

Research Article

Multimodal Biometric Cryptosystem for Face and Ear Recognition Based on Fuzzy Vault

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Abstract: Multimodal biometrics technology that uses more than two sorts of biometrics data has been universally applied for person certification and proof. Researchers have advised that the ear may have benefits over the face for biometric recognition. In this study, a technique for face and ear recognition has suggested. The face image and ear images are prearranged as input. From the pre-processed input images, the shape and texture characteristics are removed. The shape of ear and face is attained by suggesting modified region growing algorithm and texture characteristic by Local Gabor XOR Pattern (LGXP) method. To produce the fuzzy vault, the multi-modal biometric template and the input key are employed. For working out, the multi-modal biometric template from face and ear will be erected and it is united with the stored fuzzy vault to produce the final key. Experimental results of suggested method explain promising development in multimodal biometric validation.

Keywords: Biometric recognition, fuzzy vault, LGXP, modified region growing algorithm, multimodal biometrics

INTRODUCTION

Biometrics is the science and technology of calculating and examining biological information of human body, removing a feature set from the gained data and comparing this set against to the template set in the database (Gudavalli *et al.*, 2012). Biometric refers to recognizing a person on the basis of his physiological or behavioral features. It comprises fingerprint, hand geometry, palm print, voice, face and iris recognition, etc., (Khan and Zhang, 2008). To develop human recognition, biometric researchers are investigating the employ of ancillary features such as scars, marks, tattoos and height and body shape in conjunction with primary characteristics like the face (Ross and Abaza, 2011). A conventional biometric system functions in one of the two subsequent modes, that is, enrollment and proof mode (Chin *et al.*, 2011; Raghavendra *et al.*, 2010). The use of biometric data is a famous technique for authentication, but the doubt that occurs due to the need of distinctiveness in biometrics has direct there to be a great deal of attempt invested into multimodal biometrics (Maple and Schetinin, 2006).

The biometric data generally demonstrates three features in the application of Biometrics Authentication (BA) technologies: large numbers of individuals, small model size and high dimensionality (Yaoa *et al.*, 2007). Even though unimodal biometric systems are progressed and enhanced, there are restrictions such as noise on voice and illumination (Ichino *et al.*, 2006). Proposals have been prepared in the occasional

literature that the shapes and features of human ear are extensively dissimilar over the years and may be in fact adequately variant such that it is feasible to distinguish among the ears of all individuals (Rahman *et al.*, 2007). Unimodal biometric systems have to challenge with a diversity of problems such as noisy data, intra-class variations, restricted degrees of freedom, non-universality, spoof attacks and unacceptable fault rates (Ross and Jain, 2004).

In biometric recognition system, Multimodal biometrics has lately drawn substantial interest for its high concert (Ahmad *et al.*, 2010). A multimodal biometric system that eases the restrictions of the unimodal biometric systems by combining the data from the relevant biometric sources is improved (Hanmandlu *et al.*, 2011). By supplying multiple pieces of proof of the similar uniqueness, Multimodal biometric systems try to find to ease some of these problems (Basha *et al.*, 2010). Multimodal biometrics has turn into an essential research tendency in enhancing biometric precision (Dahel and Xiao, 2003). Multimodal biometrics technology that uses more than two sorts of biometrics data has been universally applied for person authentication and verification (Choi and Shin, 2009).

Identifying people by their ear has newly obtained important concentration in the literature. More than a few reasons report for this trend: first, ear recognition does not suffer from some problems related with other non contact biometrics, such as face recognition; second, it is the most promising candidate for combination with the face in the framework of multi-

pose face recognition; and third, the ear can be applied for human recognition in surveillance videos where the face may be occluded entirely or in part. Besides to deviation in illumination, other open research problems comprise hair occlusion; ear print forensics; ear symmetry; ear categorization; and ear uniqueness. Multimodal ones contain obviously benefits comparing with single biometric verification technologies. Multimodal biometric is proficient to incorporate different single biometric verification and employs of the merits of all types of single biometrics to develop the concert of the system and attain a more robust system (Yang, 2010).

