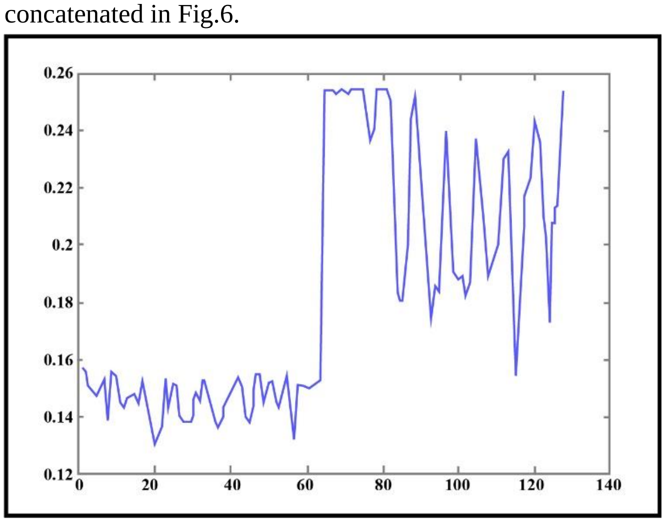

Fig. 9 Concatenated Feature Vector of Feature Fingerprint and Palmprint

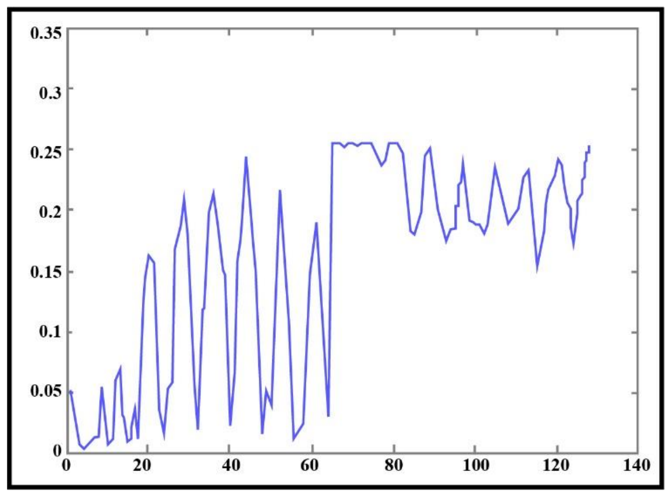

Fig. 10 Concatenated Feature Vector of Level Fusion of Feature Level Fusion of Face and Fingerprint

Therefore, the combined size of all the features in the feature vector is 32.

Figures 7 and 8 compare the results of fusing facial, palm, and fingerprint traits using the Casia and local databases. There was a 128-point correlation between palmprints and fingerprints, proving that the two could be fused into a single Accuracy is improved when combining many characteristics.

The integrated feature vector of a fingerprint and palmprint is shown in Fig. 9; it has 128 features in total, the first 64 of which come from the palmprint and the remaining 64 from the fingerprint. The magnitude of features is represented by the X-axis, while the size of the feature vector is shown by the Y-axis. Similarly, the joined face and fingerprint feature vector are shown in Fig. 10.

