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FACE, IRIS, AND FINGERPRINT MULTIMODAL IDENTIFICATION SYSTEM BASED ON LOCAL BINARY PATTERN WITH VARIANCE HISTOGRAM AND COMBINED LEARNING VECTOR QUANTIZATION

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ABSTRACT

Believing of the importance of biometrics in this research, we have presented a fused system that depends upon multimodal biometric system traits face, iris, and fingerprint, achieving higher performance than the unimodal biometrics. The proposed system used Local Binary Pattern with Variance histogram (LBPV) for extracting the preprocessed features. Canny edge detection and Hough Circular Transform (HCT) were used in the preprocessing stage while, the Combined Learning Vector Quantization classifier (CLVQ) was used for matching and classification. Reduced feature dimensions are obtained using LBPV histograms which are the input patterns for CLVQ producing the classes as its outputs. The fusion process was performed at the decision level based on majority voting algorithm of the output classes resulting from CLVQ classifier. The experimental results indicated that the fusion of face, iris, and fingerprint has achieved higher genuine acceptance recognition rate (GAR) 99.50% with minimum elapsed time 24 sec. The evaluation process was performed using large scale subjects claiming to enter the system proving the superiority of the proposed system over the state of art.

Keywords: *Face, Iris, Fingerprint, Combined Learning Vector Quantization, Local Binary Pattern Variance, SDUMLA-HMT, Genuine Acceptance Rate, and majority voting.*

1. INTRODUCTION

Human recognition based on multimodal biometric systems has rapidly increased recently in order to verify, identify, and detect humans that are subject to open and/or closed system organization that, need security keys for the authentication process. The appearance of multimodal biometric systems was mainly due to the limitations of unimodal biometrics including [1]:

1. Noise resulting from sensed data as in fingerprint acquired from different sensors.
2. Intra-class variation with different poses likes in face recognition systems.
3. Distinctiveness which is the measure of variations or difference in biometric pattern among the general population as in hand geometry, and face have distinctiveness problem.
4. Non-Universality by which the biometrics may not able to acquire meaningful biometric data from a subset of individuals entered to the system.
5. Spoof attacks like as in fingerprints spoofing.

All these limitations can be solved using multimodal biometric systems through fusing two or more biometric traits, enhancing the advantages for each biometric trait while keeping away from the disadvantages of these traits. Table 1 illustrates the comparison between various biometric traits based on universality, collectability, performance, acceptability, distinctiveness, permanence, and circumvention assuming that H, M, and L are high, moderate, and low. In this research, we are seeking to overcome the limitations of unimodal biometric system using the most popular and scored biometric traits as illustrated in Tables 2 & 3 including face, iris, and fingerprints. Table 3 clarifies the advantages of face, iris, and

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fingerprints based on these seven metrics, for example the need of high universality can be achieved by merging face and iris. Ensuring high performance of recognition system, a fusion of fingerprint and iris are performed. The experimental results achieve high performance and genuine acceptance recognition rate when a fusion of face, fingerprint, and iris were performed.

Spoof attacks can't occur as long as the system needs two or more biometrics to check the genuine/imposters person's claims to enter the system. If the person gets injury from any parts of his biometrics, the other biometrics will be used. The problem of intra-class variations is introduced and solved using our proposed system so that three poses of face images entered to the system are presented. Any person claims to enter the system, the system can easily recognize and detect that person by comparing the input templates with the templates stored in the database. Figure (1) summarize and classifies the most popular available techniques used for personal authentication and verification systems [2].

Table 1: Comparison various types of biometric traits [1].

Biometric identifier	*Universality*	*Distinctiveness*	*Permanence*	*Collectability*	*Performance*	*Acceptability*	*Circumvention*
DNA	H	H	H	L	H	L	L
Ear	M	M	H	M	M	H	M
Face	H	L	M	H	L	H	H
Facial thermogram	H	H	L	H	M	H	L
Fingerprint	M	H	H	M	H	M	M
Gait	M	L	L	H	L	H	M
Hand geometry	M	M	M	H	M	M	M
Hand vein	M	M	M	M	M	M	L
Iris	H	H	H	M	H	L	L
Keystroke	L	L	L	M	L	M	M
Odor	H	H	H	L	L	M	L
Palmprint	M	H	H	M	H	M	M
Retina	H	H	M	L	H	L	L
Signature	L	L	L	H	L	H	H
Voice	M	L	L	M	L	H	H

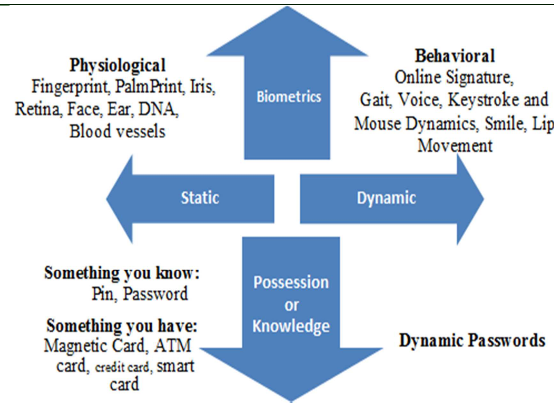

Figure 1: Recent authentication techniques [2].

Table 2: Biometric properties and description [3]

Universality	Each person should have the characteristic.
Distinctiveness	Any two persons should be sufficiently different in terms of the characteristic.
Permanence	The characteristic should be sufficiently invariant (with respect to the matching criterion) over a period of time.
Collectability	The characteristic can be measured quantitatively.
Performance	Refers to the achievable recognition accuracy and speed, the resources required to achieve the desired recognition accuracy and speed, as well as the operational and environmental factors that affect the accuracy and speed.
Acceptability	Indicates the extent to which people are willing to accept the use of a particular biometric identifier (characteristic) in their daily life.
Circumvention	Reflects how easily the system can be fooled using fraudulent methods.

Table3: The proposed multimodal biometric system biometrics characteristics

Biometric identifier	*Universality*	*Distinctiveness*	*Permanence*	*Collectability*	*Performance*	*Acceptability*	*Circumvention*
Face	**H**	L	M	**H**	L	**H**	**H**
Fingerprint	M	**H**	**H**	M	**H**	M	M
Iris	**H**	**H**	**H**	M	**H**	L	L

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Graphical User interface of the proposed system is shown in Figure (2) by which all steps are illustrated starting with the enrollment process. The input images of face, iris, and fingerprint for each subject are enrolled and stored in the database. The proposed system is capable of updating the input subjects at any time. All input templates even the updated templates are stored in the database folder called DBI. DBI folder contains all stored images for each subject claims to enter the system before preprocessing stage. The preprocessing step is performed for each biometric trait e.g. face, iris, and fingerprint. The preprocessed images results from Canny edge detection and Hough Circular Transform (HCT) are then stored in DBII.

The preprocessing stage is applied in order to enhance the input images stored in DBI forming DBII. The extracted featured results from local binary pattern with variance (LBPV) are then stored in DBIII. The discriminating features are extracted, and then encoded in a convenient representation template for storage and processing. Identification process is executed for face, iris, and fingerprint and the fusion process is based on decision level using majority voting algorithm. The experimental results show that the proposed system gained high recognition rate than state of art. This research has been organized as follows: (2) Literature survey, (3) General framework of the proposed scheme, (4) Experimental results, (5) discussion and (6) Conclusion and future work.

