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Matlab Implementation of Face Recognition Using Local Binary Variance Pattern

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Abstract— Face images can be seen as a composition of micro-patterns which can be well described by LBP (Local Binary Pattern). We exploited this observation on human face database for efficient representation in face recognition process. Here we divide face images into several blocks called facial regions from which we extract LBP and construct a global feature histogram that represents both the statistics of the facial micro-patterns and their spatial locations. Further, face recognition is performed on the basis of Euclidean distance. This face representation can be extracted in a single scan through the image, without any complex analysis. The algorithm performs well when all of the images are frontal.
Keywords— Face Recognition, Local Binary Pattern, Facial micro-pattern, Global feature Histogram.

I. INTRODUCTION

Biometrics consists of a set of automated methods for recognition or verification of individuals using physical or behavioural characteristics of such; as face, finger print, signature, voice, etc. This technology is based on the fact that each single person is unique and has distinctive features that can be used for identification [1]. Face Recognition is probably easier to understand, because we identify people by mainly their faces. However the recognition process used by the human brain for identifying faces has not a concrete explanation. Because it is now essential to have a reliable security systems in offices, banks, businesses, shops, etc. several approaches have been developed, among them the face-based identity recognition or verification systems are a good alternative for the development of such security systems [2].

II. LITERATURE REVIEW

Face Recognition has received significant attention during the last several years because it plays an important role in many application areas, such as human-machine interaction, authentication and surveillance, etc. Since past years, the problem of face recognition has attracted substantial attention from various disciplines and has witnessed an impressive growth in basic and applied research, product development, and applications. However, different biometric indicators are suited for different kinds of identification applications due to their variations in intrusiveness, accuracy, cost and ease of sensing [4], [5].

Several face recognition systems have already been deployed at ports of entry at international airports in Australia and Portugal , most of them provides fairly good recognition rates although presents several limitations due to the illumination conditions. In [1], author discussed about the various facial expression databases available with different variations like illumination, expression, size, shape, colour, and texture and compares performance ration on JAFFE database of facial expression recognition and consider 2-D Gabor filter to obtain palm print and texture feature extraction for authentication. They describe five modules to get satisfactory results which are Palm print Acquisition, Pre processing, Textured Feature Extraction, Matching, and at last Database is used to store template. In [5], author includes the validity of the component based methods, and how they outperform holistic methods. The local-feature methods compute the descriptor from parts of the face, and then gather the information into one descriptor. Among these methods are Local Features Analysis, Gabor features, Elastic Bunch Graph Matching , and Local Binary Pattern (LBP) . The last one is an extension of the LBP feature that was originally designed for texture description, applied to face recognition. LBP achieved better performance than previous methods, thus it gained popularity, and was studied extensively. Newer methods tried to overcome shortcomings of LBP, like Local Ternary Pattern (LTP), and Local Directional Pattern (LDiP). The last method encodes the directional information in the neighbourhood, instead of the intensity, explored the use of higher order local derivatives (LDeP) to produce better results than LBP. Both methods use other information, instead of intensity, to overcome noise. In [7], author discussed about the analytical approach proposed for the most stable, 2-d face feature extraction. Geometric features such as facial components (eyes, mouth, etc) shapes and Facial fiducially points (corners of the eyes, mouth, etc.) locations, or the presence of specific facial wrinkles, bulges, and the texture of the facial skin in areas including furrows are represented. Appearance-based independent component analysis filter features learned image (ICA), principal component analysis (PCA), local feature analysis

(LFA), Gabor filters, integral image filters (also known as box-like filters and defeat filter) are based on the age-oriented, histograms, etc features.

Several attempts have also reported using both geometric and presence features. Automatic facial expression analysis of these methods are referred to as hybrid methods, although it has been reported that based on geometric features methods often are outperformed by using Gabor wavelets or Eigen faces. There exist several methods for extracting the most useful features from (pre-processed) face images to perform face recognition. One of these feature extraction methods is the Local Binary Pattern (LBP) method. This approach was introduced in 1996 by Ojala et al.. With LBP it is possible to describe the texture and shape of a digital image. This is done by dividing an image into several small regions from which the features are extracted [4]. A number of typical algorithms are categorized into appearance based and model based schemes [7]. For appearance-based methods, three linear subspace analysis schemes are presented, and several non-linear manifold analysis approaches for face recognition are briefly described. The model-based approaches are introduced, including Elastic Bunch Graph matching, active appearance model and 3D morphable Model methods.

