Multimodal Biometrics at Feature Level Fusion using Texture Features

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Abstract

In recent years, fusion of multiple biometric modalities for personal authentication has received considerable attention. This paper presents a feature level fusion algorithm based on texture features. The system combines fingerprint, face and off-line signature. Texture features are extracted from Curvelet transform. The Curvelet feature dimension is selected based on d-prime number. The increase in feature dimension is reduced by using template averaging, moment features and by Principal component analysis (PCA). The algorithm is tested on in-house multimodal database comprising of 3000 samples and Chimeric databases. Identification performance of the system is evaluated using SVM classifier. A maximum GAR of 97.15% is achieved with Curvelet-PCA features.

Keywords: Multimodal Biometrics, Feature Level, Curvelet Transform, Template Averaging, PCA Features and SVM Classifier.

1. INTRODUCTION

Personal authentication systems built upon only one of the biometric traits are not fulfilling the requirements of demanding applications in terms of universality, uniqueness, permanence, collectability, performance, acceptability and circumvention. This has motivated the current interest in multimodal biometrics [1] in which multiple biometric traits are simultaneously used in order to make an identification decision. Depending on the number of traits, sensors and feature sets used, a variety of scenarios are possible in a multimodal biometric system. They include single biometric with multiple sensors, multiple biometric traits, single biometric with multi-instances, single biometric with multiple representations and single biometric with multiple matchers. Among all these scenarios, system with multiple biometric traits is gaining importance and this method itself is known as multimodal biometric system. Based on the type of information available in a certain module, different levels of fusion are defined [2]. Levels of fusion are broadly classified into two categories: fusion before matching also called as pre-classification which includes sensor level and feature level. Fusion after matching also called as post classification which includes match score level and decision level. Amongst these, fusion at feature level is gaining much research interest.

Most of the existing multimodal systems are based on either score level or decision level fusion [3]. Match score is a measure of the similarity between the input and template biometric feature vector. In match score level, scores are generated by multiple classifiers pertaining to different biometric traits and combined [4]. In order to map score of different classifiers into a single domain, where they possess a common meaning in terms of biometric performance, normalization technique is applied to the output of classifier before score fusion. Gupta [5] developed a multimodal system based on fingerprint, face, iris and signature with score level fusion. In all these systems texture features are extracted and score level and decision level fusion are compared using SVM classifier. The most promising recent research is certainly the information fusion at the matching score level invoking user specific weights and threshold levels. Though a few multimodal systems developed are considered to be very accurate, still they are not validated since, systems are tested on a medium size database.

Fusion at feature level involves integration of feature sets corresponding to multiple biometric traits. Feature set contains rich information about biometric data than the match score or final decision. Therefore integration at this level is expected to give improved recognition performance. Due to the constraints of feature level fusion, very few researchers have studied integration at feature level. Chetty [6] combined face and voice using visual and acoustic features with artificial neural network as a recognizer and obtained an Equal Error Rate (EER) of 2.5%. Nandakumar [7] concatenated fingerprint and iris code at feature level using fuzzy vault classifier and showed that uncorrelated features when combined gives best possible EER. Ferrer [8] proposed fusion of features extracted from hand geometry, palmprint and fingerprint. It is imperative that an appropriate feature selection scheme is used when combining information at the feature level.

This paper proposes a multimodal identification system that combines fingerprint, face and signature biometric traits. These three traits are considered due to their wide acceptance by users and also the data acquisition cost involved in these three traits are much less compared to other biometrics. Texture features are extracted from each modality independently and fusion at feature level is performed. Texture features are extracted from Curvelet Transform. Section 2 describes the proposed multimodal biometric Identification system based on feature level fusion. Section 3 describes database collection protocol and pre-processing. Section 4 describes feature extraction and dimension reduction techniques. Section 5 summarizes experimental results and section 6 gives comparisons with similar work. Section 7 concludes proposed system.

2. PROPOSED MULTIMODAL IDENTIFICATION SYSTEM

The schematic of the multimodal system at feature level fusion is shown in Figure 1. The multimodal system has two phases of operation: enrolment and identification. The enrolment module registers a person and then the three biometric traits are acquired and representation of these three traits are stored in a database. The proposed system is designed to operate in parallel mode. Fingerprint, face and signature of a person are acquired separately in data acquisition module. Required pre-processing techniques are applied on every biometric trait and features are extracted simultaneously. Features from all three biometric traits are concatenated and a feature vector is formed and stored as template in a database. Single matcher is used to evaluate the performance. SVM classifier is used for matching. During authentication, feature vector extracted from the test person is compared with the template stored in the database. Matching is performed using a recognizer which compares query feature vector with the template in the database and generates a match score. To prevent impostor from being identified, the match score from matcher is compared with a predefined threshold in the decision module. This module makes a decision as either person under test is recognized or not recognized.