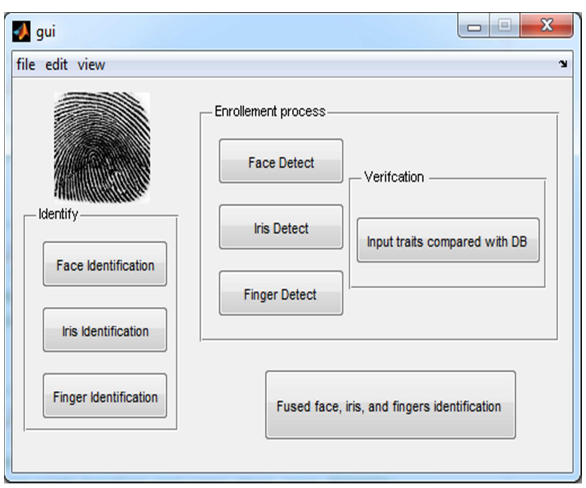

Figure 2: GUI Of The Proposed System.

2. LITERATURE SURVEY

In this section, the researchers are going to present a recent survey of the recent multimodal biometric techniques. As there are ongoing researches on multimodal biometric systems, the need of high security and speed with a little cost and complexity, is the major demand for the researchers in this field. A fusion problem is the most important part in multimodal biometric systems that attracted extensive research.

T. Sanches et al [5] proposed a multibiometric recognition system that exploits hand geometry, palmprint, and fingers presented in one hand image. Each three biometrics passed a series of steps including acquisition, preprocessing, and matching of templates to be compared with the templates stored in the database. They used 35 features of one hand that are statistically analyzed for discriminability. In order to select the best performance, they used the ratio between interclass and intraclass variability of each feature. The most discriminant features presented the highest ratio values of GAR. They used UST Hand Image Database and the evaluation results was FAR=0.31%, FRR=2.90%, and genuine acceptance rate GAR=96.80%. Although they achieved high recognition rate regarding the small size of the normalized ROIs, there wasn't nevertheless sufficient for integration in the multimodal recognition platform. While keeping the computational cost in both of feature extraction and for matching achieves lower GAR than those of the alternative solutions. The selected options could be solved using larger databases.

A. Kounoudes et al [6] presented a multimodal biometric combination of voice, face, finger, and palm for 30 individuals entered to the system using BOLYBIO datasets. They used 5 data captured sessions for each biometrics; 4 for training, and 1 for testing. They combine the single traits at the output level using simple voting scheme. The user is authenticated if the majority of individuals' modalities vote for authentication and rejected if the majority vote against. That idea is based on the weak classifier which led to powerful classifiers and achieving high performance in terms of both false acceptance rate (FAR) and false rejection rate (FRR) even in case of single modality verification is not tune for best performance. The evaluation

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results shows that for multimodal modality based on voting scheme at the output level have been achieved FAR reduced to 1.23% and FRR reached to 0.8%.

T. Zhang et al [7] presented three modalities face, palmprint and gait. They use geometry preserving projections (GPP) algorithm for subspace selection, which is capable of discriminating different classes and preserving the intra-modal geometry of samples within an identical class. The training stage is carried out for each biometric trait in subspace learning using GPP and then the classification in low-dimensional space is performed. They build two datasets one named as YALE-HKPU-USF, and the other named FERET-HKPU-USF. The recognition rate obtained using kernel GPP (KGPP) was 90.22% and 93.67 for the YALE-HKPU-USF and FERET-HKPU-USF datasets respectively compared with PCA, LDA, LPP, MFA, and GPP.

M. I. Razzak et al [8] proposed a technique that selects a few faces having minimum Euclidean distance and very close to each other and then they apply finger veins at score level fusion. They used Linear Discriminant Analysis (LDA) in order to extract both faces and finger veins entered to the system. The evaluation results show that the false acceptance rate (FAR) is reduced to 0.000026 and increased the genuine acceptance rate (GAR) to 97.4%. They used low-resolution web camera for face images and HITACHI finger veins device for finger veins images. The face and finger veins data are collected using 35 voluntary CAIRO staff and students, and they used C# environment for testing. We found that their system is tested using a small database and the GAR will be decreased for database expansion.

O. M. Aly et al [9] presented a multimodal biometric system based on fusing iris, palmprint, and finger-knuckle. The fusion process is performed using min-max normalization at matching score level. They used log-Gabor in order to extract both iris and palmprint features. The features of finger knuckle are extracted using linear discriminant analysis (LDA). They used 100 subjects collected from CASIA, HKPU, and finger knuckle datasets. The experimental results of their system achieved high recognition rate with total EER=0%. In order to document the results obtained, they need more experiments and a larger database. Also, they need a unified database that collects all biometric traits for the same subjects.

S. Sumathi and R. Malini [10] presented a fusion system based on hand geometry and palmprint. Discrete Wavelet Transform (DWT) was used for feature extraction, and Support Vector Machine (SVM) for classification. The fusion process is performed at matching score level. The experimental results investigated that GAR=99.47%, and FAR=0% using available GPDS Hand Database.

A fused system based on merging multibiometric traits of iris, fingerprint, face and palmprint is introduced by Gawande, and Hajari in [11]. Their system passed all recognition steps starting with the preprocessing step for each biometric trait. They used feature level fusion using convolution theorem which reduces FAR and FRR. Firstly they fuse the extracted features from both iris and fingerprint to obtain one feature vector using convolution theorem. The same way for face and palm using convolution theorem have been used. The final fused multimodal template is obtained by multiplying each resulting feature vectors. They used probabilistic neural network (PNN) and radial basis function (RBF) to classify input patterns. The identification phase is performed using adaptive Cascade based on the principles of mean and variance values for each query features and those stored in the database. The verification phase is based on back- propagation neural network (BPNN) that classifies users to Genuine/imposter. The results obtained are performed on several samples of CASIA Iris Database. Fingerprint samples are collected in their college, and both face and palm geometry are standard databases. The experimental results obtained are as follow: FAR=2% FRR=1.2% and GAR=98.8. That was done using 500 input images, 400 images used for training, and 100 images for testing. We noticed that they built their results on heterogeneous data collected the biometric traits using different databases resulting in an inaccurate and unrealistic identification process.

S. A. Nair et al [12] used palmprint, iris, and fingerprint traits extracted individually and fused together using sparse fusion mechanism. This mechanism interpreted the test database by sparse linear combination of training data. The observations from different modalities of the test subjected to share their sparse representation. They used peak signal to noise ratio (PSNR) in order to measure the quality of the input images based on Sopel edge detection. The fusion process was in

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feature extraction level which is required to preserve raw information. It is noticed that the database is not determined as they only mention CASIA database, also the size of templates not calculated. The purpose of that research was to fuse input images in feature extraction level and for noise improvement of the input templates. The major limitation is the difference between features extracted from different sensors as well as the large dimension of the resulted features.

N. Yusoff and M. F. Ibrahim [13] presented a combination of face, and voice using spike-time dependent plasticity (STDP). The training is based on spike neural network (SNN) paradigm consists of a number of neural networks that each group may represent stimuli or response. They used (PCA)-based Eigenfaces with singular value decomposition (SVD) and wavelet packet decomposition (WPD) in order to extract both face, and voice features respectively. Their proposed method is implemented using C++ and tested using MATLAB. The learning result of real images and sound was 77.33% accuracy.

In [14] different biometric traits have been used namely: Face modality of AR-Face database, iris modality of CASIA-Iris database, palmprint modality of PolyU-Palmprint (Pp) and Finger Knuckle Print (FKP) modality of DZhang FKP database. They used Log-Gabor filters to extract finger knuckle print features, then they use local phase quantization (LPQ) method to extract both the iris and palmprint features, finally they used principal component analysis (PCA) to extract the face features. Results investigated that the multimodal authentication process gained higher performance than a single modality.

In this research, we are seeking to overcome the shortages and limitation of the previously proposed approaches. Using SDUMLA-HMT [15] standard datasets for unified subjects and different biometric traits helps us to precise the results achieved as it will be illustrates in details later in this research.

