Person Identification using fusion of Fingerprint and Hand Geometry

Sampada Abhijit Dhole, Varsha Hemant Patil

Abstract— Biometric system is essentially a pattern recognition system that makes use of biometric traits to recognize individuals. Authentication systems built on only one biometric modality may not fulfil the requirements of demanding applications in terms of properties such as performance, acceptability and distinctiveness. Most of the unimodal biometrics systems have problems such as noise in collected data, intra-class variations, inter-class variations, nonuniversality etc. Some of these limitations can be overcome by multiple source of information for establishing identity, such systems are known as multimodal biometric systems. The multimodal biometric systems are gaining popularity because of accurate and reliable identification of the person. Early integration strategies are expected to result in better performance than late integration strategies. A novel approach of combining fingerprint and hand geometry biometric at feature level fusion are presented. Feature level integration of two different uncorrelated biometric traits provides sustainable improvement in performance accuracy compared to their unimodal counterpart.

Keywords—Feature level fusion, contourlet transform, normalization

I. Introduction

In the era of Information Technology, openness of the information is a major concern. As the confidentiality and integrity of the information is critically important, it has to be secured from unauthorized access. Security refers to prohibit some unauthorized persons from some important data or from some precious assets. So we need accurate, automatic personal identification in various applications such as ATM, driving license, passports, citizen's card, cellular telephones, voter's ID card etc. In addition to identification, security is equally important. The past methods of identification such as PIN, passwords etc. are unreliable, since there is possibility of frauds. Solution to such problem is given by using biometric identities.

Biometric is Physiological (e.g., fingerprints, face, iris) and behavioral (e.g., speech) characteristics of person which is absolutely unique to him. . Biometrics identifies the person by what the person is rather than what the person carries, unlike the conventional authorization systems like smartcards. B i ometric identifiers cannot be misplaced, forgotten, guessed, or easily forged.

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Most biometric systems used in real world are unimodal. Unimodal means identity of person is done by using single biometric trait. But this system carries some problems such as Noise in sensed data, Intra-class variations, Inter-class similarities, Non-universality and Spoof attacks.

Some of the limitations imposed by unimodal biometric systems can be overcome by using multimodal biometric system which including multiple biometric traits. Multimodal biometric systems are expected to be more reliable due to the presence of multiple independent biometric traits. Multimodal biometric systems remove the problem of non-universality as it contains multiple traits which ensure sufficient features for identification. Multimodal can minimize spoofing since it would be difficult for an impostor to spoof multiple biometric traits simultaneously. Further, multimodal system requesting the user to present a random subset of biometric traits thereby ensuring that a 'live' user is indeed present at the point of data acquisition.

The goal of multi-biometrics is to reduce False accept rate (FAR), False reject rate (FRR), Failure to enroll rate (FTE), Susceptibility to artifacts or mimics. Multimodal Biometric based authentication system use various levels of fusion at sensor level, the feature extraction level, matching score level or at decision level. Multimodal biometric systems can be designed as either online or offline as per demand of application.

Multimodal biometric systems can be designed to operate in five integration scenarios: 1) *multiple sensors*-where output from different sensors are combined, 2)*multiple instances* –combine different instances *of* the same biometric trait (e.g., left and right iris), 3) *multiple samples* –combine different samples *of* the same biometric trait (e.g., two impressions of a person's right index finger), and 4) *multiple biometric traits*-combines different biometric traits(e.g., face and iris). 5) *multiple representations and matching algorithms for the same biometric*-combines different algorithm for e.g. texture based and minutiae based fingerprint matcher are combined .

In multimodal systems, four fusion levels are present: sensor, feature, matching and decision. The sensor and feature levels are considered to as a pre_mapping fusion while the matching score and the decision levels are considered to as a post-mapping fusion. The biometric data are combined before classification in pre-mapping fusion, while in post_mapping fusion; each biometric data are modelled separately then all the biometric traits are combined after mapping into matching score/decision space. The amount of information available for fusion is decreased after each layer of processing in a biometric system. Fusion at the feature level involves the integration of feature sets corresponding to multiple modalities. Since the feature set contains richer information about the raw biometric data than the match score or the decision, integration at this level is expected to provide better recognition results.