4. Feature Level Fusion Using Contourlet Transform Features

DWT does not provide directions other than horizontal, vertical, and diagonal. Curves with abrupt transitions are difficult for the wavelet to process. As the size of the feature vector grows, the computing time needed for feature extraction also increases, which slows down the retrieval speed [28]. The curvelet transform is useful for displaying discontinuities in curves but inevitably leads to the continuous domain. There is a transition from the discrete to the continuous domain in the contourlet transform. The contour more accurately represents the image's lines, edges, contours, and curves let transform than the wavelet or curve let transforms, thanks to the transform's directionality and anisotropy. Combining multiscale decomposition with directed decomposition results in the contourlet transform. The multiscale decomposition provided by the Laplacian pyramid allows the picture to be transformed into a coarse level and a collection of laplacian sub-bands. Critical downsampling at a directional stage allows for easy and adaptable sub-band partitioning of the overall frequency spectrum [29]. The basis function used in the contourlet expansion may have a variety of scales and orientations, and its aspect ratio can be varied as needed[31]. With such a wide variety of basic functions, the contourlet transform can accurately capture the smooth contours that are often the most prominent aspect of a picture. In Fig.11., we see the contourlet transform at level four, with orientations 0, 2, 3, and 4 representing the coarse, medium, and fine scales, respectively. The input picture is divided into two bands of equal width using a filter of order 'n' for each 'k' resolution [32]. If you want to see your picture as it was originally captured, start with the highest resolution setting (level 1). This setting has an input size of 256x256. The 128x128 pixel size is the next step up in resolution. Subsampling at levels 3 and 4 further reduces the input picture size to 64x64 and 32x32, respectively. Here, the contourlet transform performs to extract features, and then sum, max, and min are applied to those features to create a unified feature vector during the fusion stage [33]. Linear analytical thinking is used to reduce the feature vector's dimensionality.