3. GENERAL FRAMEWORK OF THE PROPOSED SCHEME

In this section, a new technique for human recognition using multimodal biometrics is presented. The proposed system based on using local binary pattern with variance (LBPV) for feature extraction, and using combined learning vector quantization classifier (CLVQ) for classification and matching. Three biometrics traits iris, face, and fingerprint were fused at decision level based on majority voting algorithm using SDUMLA-HMT database [15]. The proposed system involves a series of steps which are: data collection, enrollment, preprocessing, feature extraction, matching, classification, and decision as in Figure (3).

3.1 Data collection and Enrollment

Data collection is the first step through which the characteristic of the input patterns to the system is measured. The users' characteristic must be presented to a sensor. The output of the sensor, which is the input data upon which the system is built, the convolution of: (a) the biometric measure; (b) the way of the measure presented; and (c) the technical characteristic of the sensor [16].

The Enrollment process is vital step by which acquisition of set images stored in the database. These images are ready for preprocessing, feature extraction, matching, and classification. As shown in Figure (3) the system captures the biometric traits images for each individual entered to the system i.e. iris, face, fingerprint, and then stores the resulting digital format templates in the database. We used three databases folders for each biometric trait, each database folder, contains three subfolders inside it which are: input images, images after preprocessing, and templates after feature extraction process. The resulting templates stored in the database are then used for comparison with new samples entered to the system to determine whether there is a match for the recognition process. The forthcoming sections illustrate in details every stage in the proposed system.

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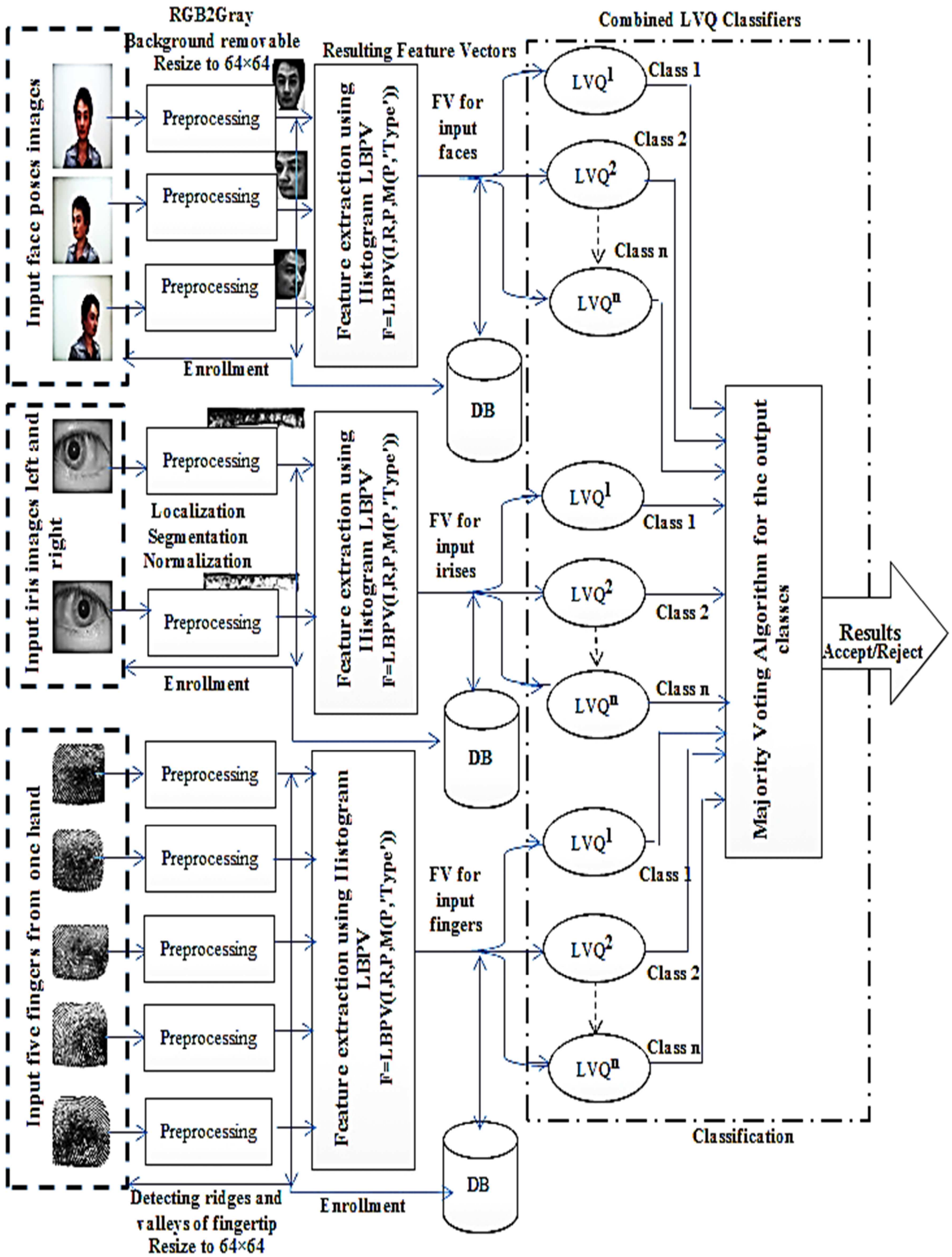

Figure 3: General structure of the proposed system.

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3.2 Preprocessing

The preprocessing step of any biometric system includes localization and detection of interested parts, segmentation which is the process of finding the biometric pattern within the input images, and finally normalization and resizing the input images. In this research, the preprocessing step is performed for face poses, iris images, and fingerprint images. Figure (4) shows the general block diagram of the preprocessing stage of the proposed system.

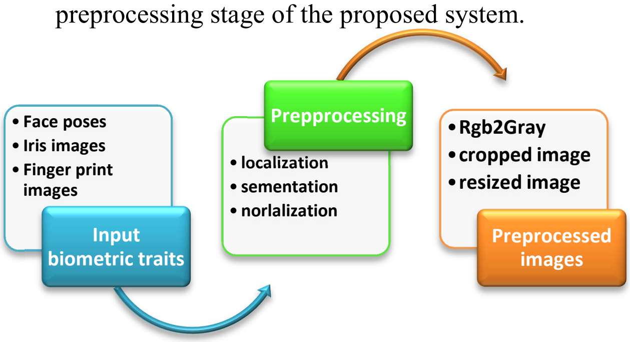

Figure 4: Preprocessing step for the proposed system.

3.2.1 Face Detection

For each individual submitted to the system, three poses of face images which are: normal, right, and left pose were taken in order to solve the posed problem in face recognition system.

The three poses images are firstly enrolled to the system before preprocessing, and then the preprocessing step is performed to get the preprocessed templates which are stored in a subfolder inside the database for the same person entered to the system. Figure (5) summarize face detection algorithm used in this research. First the input face images with a size of 640×480 are entered to the system. The RGB colored images are transformed to grayscale level with a fixed dimension of 256×256. Canny edge detection with a suitable threshold is used to detect the interested parts of the input images. A binary masked image is applied after creating a rectangular mask to detect face image. The resulting images are obtained from multiplying the input face images with the binary matrix to detect the face. Finally, the cropped images with a fixed size of 64×64 are obtained and stored in the database, ready for feature extraction step using LBPV.