LITERATURE REVIEW

Unimodal biometric systems come across a diversity of security problems and offer sometimes intolerable fault rates. By setting up multimodal biometric systems, a few of these disadvantages can be overcome. Joining dissimilar biometric sources, Multimodal biometrics offers high identification precision and population coverage. Several of the latest strategies have been offered beneath:

A new authentication scheme of DRM system for remote users has been suggested by Wang *et al.* (2009) based on multimodal biometrics verification and watermarking and smart cards, which comprises two authentication phases, i.e., the client server authentication and the server authentication. For the client server authentication, they have incorporated watermarking method and multimodal biometric system which was based on highly protected iris recognition and face recognition for offering more secure and dependable personal recognition. Hence their suggested plan can accomplish the rights management of digital content precisely through the illegal user access control.

Monwar and Gavrilova (2009) have offered an efficient fusion plan that unites data offered by multiple domain specialists based on the rank-level fusion integration technique. The multimodal biometric system improved by them acquires a number of distinctive qualities, starting from utilizing principal component study and Fisher's linear discriminant techniques for individual matchers distinctiveness authentication and employing the new rank-level fusion technique in order to strengthen the results attained from dissimilar biometric matchers. The results have pointed out that the fusion of individual modalities can develop the on the whole presentation of the biometric system, still in the existence of low quality information.

The concert of sum rule-based score level fusion and Support Vector Machines (SVM) -based score level fusion has been inspected by He *et al.* (2010). Three biometric features were regarded in their study: fingerprint, face and finger vein. Their experiment results had recommended that by joining the three modalities fingerprint, face and finger vein in a

multimodal biometric system effects in a verification system with very high precision. The sum rule-based fusion had attained a mean GAR of 0.996 at a FAR of 10^{-5} ; fusion based on SVM classifier had accomplished even higher accuracy, a mean GAR of 0.999 and a mean FAR of 3×10^{-7} .

For ear identification, an enhanced manifold learning technique, called Uncorrelated Local Fisher Discriminate Analysis (ULFDA) has been suggested by Huang *et al.* (2011). The plan of their suggested technique is to look for a characteristic sub manifold such that the within-manifold scatter is minimized and between-manifold scatter is maximized concurrently in the implanting space by means of a novel difference-based optimization objective function. The effects of the suggested algorithm have illustrated that, it not only gets the optimal and lossless discriminative data, other than furthermore promises that all removed characteristics are statistically uncorrelated.

Yuan and Mu (2012) have suggested a 2D ear recognition strategy based on local data fusion to deal with ear recognition under incomplete occlusion. Initially, the entire 2D image was detached into sub-windows. Next, for feature extraction on each sub-window, Neighborhood Preserving Embedding was applied. Thirdly, for recognition with partly occluded images, a sub-classifier fusion strategy was applied. Experimental results on the USTB ear dataset and UND dataset have demonstrated that by means of just few sub-windows can signify the most significant region of the ear and the multi-classifier model gets higher recognition rate than employing the complete image for recognition.

A novel strategy for dependable personal identification by means of gray-level ear images has been examined by Chan and Kumar (2012). By means of 2-D quadrature filtering, their improved strategy has removed robust phase information. They have relatively assessed the presentation of 1-D and 2-D local phase information by Cauchy, Gaussian derivative and log-Gabor band-pass quadrature filters. The experimental effects with 2-D quadrature filters were highly promising and have accomplished considerably enhanced concert as compared to conventional phase encoding by means of 1-D quadrature filters.

Pflug and Busch (2012) have offered a review on the condition of the art in 2D and 3D ear biometrics, covering ear finding and ear identification systems. They have classified large number of 2D ear recognition strategies into holistic, local, hybrid and statistical techniques. They have gathered a structured review of accessible databases, presented ear detection and recognition strategies and unsolved problems for ear recognition in the perspective of smart surveillance system. They have demonstrated that this novel feature was an important extension for face recognition systems on the approach to create invariant automatic recognition.