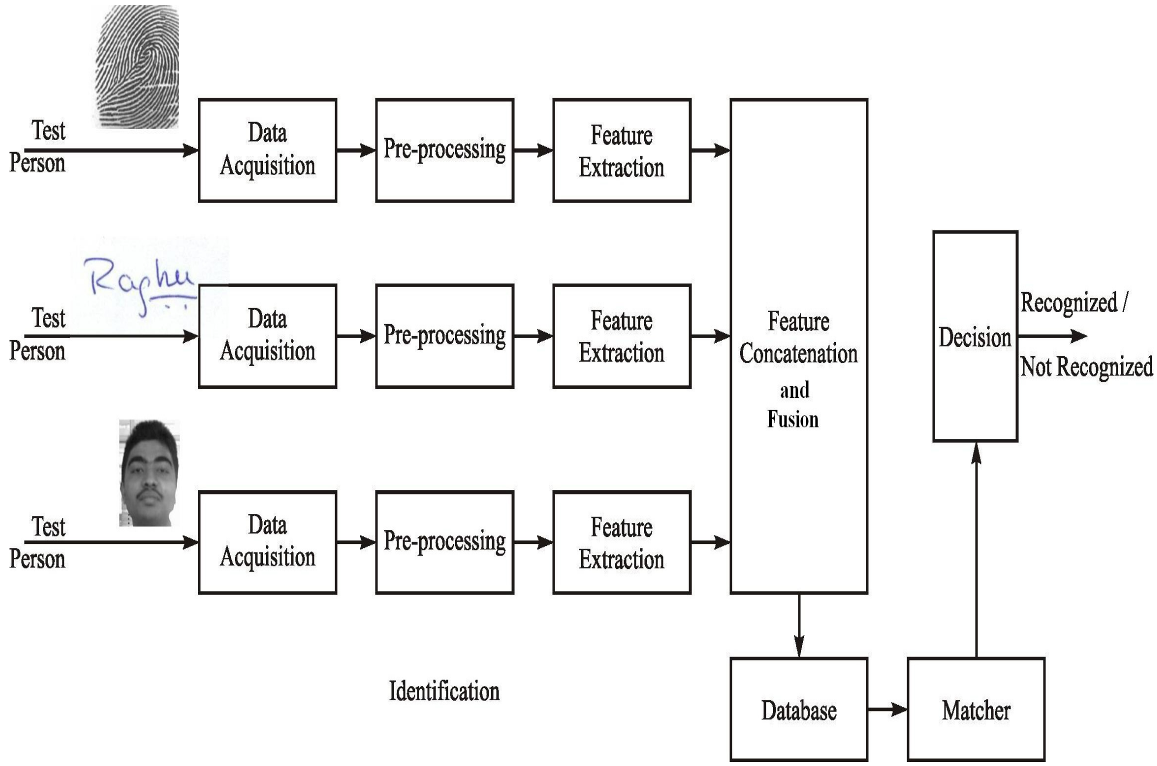


FIGURE 1: Block Diagram of Proposed Multimodal Biometric System Based on Feature Level Fusion.

2. DATABASE COLLECTION and PRE-PROCESSING

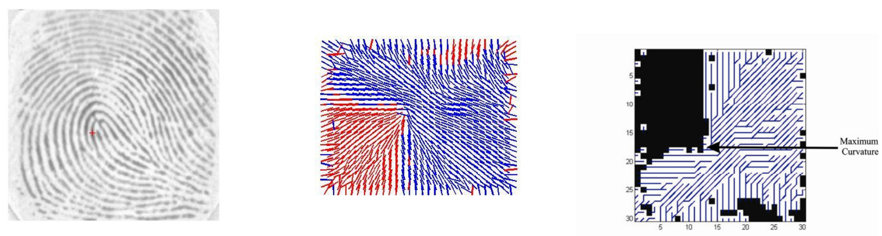
A multimodal database including fingerprint, signature and face samples are essential to test the performance of the proposed system. Since there is no standard database freely available to meet the requirement of the proposed algorithm, ECMSRIT multimodal database and Chimeric databases have been formed. ECMSRIT database is collected from fingerprint, off-line signature and face samples of 100 users. Collection of these unimodal traits are described below:

Nitgen fingerprint scanner is used to collect fingerprints. It is an optical sensor with ultra-precise 500dpi resolution. To locate centre point of fingerprint, it is divided into non-overlapping blocks. Gradient in x and y direction at each pixel in a block is obtained. A 2D Gaussian filter is applied to smooth the gradient. A slope perpendicular to direction of gradient in each block is computed. Blocks with slope values ranging from 0 to pi/2 are considered. In each block a path is traced down until a slope that is not ranging from 0 to pi/2 and that path is marked. Block with highest number of marks gives slope in the negative y direction. This provides the centre point of fingerprint. Region of interest around the centre point is cropped and normalized in size to 128 *128 pixels. Figure 2 represents centre point detection and cropping of fingerprint. Figure 2 (a) represents scanned fingerprint, (b) shows orientation of fingerprint, (c) represents maximum curvature points, (d) shows centre point and (e) shows cropped fingerprint and (f) shows third level LL subband of Curvelet transformed fingerprint.