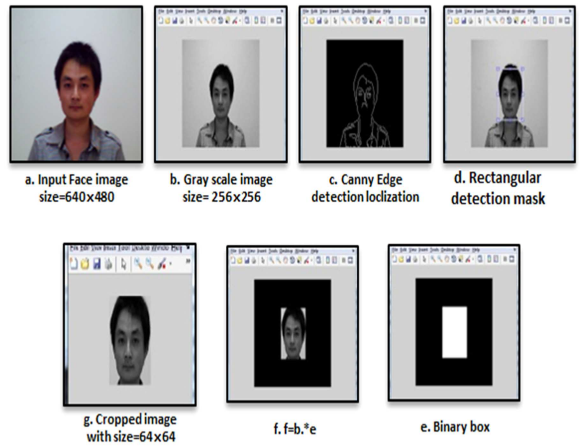

Figure 5: Preprocessing steps for face detection.

3.2.2 Iris Detection

Iris preprocessing in recognition process are includes the localization, the segmentation, and the normalization. Figure (6) investigate the steps of iris localization used in this research. Using canny edge detection and Hough circle transform achieves better results for iris localization and segmentation. Daugman rubber sheet model for iris normalization were used [17]. The experimental results showed that iris recognition system alone achieves better results than any other behavioral or physiological biometric. The use of multimodal biometrics is argent required need especially in case of the absence of any biometric trait the rest will be done the task for recognition process. However, there are some disadvantages of using iris as a biometric measurement [18]:

Begin

Step1. Read an input image (I2)

Step2. Using Canny Edge Detection for the input images.
Setting suitable threshold I1(i , j) and I2(i , j).
eI = edge (I2 , 'canny' ,suitable threshold);

Step 3. Determine the projection point inside the pupil by detecting the vertical and horizontal direction accumulator using Hough Circle Transform (HCT).
[y detect , x detect , Accumulator] = Hough circle (2 , 45 , 4)
For i = 1 to length of y detect
Plot (x detects , you detect , '. r')
End for;

Step 4. The output: pupil isolation
M = Circle (c , r , detect , y detect ,45)
*Out I = M*double (Input image)*
*Out I2 = (1 – M) * double (I2)*

End.

Figure 6: Proposed iris localization algorithm.

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(i) Small target (1 cm) to acquire from a distance (about 1 m) therefore it is hard to detect from a distance.
(ii) Illumination should not be visible or bright.
(iii) The detection of iris is difficult when the target is moving this is because it is dependent on the head movement, eye movement, and the pupil.
(iv) The cornea layer is curved, wet and there are some reflections. This causes distortions in the image.
(v) Eyelashes, corrective lens, and reflections may blur iris pattern, it also partially occluded by eyelids, often drooping.
(vi) Iris will deform non-elastically when the pupil changes its size.
(vii) Iris scanning devices are very expensive (cost).
(viii) Iris scanning is a relatively new technology and is incompatible with the very substantial investment that the law enforcement and immigration authorities of some countries have already made in fingerprint recognition.

Some of these disadvantages can be easily solved by using high-quality camera with a high-resolution pixel to get a free noise iris image. Also using canny edge detection and Hough Circle Transform can solve a noise problem to detect the pupil and to overcome the illumination problem. The preprocessing steps for iris detection are summarized in Figure (7). Input iris images from SDUMLA-HMT datasets have a dimension of 640×480 are resized to a fixed dimension of 256×256 and transformed to gray scale level. Canny edge detection and HCT are used to localize iris region

and to isolate the pupil by using a masked binary mask. Now the iris image with 64×64 fixed dimension has been cropped and ready for feature extraction using LBPV.

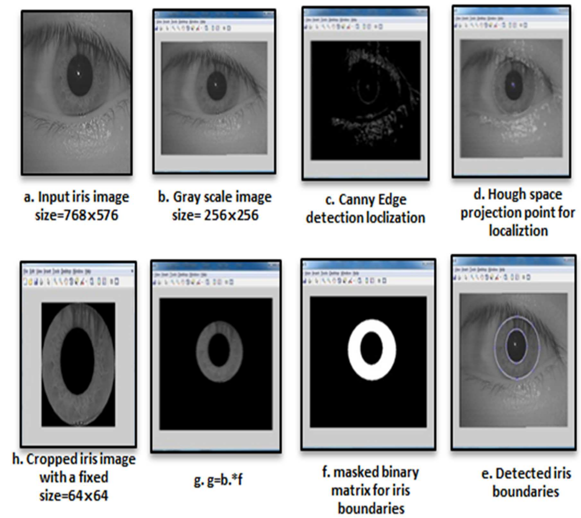

Figure 7: Preprocessing steps for iris detection.

3.2.3 Fingerprint Detection

A fingerprint is a pattern of ridges and valleys on the surface of fingertip. Fingerprint recognition is considered as the most popular biometric used in recognition and identification of persons entered to the system. Segmentation process is the most important step in fingerprint detection. Fingerprint is splitted into smaller regions by which the resulting local image features can be easily enhanced, analyzed, and extracted. In this paper, we use both Canny edge detection and Hough Circular Transform (HCT) in order to localize, segment, and enhance fingertip. The input fingerprint images have a fixed dimension of 200×152 from FT-2BU capacitance fingerprint scanner collected by SDUML-HMT database.

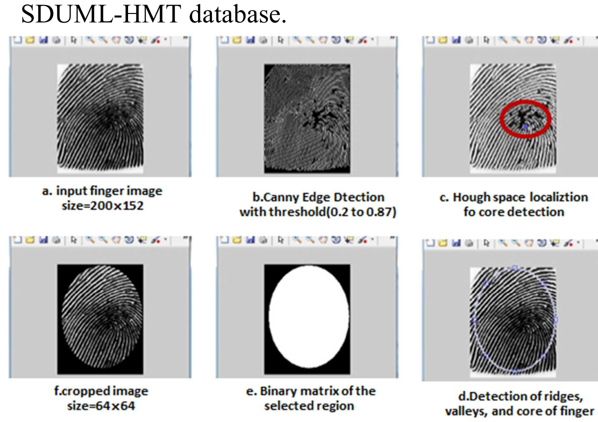

Figure 8: Preprocessing steps for fingerprint detection.

We get the final cropped fingerprint image after enhancement and localization of all input fingerprint images as shown in Figure (8). The

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resulting images with a fixed dimension of 64×64 are stored in the database, and then applies to feature extraction stage using LBPV histograms.

3.3 Feature Extraction

Data collection, enrollment, and preprocessing are the subsystems that take the longest time through the multimodal biometric system building process. Every person entered to the system takes undetermined time to enroll their biometric traits especially multibiometric traits. The robustness system requires speed, reliability, less cost, that is can be achieved using feature extraction and matching techniques with a very fast recognition methodology. In this research, we have elected the local binary pattern variance (LBPV) algorithm as feature extractor and Combined LVQ for matching and classification part. Believing that, this combination of LBPV and CLVQ classifier will achieve better recognition rates in less time with reliable results.

Local binary pattern with variance (LBPV) histograms are introduced by Z. Guo, L. Zhang, and D. Zhang [19] in order to overcome the drawbacks of local binary pattern (LBP) including losing the global spatial information as well as the global features of preserving information of little local textures. LBPV is used to characterize the local contrast information into one dimensional LBP histogram. LBPV is training free with no need of quantization. The LBP codes are computed using P sampling points of an intensity image I, for a circle of radius R, as in equation (1) and (2).

$$LBP_{P,R} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \qquad (1)$$

$$S(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \qquad (2)$$

Where g_c and g_p represents the gray value of the central pixel and the gray value of the p^{th} neighbor respectively. While the rotation invariant variance of an image is computed in equation (3) and (4):

$$VAR_{P,R} = \frac{1}{P}\sum_{p=0}^{p-1}(g_p - u)^2 \qquad (3)$$

Where

$$U = \frac{1}{P}\sum_{p=0}^{p-1} g_p \qquad (4)$$

$VAR_{P,R}$ needs quantization as it has continuous values. The joint distribution $LBP_{P,R}/VAR_{P,R}$ exploits the information of local spatial pattern and local contrast of an input images. The quantization process is done by calculating the feature distributions from all the training images to guarantee the highest quantization resolution. The threshold values are computed to partition the total distribution into N bins with an equal number of entries. These threshold values are used to quantize the VAR of the test images [20].