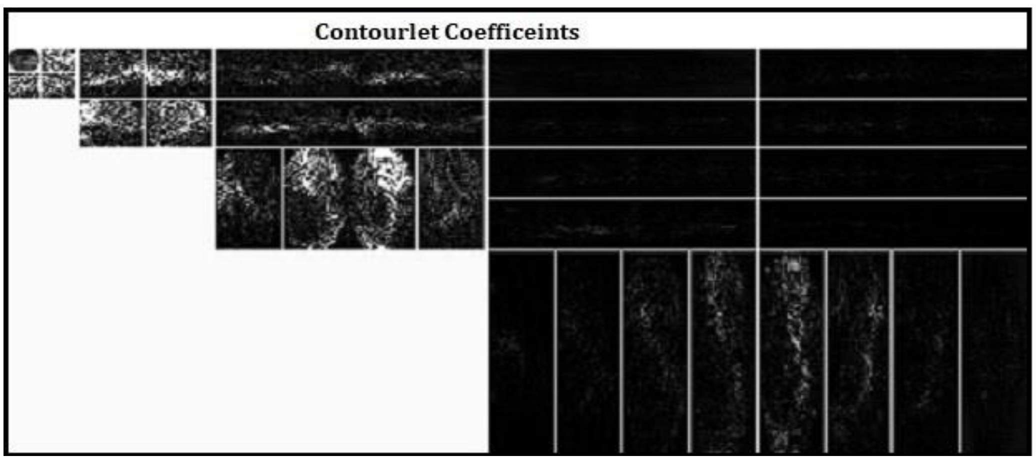

Fig. 11 Contourlet Transform decomposition for fingerprint image

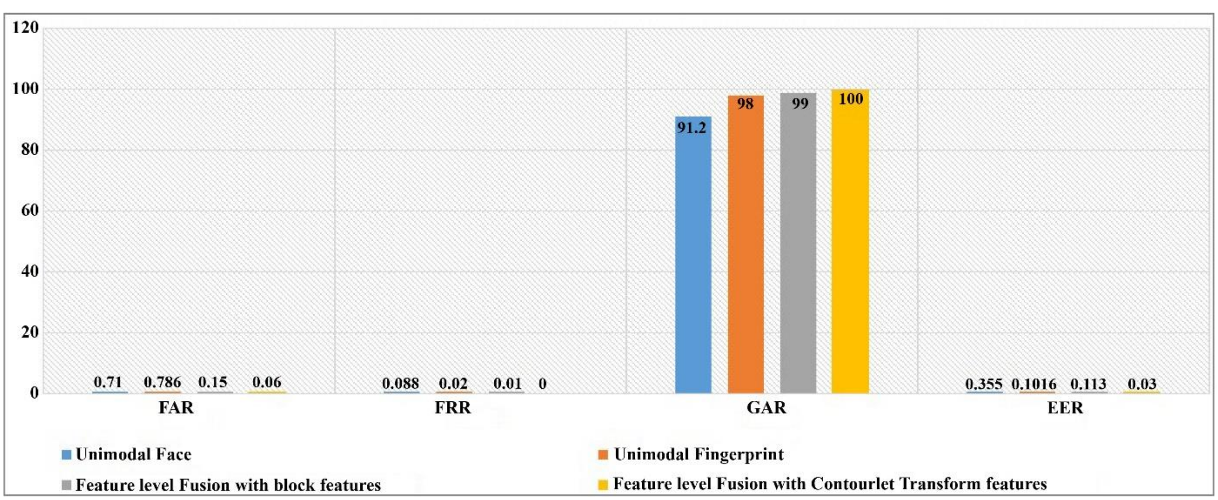

Fig. 12 Comparison of fingerprint and face multimodal identification system

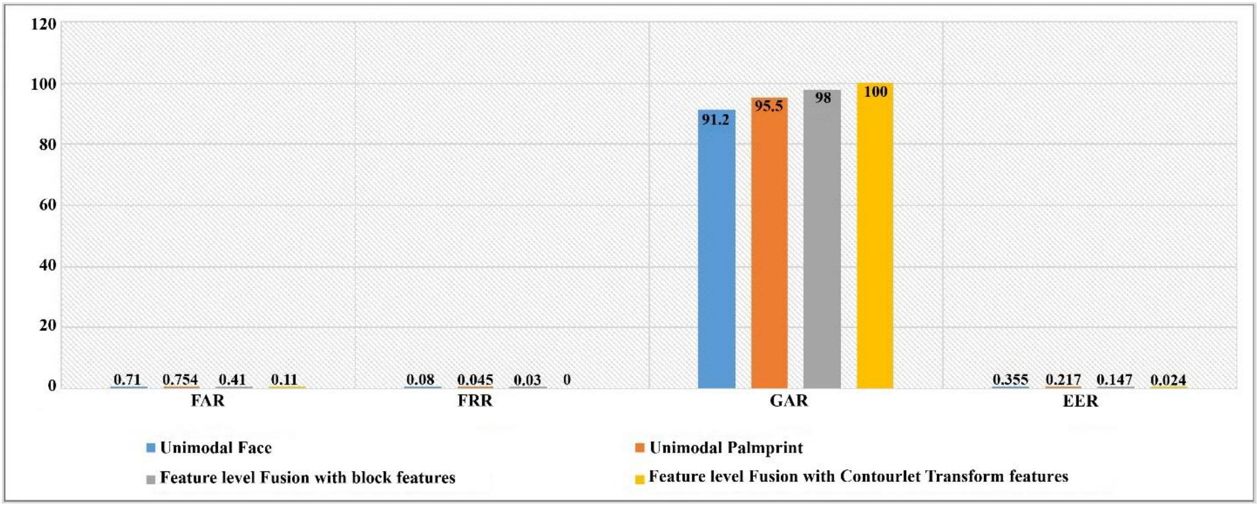

Fig. 13 Comparison of palmprint and face identification System

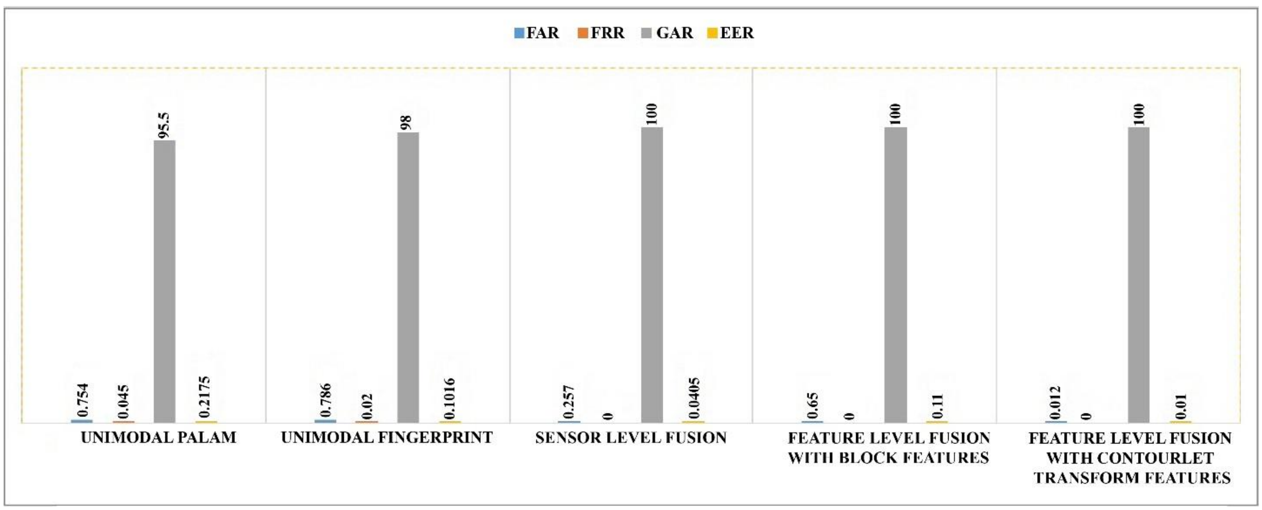