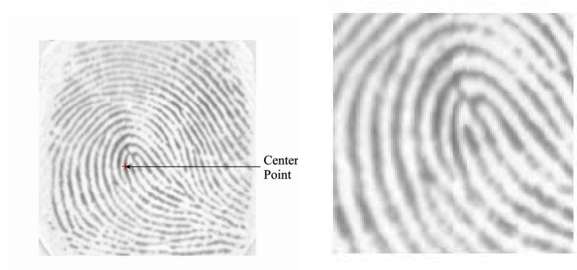
Still face images are collected using digital camera LifeCam Nx-6000 with a 2.0 mega pixels sensor. The 2D colour face image is converted to a gray scale image. Canny edge detection mask with suitable threshold value is applied on image with a uniform background to extract outer curvature of the face. From this only foreground face image of size 128 * 128 is cropped Figure 3 (a) shows edge detection and (b) represents cropped face and (d) represents third level LL subband of Curvlet transformed face.

The signatures were taken on a A-4 size white paper. These were scanned using an 8-bit, 300 dpi resolution scanner. The scanned signatures were cut out from the scanned page in their original orientation and size using an image editor. The scanned signature is binarized. Since the signature consists of black pixels on a white background, the image is then complimented to make it a white signature on a black background. When a signature is scanned, the image obtained may contain some noise components like the background noise pixels and these noise pixels are removed by employing median filter. To avoid inter-personal and intra-personal size variations of signatures, size is normalized to 128 * 256. Figure 4 (a) shows input signature, (b) noise removed, (c) complemented and (d) represents normalized signature sample.

The size of MSRIT database is 10 x 3 x 100= 3000. Chimeric database-I is formed by FVC2002-DB3 fingerprint, ECMSRIT signature and ORL face databases. As ORL face database has only 40 users, Chimeric database-I is formed by considering only 40 users from fingerprint and signature databases. Chimeric database-I consists of 8 samples of each person for each trait with total of 8 x 3 x 40 = 960. Chimeric database-II is formed by FVC2004-DB3 fingerprint, CEDAR signature and Faces-94 face databases. As the CEDAR signature database has only 55 users, Chimeric database-II is formed by considering only 55 users from fingerprint and face databases. FVC2004-DB3 has only 8 samples per user and Chimeric database-II consists of 8 samples of each person for each modality with total of 8 x 3 x 55=1320 samples.

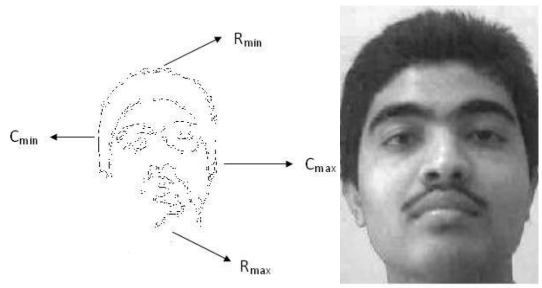


a) Input fingerprint (b) Orientation (c) Maximum curvature points



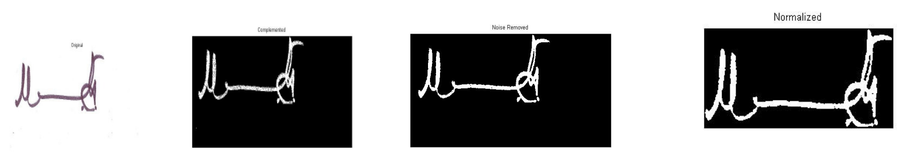
(d)Fingerprint with centre (e) Cropped fingerprint

FIGURE 2: Result of Pre-Processing of Fingerprint.



(a) Edge Detection. (b) Cropped Face.

FIGURE 3: Result of Pre-Processing of Face.



a) Input Signature (b) Noise Removed (c) Complemented (d) Normalised

FIGURE 4: Result of Pre-Processing of Signature.

4. FEATURE EXTRACTION

4.1 Extraction of Texture Features using Curvelet Transform

Texture features are extracted by applying Curvelet transform on each trait. Curvelet transform [10,11,12] is based on multi-scale ridgelet transform [12] combined with spatial bandpass filtering operation at different scales. It is better for representing point discontinuities. Figure 5 shows the flow graph of Curvelet transform. The transform involves following steps: (1) The subbands of input trait is obtained using DB4 wavelet transform. (2) The 2D fast Fourier transform of the LL subband is obtained. (3) Using interpolation scheme, the samples of the Fourier transform obtained on the square lattice is substituted with sampled values on a polar lattice. (4) Inverse fast Fourier transform is computed on each radial line. (5) 1D Wavelet transform is computed at each radial line using DB4 filter and approximate coefficients are used as features.