The major particular drawbacks of this quantization involve the need for a training stage in order to determine the threshold value for each bin. Second, the quantization is depends on multiple training samples resulting from different classes of textures with different contrasts and finally, it is difficult to obtain an adjustable number of bins in terms of performance and feature dimension. In [19] They listed solutions for solving $LBP_{P,R}/VAR_{P,R}$ problem by using LPBV descriptor, which is much smaller than LBP, Training free, and with no need of quantization. Traditional LBP histogram calculation achieves rotation invariance by clustering each row into one bin, which may cause the loss of global information, and hence two different texture images may have the same number of locally rotation invariant patterns. The VAR values are computed for the P sampling points with radius R and thus instead of computing the joint histogram of LBP and VAR globally, the LBPV computes the VAR from a local region and accumulates it into the LBP bin. This could be considered as the integral projection along the VAR coordinate. The LBPV histogram is determined using equation (5) as following:

$$LBPV_{P,R}(k) = \sum_{i=1}^{N}\sum_{j=1}^{M} w(LBP_{P,R}(i,j),k), k \in [0,1] \qquad (5)$$

$$w(LBP_{P,R}(i,j),k) = \begin{cases} VAR_{P,R}(i,j), & LBP_{P,R}(i,j) = k \\ 0 & otherwise \end{cases} \qquad (6)$$

In this research, we have used LBPV histograms in order to extract the features resulting from the preprocessing step for each biometric traits; face poses, iris images, and fingerprint images. The weighted sum of the resulting features is calculated using equation (7) which is derived from equation (5) and (6) in order to determine the total feature vector obtained from input face poses.

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$$F(LBPV_{P,R}(k))_{\tau} = LBPV_{P,R}(k)_1 + LBPV_{P,R}(k)_2 + ... + LBPV_{P,R}(k)_{\tau} \quad (7)$$

Where τ is the total number of features entered to the system. As shown in Figure (3) the resulting features from each biometric traits is given by

F=LBPV(I,R,P,M(P, Type)). Where I is the input image with size M×N, R is the radius, P is the sampling points, and Type representing the mapping type for LBPV codes.

In this research, we will use the three possible values for mapping the type of uniform LBPV patterns including:

i. 'u2' for uniform LBPV.
ii. 'ri' for rotation invariant LBPV.
iii. 'riu2' for uniform rotation- invariant LBPV.

Once the features are extracted using LBPV, combined LVQ classifier are applied in order to classify, and match the resulting templates which are stored previously in the database after feature extraction stage.

3.4 Combined LVQ Classifier

The last stage in the proposed multimodal biometric system is the matching and classification of the input templates stored in the database. Classification is an important step as it is used to classify objects and observations from different sources. Combined LVQ classifier is a combination of learning vector quantization (LVQ) classifiers. These classifiers may be weak and/or strong, where the weak classifiers are generated using automatic elimination of redundant hidden neurons of the network. In this research, we elected the LBPV to extract the biometric features for the stored templates. The extracted features are entered to each LVQ classifier as feature vector and the output are the classes. The decision is based on majority voting algorithm available from input classifier. We believe the proposed system is capable of achieving better classification results with less training time, and high performance. The evaluation results investigated that high recognition rates are achieved with a large and variable database.

The illustrative architecture of the LVQ is shown in Figure (9) [21]. The resulting extracted features from LBPV are the input vector for each LVQ and the output layer is dependent on the weighted vectors for the competitive layer. The Euclidean distance between the input vector and the weighted vector is determined as in equation (8).

$$D(j) = \sqrt{\sum_{i=1}^{n} (x_i - w_{ij})^2} \quad (8)$$

Where i are the number of input features of $x=(x_1, x2,...x_n)$, and j represented the output neurons. The LVQ training algorithm is shown in Figure (10) [22].

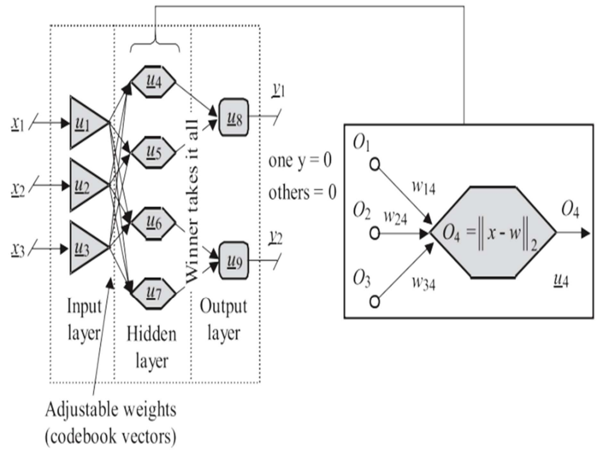

Figure 9: Learning Vector Quantization Architecture [21].

Step 0. Initialize weight vectors to the first m training vectors, where m is the number of different categories and set α(0). This weight initialization technique is presented here is only one of many different method such as random value, one of the training samples, and the mean of the training sample for this class.
Step 1. While stopping condition false, *do steps 2 to 6.*
Step 2. For each training input vector *x*, *do steps 3 to 4.*
Step 3. Find *j* so that the Euclidean distance *D(j)* is minimum.
Step 4. Update the weights of j neurons as follows:

if T=Cj then
Wj(new) =Wj(old)+ α(x- Wj(old))
if T ≠ Cj then
Wj(new) =Wj(old)- α(x- Wj(old))

Step 5. Reduce learning rate α.
Step 6. Test stopping condition: This may be a fixed number of iterations or the learning reaching a sufficiently small value.
Note: *α is the learning rate where 0 ≤ α ≤ 1.*
T is correct category for input x.
Cj is the category represented by the pre-assigned jth neurons.

Figure 10: LVQ training algorithm [22].

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The combined classifier is defined as the combination of classifiers that are used to overcome the problems of variance and bias. Combined classifiers are used for complex pattern recognition systems as well helping to achieve better efficiency and performance of the whole system. Equation (9) shows a simple form of combined classifier [23].

$$f_k(x) = \sum_{k=1}^{K} w_k h_k(x) \quad (8)$$

$h_k(x)$ are a sets of total K models defined on a feature vectors, and w_k the weighting factor for the k^th model. In the case of multiple classes, the combined model becomes a combined classifier C(x), such that:

$$C(x) = I\,(f_{k(x)}) \quad (9)$$

And;

$$I(z) = \begin{cases} 1 & z > 0 \\ 0 & z \le 0 \end{cases} \quad (10)$$

The fusion is in decision level by which multiple decisions are collected from the combined classifier outcomes. There are different methods for combining the outcomes from divergent classifiers are: majority voting, collection of ranked outputs, and front end supervised classifier. In this research, we have elected the majority voting algorithm to decide whether acceptance/rejection patterns results from combined LVQ classifier. Figure (11) clarifies the algorithm steps of the proposed LBPV/combined LVQ classifier.

Step 1. Initialize the Combined LVQ classifier network.

Step 1.1: Upload features from LBPV histograms.

$F(LBPV_{P,R}(k))_\tau = LBPV_{P,R}(k)_1 + LBPV_{P,R}(k)_2 + ...+ LBPV_{P,R}(k)_\tau$

64×64 Byte→ for P=8, R=1 →No. of bins=455(HLBPV).

64×64 Byte→ for P=16, R=2→ No. of bins=165(HLBPV).

