Dimension Reduction of Hand and Face Feature Level Fusion in Multimodal Biometric Authentication

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Abstract*: *The proposed work is a multimodal biometric authentication approach with image texture feature dimension reduction of trained feature vector which leads reduction in memory size and in turn reduces the computational time. In this paper hand and face features are used for person identification. The texture features of hand image are extracted using Haar and several Daubechie's of 2D-DWT followed by 2D- edge detector gives better identification with reduction in feature vector and face features are extracted by neighborhood common characterization with block based segmentation approach to estimate the disparity in face. The neighborhood common characterization based structure recognition with a person representative per sample is more effective. The neighborhood features are constructed by extracting the similar blocks in the image, the intra pixel disparity feature is obtained by exploiting external common images to estimate the feasible facial disparities. Neighborhood common characterization reduces the overall residual of the given features over the local feature, common disparity dictionary, and shape based residual of a block. Neighbourhood common characterization representation, of face recognize with one representative per person more effectively. The system uses either of the biometric traits for person identification with 99.98% of authentication rate.

Index Terms*: *Authentication, Biometric traits, Classifier, Face recognition, Multimodal, Neighborhood common characterization, One per single subject.

I. INTRODUCTION

For reliable authentication, unmoral biometric system is inadequate for person identification. To improve the system reliability a multimodal biometric authentication came into existence in recent years. Depending on the specific applications, preference of biometric traits is a challenging task for researchers. Multimodal biometric system ensures higher accuracy with high level security and also ensures the authentication due to illness or disability. Multimodal biometric authentication based on both palm vein and print images. Initially image-level wavelet strategy is applied on palm vein and palm print images. Fusion image features are extracted using deep scattering convolution network and multi-class support vector machine classifier is used for authentication [1]. Heterogeneous face recognition based on the input face images from other domains such as sketches to photographs, thermal images to photographs and near-infrared images to photographs. Deep Convolution Neural Networks technique is applied to extract the fine level information and further adapt the system for domain specific and transformation technique is used to obtain the generic face features. It substantially improves the recognition rate [2]. Pose invariant recognition reduces the intra-pixel difference and retains the face with more information by adaptive pose alignment (APA). The APA initially estimate the facial pose by considering the multiple poses by exploiting the distinct information which in turn reduces the differences. The next step is based on this distinct information of multi poses which creates adaptive reference template. Finally test and train faces are aligned with respect to the reference template. This method improves the recognition rate with traditional methods [3]. Reduced feature vector dimension of Iris, fingerprint and face are incorporated in multimodal system using Contour let Transform (CT) and Local Derivative Ternary Pattern (LDTP) model. Then weighted rank level fusion is used to fuse the features, finally deep learning is used for matching and achieves recognition rate about 96% [4]. To achieve desired authentication, the author introduced a system based on social behavior information fused with traditional biometric traits such as face and ear .The person behavior is extracted from one of the most popular online social network twitter and monitored the patterns like Re-tweet, Hash tag, URLS and Replies are analyzed weekly, monthly are fused with the PCA based feature extraction of face and ear. The system performance is better than the traditional biometric [5].2D log-Gabor filter is used to extract the information of face and iris (left and right) and Spectral Regression Kernel Discriminant Analysis (SRKDA) is used to reduce the feature dimension .The significant feature level fusion is used to fuse face and iris features .In order to match the test and trained features the Euclidean distance is used to measure the distance and decision about acceptance or rejection is drawn [6]. Multimodal biometric authentication based on weighted hybrid fusion of ear print, fingerprint, palm print fusion features (FF) and unimodal palm print features (UF). Mean-extreme based confidence weighted (MEBCW) method is used to calculate the weights of FF and UF and weighted hybrid fusion (WHBF) is used to fuse matching scores of FF, UF with weights of FF, UF. Decision is based on the output of WHBF. The experimental result gives better recognition rate [7].

