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Multi-Modal Biometric Recognition System: Fusion of Face and Iris Features using Local Gabor Patterns

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Abstract: Biometrics, described as the science of recognizing an individual based on her physiological or behavioral traits, is beginning to gain acceptance as a legitimate method for determining an individual's identity. Multimodal biometric system utilizes two or more individual modalities, e.g., face, gait, iris and fingerprint, to improve the recognition accuracy of conventional unimodal methods. Multimodal biometric systems overcome problems such as noisy sensor data, non-universality or lack of distinctiveness of the biometric trait, unacceptable error rates, and spoof attacks by consolidating the evidence obtained from different sources. In this paper, we have developed an efficient technique for multimodal biometric recognition using the face and iris images. In our proposed technique, features from face and the iris images are extracted and the features from both the modalities are concatenated to form a combined feature vector, which also contains the number of irrelevant pixels in the iris image. The extraction process is done utilizing both the local Gabor patterns and the LBP to form LGXP (Local Gabor XOR Patterns). For recognition, the combined feature vector of a face and iris image are extracted and is compared with the database. The average matching score is calculated, which is based on the distance measure and also on the given weightage based on the irrelevant pixels. Based on the average matching value, the decision is to be made whether the test image is recognized or not. For experimental evaluation, we have used the face and iris image databases and the results clearly demonstrated that the proposed technique provided better accuracy in biometric recognition.

Keywords:- Biometrics, Multi-modal biometrics, Face Recognition, iris recognition, Gabor feature, LBP operator (Local Binary Pattern), Local Gabor XOR Patterns.

I. INTRODUCTION

Biometric authentication has been getting widespread attention over the past decade with growing demands in automated secured personal identification [9]. This is owing to the reason that old-fashioned automatic personal identification tools, which use approaches such as Personal Identification Number (PIN), ID card, key, etc., to verify the identity of a person, are no longer considered reliable enough to gratify the security necessity of person authentication system [10]. A biometric scheme delivers automatic recognition of a person depending on some particular unique feature held by the individual [11].

Biometric traits comprises fingerprints, hand-geometry, face, voice, iris, retina, gait, signature, palm-print, ear and more [10]. A worthy biometric is described by usage of a feature that is; highly unique- so that the probability of different peoples having the same feature will be negligible, stable – so that the characteristics does not vary with time, and be easily captured – in order to provide ease to the user, and avoid distortion of the feature [11]. Some of the restrictions levied by unimodal biometric systems can be overwhelmed by adding several sources of information for the process of personal identification [12]. These systems, commonly referred to as multimodal biometric systems, are estimated to be more dependable because of presence of several, autonomous fragments of evidence [34]. These methods are able to encounter the rigorous performance foods levied by numerous applications. They address the problem of non-universality, since multiple traits safeguard adequate population coverage. They also prevent spoofing since it would be hard for a deceiver to spoof multiple biometric traits of a genuine user simultaneously [35].

One of the generally used biological features is the face recognition [14]. Face recognition has the aim of identifying individuals in photographs or videos from their facial appearance. When comparing is done with other biometrics, face recognition is found passive and does not necessitate supportive persons who are close to sensor or in contact with it [13]. Automatic recognition of human faces is an aggressively investigated part, which discovers many applications such as surveillance, automated screening, authentication or human-computer interaction. The face is an effortlessly collectible, universal and non-intrusive biometric [33], which makes it perfect for applications where other biometrics such as fingerprints or iris scanning are not possible.

Iris is the one of most reliable and accurate biometric feature among the present biometric features. Iris recognition is a largely recognized unmatched biometrics recognition technique in the world [15] considering its firmness, independence and non-invasiveness and it also has the potential for applications in widespread extents [17]. Iris is an externally visible, yet protected organ whose unique epigenetic pattern stays firm all over the adult life [18]. These physiognomies make it suitable for use as a biometric for identifying individuals. Image processing techniques can be used to obtain the unique iris pattern from a digitized image of the eye, and encrypt it into a biometric template, which can be stored in a database [19]. This biometric template comprises of an objective mathematical exemplification of the unique info stored in the iris, and permits evaluations to be done amongst the templates [18].

When a person desires to be recognized by iris recognition system, his/her eye is first photographed, and then a template is made for their iris region [19]. This template is then checked with the other templates which are stacked in a database until either a matching template is found and the subject is identified, or no match is found and the subject remains unidentified [20].

Biometric identification methods that make use of a single feature for identification (known as unimodal biometric systems) are regularly affected by several practical problems like noisy sensor data, non-universality or lack of distinctiveness of the biometric trait, unacceptable error rates, and spoof attacks [21]. This is because of the fact that the accuracy of single biometric system is easily affected by the dependability of the sensor used. Moreover, the single biometric systems have many domain-specific restrictions [10]. Multimodal biometric systems overwhelm many of these limitations by combining the proofs obtained from various bases [23], [22]. Multimodal biometrics has produced better accuracy [26] and population coverage, while decreasing susceptibility to spoofing. The vital feature to multimodal biometrics is the combination of several biometric modality data at the feature extraction, matching score, or decision levels [25], [24]. Many multimodal biometrics techniques and approaches have been proposed by various scientists [1-4]. In these works, the fusion of the many biometric features is made use of to make the unique recognition result. Directing at the same issue, we have integrated two biometric recognition systems, such as face and iris. The purpose is to improve overall error rate by utilizing as much information as possible from each biometric modality.