In feature level fusion, Signal coming from different biometrics is first preprocessed and feature vector are extracted. These feature vectors are combined to form composite feature vector. One single feature vector is obtained by merging extracted features and applying appropriate feature normalization, selection and reduction techniques.

Fingerprint recognition is mostly preferred in security and law enforcement process. Fingerprints have been in use for biometric recognition since long because of their high acceptability, immutability and individuality. Immutability refers to the persistence of the fingerprint over time whereas individuality is related to the uniqueness of ridge details across individuals. For fingerprint matching there are many approaches like correlation based, minutiae-based [14, 15] and ridge feature based. One of the most widely used among them is Minutiae based approach [14]. Structural patterns of a fingerprint have very rich information in them which can be used for fingerprint recognition. These features or patterns can be categorized as Global and local features [24]. Global features are ridge orientation, ridge spacing, core and delta. On the other hand minutiae are local feature which are extracted by identifying discontinuities found in ridges. Some of the important minutiae features are ridge endings, bifurcations, crossovers and islands. Among these, ridge endings and bifurcation are the commonly used minutiae features [14]. Minutiae can either be extracted directly from grey scale image or by using a thin binary image. Very expensive processing techniques like thresholding, noise removal, normalization, thinning, segmentation, orientation calculation are required for minutiae based approach which is time consuming. But still results in false minutiae. To eliminate such problem after feature extraction false minutiae detection and removation is done, but is also eliminates valid minutiae points along with false ones. If quality of fingerprint image is low then it is difficult to extract Minutiae points. So it is required that the matching features should be rich and strong enough that the bad image quality does not affect the matching process [25].Texture features are more stable than minutiae features. For extraction of texture features DWT, Gabor, Curvelet transform can be used. Wavelet provides the time and frequency information which is not being provided by the Fourier and Short Time Fourier Transforms [26]. Wavelet analysis tells us that which frequencies will exist during the specific intervals.

Hand geometry recognition systems are based on a number of measurements taken from the human hand, including its shape, size of palm, and length and widths of the fingers. The technique is relatively very simple to use and inexpensive. Environmental factors such as dry weather or individual anomalies such as dry skin do not appear to have any negative effects on the verification accuracy of hand geometry-based systems. The hand images can be obtained by using a simple setup including a web cam, digital camera. However, other biometric traits require a specialized, high cost scanner to acquire the data. The user acceptability for hand geometry based biometrics is very high as it does not extract detail features of the individual. An individual's hand does not significantly change after a certain age. Template size of hand geometry is extremely small if it is compared with other biometrics systems.

Golfarelli et al. [4] addressed a new approach for person identification using hand geometry features. The researcher considered 17 geometrical features of hand. They also reported problem of performance evaluation in biometric verification systems. Sanchez-Reillo et al. [6] defined and implemented a biometric system based on hand geometry features based on distance and angles of hand images. Total 31 geometrical features are extracted which included width, heights, deviations, and angles between the inter-finger Points. Various distance measures and classification approach such as Euclidean distance, Hamming distance, Gaussian Mixture Models (GMMs) and Radial Basis Function Neural Networks are used. GMM provides success rate of 96% which is best among all.

II. Feature Level Fusion of Fingerprint and Hand Geometry

In feature level fusion, the features are extracted from the all biometrics traits. Later the extracted features can be combined together into a final feature vector of higher dimension. Integration at feature level provides better identification results as compare to score level and decision level fusion as feature set contains richer information about input data. In feature level fusion, new feature vector is obtained by concatenated of feature vector obtained from different biometric modality