Steps 2 through 5 form Ridgelet transform [12] and Steps 2 to 4 represent finite Radon transform[13] for digital data. Figure 6 (a), (b) and (c) show third level LL subband of Curvelet transformed fingerprint, face and signature respectively. For example, consider a normalized signature of size 128 x 256. Following the steps described above, third level Curvelet transformed LL subband coefficients of size 25 x 20 will give feature dimension of 500.

Curvelet feature dimension is decided based on d-prime number (d'). Performance of the biometric system has been predicted by calculating d' value [3]. It measures separation between the means of the genuine and impostor probability distributions in standard deviation unit. To evaluate d', genuine and impostor match scores are calculated. A match score is found to be genuine if it is a result of matching two samples of the same user and is known as impostor score if two samples of different users are compared. During training period all samples in the database are considered to find genuine and impostor score. Let P be the number of persons enrolled in the system and let S be the number of samples of the trait obtained from each person, then number of genuine scores G_{score} and number of impostor scores I_{score} are given by

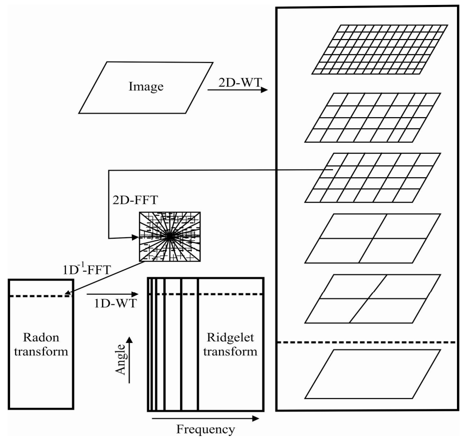


FIGURE 5: Flow Graph of Curvelet Transform.

$$G_{score} = P \times (S-1) \times \frac{S}{2} \quad (1)$$

$$I_{score} = P \times S^2 \times \frac{(P-1)}{2} \quad (2)$$

From these genuine and impostor scores mean and standard deviation are calculated to evaluate d'. The d' value is given by

$$d' = \sqrt{2}\,\frac{\mu_{genuine} - \mu_{impostor}}{\sqrt{\sigma^2_{genuine} + \sigma^2_{impostor}}} \quad (3)$$

Where μ and σ are the mean and standard deviation of genuine and impostor scores. For each trait, different dimension of Curvelet features are evaluated and corresponding d' value has been calculated. Figure 7 shows the variation of d' value for different feature dimensions. From the graph it is observed that as feature dimension increases, d' value increases and higher the value of d' better is performance. The d' value remains constant for a feature dimension of 500 and above. Hence, for each trait a maximum feature dimension of 504 has been considered to evaluate recognition performance of the system. In feature level fusion the features from each trait are concatenated. With concatenation feature dimension increases and to reduce the dimension few reduction techniques [14] are adapted.

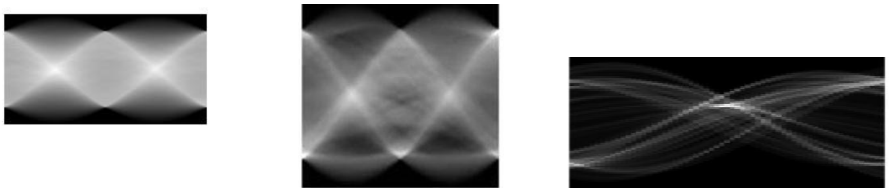


FIGURE 6: Third Level LL Subband of (a) Fingerprint (b) Face and (c) Signature.

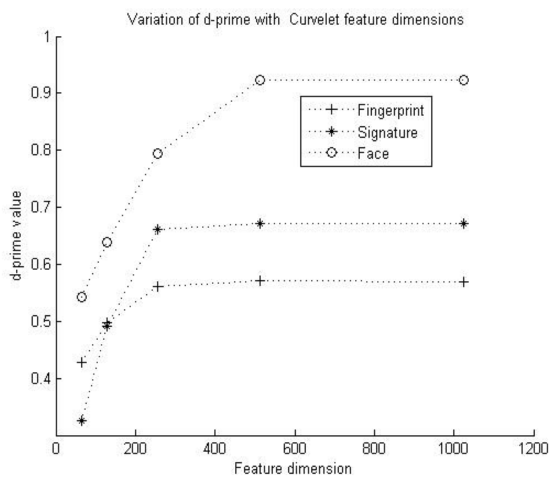


FIGURE 7: Variation of d' Value for Different Feature Dimension.