III.METHODOLOGY

The process of person identification by using face recognition can be split into three main phases. These are face representation, feature extraction and classification [6]. Face representation is the first task, that is, how to model a face. The way to represent a face determines the successive algorithms of detection and identification. For the entry-level recognition (that is, to determine whether or not the given image represents a face), the image is transformed (scaled and rotated) till it has the same 'position' as the images from the database. In the feature extraction phase, the most useful and unique features (properties) of the face image are extracted. With these obtained features, the face image is compared with the images from the database. This is done in the classification phase. The output of the classification part is the identity of a face image from the database with the highest matching score, thus with the smallest differences compared to the input face image [4]. Also a threshold value can be used to determine if the differences are small enough. After all, it could be that a certain face is not in the database at all. A model for face recognition is shown in Figure-01.

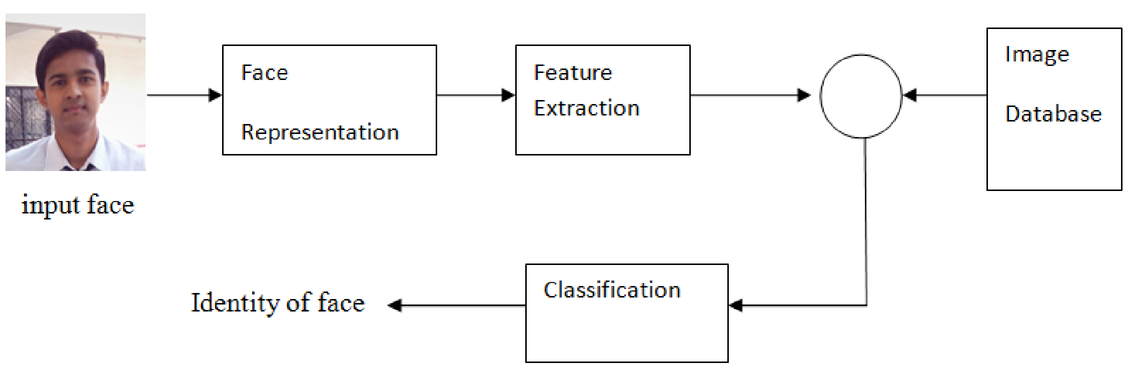

Fig.01 Principle used for an identification process of face recognition

A. Classification Of Face Recognition

Face recognition scenarios can be classified into two types: Face verification (or authentication) and Face identification (or recognition). In Face Verification it is a one-to-one match that compares a query face image against a template face image

whose identity is being claimed. To evaluate the verification performance, the verification rate (the rates at which legitimate users are granted access) vs. false accepts rate (the rate at which imposters is granted access) is plotted, called ROC curve. A good

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verification system should balance these two rates based on operational needs [2]. In face Identification it is a one-to-many matching process that compares a query face image against all the template images in a face database to determine the identity of the query face. The identification of the test image is done by locating the image in the database that has the highest similarity with the test image. The identification process is a "closed" test, which means the sensor takes an observation of an individual that is known to be in the database. The test subject's (normalized) features are compared to the other features in the system's database and a similarity score is found for each comparison. These similarity scores are then numerically ranked in a descending order. The percentage of times that the highest similarity score is the correct match for all individuals is referred to as the top match score. If any of the top similarity scores corresponds to the test subject, it is considered as a correct match in terms of the cumulative match. The percentage similarity scores is the correct match for all individuals is referred to as the "Cumulative Match Score". The "Cumulative Match Score" curve is the rank n versus percentage of correct identification, where rank n is the number of top similarity scores reported [7]. Image-based face recognition techniques can be mainly categorized into two groups based on the face representation which they use (i) Appearance based- It uses holistic texture features.(ii) Model based- It employs shape and texture of the face, along with 3D depth information.