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Face recognition system uses face of different postures. Using linear and non linear transformation technique is applied to extract the unique information from distinct posture images. Further these unique features are arbitrarily mapped to obtain the distinct feature vector. Auto encoders and deep convolution neural network is used to improve the system performance [8]. Information level and Decision level fusion techniques are applied on ECG and fingerprint for authentication. Two layer convolution neural network (CNN) is used to extract the features of biometric traits. Q-Gaussian multi support vector machine (QG-MSVM) is used as a classifier for better authentication [9]. Combination of Log-Gabor filter with spectral regression kernel discriminate (SRKD) analysis is used to extract traits such as face and iris (Left and Right).These combined features are used to classify the given test traits [10]. Local binary patterns, Weber local descriptor, and binary statistical image features of ear and palm image were used to discriminate the features for person identification [11]. Individual classifier is used for iris, finger vein and fingerprint then it is integrated through optimal score level fusion technique with 98.4% accuracy [12]. Feature encryption based multimodal biometric authentication of fingerprint, finger vein, and retina are used for authentication. Because of encryption and decryption this method is more secure [13]. Particle Swarm Optimization (PSO) and Belief functions based person recognition using face and voice. PSO is used in multimodal biometric system to select the better fusion rule and its parameters. The transformation methods like weighted sum rule and belief functions are incorporated in PSO to improve the system performance. These two combinations give better accuracy if the classifiers results are indistinguishable otherwise system accuracy drastically deteriorate [14]. Palm vein recognition based on multi sample of a person and features of those multi sample images are considered as template of that person for registration. Scale-invariant feature transform (SIFT) is used to extract the features of multiple images and identify the similarities and dissimilarities. Only dissimilarity features are registered as a template database of a person. Matching the test sample based on the pre-set threshold, if the test threshold is more than pre-set threshold value is considered as in the template [15].

In this paper, the hand and face biometric traits are used for human authentication. These two traits are processed separately and the method utilizes any one biometric trait for a person authentication. Hand texture feature extraction method is uses 2D- DWT in the initial stage in order to reduce the dimension for further processing, and 2D- edge detection is introduced to extract the fine features in the hand image, and finally considered only the significant features by setting the threshold levels in order to improve the texture features. The minimum distance classification is applied for authentication.

A neighborhood common characterization based face recognition with a person representative per sample. The training representation of the data set is considered to construct features. To create face local-group pixel intensity disparity information which is absence in the dataset, a common training feature vectors are accommodate a main sub vectors and distinct disparity sub vectors is considered. A common distinct feature is then created as the difference between the main subset and the disparity subsets. By creating the distinct facial parts in face recognition, the system adopt a neighborhood characterization approach based on subsets by consider the residuals. The neighborhood common characterization is to reduce the dimension of training dataset by removing redundant present in the all subset. Since the entire redundant are considered as non-Gaussian distribution, the optimization technique is introduced to eliminate the difficulties to present in the residual calculation. Finally, classification is used for all residual representative of each class to improve the system performance.

II. PROPOSED METHODOLOGY

The method proposed here is divided into three parts. 1) Hand texture feature extraction 2) Face feature extraction 3) Feature level fusion 4) Classification.

Fig. 1 shows the authentication system which uses two biometric traits such as hand and face. The proposed system significantly reduces the feature dimension in order to

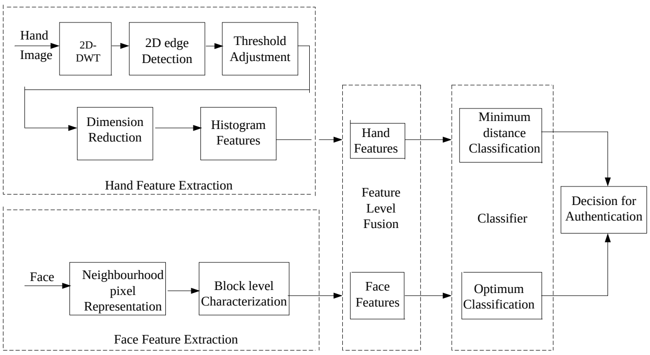

Fig. 1 Proposed Model.

Authenticate effectively. The reduction in features takes place in the initial stage itself by considering CV and CH of 2D-DWT in hand texture feature extraction block. Further only edge texture Information and threshold adjustment are carried out to avoid uncertainty in the pixel. The histogram features significantly reduces the dimension of trained database. And face feature extraction block also reduces dimension by processing a neighborhood pixel and block wise representation of face. The separate classifiers are used to classify the test hand and face for authentication. Decision of this system is based on any one of the biometric trait for authentication.