4.2 Dimension Reduction Techniques

Let FP, FS and FF be three feature vectors extracted by applying Curvelet transform on fingerprint, signature and face respectively. Let fp, fs and ff be the dimension of each trait. Feature vectors of three traits are represented by

$$FP = [P_1, P_2......fp]$$

$$FS = [S_1, S_2......, fs]$$

$$FF = [F_1, F_2....., Ff] \tag{4}$$

All three feature vectors are concatenated to form a new feature vector F_c where $F_c = FP + FS + FF$

The dimension of F_c is equal to fp+fs+ff. In the proposed algorithm approximate coefficient features of dimension 504 is extracted from each of the trait and concatenated, resulting in dimension 504+504+504= 1512. F_c is stored as new template in the database for matching.

(1) Template Averaging: The concatenated feature vector shows increase in size but homogeneous in nature. Therefore the size of concatenated feature vector F_c is reduced by applying averaging and this method is known as template averaging [3] and this method is very simple. Average of feature vector calculated from three traits is

$$F_a = \frac{FP + FS + FF}{3} \qquad (5)$$

(2) PCA Features: In this method, to reduce the dimension of concatenated feature vector, Principal Component Analysis (PCA) [15] is applied to F_c. PCA [16] transforms a number of correlated variables into number of uncorrelated variables referred as principal components. PCA reduces dimension without loss of information and preserves the global structure. Two dimensional PCA (2DPCA) [14] has been applied on the concatenated features from three traits. Algorithmic steps involved in applying 2DPCA are (1) Subband coefficients from Curvelet transform are extracted from each trait and concatenated. Let A be the concatenated matrix. Covariance of matrix of A is calculated. (2) Eigen values and eigen vectors of covariance matrix are calculated. Eigen vector with highest eigen value is called as principal component of the matrix A. Choosing first v eigen values from covariance matrix A, a transformed matrix B is obtained as B=A x P where P=[P_1,P_2 …Pv] is the projection matrix whose columns are the eigen vectors of covariance matrix in the decreasing order of the eigen values. B is the required feature matrix which is stored as PCA feature vector F_{pca} in the database for matching. By applying Curvelet transform for fingerprint, face and signature, subband matrix of size 18x28, 18x28 and 20x25 are extracted and concatenated to form a matrix A of size 60x 25. 2DPCA is applied on A and by considering first eight eigen values, the transformed matrix 60x8 gives a feature dimension of 480.

(3) PCA Features without Fusion: To reduce the dimension at feature level fusion, 2DPCA is applied on the subbands of Curvelet transform of each trait independently. The subband PCA features are concatenated to form a feature vector F_p and stored as templates in the database. 2DPCA is applied on Curvelet subband obtained from each trait independently and selecting nine largest eigen vectors from fingerprint, face and eight eigen vectors from signature, PCA feature of dimension 162, 162 and 160 is obtained and concatenated to form feature dimension of 484.

(4) Statistical Moment Features without Fusion: Moment features are extracted from subbands of Curvelet transform [18] from each trait and calculated as described below

Mean of each subband is calculated. Let μ_k be the mean value of k^{th} subband. Second order moment or variance of each subband σ_k is calculated using

$$\sigma_k = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(W_k(i,j) - \mu_k \right)^2 \qquad (6)$$

Where W_k indicates the subband coefficients of k^{th} ban and MxN be the size of subband.

Third order moment is calculated as

$$\mu_{3k} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(W_k(i,j) - \mu_k \right)^3 \qquad (7)$$

Fourth order moment is calculated as

$$\mu_{4k} = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(W_k(i,j) - \mu_k \right)^4 \qquad (8)$$

Energy of each subband is calculated as

$$E_k = \sum_{i=1}^{M}\sum_{j=1}^{N} W_k^2(i,j) \tag{9}$$

The resulting feature vector of kth subband is given by

$F_{mk} = [\ \mu_k\ \sigma_k\ \mu_{3k}\ \mu_{4k}\ E_k\ ]$

These moment features from each trait are concatenated to form a new feature vector F_m and stored in a database. First, second and third level Curvelet decompositions are applied on each trait and results into 12 subbands. From these 12 subbands moment features of size 60 are calculated and when concatenated from three traits give a feature dimension of 180.

(5) Feature Concatenation by extracting Significant Coefficients: Curvelet subband coefficients are extracted from each trait and sorted. Significant coefficients from each trait are selected and concatenated to form a feature vector F_r. Dimension of F_r is made comparable to feature dimension of unimodal system. For example, by applying Curvelet transform on each trait 504 subband coefficient features are sorted and only first 168 features from each trait are concatenated to form a feature vector of dimension 168+168+168= 504.