A novel strategy for more precise ear recognition and verification problem has been explored by Kumar and Chan (2013) by means of the sparse representation of local gray-level orientations. They have utilized the computational plainness of localized Radon transform for the robust ear shape depiction and moreover have examined the efficiency of local curvature encoding by means of Hessian based feature depiction. They have offered the experimental effects from publically accessible UND and IITD ear databases which have attained important development in the concert, both for the recognition and authentication problem.

The routine removal of Local 3D Features (L3DF) from ear and face biometrics and their arrangement at the feature and score levels for robust identification has been offered by Islam *et al.* (2013). They are the foremost to offer feature level fusion of 3D features removed from ear and frontal face information. Scores from L3DF based matching were furthermore fused with iterative closest point algorithm based matching by means of a weighted sum rule. They have in addition attained recognition and verification (at 0.001 FAR) rates of 99.0 and 99.4%, correspondingly, with neutral and 96.8 and 97.1% with non-neutral facial expressions on the major public databases of 3D ear and face.

Huang *et al.* (2013) have progressed a robust face and ear based multimodal biometric system by Sparse Representation (SR), which has incorporated the face and ear at feature level and can successfully correct the fusion rule based on dependability difference among the modalities. SR-based classification methods were used in multimodal classification phase, i.e., Sparse Representation based Classification (SRC) and Robust Sparse Coding (RSC). Lastly, they have obtained a group of SR-based multimodal recognition techniques, together with Multimodal SRC with feature Weighting (MSRCW) and Multimodal RSC with feature Weighting (MRSCW).

Problem definition: In physiological and forensic functions, a distinctive feature of human for authentication is extensively applied. The most generally employed biometric features are face, fingerprint, palm print and iris. It is commonly considered that there is no solitary universal or superior biometric modality and each modality has its distinctive application, deployment benefits and imaging necessities. Noise, non-university, precision, spoof attacks are a few of the main issues and practical problems on a unimodal biometric features. Combination of biometrics systems are applied in order to overcome these problems, which is more dependable when compared to unimodal. Both Face and ear does not have arbitrary formation but has various normal parts. So a multimodal biometrics human authentication system by means of Face and Ear is to be improved in

order to conquer the issues of other multimodal biometric system. This system engages modified region growing algorithm and LGXP method for shape and texture extraction. For providing security, Fuzzy vault is comprised.

PROPOSED METHODOLOGY

In the literature, Contact-based recognition methods have been often offered. However, lately, contactless based method has obtained important consideration among the researchers due to the retention of actual distinctiveness. The two dissimilar contact-less based modalities to employ the actual distinctiveness without any pressure or human intervention. For multi-modal biometric recognition face and ear modalities are applied now. The suggested methodology includes of 3 phases such as Image Preprocessing, Feature extraction and Authorization. The input face image and ear images are pre-processed before its characteristic removed so as to have improved results. Pre-processing formulates the image fit for additional processing of feature removal and gets rid of the noise and shadow in the input image. Using a Gaussian filter Image, preprocessing is prepared. By convolution with a Gaussian function, Gaussian filter adapt the input signal. Widespread characteristic set accomplishes high recognition rate. At this point shape and texture characteristics are removed from the input images. To remove the precise shape of ear and face, the shape feature is applied which is acquired by using modified region growing algorithm and texture characteristic by LGXP method. Both these characteristics will remove the distinctiveness of the images.

Consequently, features are removed from the images beside with the chaff points will be used to outline characteristic points in the multi-biometric template. To produce the fuzzy vault, the multi-modal biometric template and the input key are applied. For decoding, the multi-modal biometric template from face and ear are erected and it is joined with the stored fuzzy vault to produce the final key.

The ear and face images were set as input. The images were focused to three significant processes specified below:

- Image preprocessing
- Feature extraction
- Authorization

Image pre-processing: In order to acquire improved results for the purpose of feature removal, Image Pre-processing is made. The face and ear images were cropped in this step. Cropping is made by hand. In the ear images the areas which do not comprise the ear is

colored to black and in the face images the areas which do not comprise the face were colored to black. The colored images are subsequently changed to the grayscale images. Gaussian filter is applied for noise suppression for image pre-processing. The noise is smoothed out; at the similar time the signal is less deformed. The exploit of Gaussian filter as preprocessing for edge finding will diminishes edge position dislocation, edges vanishing and phantom edges. Mathematically, a Gaussian filter adapts the input signal by convolution with a Gaussian function; this alteration is as well known as the Weierstrass transform.