In the proposed approach, it consists of three modules 1) Feature extraction from face image, 2) Feature extraction from iris image and 3) Fusion of face and iris features. Initially, the features from the face as well as iris images are extracted by means of Local Gabor XOR Patterns that is the combined representation of Gabor feature and the LBP operator (Local Binary Pattern). Local Gabor patterns are constructed by encoding the Gabor phase utilizing the LGXP operator in a way that, the effective representation of face and iris feature can be made possible. Furthermore, to improve the performance in recognition, the features are extracted from the block-based representation of the face and iris images. Finally, the feature patterns obtained from the two modalities are fused using the proposed technique and it is stored as a combined feature vector for the face and iris images. For recognition, the combined feature vector of a face and iris image are extracted and a score is computed using distance measure and the weightage calculated. Based on the computed score value, the decision is to be made whether the test image is recognized or not. For experimental evaluation, we used the face and iris image databases and the results clearly demonstrated that the proposed technique provides better accuracy in biometric recognition.

The rest of the paper is organized as follows: Section II discusses some of the recent research works related to the proposed technique. Section III describes the proposed technique for iris and face recognition with all necessary mathematical formulations and figures. Section IV discusses about the experimentation and evaluation results with necessary tables and graphs and section V concludes the paper.

II. RELATED WORKS

The proposed technique concentrates on the extraction and recognition of features from the iris images and the face images. Several researchers have performed numerous researches using various techniques for the extraction of iris and face features. Here, we have presented some of the significant researches.

ShufuXie *et al.* [1] presented local Gabor XOR patterns (LGXP), which encrypted the Gabor phase by using the local XOR pattern (LXP) operator. Then, they presented block-based Fisher's linear discriminant (BFLD) to decrease the dimensionality of the proposed descriptor and at the same time improve its discriminative power. Lastly, by using BFLD, they merged local patterns of Gabor magnitude and phase for face recognition. Then they assessed the method on FERET and FRGC 2.0 databases. They did comparative experimental studies of different local Gabor patterns. They also made a detailed evaluation of their combination with BFLD, as well as the fusion of various descriptors by using BFLD. Extensive experimental outcomes confirmed the efficiency of LGXP descriptor and also showed that fusion approach outdid most of the state-of-the-art approaches**.** Jie Lin *et al.* [2] presented a system for individual recognition by the fusion of iris and face. The system united the iris and faces features as a new feature for representing persons and then worked on the modified PUM on the new features for recognition. The iris feature was given a greater weight. They enhanced the method to build a better stratagem for joining the face and iris on recognition. The enhanced technique has been evaluated on combined-face and iris databases, using face testing images exposed to numerous sorts of partial distortion and occlusion. The system had verified better-quality performance over other systems.

Jun-Ying Gan and Jun-Feng Liu [3] presented a technique to the fusion and recognition of face and iris image based on wavelet features and kernel Fisher discriminant analysis (KFDA). At first, the dimension was condensed, the noise was removed, the storage space was saved and the efficiency was enhanced by discrete wavelet transform (DWT) to face and iris image. Secondly, face and iris features were extracted and fusion by KFDA. Lastly, nearest neighbor classifier was chosen to perform recognition. Experimental results on ORL face database and CASIA iris database proved that not only the dasiasmall sample problem was overcame by KFDA, but also that the correct recognition rate was greater than that of the face recognition and iris recognition. Shoa'aJadAllah Al-Hijaili and ManalAbdulAziz [4] have presented a work to apply the multimodal biometric fusion system to the highest level of security in the hierarchical architecture of electronic medical record (EMR). Multimodal biometric identification system was developed by merging information from both face and iris unimodal. After suitable normalization of scores, fusion was done at the matching score level using weighted scores.

The effect of different number and quality of training and testing image combinations were tested on four combination sets (CS1-CS4). They found that the multimodal biometric was a method to decrease the quality requirement of images.

Baochang Zhang *et al.* [5] designed an object descriptor for face recognition by means of histogram of Gabor phase pattern (HGPP). In HGPP, the quadrant-bit codes were first mined out from faces based on the Gabor transformation. Global Gabor phase pattern (GGPP) and local Gabor phase pattern (LGPP) were then suggested to encode the phase variations. They were then both separated into the non-overlapping rectangular regions, from which spatial histograms were extracted and concatenated into an extended histogram feature to denote the original image. Lastly, the recognition was executed by using the nearest-neighbor classifier with histogram intersection as the similarity measurement. The technique was positively applied to face recognition, and the experimental outcomes on the large-scale FERET and CAS-PEAL databases showed that the proposed algorithms expressively accomplished well.