Fig. 14 Comparison of palmprint and fingerprint multimodal identification system

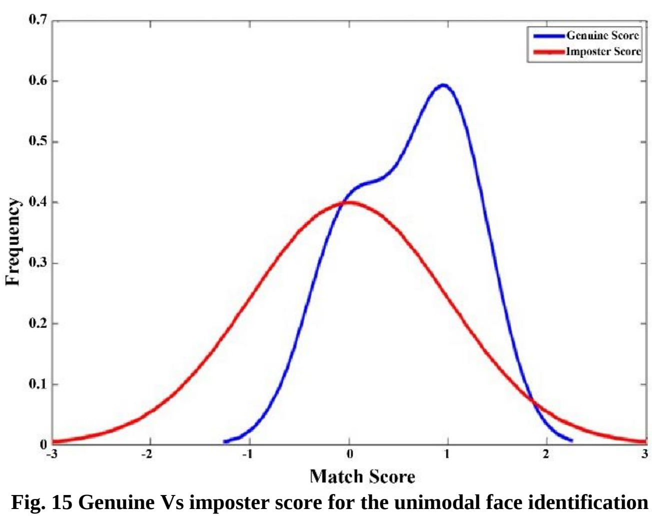

Fig. 15 Genuine Vs imposter score for the unimodal face identification system

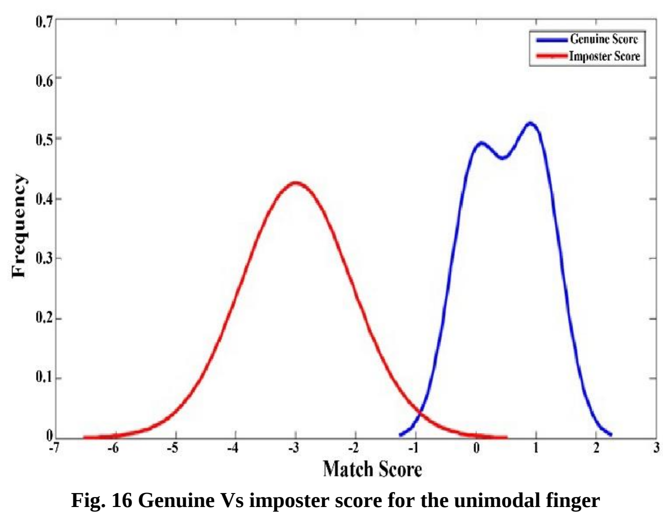

Fig. 16 Genuine Vs imposter score for the unimodal finger identification system

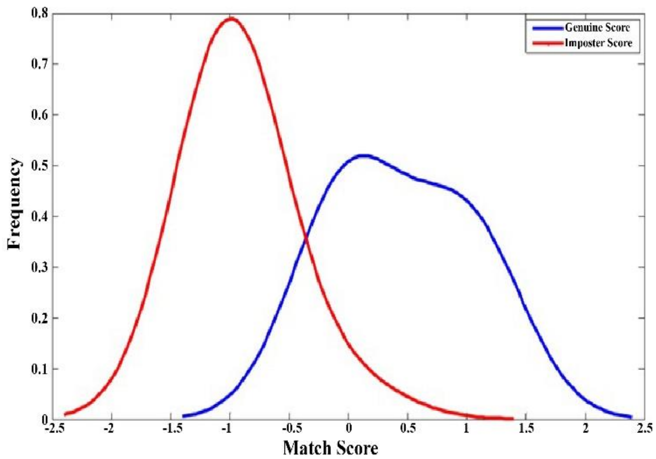

Fig. 17 Genuine Vs imposter score for unimodal Palm print identification system