A. Fingerprint Feature Extraction System

For feature extraction of fingerprint contourlet transform is used.DWT gives only horizontal, vertical and diagonal directional features. The wavelet doesn’t handle curve discontinuities well. The drawback of Gabor filter is that feature vector size becomes very large and computational time required for feature extraction is high which limits retrieval speed. Curvelet transform gives curve discontinuity well but is converges into continuous domain. Contourlet transform starts with a discrete-domain and then convergence to a continuous-domain. Contour let transform representing the image such as lines, edges, contours and curves better than wavelet and curve let transform because of its properties directionality and anisotropy Contourlet transform is constructed by combining two decomposition stages, multiscale decomposition followed by directional decomposition. Laplacian pyramid gives multiscale decomposition to transform image into coarse level and set of laplacian sub bands. Directional stage critical down sampling to further partition into different and flexible number of frequency sub bands. The contourlet expansion is composed of basis function oriented at various directions in multiple scales, with flexible aspect ratios. With this rich set of basis functions, the contourlet transform effectively capture smooth contours that are the dominant feature in images.

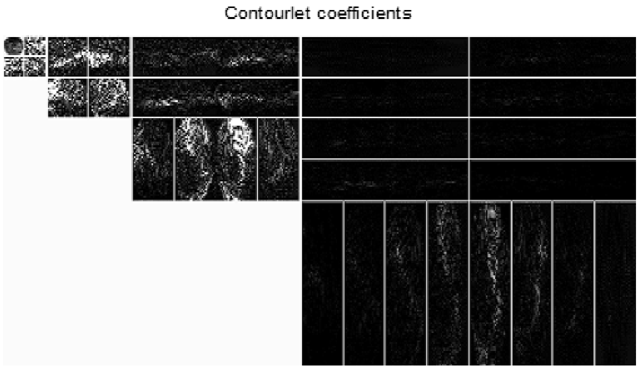


Fig.1:- Contourlet Transform decomposition for fingerprint image

Figure 1 shows level four contourlet transform, with 0, 2, 3 and 4 directions from coarse to fine levels respectively. At each resolution level 'k' the input image is decomposed in 2n sub bands where order of filter is 'n'. The first resolution level (highest resolution) has actual size of input image means 256*256. The next resolution level image size is 128*128. Similarly input image is further reduced by subsampling at level 3 and 4 and corresponding size of images are 64*64 and 32*32.

B. Hand Geometry Features extraction ststem

This system measures one length and three measurement of width of each finger. Also width of palm and four other distances between thumb valley points to index, ring, middle and little valley point is measured. Total 16 features are obtained from four fingers which includes one finger length and three finger width for each finger. Palm width and four distance from thumb valley point to other valley points gives total 21 features as shown in figure 1

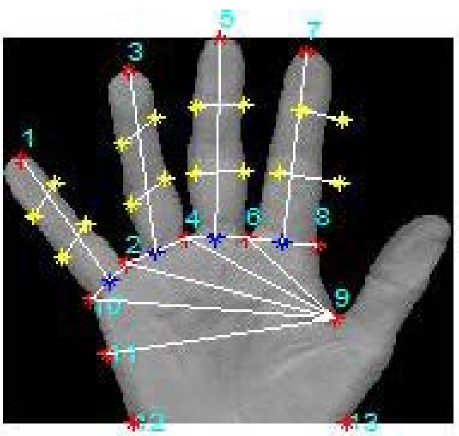


Fig 2:- Hand geometry 21 features

Total 21 features are extracted as follows,

- Finger length is obtained by measuring distance from fingertip to middle point of finger baseline. The proposed system extract one measurement of length from each finger so four features are taken from finger length.
- Finger width are measured at 3 different locations on finger such as at the middle of the finger length, at the one-third, and at the distance between two minima points of the finger as shown in figure 1.
- The distance from 9 to 11 is palm width shown in figure 1.
- Distance D1 (9 to 10) is, distance between thumb valley point and little valley point.
- Distance D2 (9 to 2) is, distance between thumb valley and valley point of ring finger.
- Distance D3 (9 to 4) is, distance between thumb valley point and valley point of middle finger.
- Distance D4 (9 to 6) is, distance between thumb valley point and index valley point.

C. Normalization Technique for Hand Geometry:-

The face, fingerprint, pam print and hand modality contains heterogeneous feature vector. Min_Max normalizing technique is employed on features vectors for hand geometry modalities before concatenate them to form a single one. The main purpose of feature normalization is to modify the location and scale parameters of individual feature values to transform the value into a common domain. It is assumed that the ranges of feature values of hand modalities are [0, 100].