5. EXPERIMENTAL RESULTS

Performance of the proposed algorithm is tested for identification mode using SVM classifier. In SVM classifier method [19, 20], each person in the database has an associated SVM. The test samples are assigned the label of the person whose SVM gives the largest positive output. SVM classifier with a polynomial kernel of order 2 is selected. Penalty parameter C is tuned from 2 to 10 to get better results. In this experiment, C is set to a value 2.

Samples in each of the databases are split into training and test set. Training and test samples are selected in different ratios starting from 1:9,2:8,3:7 ....,9:1 and corresponding recognition rate for five trials have been calculated using Euclidean distance measure. The average recognition rate is calculated and result is compared with the results obtained from different sets of train and test ratios and the ratio which gives maximum recognition rate is considered for performance evaluation. In this experiment train to test ratio of 6:4 is considered and each database is randomly split 30 times at each time performance of the system is evaluated and average of these 30 times result is considered as final result. Genuine and impostor scores are calculated for the six different feature vectors. Figure 7 shows histogram plots evaluated on ECMSRIT database for six feature sets.

From figure8 it is seen that separation of genuine and impostor scores are more in F_{pca} and F_a features compared to other features. Based on these distribution curves, the threshold is varied to calculate FAR and FRR from which EER has been calculated for each of the feature vector. Figure 9 shows threshold vs FAR and threshold vs FRR for all feature vectors evaluated. Figure 9 indicates FAR and FRR varies for each algorithm and each feature vector, resulting to variation in EER. Table 1 indicates a minimum EER of 5.32% is obtained for F_{pca} and a maximum EER of 22.35% is obtained for F_r features.

Features	Feature Dimension	Optimal Threshold	FAR (%)	FRR (%)	EER (%)
F_c	1512	0.46	19.85	18.54	19.31
F_a	504	0.45	12.07	11.78	12.00
F_{pca}	480	0.38	5.34	4.35	5.32
F_p	484	0.31	16.46	15.53	15.33
F_m	180	0.14	20.54	17.78	20.54
F_r	504	0.35	25.25	22.34	22.35

TABLE 1: EER (%) for Different Features.

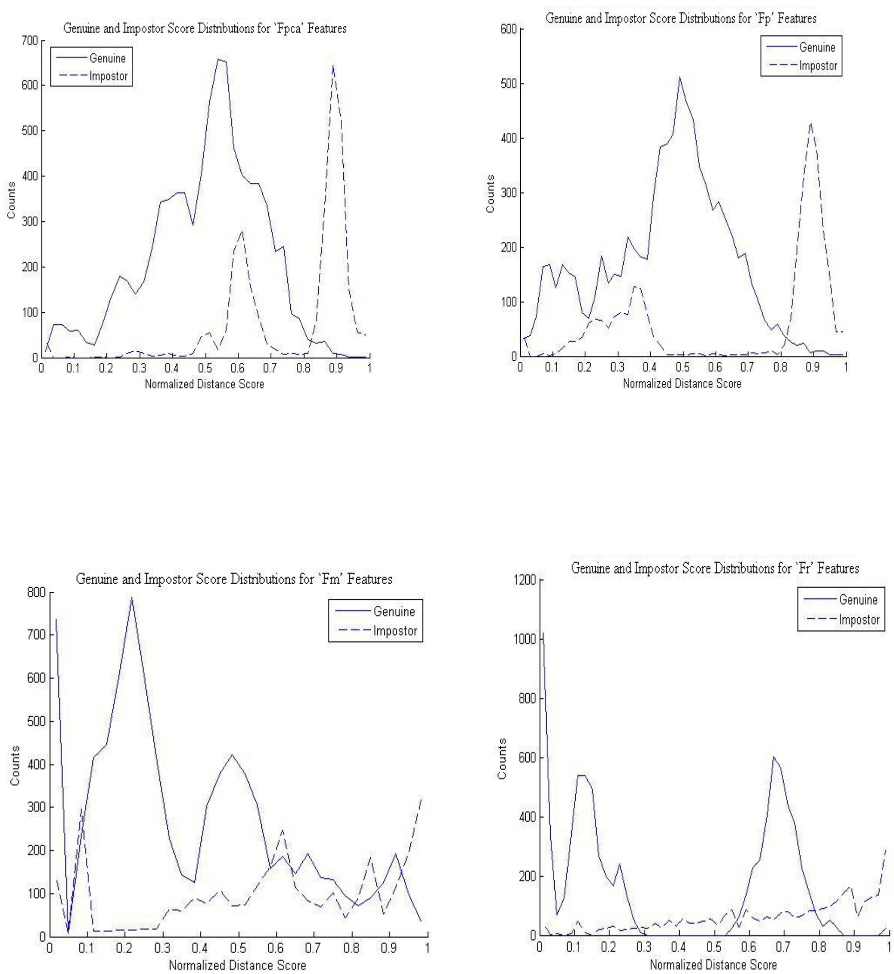


FIGURE 8: Histogram Plots for Genuine and Impostor Scores.