Harin Sellahewa and Sabah A. Jassim [6] proposed adaptive methods to face recognition to win over the opposing effects of changing lighting conditions. Image quality, which was measured in terms of luminance distortion in comparison to a known reference image, was used as the base for familiarizing the application of global and region illumination normalization techniques. Image quality was also used to adaptively process fusion parameters for wavelet-based multi-stream face recognition.

Zhenan Sun and Tieniu Tan [7] presented a technique using ordinal measures for iris feature representation with the aim of embodying qualitative relationships between iris regions rather than exact dimensions of iris image structures. Such a illustration caused loss of some image-specific information, but it achieved a good trade-off between uniqueness and toughness. They presented that ordinal measures were intrinsic features of iris patterns and largely invariant because to the illumination changes. Besides, firmness and low computational complexity of ordinal measures resulted in highly efficient iris recognition. They established multi-lobe differential filters to calculate ordinal measures with flexible intra-lobe and inter-lobe parameters such as location, scale, orientation, and distance. Experimental results on three public iris image databases proved the efficiency of the proposed ordinal feature models.

Ryan N. Rakvic *et al.* [8] proposed a more direct and parallel processing alternative using field programmable gate arrays (FPGAs), proposing an opportunity to increase speed and potentially alter the form factor of the resulting system. Within the means of this project, the most time-consuming operations of a modern iris recognition algorithm were deconstructed and directly parallelized. Furthermore, the parallel algorithm on FPGA also significantly outstripped the calculated theoretical best Intel CPU design. Lastly, on a state-of-the-art FPGA, they settled that a full implementation of a very fast iris recognition algorithm was more than feasible, resulting in a potential small form-factor solution.

III. PROPOSED MULTI-MODAL BIOMETRIC RECOGNITION SYSTEM USING FACE AND IRIS FEATURES

Multimodal biometrics has shown a marked improvement in accuracy when compared to the single modal biometrics and have acquired vast applications in diverse fields. In the recent past, multimodal biometrics has have acquired deep interest among the scientific community. Use of multimodal biometrics have decreased problems such as noisy sensory data, error rates, spoof attacks and many more, which were the main disadvantages of using a single trait for recognition. In the proposed technique, we combine the iris and the face traits for the recognition system. Iris is the most dependable biometric in human body as it is unique and stable for the entire life period. A thin circular diaphragm, which lies between the cornea and the lens of the human eye, is called the iris. Extracting features is very much a complicated task and also is vital for iris recognition [30]. Face recognition techniques have also attracted much attention and has many potential applications in diverse fields. However lots of variations of image appearance such as pose variation, occlusion, image orientation, illuminating condition and facial expression are difficulties faced by the face recognition techniques. And combining these two prominent biometrics (face and the iris) would result in a more accurate and efficient recognition. In order to extract the features of the iris and the face, we make use of Gabor patterns and extract the features using the LGXP technique.

At first, the features are extracted from both the iris and the face image and then concatenated to form the combined vector which also consists of the number of irrelevant pixels in the iris image. The flow diagram of the Proposed System is sown in figure 1.