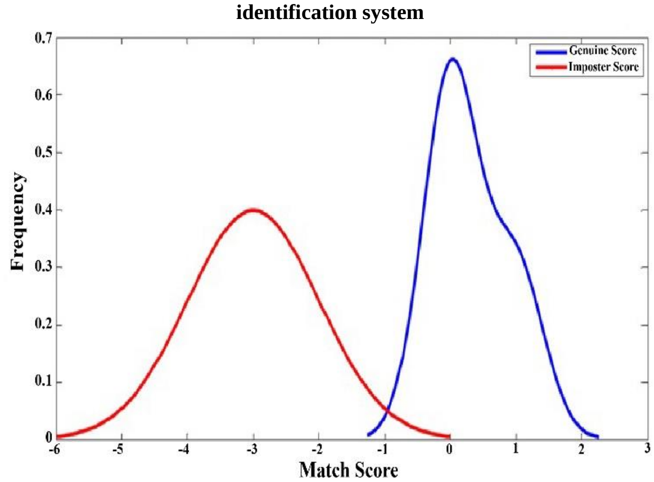

Fig. 18 Genuine Vs imposter score for Multimodal face and palm print identification system

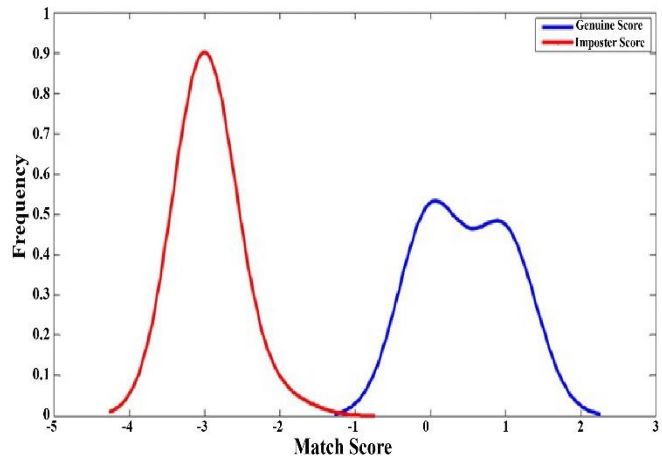

Fig. 19 Genuine Vs imposter score for Multimodal print and fingerprint Identification system

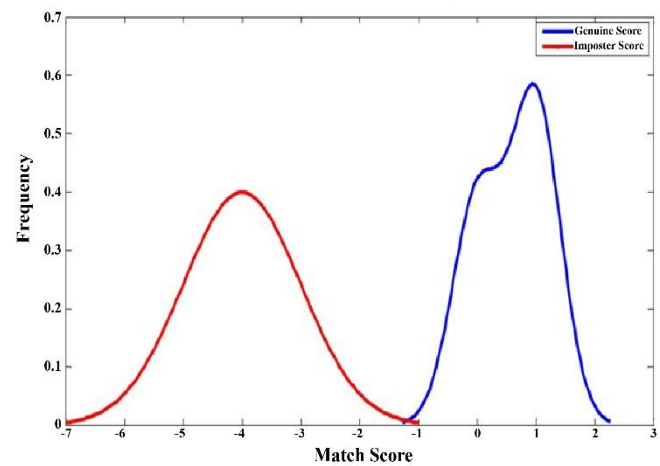

Fig. 20 Genuine Vs imposter score for Multimodal palm face and Fingerprint Identification system