64×64 Byte→for P=24, R=3→ No. of bins=100(HLBPV).

Input layer size:

Training set size = (50, or 100, or 200, or 500)

Number of classes (Nc):

Nc= 5, or 10, or 20, or 50 Class.

Number of hidden layer neurons(NH):

NH=NC × # of templates/person.

NH= (50, or 100, or 200, or 500) hidden neurons.

Learning Rate (α):

α = 0.01, 0.02, 0.03, 0.04, 0.05.

Number of training epochs (β) (# of iterations):

β = 100, 300, 500, 1000.

Number of required classifiers (γ)

γ = 5, 10, 20, 50.

Number of blind neurons (NB)

NB = 0.

Step 1.2: Initialize the weighted matrix for competitive layer w1.

Step 1.2: Initialize the weighted matrix for linear layer w2.

Step 2: Training patterns stage.

Step 2.1: For each classifier:

Select a specific # of CLVQ parameters: (α, β, γ, NH).

Train on LVQ

Test on LVQ on the training sets.

Repeat for a specified LVQ.

Step 2.2: Determine the diversity matrix between each classifier.

Step 2.3: Determination of the diversity threshold level.

Step 3: Testing patterns stage.

Step3.1: Determine number of committee classifiers.

Step3.2: Combination of decisions based on committee classifiers.

Step3.3: Final Accept/Reject decision based on majority voting algorithm.

Step3.4: Saving the results in a file.

Step 4: Majority Voting Algorithm

For i = 1 to No of LBPV patterns for test.
For j = 1 to Nc
vote[j]= 0;
End for;
For X= 1 to No of committee classifier.
Y= Recognition result [X, i];
vote[Y] = vote[Y] + 1;
End for;
Winner Class = Max (vote);
End for.

Figure 11: Proposed (LBPV/Combined LVQ Classifier) Algorithm.

4. EXPERIMENTAL RESULTS

Evaluation results are performed using SDUMLA-HMT database. The data base contains 5 biometric traits which are: face, fingerprint, finger vein, iris, and gait. Numbers of subjects are 106 subjects including 61 males and 45 females with age between 17 and 31. Table 4 illustrates the description of samples used in the proposed system taken from SDUMLA-HMT database.

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Table 4: The Gallery Database Collected Out Of SDUMLA-HMT Database.

Biometric Traits	***# of images***	***Images size & format***	***Trained images***	***Tested images***
Face	8904 7×(3+4+2+3) × 106 7 cameras. 3 poses. 4 expressions. 2 accessories. 3 illuminations.	640×480 pixels 24bit .bmp	318 106×3 poses	318 106×3 poses
Iris	1060 2×5×106 5 right 5 left	768×576 Gray-level .bmp	212 106×2 1 left 1 right	212 106×2 1 left 1 right
Fingerprint	25440 5×8×6×106 5 sensors 8 impressions for each 6 finger.	152×200 FT-2BU Gray-level .bmp	530 106×5 5 fingers	530 106×5 5 fingers
Total number of collected images out of SDUMLA-HMT reference database			1060	1060

As shown in Figure (3), three databases folders for each biometric trait are collected. Each database folder contains three subfolders inside it which are: input images, images after preprocessing, and templates after feature extraction process. The resulting templates stored in the database are then used for comparison with new samples entered to the system to determine whether there is a match for the recognition process. The extracted features results from LBPV histograms are categorized into two sets: A training set contains 1060 FV, and a testing set of 1060 FV. The resulting histogram of LBPV obtained is shown in Figure (12). We noticed that the histogram of LBPV is reduced which indicates feature vector reduction as seen in Figure (12. d). In similar way for iris and fingerprint, the LBPV histograms are reduced to achieve better classification and matching results. To evaluate the results of the proposed system, many experiments are performed as following: in identification mode: when 5 persons claim to enter the system out of 106 subjects as shown in Figure (13).

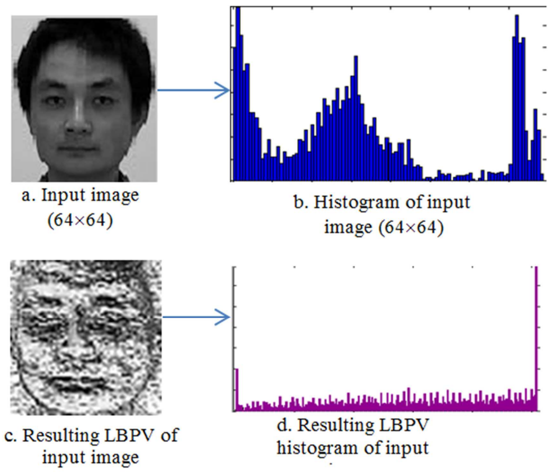

Figure 12: LBPV Histogram For Face Input Images

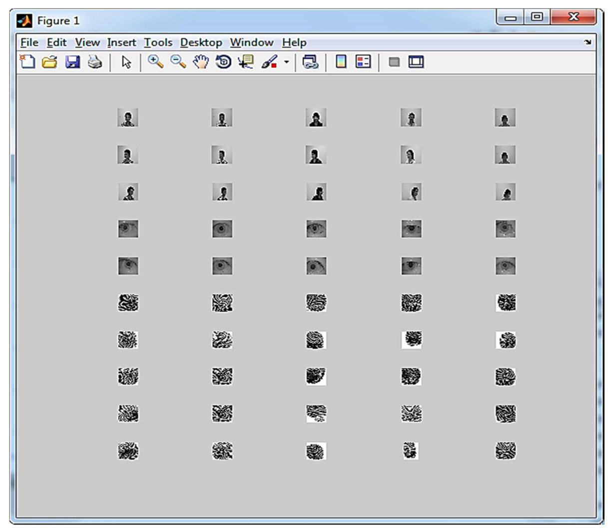

Figure 13: The 5 Person's Claims To Enter The System (10 templates per person).

Using the following combined LVQ parameter networks α=0.01, β=300, Nc=5, the results are shown in Figure (14). The horizontal bar includes the number of input templates (50 templates per 5 person's claims to enter the system), and the vertical bar includes the GAR (Genuine Acceptance Rate). Training the input 50 templates with the templates stored in the database using majority voting algorithm based on LBPV histograms with CLVQ classifier achieves better results than other unimodal biometric iris, face, and fingerprint traits. The training process of the proposed combined LVQ classifier is shown in Figure (15) by which *W* are the weighted vectors of *P* training vectors.

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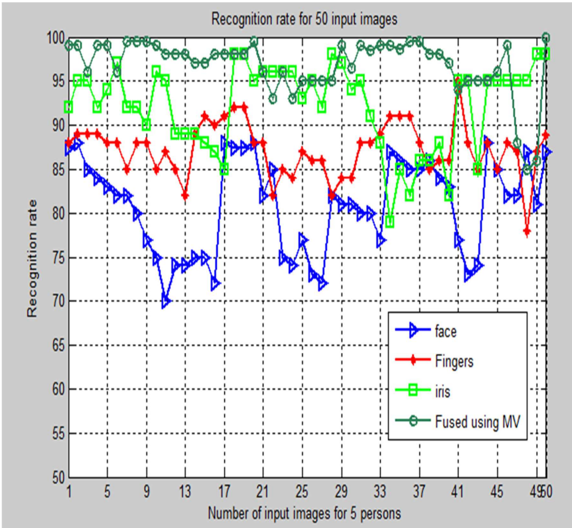

Figure 14: GAR for 50 input templates out of 5 persons. Given α=0.01, Nc=5, and β=300.

Measurements of the system performance depends up on the following factors: Number of input templates (extracted LBPV features) for each subjects, number of classes (Nc), number of hidden neurons NH, number of learning rate (α), and Number of training epochs (β).