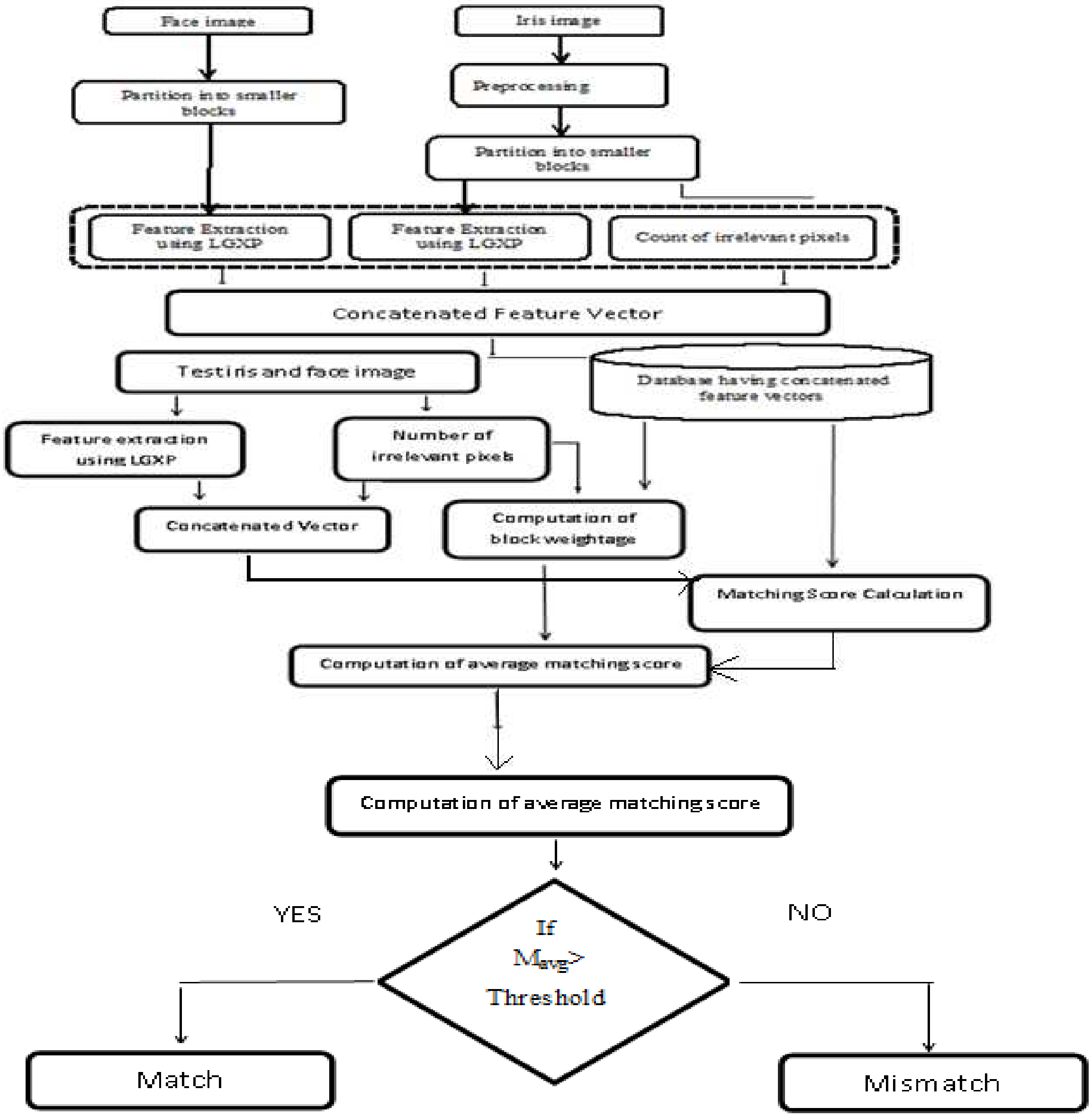

Figure 1: The flow diagram of the Proposed System

A. Preprocessing of Iris Images:

Iris image is first converted into its normalized form using the preprocessing techniques before the feature extraction is made. Mostly, the normalized form of the iris image is used by the researchers to extract the features for iris recognition. Initially, in the preprocessing procedure, iris segmentation is done which consists of detecting the iris boundary. Detecting the inner and outer boundaries of the iris texture is extremely important for effective feature extraction. Integro-differential, Hough transform and active contour model are some of the methods employed successfully for detecting the boundaries. We make use of Hough transform [29] for detecting the boundary of iris. Subsequently the segmented image is normalized where the iris image is unwrapped and transformed it into its polar equivalent. We employ Daugman's rubber sheet model [28] where the localized iris image are transformed into rectangular sized fixed image.

B. Extraction of Features from Iris and Facial Images:

In this phase, normalized iris image and the facial image is partitioned into multiple small blocks and the pixel values in each block are formed into vector. Subsequently, $1-U$ vector is applied to linear scaling and LGXP, which provides the feature vector. The irrelevant pixels (pixels in the eyelash and eyelid region) in case of iris are calculated on each block for knowing block importance. Finally, we concatenate the feature vector of both the iris and the face image and also the count of irrelevant pixels of the iris image. The important steps involved in this phase are described as follows:

i. Partitioning of the normalized iris image and input facial image into multiple small blocks
ii. Conversion of block of size $d_1 \times d_2$ into $1-U$ Vector
iii. Performing LGXP on each block

iv. Concatenation of feature vectors of both the facial image and the iris image along with the count of irrelevant pixels of the iris image

a. Partitioning of Normalized Iris Image and the Input Face Image into Multiple Small Blocks:

The normalized iris images and the input facial images are at first partitioned into small blocks. The preprocessed normalized iris image contains vertical columns and horizontal rows which denotes the radial directions and the angular directions correspondingly. At first, we partition the entire normalized iris image into multiple small blocks as shown in fig.3. For example, a normalized iris image, $norm(I)$ is partitioned into blocks D_i, where $i = \{1,2,....n\}$, where n is the total number of blocks and the size of block is defined by $d_1 \times d_2$. Similarly, the partitioning of the face image into smaller blocks is done and it is shown in figure 2.

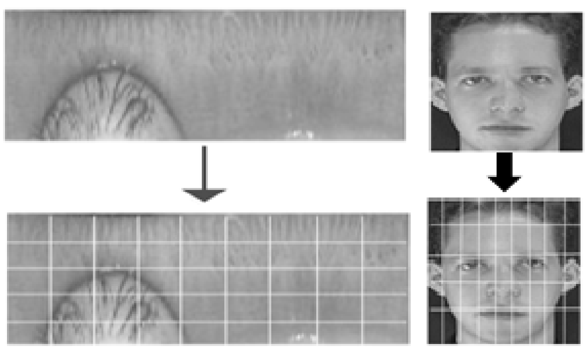

Figure. 2. Partitioning of face image and normalized iris image into multiple small blocks

b. Conversion of Block of Size $d_1 \times d_2$ into $1-U$ Vector:

In this conversion, every block is converted into its vector form. Let block D of normalized iris image $norm(I)$ be represented as follows.

$$D = \begin{pmatrix} D_1 \\ \vdots \\ D_y \\ \vdots \\ D_k \end{pmatrix}$$

Where, D_y represents gray values of the y^{th} row in the block of D,

The $1-U$ vector D_v is formed by concatenating all the rows present in the block D. Thus, Vector D_v of D is represented by,

$$D_v = \left(D_1, \ldots D_y, \ldots D_k\right)$$
$$= \left(D_{v1}, \ldots D_{vi}, \ldots D_{vm}\right)$$

D_{V_i} define the pixel value of position i inside the vector D_v, and m is the number of total components in block D.