Feature extraction: In this phase the shapes and texture characteristics of the face and ear images are extracted. Grayscale images are set as input to the feature extraction process. The shape of the face and ear images are extracted by means of modified region growing algorithm. The consistencies of the images are extracted by means of LGXP method.

Modified region growing algorithm: In the modified region growing algorithm the threshold of the image is not regarded instead the threshold of the direction image is taken for region rising process. The benefit of applying modified region growing is the shape of the image is fragmented competently and further data can be attained when comparing with region growing algorithm. For removing the evident part of the ear named pinna which presents more data about the ear shape modified region growing will be further efficient than region growing algorithm. The total number of pixels in the image is computed at this point. The total number of pixels in the image is equivalent to the size of the image. The Gray level of the chosen region in the image is the proportion of total of gray level for all pixels in the region to the total number of pixels in the region:

$$Graylevel = \frac{\text{Total of gray level for all pixels in the region}}{\text{Total number of pixels in the region}} \quad (1)$$

The modified region growing is a three step process:

- Gridding
- Selection of seed point
- Applying region growing to the point

Gridding: A single image is partitioned into numerous smaller images by drawing an imaginary grid over it in gridding. Specifically, gridding results in exchanging the image into numerous smaller grid images. The grids are frequently square in shape and the grid number to which the unique image is dividing into is a

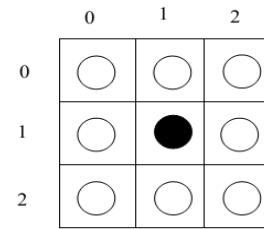


Fig. 1: Location of initial seed pixel in a 3×3 neighborhood

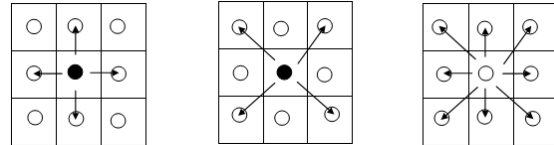


Fig. 2: Representation of neighboring pixel selection by the seed pixel

changeable. Gridding results in smaller grids so that study can be executed effortlessly.

Selection of seed point: The first step in area growing for the grid appeared is to choose a seed point for the grid. The primary area starts as the precise position of the seed. Now to discover the seed point of the grid, we have executed histogram study. The histogram is found out for each pixel in the grid. When the image is a grey scale image, the values of this image is from 0 to 255. For each grid, the histogram value that approaches most common is chosen as the seed point pixel. From this, any person of the seed point pixel is occupied as the seed point for the grid.

Applying region growing to the point: The area is grown from it after locating out the seed point. At this juncture the adjacent pixels are compared with the seed point and if the neighbor pixel pleases constrains, subsequently the region is grown else it is not grown to that pixel. Constrains for our suggested modified region growing is the “intensity” and the “orientation”. The stages in the modified region growing algorithm are as follows (Fig. 1 and 2):

Start

Find the gradient of the Image I in both x axis (I_x) and y axis (I_y).

Combine the gradient values using the formula

$$g = \frac{1}{1+(I_x^2+I_y^2)} \text{ to get the gradient vector } g.$$

Convert Gradient vector values into degrees to get the orientation values of the pixels of the image.

Spilt the Image I into Grids G_i

Set the intensity threshold T_1 and the orientation threshold T_0 .