A. Hand Texture Feature Extraction

Texture features of hand image are extracted using 2D-DWT with different wavelets. The 2D-DWT [16] wavelet is one of the powerful transformation technique which results intensity orientation of an image texture in different directions. 2D edge detection is used to extract the significant texture feature of hand image.

B. Discrete Wavelet Transform (DWT)

The wavelet transform has attained extensive approved in image analysis. The transform represents an image into a set of small waves. These small waves are called wavelets that are obtained from one wavelet called basic wavelet by scaling and transposing.

The DWT has been initiated as an immensely well organized and adaptable method for separate band segmentation of an image. The wavelet coefficients are helpful to analyze the image texture more effectively. In DWT, The significant image texture information is concentrates in specific wavelet coefficients are maintaining specific band information in the pixels. The proposed method uses single-level 2D- DWT to extract the detailed information both in spatial and in frequency domain of hand image, which allows analyzing texture information at different scales. The transformation returns the average coefficient matrix and comprehensive coefficient matrices such as horizontal, vertical and diagonal. This method consider only horizontal (CH) and vertical (CV) detail coefficient matrices to analyze the edges and borders of hand image. The CH coefficients give the intensity variations along the horizontal directions which give the edges and lines present in horizontal direction. The CH coefficients are helpful to analyze the texture information horizontally. Similarly CV coefficients are helpful to analyze the intensity orientations in vertical direction and hence in this stage itself, the method reduces half of the dimension of hand image.

C. 2D-Edge Detection

Further modified edge detection algorithm is applied on CH and CV to retain the significant texture features, which in turn reduces the dimension drastically. The algorithm uses multi-step to extract features of edges along with noise suppression simultaneously [17]. 1) The filter in Eq. (2) smoothen the DWT coefficients with Gaussian function and highlights the edge regions with its first order derivative for. Here the size of the filter is $N \times N$.

$$h_X(x,y) = g(x,y) \times g'(x,y) \qquad (2)$$

$$g(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{x^2 - y^2}{\sigma^2}\right)$$

$$g'(x,y) = -\frac{x}{\sqrt{2\pi}\sigma^3} exp\left(-\frac{x^2 - y^2}{\sigma^2}\right)$$

The filter $h_X(x,y)$ is not rotated for filtering CH and similarly $g'(x,y) = -\frac{y}{\sqrt{2\pi}\sigma^3} exp\left(-\frac{x^2 - y^2}{\sigma^2}\right)$ for filter $h_Y(x,y)$ which is rotated by $\theta = \frac{\pi}{2}$ for filtering CV coefficients. The filtered output $F_x = h_X(x,y) * I_x$ And $F_y = h_Y(y) * I_y$,Where I_x =CH, I_y =CV.

2) Calculate the gradient as in Eq. (3) to find the resultant orientation present in texture.

$$G = \sqrt{I_x^2 + I_y^2} \qquad (3)$$

3) Suppress non-maxima coefficient in the edges of G is obtained thin the edge ridges.
4) Thinning the edges by eliminating the edges which are not connected with other edges which are insignificance and are not containing any robust edge information.

a. *Classification*

The simple classier is used to for the authentication of person hand image. It measures the distance between the histogram features of test and train as in Eq. (4).

$$D_{vector} = arg\left(min\left(\sum_{p=1}^{N} \frac{|H_{test} - H(p)_{train}|^2}{|H_{test} + H(p)_{train}|^2} \right)\right) \qquad (4)$$

Where N is the number of persons used for trained hand images. The minimum value vector D_{vector} decides the given test image is authenticated or not. If difference is zero, authentication is successful otherwise, authentication fail.

C. Face Feature Extraction

Face can be easily captured by the camera without any physical contact and hence face is one of the significant biometric traits for recognition. The method introduced here is to achieve better recognition rate by incorporating neighbourhood common representation with one person per subject which yields unique features of face.

a. Neighbourhood Common Representation (NCR)

Face recognition for one representative per subject can be categorized into three section NCR [18] based methods to compensate the extra feature are used as training dataset with optimum classification. In face recognition with one representative per subject have a data set D_s of N number of persons, each person have the following formula.
$P = [p_1, p_2, p_3, ...p_n] \in R_{D_s} \times N$, *where* $p_n \in R_{D_s}$ is the only single person category c , where $c = 1, 2, ..., n$. Given test a person $T_p \in R_{D_s}$, representation based on the classification used to identify from the data set D_s as in Eq. (5) where r is the different feature information which are not present in the common dataset are called as residual of the general dataset.

$$T_p = P + r \qquad (5)$$

If data set has number of training representations for each person, most of the facial disparity sample is fused by the several samples from the similar category, and consequently proper classification carried out by comparing the remaining residual of every category.