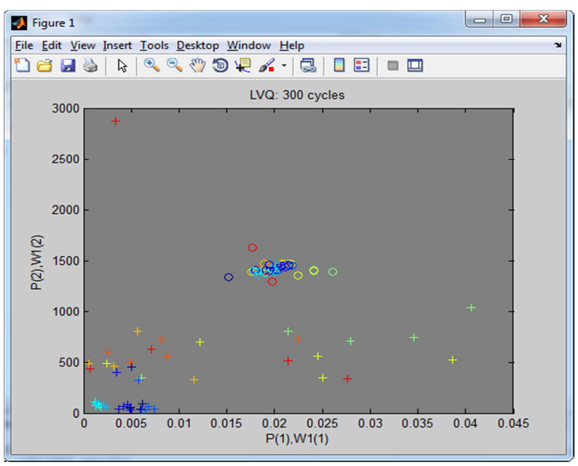

Figure 15: Combined LVQ classifier training with β=300, NH=200 and threshold=0.035.

The threshold value of the diversity matrix between each classifier is determined as shown in Figure (15) as 0.035, where the values above this value are rejected and accept the values under 0.035 are accepted. The threshold value is calculated and adjusted using trial and error method. The relation between mean square error (MSE) and the number of iteration (β) of the proposed system is shown in Figure (16). Table 5 shows the GAR results for different LBPV histograms for (P=8, R=1), (P=16, R=2), and (P=24, R=3). Given α=0.01, β=300, and NH=100 for 100 templates per 10 persons claims to enter the system out of 106. Table 6 summarizes the GAR using differentα, β, and NH for training and testing modes.

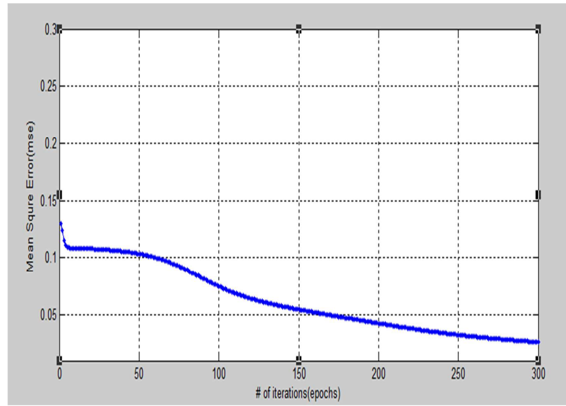

Figure 16: Mean square error (MSE) versus the number of training epochs (β).

We found that from Table (5) higher GAR is obtained in the case of using $LBPV_{24,3}$ with α=0.01, β=300, and NH=100 for 100 templates per 10 persons. Higher α, β, and NH leads to higher genuine acceptance rate (GAR) as shown in Table (6). The elapsed time is determined with respect to the different training and testing modes. The elapsed time varies according to the number of persons claimed to enter the system. For 5 persons claiming to enter the system the elapsed time was 24 sec, and in case of 10 persons claiming to enter the system the overall elapsed time was 88 sec. The GUI for the proposed system is shown in Figure (2) which summarizes all steps shown in Figure (3). The performance is calculated for every stage in whole proposed system including preprocessing, feature extraction, and classification that are shown in Figure (17). The elapsed time is determined for different parts of the proposed multimodal biometric system as shown in Figure (18). Table (7) summarizes the performance and elapsed time for the proposed system.

Table (8) summarizes a variety multimodal biometrics for recent approached listed in the survey and the proposed system. The evaluation metrics involve biometric fusion, methodology, database used, fusion level, and system performance. The evaluation results in Table (7) indicate the superiority of the proposed system over the state of art.

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Table 5: The GAR For Multimodal Biometric Traits Face, Iris, And Fingerprint Traits For Different $LBPV_{P,R}$.

Biometric Traits	Face			Iris			Fingerprint			Fused		
	$LBPV_{8,1}$	$LBPV_{16,2}$	$LBPV_{24,3}$	$LBPV_{8,1}$	$LBPV_{16,2}$	$LBPV_{24,3}$	$LBPV_{8,1}$	$LBPV_{16,2}$	$LBPV_{24,3}$	$LBPV_{8,1}$	$LBPV_{16,2}$	$LBPV_{24,3}$
class 1	77.43	84.77	88.09	82.43	90.77	94.09	81.43	89.77	90.09	88.43	96.77	96.09
class 2	66.43	81.09	89.07	71.43	87.09	95.07	70.43	86.09	91.07	77.43	93.09	97.07
class 3	66.22	81.03	89.99	71.22	87.03	95.99	70.22	86.03	91.99	77.22	93.03	97.99
class 4	66.44	82.98	90.87	71.44	88.98	96.87	70.44	87.98	92.87	77.44	94.98	98.87
class 5	66.54	83.98	91.45	71.54	89.98	97.45	70.54	88.98	93.45	77.54	95.98	99.45
class 6	77.13	84.67	92.54	82.13	90.67	98.54	81.13	89.67	94.54	88.13	96.67	99.95
class 7	86.62	85.54	93.75	71.62	91.54	99.75	80.62	90.54	95.75	77.62	97.54	99.56
class 8	75.08	83.73	88.34	90.08	89.73	94.34	79.08	88.73	90.34	66.08	95.73	98.34
class 9	84.89	86.44	87.54	86.89	92.44	93.54	88.89	91.44	89.54	75.89	98.44	99.50
class 10	77.76	85.43	86.45	82.76	91.43	92.45	89.76	90.43	88.45	88.76	97.43	98.45

Table 6: Training And Testing GAR For Different α, β, And NH.

α	NH	β	GAR (Training)	GAR (Testing)
0.01	100	300	97.28	97.34
		500	98.34	98.45
		1000	98.72	98.82
	200	300	97.33	97.65
		500	98.56	98.66
		1000	98.90	99.01
	500	300	97.95	98.02
		500	97.96	98.87
		1000	98.88	99.07
0.1	100	300	98.77	98.93
		500	98.79	98.99
		1000	99.30	99.38
	200	300	98.87	98.88
		500	98.32	98.75
		1000	99.32	99.45
	500	300	97.89	97.90
		500	97.98	98.98
		1000	99.33	99.45
0.3	100	300	97.23	97.65
		500	98.65	98.78
		1000	98.61	98.84
	200	300	97.88	97.92
		500	98.07	98.09
		1000	99.43	99.45
	500	300	97.75	97.87
		500	98.87	98.94
		1000	99.49	99.50

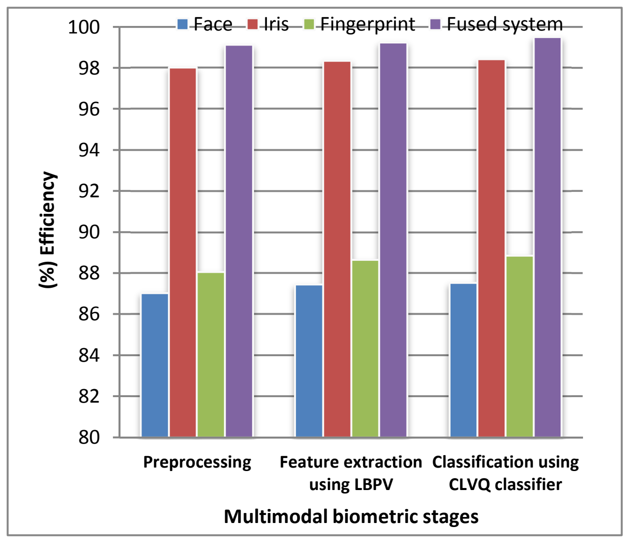

Figure 17: The Efficiency Of Different Parts Of Proposed Multimodal Biometric Traits System.