For each Grid (denoted as G_i) do

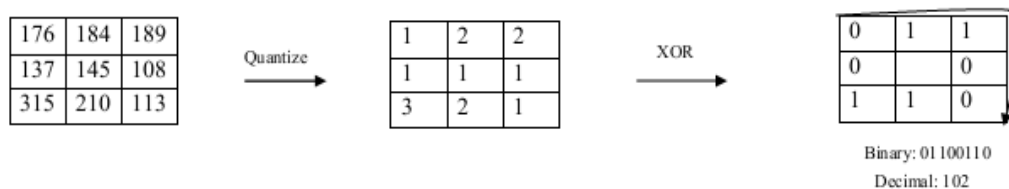


Fig. 3: Example of encoding method of LGXP

Find the histogram (denoted as Hist) of the every pixel P_j in the grid G_i

Find the most frequent histogram of the G_i^{th} grid and denote it as $\text{Freq}_{\text{Hist}}$

Select any pixel P_j corresponding to the $\text{Freq}_{\text{Hist}}$ and assign that pixel as the seed point SP having intensity I_p and orientation O_p .

Check for intensity constraint $\|I_p - I_N\| \leq T_I$ and the orientation constraint $\|O_p - O_N\| \leq T_O$, for the neighboring pixel having intensity I_N and orientation O_N ,

If both the constraints are satisfied and met, Region is grown to the neighboring pixel.

Else

The region is not grown to the neighboring pixel.

End For

Stop

LGXP technique: The face and ear images were specified to the gabor filter. Gabor filter was initially launched by Dennis Gabor for 1-D signals and Daugman widened the Gabor filter for 2-D. Gabor characteristics have been recognized to be efficient for face identification. For feature extraction, the Gabor filters are band pass applied. A bank of filters is employed with dissimilar orientations so as to extract frequency data and thus the characteristics at dissimilar orientations, as all facial characteristics are not there at similar orientation. At every orientation, Scaling is made so as to acquire maximum frequency data at every orientation i.e., orientation and scaling assists in extracting maximum frequency data. In LGXP, phases are initially quantized into dissimilar variety, then LXP operator is used to the quantized phases of the central pixel and every of its neighbors and lastly the resulting binary labels are concatenated collectively as the local model of the central pixel (Fig. 3 and 4).

Fuzzy vault generation phase: By the adding up of secret key idea into the feature set, Fuzzy vault develops the safety of template security. To figure feature set, the shape and texture characteristics extracted unites with chaff points. To raise the security of the feature combination, the chaff points were attached. The number of secret key points produced is openly reliant on the number of digits in the secret key and if secret key is 4 bit long, then 4 points will be included to the feature vector to create the fuzzy vault (Fig. 5).

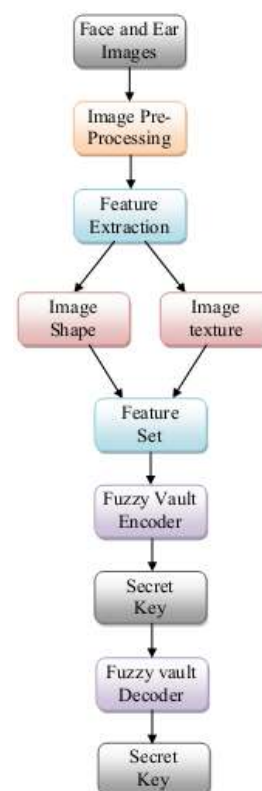


Fig. 4: Architecture of the proposed method

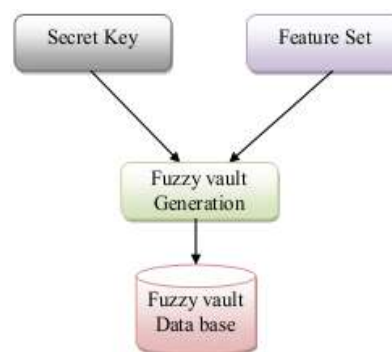


Fig. 5: Architecture of fuzzy vault encoding process

Away from each other, from the face and ear feature points, for feature set, a few extra random points are attached known as chaff points. To develop the security, Chaff points are included while forming the united feature vector. Let the chaff points for person i