Sometime the Eq. (5) is will give wrong representation to identify the face because the given image has some illumination variations are differentiate with the person sample that category. The several numbers of representations are used to represent the Eq. (5).The method test the given sample T_p with the dataset P and the common disparity features D as:

$$T_p = P + D + r \qquad (6)$$

Where the vectors of T_p over P, D, r representation in Eq. (6) is a common model, which uses a common intra pixel disparity dictionary D to consider for the variations in the given test image.

b. Subset based local generic representation

The faces of human usually different structure in different parts, and have different significance to identity the face. Taking this aspect into an account, the proposed method uses localize common model in Eq. (6) and introduces a block wise local common characterization technique [19]. To improve the feature information of local representation and better to consider the local changes of a block, and extract local nearest blocks information at specific position from individual subject, then sum all individual subject. The subject sample of similar features can enhance the texture and strengthen the local features. The method uses eight nearest neighboring blocks as in Eq. (7) to the consider the block at location i are extracted carefully.

$$T_{p_i} = P_i + D_i + R_i, \quad i = 1, 2, ..., K \qquad (7)$$

c. Optimization and Classification

The half-quadratic optimization [number] is introduced to eliminate the optimization difficulties to represent the residuals more effectively [20].

The proposed classification label the given face T_P whether this person is true authenticated or not by using the particular category sub set dictionary and the common disparity dictionary, then can determine the residual of individual blocks by category wise . Finally add significance residual over all blocks can be evaluated. This classification gives leas residual over entire blocks. The Eq. (8) is used to identify the person for authentication.

$$C_P = arg\left(min\left(\sum_{i=1}^{K} \left(| T_{P_i} - P_i - D_i |^2 \right) + \| A_R \|^2 \right) \right) \qquad (8)$$

Where C_P classification for the given person, it takes minimum distance for authentication. A_R is the residual vectors.

D. Decision for Authentication

In this paper, proposed system uses any one of the biometric traits for a person authentication. Hand texture feature extraction method is effective because of DWT, edge detection, which results in required fine features and minimum distance classification. Similarly the face feature extraction method is also effective, as it introduces a neighbourhood common pixel representation and block level characterization produces essential face feature with an optimal classification results in proper categorization.

III. RESULT AND DISCUSSION

Database contains hand and face images of 300 subjects of hand and face of different poses. For each subject both left and right hand images of size 320x240 are collected for processing. There are no pegs to restrict postures and positions of hands. Six typical hand images in the database are shown in Fig. 2.All hand images are 8 bit gray-level JPEG files. The proposed work used 300 images of any pose (both left and right) as a training dataset. Fig. 3. Shows left and right image of a subject. The texture information of the input image not clearly visible but the method proposed is able to authenticate the input image of any pose effectively.

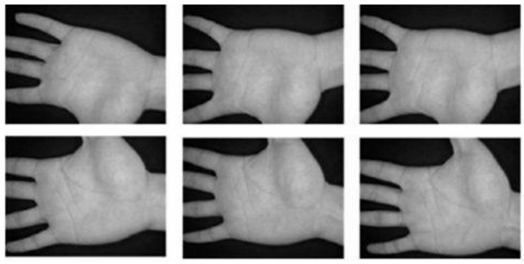

Fig. 2 Different poses of a person hand

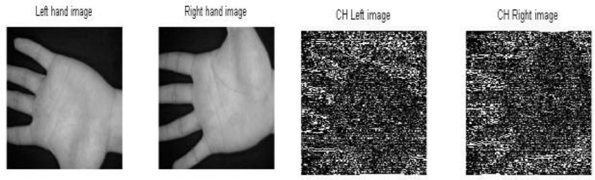

Fig. 3 Left , right and CH images

The dB4 wavelet of horizontal and vertical texture structural information of DWT coefficient image as shown Fig. 3 and Fig. 4 respectively. The variations of lines and borders structural information and their connectivity of input images are used as a base image for further processing to identify the proper line structure information of hand image. The Fig. 4 shows that the Filter response of left and

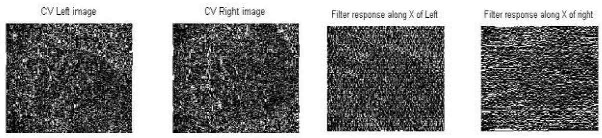

Fig. 4 Left , right of CV and Filter response of CA images

Right hand of horizontal CH image of size 320x240. The responses smoothen the spurious variations present in horizontal CH coefficient and also highlighted the lines which are smoothen in that region. So that response shows the line variation along x- direction are useful to identify the lines in horizontal direction.