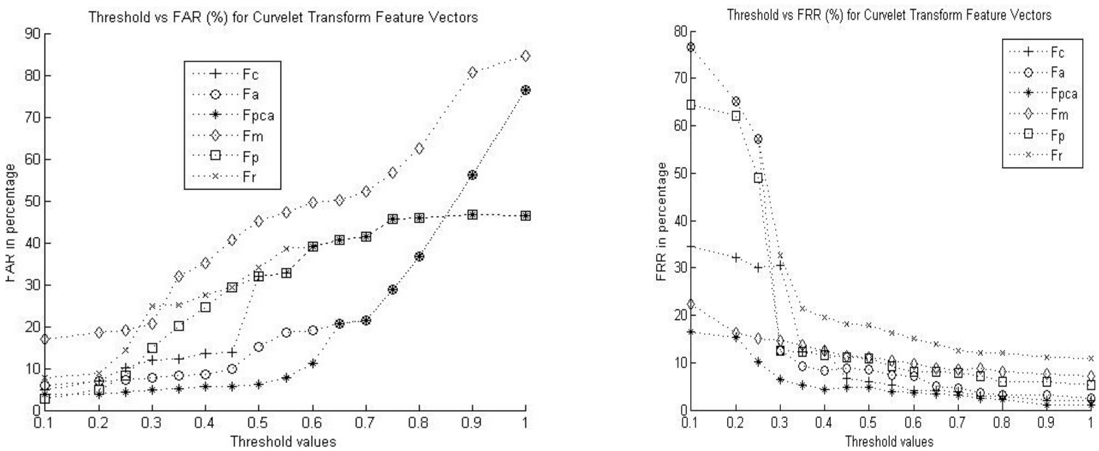


FIGURE 9: FAR and FRR vs Threshold for Different Feature Sets.

Biometric Traits	Feature Vector	Feature Dimension	GAR (%)
Fingerprint+ Signature Fingerprint +Face Face +Signature	F_c	504+504=1008	94.52 94.36 93.14
Fingerprint+ Signature Fingerprint+ Face Face+ Signature	F_a	504	93.52 95.26 92.24
Fingerprint+ Signature Fingerprint+ Face Face+ Signature	F_{pca}	480	93.82 96.64 96.16
Fingerprint+ Signature Fingerprint+ Face Face+ Signature	F_p	484	94.08 94.86 93.04
Fingerprint+ Signature Fingerprint+ Face Face+ Signature	F_m	120	89.05 90.05 88.26
Fingerprint+ Signature Fingerprint+ Face Face+ Signature	F_r	504	89.65 90.45 89.26

TABLE 2: Performance of Identification based on Curvelet Feature Vectors by Combining Two Traits in ECMSRIT Multimodal Database.

Multimodal Database	Feature Vector	Feature Dimension	GAR(%)
ECMSRIT Chimeric Database-I Chimeric Database-II	F_c	504+504+504=1512	96.82 96.04 96.84
ECMSRIT Chimeric Database-I Chimeric Database-II	F_a	504	96.92 95.22 95.02
ECMSRIT Chimeric Database-I Chimeric Database-II	F_{pca}		97.15 96.32 96.14
ECMSRIT Chimeric Database-I Chimeric Database-II	F_p		96.08 94.93 94.82
ECMSRIT Chimeric Database-I Chimeric Database-II	F_m		92.67 92.35 92.86
ECMSRIT Chimeric Database-I Chimeric Database-II	F_r		92.35 91.25 91.89

TABLE 3: Performance of Identification based on Curvelet Feature Vectors by Combining Three Traits.

Table 2 shows the performance of the system at feature level fusion considering two traits at a time. Results show that GAR obtained from fingerprint and face is more compared to other two combinations and maximum GAR of 96.64% is obtained for F_{pca} features. Table 3 shows the performance at feature level fusion from all three biometric traits and a maximum GAR of 97.15% is obtained for F_{pca} features. Results show that GAR is better in ECMSRIT database compared to Chimeric databases. This is because in Chimeric databases the three biometric traits are not from the same person. The performance of the proposed algorithm is better for correlated traits compared to non-correlated traits. The test samples are rotated in steps of 2^o to verify rotation invariance for F_c, F_{pca} and F_a. Feature sets as these feature sets give better GAR compared to other three feature sets. The results show that the GAR for rotated samples also remains almost same and confirms that Curvelet transform is rotation invariant.