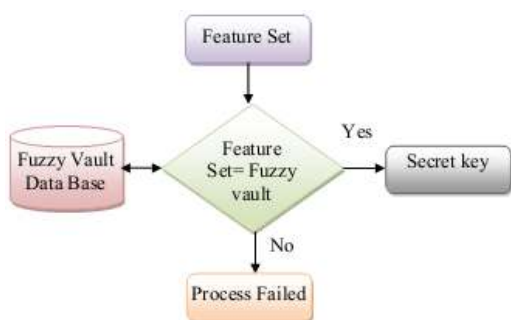


Fig. 6: Architecture of fuzzy vault decoding process

be symbolized as $Ec_i = \{ec_{i1}, ec_{i2}, \dots, ec_{iNc}\}$, where Nc is the total number of chaff points included. The combined feature vector is created by joining the feature points from face and ear and the chaff points. Consequently the combined feature vector for a user i can be symbolized as $E_i = \{Ef_i, Ea_i, Ec_i\}$ which can be made bigger to $E_i = \{ef_{i1}, ef_{i2}, \dots, ef_{iNf}, ea_{i1}, ea_{i2}, \dots, ea_{iNa}, ec_{i1}, ec_{i2}, \dots, ec_{iNc}\}$ and the total number of extracted points in the joined feature vector is $Np+Nh+Nc$. In our method, although we extract all the common points, we formulate utilize of only a little points in order to diminish the complexity and time of implementation. Generation phase encoding and decoding is made in the fuzzy vault. In the encoding process the inputs specified are the feature set and the secret key. Secret key was produced by the user. The fuzzy vault is produced by giving the feature set and the secret key. The Fuzzy vault produced was accumulated in the database. The fuzzy vault and the feature vector were compared in the decoding process. If both matches next the validation are offered and the secret key was produced, or else the authentication will not pass (Fig. 6).

RESULTS AND DISCUSSION

Dataset description: We have applied two databases for face and Ear identification. For face we have applied Yale database and ear we have applied IIT Delhi ear image database. We have believed that, the face and ear image of the single person is identified.

Face: The Yale Face Database contains 165 grayscale images of 15 individuals. <http://cvc.yale.edu/projects/yalefaces/yalefaces.html>. There are 11 images per subject, one per dissimilar facial expression or arrangement: center-light, w/glasses, happy, left-light, w/no glasses, normal, right-light, sad and sleepy, surprised and wink. We have employed only male images. Subjects are of healthy conditions and are from all folks of life with students, engineers, workers etc. We have employed 15 face images for our purpose.

Ear: The IIT Delhi ear image database contains the ear image database gathered from the students and staff at

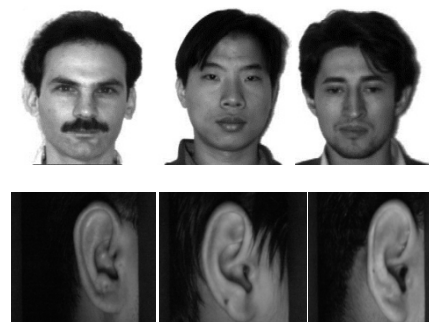


Fig. 7: Images of the face and ear taken from the respective databases

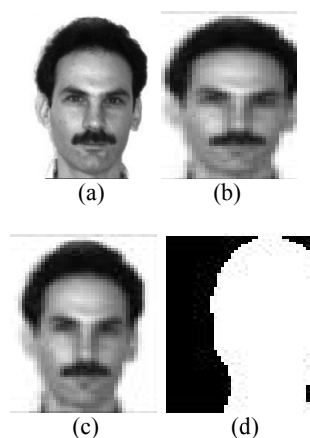


Fig. 8: Face image outputs at various stages

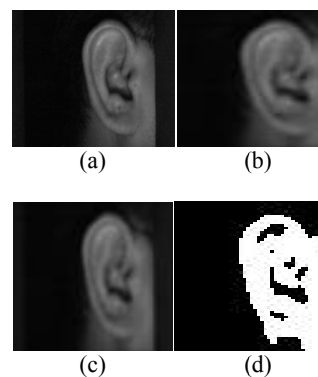


Fig. 9: Ear image outputs at various stages

IIT Delhi. http://www4.comp.polyu.edu.hk/~csajaykr/IITD/Database_Ear.htm. Using simple imaging setup all the images are obtained from a distance and the imaging is executed in the enclosed environment. This database is obtained from the 121 dissimilar subjects and every subject has at least three ear images. The entire the subjects in the database are in the age group 14-58 years. We have employed 15 images for our purpose (Fig. 7).