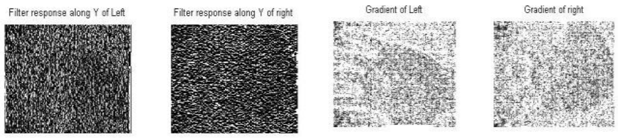

Fig. 5 Left, right Filter response of CH and Gradient images

Similarly the Fig. 5 shows that the Filter response of left and right hand of vertical CV image of size 160x120. So that response shows the line variation along y- direction are useful to identify the lines in vertical direction. The Fig. 5 shows the gradient of left and right image of filters output are calculated using gradient equation mentioned in Eq.(3).

This is the magnitude response along x-direction and along y-direction, gives exact line variations in the texture information of an input image with less intensity variation. The Fig. 6 shows the threshold image of left and right hand, which suppress the intensity levels below the threshold and retaining

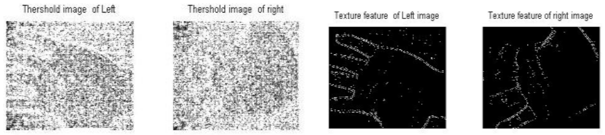

Fig. 6 Left, right Threshold and thinning image

The intensity levels above the threshold to reduce the texture features dimension so as to reduce the memory size to store trained data vector. The Fig. 6 shows texture structural information of left and right of hand image gives the final vectors to keep as a trained data vector after thinning process. Histogram feature of left and right hand images that only features are concentrated on either side of histogram, however no features in the middle of the histogram gives more reduction in feature dimension leads to save memory to store trained data vector.

Face recognition performance of neighborhood common characterization uses the database contains 300 images, some of the examples of the different persons are as shown in Fig. 7 are used as a main dataset. The experiment uses all images to train the general features, different gestures and different poses of images, with different expression ,these situations usually occurs in reality so that experiment verify all the possible every situation in this paper. The different gestures of a person as shown in Fig. 8 .To determine the residuals, as shown in Fig. 9 which are obtained by subtracting the general data with each person gestures. The proposed method results good performance with the existing methods, which mentioned in the Table 3.

Fig. 7 Genaral dataset of persons.

The method uses a subset of each person of different gestures with common training set, uses neighborhood common characterization for face feature extraction. The experimental performance based block based gives very a comprehensive feature which is albescence in the common features. Because of different residuals with block based are helpful to improve authentication. To proposed system uses images of size 60×60 pixels to reduce the dimension. Because of block based approach as shown in Fig. 10 this method achieves better accuracy for any face disparity in the given image.

Fig. 8 Different gesture of a person

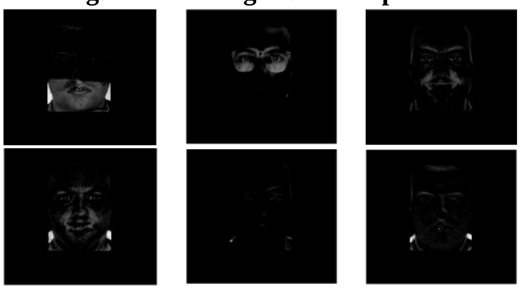

Fig. 9 Residual of the single person

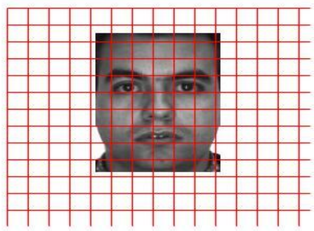

Fig. 10 Blocks of the test image

The proposed method performance as shown in Table 1. is tested with a 100 subjects of hand and face images. Only one pose of left and right hand images are used to train the hand features and test can identify effectively for eight different posses of left and right hand images. The hand feature extraction with various basis functions of DWT results better authentication but there is computational time difference due to the different wave function. The incorporation of DWT with edge detection for hand, significantly reduces the feature dimension of each subject as mentioned in Table 1.The feature dimension of each subject is in double type as in

'Dell system' with core ' i5' but the feature dimension remain same for different wave function because the wave functions does not affect the dimensions only it affects the computational time. For face, the person authentication is varying with person gesture since the intensity of pixel is varying with the gestures.