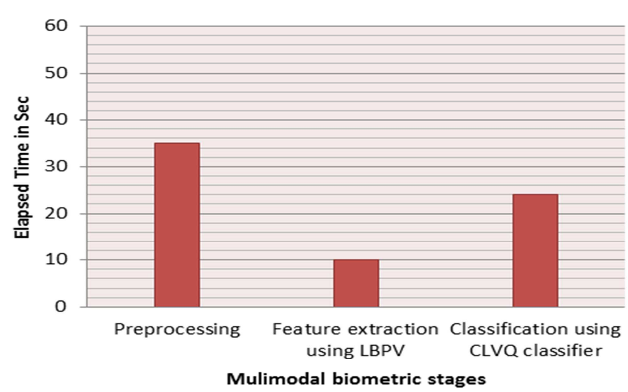

Figure 18: The Elapsed Time Of Different Parts Of Proposed Multimodal Biometric Traits System.

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Table 7: Efficiency And Elapsed Time For The Proposed Multimodal Biometrics System Stages.

Multimodal biometric stages	*Efficiency (%)*	*Elapsed Time(sec)*
Preprocessing	99.12	35
Feature Extraction using LBPV	99.23	10
Classification using CLVQ classifier	99.50	24

5. DISCUSSION

In this research, we have presented a new technique for a multimodal biometrics system based on fusing face, iris, and fingerprint traits. Canny edge detection and Hough circular transform (HCT) are used for preprocessing stage. Local binary pattern with variance (LBPV) histograms are used to extract the preprocessed iris, face, and fingerprint images where, the resulting feature vector length is very small with a low dimension that reaches up to 3000 bit. The features extracted from LBPV templates are then classified using combined learning vector quantization classifiers (CLVQ) with variable parameters that are directly affecting the recognition process results. These parameters include:

1. P, R: represented the P sampling pixel of radius R of the preprocessed templates for feature extraction using LBPV. The results shows that in case of P=24, and R=3 higher GAR achieved.
2. Nc: number of classes used in the classification process which are relays on the subjects claims to enter the system.
3. NH: number of hidden neurons which are depends up on the input templates that entered the system.
4. α: represents the learning rate of the entire LVQ network ranges from 0.01 to 0.5. Increasing of α leads to improvements of GAR results of the whole system.
5. β: represents the training epochs or the number of iteration of the entire LVQ network. Also increase of β will increase the recognition rate of the whole systems.

A decision level fusion is performed through which majority voting algorithm is used to choose the acceptable classifiers. For the training process, we have used different number of subjects' claims to enter the system. Starting with 5 subjects representing 50 templates and the GAR was 99.50% with 24 sec elapsed time. Then using 10 subject representing 100 templates entered to the system and the average GAR was 99.25% with 88 sec elapsed time. Finally the proposed system was examined using large scale subjects by which 20 and 50 subjects representing 200 and 500 templates claimed to enter the system. The average GAR was 99.2% and 99.09% with elapsed time 120 sec and 180 sec for 20 and 50 subjects respectively. The experimental results indicate the robustness of the proposed system accomplished by high recognition rate, high recognition speed, and minimum needed time. The major limitation of the proposed system is the complexity of different parts, including preprocessing, feature extraction, and classification. That can solved by using different fusion stages such as sensor or feature extraction fusion levels. The proposed system needs scalability i.e. large scale datasets more than 106 subjects so we are intended to use additional databases as CASIA multimodal biometric database in a heterogeneous mode test. The comparison results of our proposed system with recent approaches proofs that the proposed system are more reliable and achieves high recognition rate than other approaches with minimum elapsed time.

6. CONCLUSION AND FUTURE WORK

A sequential hybrid multimodal biometric system based on Local Binary Pattern with Variance (LBPV) histograms and Combined Learning Vector Quantization (CLVQ) classifier is proposed in this research. The proposed system is fused at decision level using majority voting algorithm of the input classes resulting from CLVQ classifier. LBPV histograms are elected to achieve better matching performance producing a lower feature dimension resulted from the preprocessed input templates. The preprocessing stages are performed for face, iris, and fingerprint images using canny edge detection and Hough circular transform. The posed problem of face recognition was handled using three poses of face images to detect persons trying to access the system from any side of his face. The evaluation results indicates higher recognition rate with minimum needed time compared to the state of art. Researchers intended to proceed with the proposed system to enhance system complexity produced by different stages through using different fusion levels at sensor and feature extraction.

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Heterogeneous mode test using CASIA multimodal biometric database is also required in order to evaluate large scale multi modal biometric systems.

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Table 8: Recent Multimodal Biometric Approaches And The Proposed Multimodal Biometric System.

Author	*Biometric Traits Fusion*	*Methodology*	*Database Used*	*Fusion Level*	*Performance*
A. K. Jain, and A. Ross [4]	Face + Fingerprint + Hand geometry	Learning user-specific matching thresholds and weights for individual biometric traits.	Digital Biometrics sensor database. Panasonic CCD.	Matching score level fusion	FAR=2% GAR=98%
T. Sanches et al [5]	Hand geometry+ Palmprint+ Fingerprints	35 features of one hand that are statistically analyzed for discriminability. HD for matching.	UST Hand Image Database.	Matching score Level fusion	FAR=0.31% FRR=2.90% GAR=96.80%
A. Kounoudes et al [6]	Voice + Face + Finger + Palmprint	HMM + MFCC coefficients. Simple voting scheme.	30 individual using BOLYBIO.	Decision level using majority voting algorithm	FAR = 1.23% FRR = 0.8%
T. Zhang et al [7]	Face + Palmprint + Gait.	GPP + KGPP	YALE-HKPU-USF FERET-HKPU-USF	Decision level fusion.	GAR = 90.22% GAR = 93.67%
M. I. Razzak et al [8]	Face + Finger Vein	LDA for feature extraction, ED for matching.	35 voluntary CAIRO staff and students.	Matching score level fusion.	FAR=0.000026 GAR=97.40%
O. M. Aly et al [9]	Iris + Palmprint + Finger-knuckle	Log-Gabor LDA	CASIA, HKPU, and finger knuckle datasets.	Min-Max normalization at matching score level.	EER=0% GAR= 99.03%
S. Sumathi and R. Malini [10]	Hand geometry + Palmprint	DWT for feature extraction. SVM for classification.	GPDS Hand Database.	Matching score level fusion	GAR=99.47% FAR=0%
U. Gawande, and K. Hajari [11]	Iris + Fingerprint + Face + Palmprint	PNN + RBF +Convolution theorem	CASIA Iris Database, Fingerprint samples collected in their college, and both Face and palm geometry databases is standard database.	Feature Extraction Level fusion.	FAR=2% FRR=1.2% GAR=98.8%
S. A. Nair et al [12]	Palmprint + Iris+ Fingerprint	Sparse fusion mechanism	CASIA database.	Feature extraction level	Not determined
N. Yussof, and M. F. Ibrahim [13]	Face + Voice	STDP + PCA +WPD +SVD	ORL datasets samples for face and TIDigits speech samples.	Feature extraction level	GAR= 77.33%
H. Almahfaza, and M. Z. AlRawashdeh [14]	Face + Iris + Palmprint + FKP	Log-Gabor filters + LPQ + PCA	CASIA-Iris database. Poly U- Palmprint. D. Zhang FKP database	Feature extraction level fusion.	FAR=1% GAR=94%
M. Y. Shams et al Proposed system	Face +Iris+ Fingerprint	Canny edge detection + HCT for preprocessing. LBPV for feature extraction. CLVQ for classification.	SDUMLA-HMT datasets contains 106 subjects.	Decision level using majority voting algorithm	EER=0.03% GAR= 99.50%