Table 1. Feature vector size before and after applying the LDA algorithm

Biometric Modality	Feature vector size Before applying LDA	Feature vector size after applying LDA
Fingerprint_Palmprint	62	20
Fingerprint_Face	62	20
Palmprint_Face	62	20

4.1. Linear Discriminate Analysis (LDA)

LDA linearly combines unrelated information to generate the highest possible differences between the means between the target classes. In LDA, the goal is to use a scatter matrix to discover a transform where the characteristic clusters are most distinguishable following the linear transformation [34]. To achieve its goals, LDA attempts to maximise the scatter matrix's measure across classes while minimising the scatter matrix's measure within classes.

Table.1 shows how the feature vector size of feature level fusion is reduced after applying the LDA algorithm [12, 35]. A total of 31 features are present for fingerprint, palmprint and face after applying the contourlet transform. So after feature concatenation for feature level fusion total feature vector becomes 62(31+31). After applying the LDA feature vector size becomes 20.

5. Results and Discussion

The presented method's experimental evaluations are carried out on the standard database (CASIA database) and locally captured. The database used in this investigation consists of 1,000 photos across all accessible modalities, gathered from 200 unique participants and 5 representative samples of each participant. Light levels, age, and the natural bending of lines all have a role in the variability seen in palm print and fingerprint databases. Alterations in lighting, ageing, expression, stance, and camera angle were made to the face photos. The methods discussed in section 2 are applied, and results are analyzed with respect to FAR, FRR, GAR and EER for all modalities. Figure.12., Figre.13. and

Fgure.14. provide a comparison of face, fingerprint, and facepalm print modalities in unimodal and multimodal biometric technology, respectively. Compared to feature-level block characteristics and their unimodal counterpart, the performance of a feature-based fusion with a contourlet transform is much higher.

Fig. 15, 16, and 17 show the genuine imposter graphs for the unimodal biometric identification system. The overlap region of genuine and imposter scores for unimodal fingerprint identification is less than the unimodal face palm print identification system. So the accuracy of fingerprint identification system is more than Face, Palm print Recognition System

Figures 18., 19 and 20 show Genuine Vs imposter scores for multimodal biometric identification systems using feature-level fusion, which shows more accuracy than their unimodal counterparts. Overlap region of Genuine and imposter graphs for multimodal biometric identification using fingerprint and palm print is less compared to other multimodal biometric recognition systems. So the accuracy of multimodal biometric identification using fingerprint and palm print is high compared to other multimodal biometric identification systems.

This article demonstrates feature-level fusion using block variance features and contourlet transform features. Because the contourlet transform decomposes the picture into low and high-frequency curvelet coefficients at varying scales and angles, it is superior to block features for feature-level fusion. Contourlet transform can extract unique textural patterns from palmprint, face and fingerprint images. The presented feature level fusion using palmprint and fingerprint achieved the best recognition rates of 99.98%, and the ROC curve shows that the system achieved 100% GAR.

6. Conclusion

Multimodal biometric identification systems are utilised for person recognition since unimodal systems have problems with things like noise in sensed data, intra-class differences, inter-class similarities, non-universality, spoof assaults, etc. Multimodal systems, which **consider** both fingerprints and hand geometries, solve the problem of non-universality by providing better population coverage than single-modal systems. Because subjects deemed unfit for one biometric modality may utilise another, the reported findings show that it is exceedingly difficult for an attacker to fake numerous biometric features concurrently with a validly registered person. Compared to previous integration approaches and the unimodal analogue, integrating two separate, uncorrelated biometric features at the feature level delivers a consistent gain in performance accuracy. The accuracy of the Multimodal biometric system is shown to increase when biometric qualities are selected at random, as shown by the experiments. In addition, the system would know it communicates with a real person since biometric features would be picked randomly. Commercial, governmental, and even forensic uses may all benefit from this effort.

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