Table 1. Performance of the proposed system

Hand (100 images) PA - percentage of authentication CT- Computation Time (sec)				Face (100 images) FD - Feature Dimension of each subject FG-Facial Gesture			
Wave Name	PA	CT	FD	FG	PA	CT	FD
Haar	99.7	250	10	Smile	98	285	25
Db1	99.9	175	10	Laugh	98	290	30
Db2	99.9	169	10	Expression	98	298	45
Db3	99.9	185	10	Wearing Spectacles	96	300	50
Db4	99.9	200	10	Mask lower portion	95	310	50

Especially for masking the lower portion of the face image gives less authentication than the other gestures because masking some portion of the image significantly lacks the person features .The computational time and reduction in feature are different for different gestures. But for a person authentication system uses only one of the biometric traits hence overall system performance is better than the existing feature fusion techniques.

Table 2. Evaluation of the proposed system

	Authentication	Non Authentication
True	TA=99.99 %	TNA-99.77 %
False	FA-0.01 %	FNA-0.23 %
Over all system accuracy = 99.98 % Specificity = 0.997 Sensitivity =0.999		

The Proposed system metric measures are as shown in Table 2. Which includes both hand and face images. Where T_A is true authentication means both the test images are authenticated but are present in the training dataset, T_{NA} is true non authentication means both test images are not authenticated but not present in the training dataset, F_A is false authentication means both the test images are not authenticated but present in the training dataset, F_{NA} is false non authentication means both the test images are authenticated but not present in the training dataset. The overall authentication system is best as F_A and F_{NA} are less in percentage.

Table 3. Performance comparison

Biometric Trails	Method	% of Authentication Rate
Palm Vein + Palm Print	DSCN + SVM for Feature Extraction	99.97
Face+Iris+finger print	CT+LDTP	96
Face Images of different domains	DCNN + Domain Transformation	91
Multiple pose Images	Model H[3]	99.95
Face + Iris	2D-log Gabor filter + SRKDA	99.50
Ear print + Fingerprint + Palm print	HBF WHBF	98.67 99.2
Faces of different postures	Auto encoder + DCNN	84
Fingerprint + ECG	Two layer CNN + QG-MSVM	98.66
Face + Iris	Log-Gabor filter + SRKD	99.50
Ear + Palm	Local Binary pattern + WLD + Binary stastical image feature	98.90
Finger print + Finger vein + Retina	Encryption + Decryption	95.3
Face + Voice	PSO + Belief functions	99.3
Multi samples of palm vein	SIFT + pre-set threshold	99.27
Proposed Method	**DWT+Edge detection And NCM+Block segmentation**	**99.98**

The S_n and S_p is the sensitivity and specificity of the system means the system is very much sensitive and specific for authentication and non authentication users.

$$S_n = \frac{T_A}{T_A + T_{NA}} = 0.999$$

$$S_p = \frac{T_{NA}}{F_A + T_{NA}} = 0.999$$

$$A_C = \frac{T_A + T_{TA}}{T_A + T_{NA} + F_A + F_{NA}} = 99.98\%$$

where A_C is overall system accuracy.

The proposed method gives better authentication rate than the different methods as shown in Table 3.

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IV. CONCLUSION

A proposed multi modal biometric authentication system is experimentally working significantly fine for different gestures of face and different poses of hand images. System works efficiently with any one the biometric traits for person authentication. Since texture features of hand image are extracted using 2D-DWT with different waves and to get fine texture information, the system introduced strong edge detection to keep the significant feature in order to achieve better authentication. This process remarkably reduces the feature dimension of the trained dataset. And for face the system introduced a well local feature extraction of face sample are characterised with neighbourhood common information and also uses block wise information of local representation and common features. A common intra pixel disparity feature created from common features, and also compensates for the variation features which are absence in the data set. As a result of multimodal biometric system with less feature dimension gives better authentication rate and least number of false identification.

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