Experimental results: This section provides the image at the dissimilar stages of implementation. The face and

ear images are signified beneath at the dissimilar stages of implementation. In Fig. 8 and 9, A symbolizes the input image, B symbolizes the filtered image, C symbolizes the cropped image and D symbolizes the shape extracted image.

Performance measures: The performance of the proposed system was evaluated using the following measures:

- False Matching Rate (FMR)
- False Non Matching Rate (FNMR)
- Genuine Acceptance Rate (GAR)
- Dice Coefficient (DC)
- Jaccard Coefficient (JC)

False Matching Rate (FMR): False Matching Rate (FMR) is the possibility that the system inaccurately matches the input model to a non-matching template in the database. It calculates the percent of illogical inputs which are imperfectly acknowledged:

$$FMR = \frac{\text{Invalid inputs which are incorrectly accepted}}{\text{Total number of inputs}} \quad (2)$$

False Non Matching Rate (FNMR): False Non Matching Rate (FNMR) is the possibility that the system not succeeds to identify a match among the input model and a matching template in the database. It calculates the percent of valid inputs which are imperfectly discarded:

$$FNMR = \frac{\text{Invalid inputs which are incorrectly rejected}}{\text{Total number of inputs}} \quad (3)$$

Genuine Acceptance Rate (GAR): GAR is the assessment of the presentation that properly classified the genuine model as authentic:

$$GAR = 1 - FNMR \quad (4)$$

Dice coefficient: Dice Coefficient (DC) was intended to be applied to presence/absence data and is given by:

$$DC = \frac{2|A \cap B|}{|A| + |B|} \quad (5)$$

where, A and B are the number of species in samples A and B.

Jaccard coefficient: The Jaccard Coefficient (JC) measures similarity between sample sets and is defined as the size of the intersection divided by the size of the union of the sample sets:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (6)$$

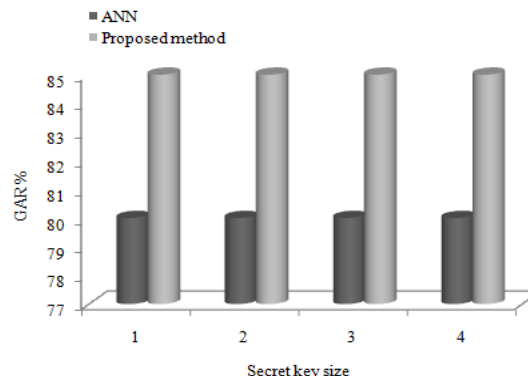


Fig. 10: Plot of GAR values without noise

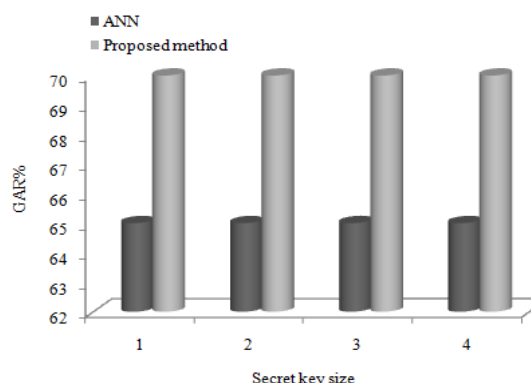


Fig. 11: Plot of GAR values with noise

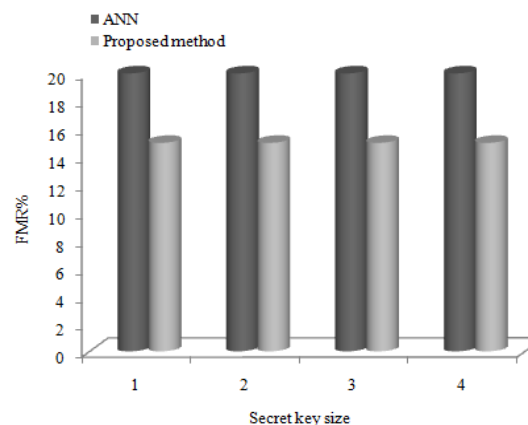


Fig. 12: Plot of FMR values without noise

where, A and B are the number of species in samples A and B.