After the concatenation process and prior to the use of the obtained vector D_v directly for the subsequent step, change the average of each and every data set to zero by applying linear re-scaling [16] to each vector and normalize the standard deviation to unity. Hence, by calculating the mean $\bar{v}$ and variance $\sigma_v^{\ 2}$ of vector D_v, the linear re-scaled D_V^N can be computed using the following formula,

$$D_V^N = \left(D_V^N(1), D_V^N(2), \cdots D_V^N(i), \cdots D_V^N(m)\right)$$

Where, $D_V^N(i) = \dfrac{D_{V\,i} - \bar{v}}{\sigma_v}$, $1 \le i \le m$

$$\vec{v} = \frac{1}{m}\sum_{i=1}^{m} D_{V\,i} \ ,$$

$$\sigma_v^{\ 2} = \frac{1}{m-1}\sum_{i=1}^{m}\left(D_{V\,i} - \bar{v}\right)^2$$

c. Performing LGXP on Each Block of both the Normalized Iris Image and the Input Face Image:

In this, we apply LGXP to the normalized iris image and also to the face image. LGXP is applied on each of the rescaled 1-U vector D_V^N in order to obtain the feature of block D. After all the iterations, the LGXP generates a residual vector for both the iris and the face image. The feature vector F^q (residual) of the block in face image and the feature vector I^q which is feature vector of the iris are represented as follows:

$$F^q = (F_1^q, F_2^q, \ldots\ldots\ldots\ldots, F_m^q)$$
$$I^q = (I_1^q, I_2^q, \ldots\ldots\ldots\ldots....., I_m^q)$$

where, F^q *and* I^q represents the residual of the LGXP results of D_V^N.

a) LGXP: Local Gabor XOR Patterns: Initially the image is passed through the Gabor filter, where the convolution of the image with the Gabor kernels is done to get the required output, i.e.,

$$G_{\mu,v}(z) = I(z) * \varphi_{\mu,v}(z)$$

Here, $I(z)$ denotes the input image, and * denotes the convolution operator; z denotes the pixel and μ, v denotes the Gabor kernel with orientation and scale, which is defined as follows

$$\varphi_{\mu,v}(z) = \frac{||k_{\mu,v}||^2}{\sigma^2} e^{\frac{(-\left||k_{\mu,v}|\right|^2 ||z||^2)}{2\sigma^2}} \left[\, e^{ik_{\mu,v}z} - e^{-\frac{\sigma^2}{2}}\right]$$

Where $\left||x|\right|$ denotes the norm operator, the wave vector is defined as follows:

$$k_{\mu,v} = k_v e^{i\emptyset_\mu}$$

Where $k_v = \frac{k_{max}}{f^v}$ and $\emptyset_\mu = \frac{\pi\mu}{8}$; k_{max} is the maximum frequency and f is the spacing between kernels in the frequency domain.

For each Gabor kernel, at every image pixel, a complex number containing two Gabor parts, with real part $Re_{\mu,v}(z)$ and imaginary part $Im_{\mu,v}(z)$ can be generated. Based on these two parts, magnitude $A_{\mu,v}(z)$ and phase $\emptyset_{\mu,v}(z)$ can be computed by the following formulas:

$$A_{\mu,v}(z) = \sqrt{Im^2_{\mu,v}(z) + Re^2_{\mu,v}(z)}$$

$$\emptyset_{\mu,v}(z) = arctan(\frac{Im_{\mu,v}(z)}{Re_{\mu,v}(z)})$$

In LGXP, we make use of the phase information of each pixel and then processing it and plotting histograms in response to the analysis made on each pixel. Here, the basic idea is to alleviate the sensitivity of Gabor phase to the varying positions. We can see that, when the two phases belong to the same interval they have almost similar local features and otherwise, they reflect different local features.

The LGXP works as follows:

i. At first, in a LGXP Descriptor phases are quantized into different ranges. The number of phase ranges is made such a way that to make the patterns robust to the variations of Gabor phase, hence cannot be too high. After the quantization process each of the phase value is quantized into the quantized level values.

$$q(\emptyset_{\mu,v}(k)) = i$$

$$if\ \frac{360 * i}{b} \leq \emptyset_{\mu,v}(k) < \frac{360 * (i+1)}{b}, i = 0,1, \dots, b-1$$

$\emptyset_{\mu,v}(k)$ is the phase value of the pixel and $q(\emptyset_{\mu,v}(k))$ is the quantized value of the phase and b is the number of phase ranges.

In our case, we have taken b as 4, so that we get 4 phase ranges and are given the table below.