Let x and x' denote a feature value before and after normalization. The min-max technique computes x' as,

$$X` = \frac{x-\min(Fx)}{\max(Fx)-\min(Fx)} \qquad \text{...I}$$

Min(Fx)=0, Max(Fx)=100

Hand Geometry features before normalization:-

26	**83**	**22**	**22**	**31**	**106**	**113**	**64**

Hand Geometry features after normalization:-

0.26	**0.83**	**0.22**	**0.22**	**0.31**	**1.06**	**1.13**	**0.64**

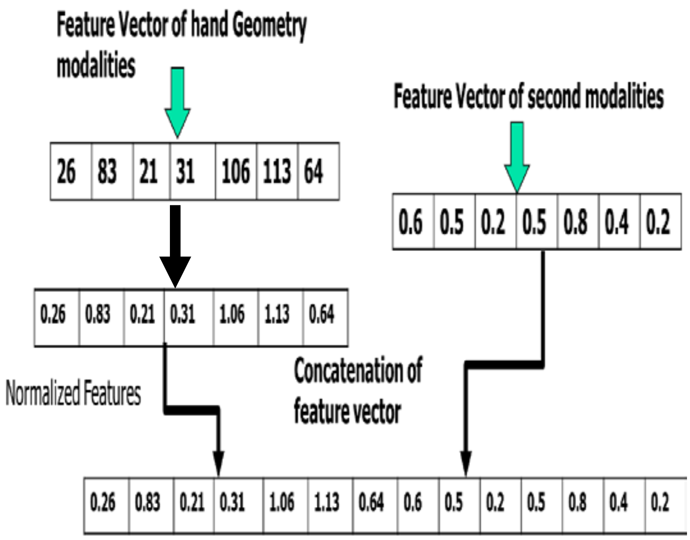


Fig. 3 Feature vector after normalization

Figure 3 shows, concatenation of feature vector after normalization of hand geometry features.

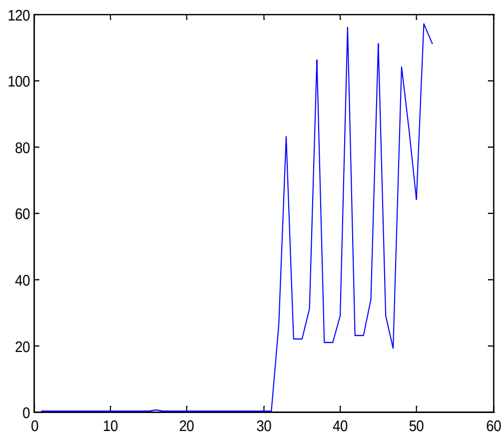


Fig 4:- Hand geometry and fingerprint concatenated features without normalization

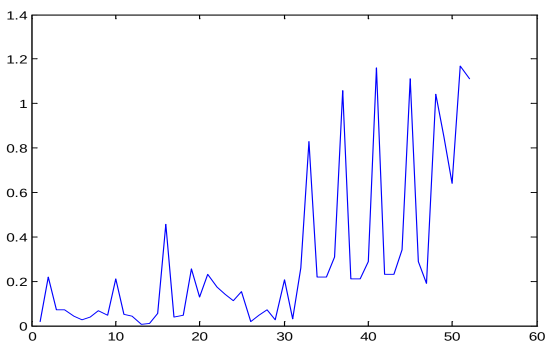


Fig. 5:-Hand geometry and fingerprint concatenated features with normalization

Figure 4 and 5 shows Hand geometry and fingerprint concatenated features without and with applying normalization.

III. RESULTS

In this paper mainly considered two points as:

- Fusion of fingerprint and hand geometry images at pre_matching fusion i.e. feature level fusion.
- To calculate the parameters like GAR, FAR, FRR and EER at feature levels and analyze their ROC curves.