The performance measure values of GAR, FNMR, FMR, DC and JC got for the suggested method is conversed below. The estimation is prepared in the existence and in the absence of noise and furthermore by differing the key size of the secret key. The suggested method results are moreover compared to the presented techniques. Our suggested technique is compared with the Artificial Neural Network (ANN) (Fig. 10 to 14).

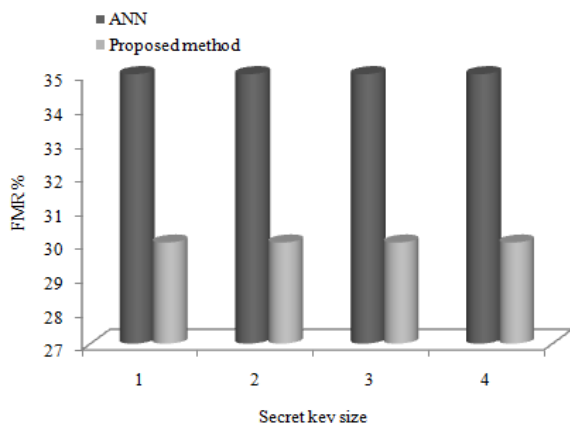


Fig. 13: Plot of FMR values with noise

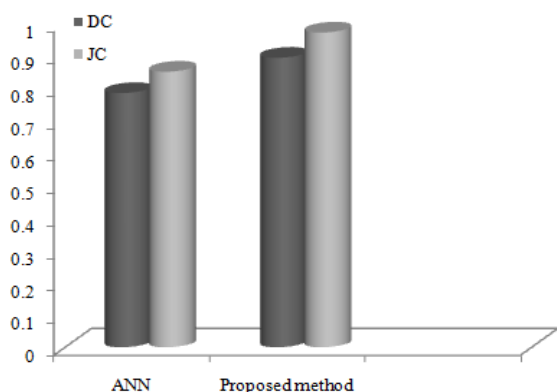


Fig. 14: Plot of coefficient values

In all cases, we evaluate the values to the ANN and it is found that the suggested method executes superior. All cases irrespective of neither the key size nor noise, acquire a high GAR and low FMR which obviously points out the efficiency and constancy of the suggested method.

CONCLUSION

Several of the problems there in unimodal systems are addressed by Multimodal biometric systems sophisticatedly. By joining multiple sources of information, these systems develop matching concert. This study offers a method to produce face and ear-based fuzzy vault for multi-biometric cryptosystem. The input images were pre-processed and are subjected to modified region growing algorithm and LGXP for extracting the shape and the texture characteristics correspondingly. Next the multi-biometric template was formed in order to use fuzzy vault. In order to raise the security, Fuzzy vault encoding and decoding was made. The estimation metrics FMR (False Matching Ratio), False Non Matching Rate (FNMR), GAR (Genuine Acceptance Ratio), Jaccard Coefficient (JC) and Dice Coefficient (DC) are used. The experimental results

Table 1: Evaluation metrics obtained without noise

		Secret key size			
		1 (%)	2 (%)	3 (%)	4 (%)
ANN	GAR	80	80	80	80
	FMR	20	20	20	20
Proposed method	GAR	85	85	85	85
	FMR	15	15	15	15

Table 2: Evaluation metrics obtained under noise

		Secret key size			
		1 (%)	2 (%)	3 (%)	4 (%)
ANN	GAR	65	65	65	65
	FMR	35	35	35	35
Proposed method	GAR	70	70	70	70
	FMR	30	30	30	30

Table 3: Evaluation metrics coefficient

ANN	DC	0.786
	JC	0.852
Proposed method	DC	0.895
	JC	0.973

shown in Table 1 to 3 propose important development in the concert of multimodal biometric authentication.

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