Table 1. Quantized phase value for the input phase

Phase Range(in degrees)	Quantized Phase Value
0-89	0
90-179	1
180-269	2
270-359	3

We have opted for four phase range levels which achieve a good balance between the robustness to phase variations and representation power of local patterns.

ii. Subsequently LGXP operator is applied to the quantized phases of the central pixel and each of its neighbors. $LGXP^i_{\mu,v}(P = 1,2, \dots, P)$ denotes the pattern calculated between z_c and its neighbor z_i, which is computed as follows:

$$LGXP^i_{\mu,v} = q(\emptyset_{\mu,v}(z_c)\ XOR\ q(\emptyset_{\mu,v}(z_i))$$

$\emptyset_{\mu,v}(z_c)$ where denotes the phase and $q(\emptyset_{\mu,v}(z_i))$ is the quantized value of the phase and where $z_c$denotes the central pixel position in the Gabor phase map with scale v and orientation μ, P is the size of neighborhood. XOR operation is defined as follows:

$$A\ XOR\ B = \begin{cases} 1, & A = B \\ 0, & otherwise \end{cases}$$

iii. Finally the resulting binary labels are concatenated together as the local pattern of the central pixel.

$$LGXP_{\mu,v}(z_c) = \left[LGXP^P_{\mu,v}, LGXP^{P-1}_{\mu,v}, \dots\dots\dots, LGXP^1_{\mu,v}\right]_{\boldsymbol{binary}} = \sum_{i=1}^{p} 2^{i-1}.\ LGXP^i_{\mu,v}$$

95	336	145
232	135	78
164	186	262

(a)

1	3	1
2	1	0
1	2	2

(b)

0	1	0
1		1
0	1	1

(c)

Figure. 3. Example of LGXP method where the phase is quantized into 4 ranges.

In the shown example (figure 3), (a) is the matrix showing the initial phase of the pixels after passing through the Gabor filter, (b) is the matrix obtained after the quantization and (c) is the matrix obtained after the XOR comparison with the center quantized value. From the matrix we infer that binary value obtained is 01011101 and its decimal value equivalent value of 93.

iv. With the pattern defined above, one pattern map is calculated for each Gabor kernel. Then, each pattern map is divided into non-overlapping sub-blocks, and the histograms of all these sub-blocks of all the scales and orientations are concatenated to form the LGXP descriptor.

$$H = \left[H_{\mu_0,v_0,1}, \dots\dots\dots\dots, H_{\mu_0,v_0,m}, \dots\dots\dots, H_{\mu_0-1,v_0-1,1}, \dots\dots\dots\dots, H_{\mu_0-1,v_0-1,m}\right]$$

Where $H_{\mu,v,i}$ $(i = 1, \dots. m)$ denotes the histogram of the i^{th} sub-block of LGXP map with scale μ and orientation v.

D. *Concatenation of Feature Vector and the Count of Irrelevant Pixels of the Iris Image and the Feature Vector of the Face Image*

We concatenate the feature vectors of both the iris and the farce image along with the count of irrelevant pixels in the face image. In order to provide accurate recognition of individuals, the most discriminating information present in an iris pattern must be extracted which will also include the noisy pixels. But if we remove all the noise blocks, then there is a chance of missing some useful information for efficient iris recognition. Therefore it is very important to know the importance of each block based on the relevant and irrelevant pixels. This is achieved by counting the number of irrelevant pixels in each block with the help of a threshold value. Thus, let the number of irrelevant pixels for a block D in the normalized iris image $norm(I)$ is represented as C_r. After finding out the number of irrelevant pixels in the iris image, we concatenate the feature vector of each block with its corresponding count of irrelevant pixels, and store the concatenated vector in the database for further processing.

The concatenated feature vector is given by:

$$T^q = (F_1^q, F_2^q, \ldots\ldots\ldots\ldots, F_m^q, I_1^q, I_2^q, \ldots\ldots\ldots\ldots\ldots, I_m^q, C_r))$$

Where F^q *and* I^q represents the residual of the LGXP results of D_V^N for the face and iris image respectively and C_r number of irrelevant pixels for a block D.

C. Feature Matching:

In feature matching, a test sample is taken and its concatenated feature vector comprising of the feature vector of both iris and the face and also the number of irrelevant pixels in the iris image is computed. Then, the matching score is calculated by comparing the feature vectors of the test iris image with the feature vectors of the iris images available in the database using a distance measure. The same process is done for the face image too. Here, block weightage is incorporated into the matching score so that the noisy blocks and important blocks obtain various score value. The following steps are involved in the matching phase.

i. Calculation of weightage based on irrelevant pixels on each block
ii. Score computation using Distance Metrics
iii. Average matching score based on weightage

a. Calculation of Weightage Based on Irrelevant Pixels:

The concatenated feature vector is computed for a test sample having both the iris and the face image and it is compared with the concatenated vectors of an iris image and face image of the database. For each block, we calculate the block weightage based on the irrelevant pixels of test sample and an iris and face image of database. Let the number of irrelevant pixels corresponding to the first block of a test sample be C_s and image of database be C_r. Then, the weightage W_y of the first block is calculated using the following formula,

$$W_y = \begin{cases} 1 - \dfrac{C_y}{d_1 \times d_2} \ ; & if \ \dfrac{C_y}{d_1 \times d_2} < 0.5 \\ 0\,; & otherwise \end{cases}$$

$$\text{where, } C_y = \max imum(C_r - C_s)$$

Using the above equation, the blocks are attained by three different set of values for instance, the block without noise obtain $W_y = 1$; the block with partial noise obtain $0.5 < W_y < 1$ and the block with noise obtain $W_y = 0$. Similarly, we compute the block weightage for every block with respect to test image and sample of the database.

b. Score Computation Using Distance Metrics:

We have adopted Euclidean distances (ED) measure for the score computation. Selecting an appropriate similarity measure for matching feature vectors is crucial and selection of distance measure compliments the proposed technique. This metric gives a score, which indicates the similarity between two feature vectors (test sample and images from database). Thus, for each block, the ED measure S_x between the feature vectors say T_r^q and T_t^q is determined using following equation,

$$S_x = ED(T_r^q, T_t^q) = \sqrt{\sum_{i=1}^{m} (T_{r_i}^q - T_{t_i}^q)^2}$$

c. Average Matching Score Based on Weightage:

In the previous steps, we have obtained a matching score and block weightage for all the blocks. These two values are then utilized to compute th0……………………e average matching score of the iris image. The following formula used for finding the average matching score M_{avg} is given as follows.

$$M_{avg} = \frac{\sum_{b=1}^{n} M_b}{\sum_{b=1}^{n}(1 - W_{y_b})}$$

$$\text{where } M = S_x \times (1 - W_y)$$

M →Weightage of block pair

We obtain the value (M_{avg}) after performing average matching of all the images. This value is used to decide whether the test sample is already present in the database or not. If the obtained value M_{avg} is less than the predefined threshold (P), then the test sample is present in the database.

IV. RESULTS AND DISCUSSION

The proposed technique for face and iris recognition is implemented in MATLAB. In this section, we discuss and analyze the proposed technique. In sub-section 4.1, the database used for the testing the proposed system is discussed. The sub-section 4.2 describes the overall experimentation used in the proposed technique. And in the section 4.3, the evaluation results are presented which shows that the proposed technique is more efficient compared to the baseline techniques.

A. Database:

For the purpose of testing and evaluation of proposed technique and rating its performance we have made of the face images from AT&T [32] and iris images from the CASIA iris image database [31]. We have made use of CASIA iris image database included 174 iris images from 50 eyes where for each eye, 7 images are captured. For the face 174 face images from AT &T were utilized having 25 faces where for each face, 7 images were captured. Face images and the Iris images from the databases are shown in figure 4 and 5 respectively.

B. Experimentation:

This section describes the experimentation of the proposed technique of the face and iris detection using iris images taken from the CASIA database and the face images taken from AT&T database. For training the features of iris, we have taken 100 iris images from different persons and an equal number of face images from them. The concatenated vector is computed for taken iris images and the face images using the proposed technique. For recognition phase, we have taken 325 iris images and face images that include trained and untrained iris images.

Figure. 4. Face images taken from AT & T face database

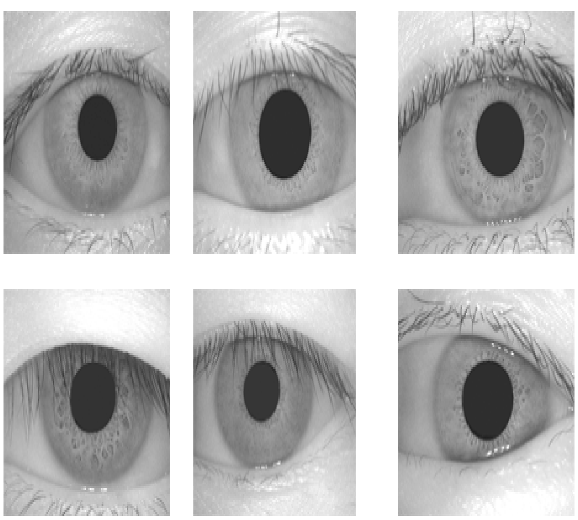

Figure. 5. Iris images taken from CASIA iris database

At first, the iris images are preprocessed which includes the stages iris segmentation and iris normalization. The input image and the corresponding segmented and normalized image are shown in figure 6. Each of the face image and the normalized iris image is partitioned into multiple small blocks and each block is converted into $1-U$ vector and rescaling is applied. Then LGXP is applied to each block for feature extraction. Then we calculate the number of irrelevant pixels in the iris image, C_r for each block which includes the pixels in the eye-lashes and the eye-lids for each block.