The experimental evaluations of the presented method is carried on the standard database (CASIA database) and Local database which is our own captured database which is formed by taking 200 different persons and 5 samples of each individual so total 1000 images of each modalities. Illumination, ageing and line orientation changes are occurred in Hand and fingerprint dataset.

Table 1 :Comparison of Fingerprint and Hand Geometry multimodal Recognition System

Biometric Modality	**Database**	**FAR**	**FRR**	**GAR**	**EER**
Finger print_Hand geometry	Local Database	0.15	0.015	98.5	0.068
Finger print_Hand geometry	Casia Database	0.101	0.008	99.2	0.052

Table 1 shows, comparison of fingerprint and Hand Geometry multimodal Recognition System for local and Casia database. It shows feature level fusion of fingerprint and hand geometry using cassia database gives more accuracy as compare to local database.

Table 2 :shows comparison between unimodal and multimodal biometric system using fingerprint and hand geometry modalities.

Biometric Modality	**FAR**	**FRR**	**GAR**	**EER**
Unimodal Fingerprint	0.186	0.02	98	0.1016
Unimodal Hand Geometry	0.517	0.10	90	0.3885
Feature level Fusion	0.101	0.08	99.2	0.214

Table 2 shows comparison between unimodal and multimodal biometric system using fingerprint and hand geometry modalities. It shows Feature level fusion gives more accuracy than their unimodal counterparts.

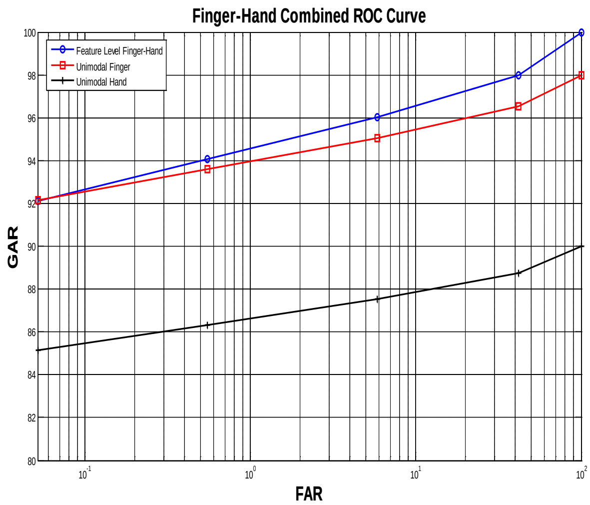


Fig. 6:-ROC for Unimodal and multimodal biometric system using cassia database

Figure 6, shows ROC curve for unimodal and multimodal system using Fingerprint and Hand geometry Biometric modalities .Feature level fusion gives better performance than its unimodal counter parts. GAR value of unimodal fingerprint recognition system is 98 using contourlet transform. GAR value of hand geometry unimodal system is 90 using 21 geometry features. After concatenation of feature vector, multimodal system gives 99.2 GAR value.

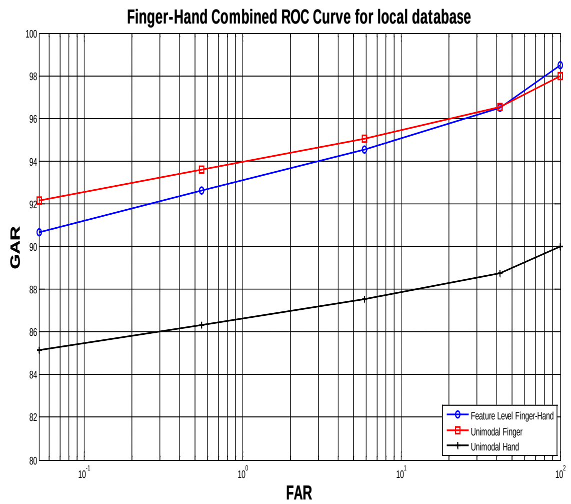


Fig. 7:-ROC for Unimodal and multimodal biometric system using Local database

Figure 7 shows comparison between unimodal and multimodal system using Fingerprint and Hand geometry Biometric modalities. Feature level fusion gives better performance than its unimodal counter parts. GAR value of unimodal fingerprint recognition system is 98 using contourlet transform. GAR value of hand geometry unimodal system is 90 using 21 geometry features. After concatenation of feature vector, multimodal system gives 98.3 GAR value.