Feature Vector	Feature Dimension	Rotation in Degrees					
		0^o	2^o	4^o	6^o	8^o	10^o
GAR (%) for ECMSRIT Multimodal Database							
F_c	1512	96.82	96.45	95.20	95.04	94.86	94.32
F_a	504	95.92	95.22	94.74	94.22	93.75	93.12
F_{pca}	480	96.78	96.22	95.74	94.22	93.75	93.12
GAR (%) for Chimeric Database-I							
F_c	1512	96.04	96.04	95.86	94.75	93.25	92.89
F_a	504	95.22	95.22	94.74	94.22	93.75	93.12
F_{pca}	480	96.32	95.02	94.78	93.21	92.56	92.12
GAR (%) for Chimeric Database-I I							
F_c	1512	96.84	95.05	94.54	93.84	92.14	91.85
F_a	504	95.02	94.89	94.74	94.22	93.75	93.12
F_{pca}	480	96.14	95.42	94.02	93.65	92.28	91.64

TABLE 4: Recognition Results by Applying Rotation to Test Samples for three Feature Sets.

Figures 9 shows the comparison between GAR obtained from unimodal identification system with subband coefficient features and multimodal identification system with F_{pca} features. F_{pca} gives maximum GAR and its dimension remains same as that of unimodal traits. When fingerprint is combined with face and signature an improvement in GAR of 9.09% and when signature is combined with face and fingerprint improvement has been 12.67%. Chart also show that improvement in GAR is less when performance of two and three traits are compared.

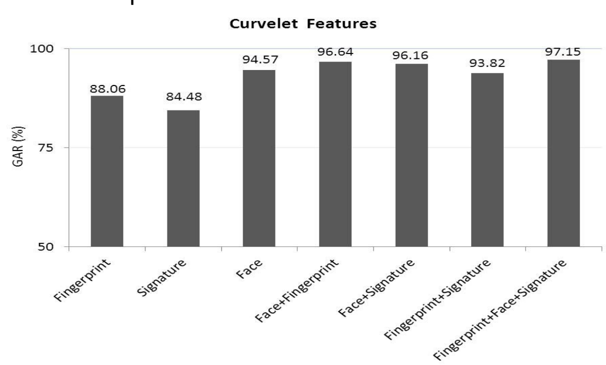


FIGURE 10: Comparison between GAR Obtained from Unimodal and Feature Level Identification for Curvelet Features.

6 COMPARISONS WITH SIMILAR WORK

Currently, as there are few multimodal system combining fingerprint, signature and face with curvelet features at feature level unimodal recognition system is considered for comparison. Table 5 gives comparison of fingerprint, face and signature recognition system based on Curvelet features. In [21] author applied Curvelet transform on a fingerprint of size 64 x 64 which was divided into four blocks. Each block is divided into 8 angular directions and standard deviation from each direction was concatenated to form feature vector. Proposed Curvelet algorithm with moment feature of dimension 40 is used for comparison and GAR obtained for 15 users is higher. In [22], author applied sixth level Curvelt transform decomposition and used 160 subband coefficients as features. Performance is evaluated using SVM classifier. The proposed algorithm with 120 subband coefficients as features has similar performance. In [23], author applied Curvelt transform on face at different scales subband coefficients are used as features. Few dimension reduction techniques are applied and performance is evaluated. GAR obtained with the subband feature dimension of 1258 is similar to the GAR obtained from proposed algorithm with the feature dimension of 504.

Unimodal Recognition System	Author	Database used	No. of users	Feature Dimension	Classifier	Performance
Fingerprint Verification	A.Mujumadar[21]	FVC2004-DB1	15	32	Fuzzy-KNN	GAR=91.7%
	Proposed Algorithm	FVC2004-DB3	15	40	Euclidean	GAR=95.02%
Signature Verification	M.Fakhlai [22]	Own	39	160	SVM	GAR=89.87%
	Proposed Algorithm	CEDAR	55	120	Euclidean	GAR=88.87%
Face Recognition	Tanaya G. [23]	ORL	40	1258	Euclidean	GAR=94.54%
	Proposed Algorithm	ORL	40	504	SVM	GAR=95.04%

Table 5: Comparison of Unimodal Recognition System based on Curvelet Features.

7. CONCLUSION

The proposed multimodal system comprises of fingerprint, off-line signature and face traits. Performance of the system is evaluated based on Curvelet transform features with SVM classifier. The algorithm is tested by combining two traits at a time and three traits together. The increase in dimension at feature level fusion is reduced by using template averaging, PCA and statistical moment features. Six different feature vectors from these algorithms have been tested at feature level fusion. F_{pca} and F_a features are obtained from concatenated feature vector while F_p, F_m and F_r feature vectors are obtained without any fusion. The dimension of reduced feature vectors are comparable with those of unimodal traits. The feature dimensions of unimodal traits are decided based on d' values. Fusion algorithm is tested on in-house created ECMSRIT multimodal and Chimeric databases. Though the size of databases are small, the performance obtained from these databases are low compared to that of ECMSRIT database. Results indicate that the proposed algorithm performs better on correlated data than uncorrelated data. From simulation results it can be summarized that when three traits are combined performance of the system increases compared to either unimodal system or by combining two traits.

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