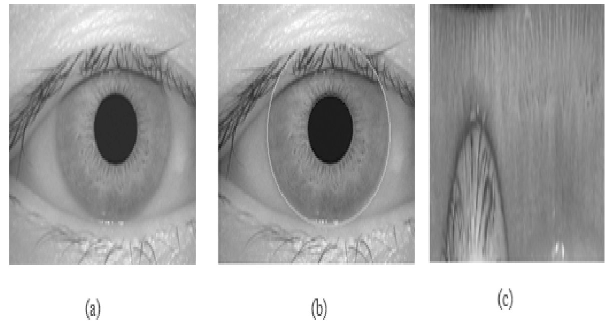

Figure. 6: (a) Input Iris image (b) Segmented iris image (d) Normalized iris image

Subsequently we form the concatenated vector having the feature extracted from the both the face and iris image, and also the number of irrelevant pixels in the iris image and is stored in the database. In the testing and evaluation phase, the concatenated vector is formed using the proposed technique and it is matched with vectors present in the database to find the average matching score M_{avg}. If the obtained value M_{avg} is greater than or equal to the threshold value, then there is a match else there is a mismatch.

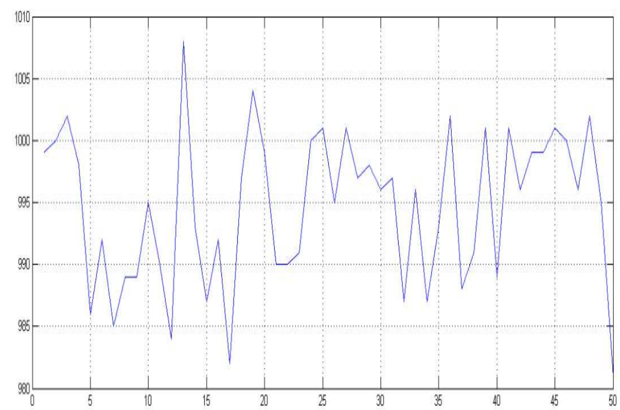

Figure. 7. The plot of LGXP of the combined iris image and face image

The above plot (Figure 7) shows the LGXP values that we got using our proposed technique. Here for every block, LGXP value is computed and plotted in the graph. The LGXP value for a block comprises of both the iris and the face image values. From the analysis made from the results obtained using the proposed technique, we can see that the performance of the proposed technique is more efficient when compared to that of the baseline technique.

C. Comparative Analysis:

In the comparative analysis, we present the evaluation results of baseline technique which is the LBP and the proposed technique LGXP. We measure the error rates in order to determine the accuracy of the face and the iris recognition system. There are two types of error rates namely, False Non-Match Rate (FNMR) and False Match Rate (FMR). FNMR is the probability rate at which the number of iris and face images which is erroneously received as Non-Match whereas FMR is the probability rate at which the number of face and iris images are erroneously received as Match. The accuracy measurement of the system is calculated using following formula:

$$Accuracy = 100 - \left[\frac{(FMR/FNMR)}{2} \right]$$

For comparison of baseline and the proposed technique, we have estimated the error rates of each technique separately using the iris database. The percentage of the recognition rates and the accuracy rate for the proposed technique using LGXP is calculated and compared to the baseline techniques and the performance of the proposed technique is evaluated.

Table 2: Comparison result of the proposed technique with the baseline technique.

CASIA Iris Database and AT & T Face Database			
	FNMR (%)	**FMR (%)**	**Accuracy (%)**
Baseline Technique (using LBP)	3.87	29.54	96.18
Proposed System (using LGXP)	4.08	20.42	97.498

Table 2 shows the performance of the proposed technique is evaluated with the help of parameters like False Non-Match Rate (FNMR), False Match Rate (FMR) and accuracy and is compared with those of the baseline technique. It is clear that the proposed technique outperforms the baseline techniques and has achieved a considerable improvement in the accuracy. We can see both FNMR and FMR have decreased by a great margin and hence resulting in the proposed technique achieving greater accuracy.

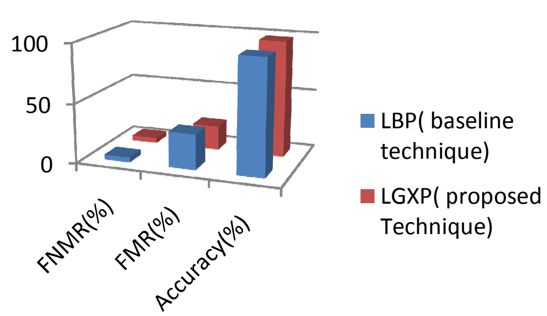

Figure. 8: Comparative results of the proposed technique and the baseline technique

In the figure 8, the graph shows the comparative results of the LGXP and LBP. It shows the comparative plot of FNMR, FMR and the accuracy. It is clear that LGXP has achieved a better result when compared to the LBP.

V. CONCLUSION

We have developed a multi-modal biometric recognition system for iris and face recognition using Local Gabor XOR Pattern (LGXP). The proposed technique consists of three modules, namely Preprocessing, Feature Extraction and Matching. The input iris image was preprocessed with segmentation and normalization processes and the normalized iris image obtained from the preprocessing step and the input face image after breaking down into blocks are done LGXP for extracting the features. The extracted features of the face and the iris along with the number of irrelevant bits in the iris are concatenated to form a single vector. For experimentation, we have used the *CASIA* iris image database and the AT & T face database and the evaluation results clearly demonstrated that the proposed technique provides better accuracy in iris and face recognition than the baseline technique.

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