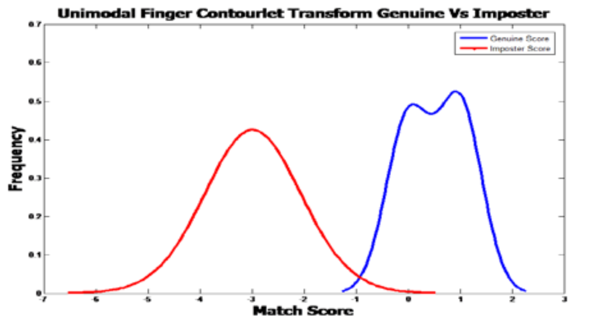


Figure 8:- Genuine Vs imposter score for unimodal fingerprint identification system

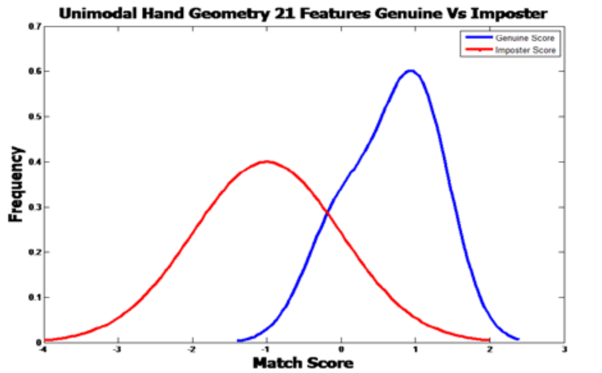
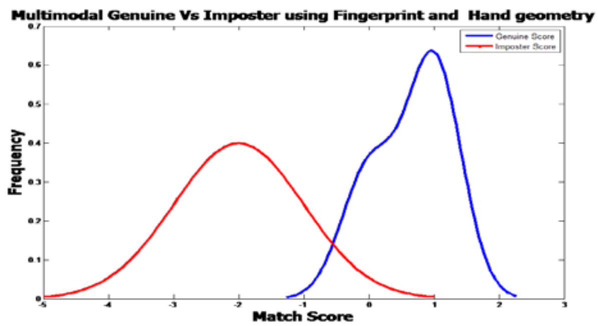


Figure 9:- Genuine Vs imposter score for unimodal hand geometry identification system

Figure 8 and 9 shows the genuine imposter graphs for unimodal biometric identification system. The overlap region of genuine and imposter scores for unimodal fingerprint identification is less as compare to unimodal hand geometry identification system. So accuracy of fingerprint identification system is more than Hand geometry Recognition System.



IV.

Figure 10:- Genuine Vs imposter score for multimodal fingerprint and hand geometry identification system

Figure 10 shows Genuine Vs imposter scores for multimodal biometric identification system using feature level fusion, which shows accuracy is more as compare to their unimodal counterparts. Overlap region of Genuine and imposter graphs for multimodal biometric identification using fingerprint and hand geometry is less as compare to unimodal biometric recognition system. So accuracy of multimodal biometric identification using fingerprint and hand geometry is high as compare to other unimodal biometric identification system.

V. Conclusion:-

For person recognition multimodal biometric recognition system is used as unimodal system suffers with various challenges such as noise in sensed data, intra-class variations, inter-class similarities, non-universal and spoof attacks etc.The issue of non-universality is addressed, as multiple modality of fingerprint and hand geometry can ensure sufficient population coverage compared to limited coverage in unimodal system. Reported results reveals that it is extremely difficult for an intruder to spoof fingerprint and hand geometry traits simultaneously of a legitimately registered individual as subject unsuitable for one modality can use other modality (e.g. manual workers having cuts and bruises on their fingerprint)

Feature level integration of two different uncorrelated biometric traits provides sustainable improvement in performance accuracy compared to other integration methods as well as their unimodal counterpart.

VI. References

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