B. Process Flowchart

The process flow chart is depicted in figure 02

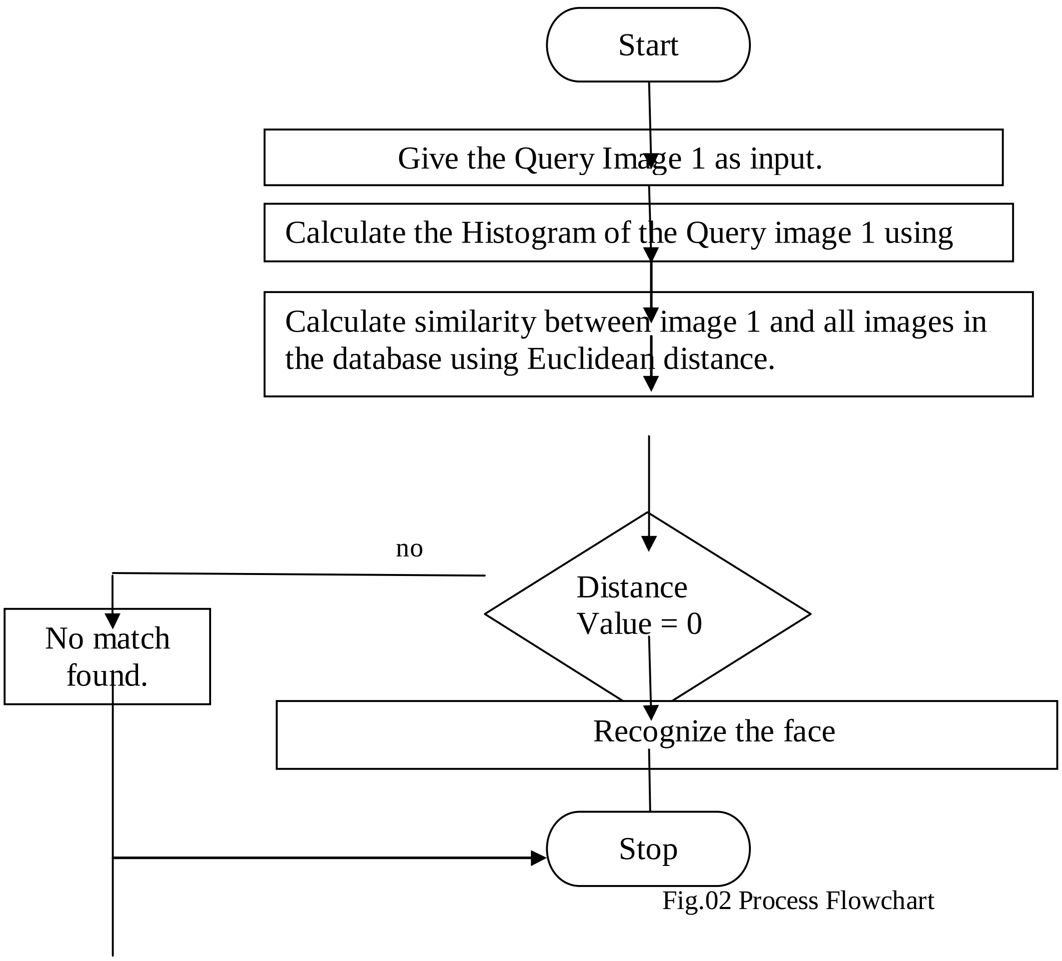

Fig.02 Process Flowchart

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C. Algorithm And Mathematical Analysis

The steps of algorithm are as follows,

Classify the each image by local binary pattern (LBP). In LBP consider the central pixel of the dividing image. After that compare central pixel with its neighbour pixel is given by,

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

$$s(x) = \begin{cases} 1; & x \geq 0 \\ 0; & x < 0 \end{cases} \qquad ......(1)$$

Where, g c =gray value of the central pixel,

gp = value of its neighbours,

P= number of neighbours,

R= radius of the neighbourhood ,

Mapping uniform pattern for P=8.All the non uniform pattern are grouped under miscellaneous label. Means the LBPPR to LBPPRriu2 , which has P*(P-1)+3 distinct output values. For this rotation invariant pattern the formula is given by,

$$H(k) = \sum_{i=1}^{N}\sum_{j=1}^{M} f(LBP_{P,R}(i,j),k), k \in [0,k]$$

$$f(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases} \qquad ....(2)$$

Find the local binary pattern variance (LBPV). It is a combination of LBPP,R/VARP,R which is powerful because it exploits the complementary information of local spatial pattern and local contrast . However, VARP,R has continuous values and it has to be quantized. This can be done by first calculating feature distributions from all training images to get a total distribution and then, to guarantee the highest quantization resolution [8].

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

$$w(LBP_{P,R}(i,j),k) = \begin{cases} VAR_{P,R}(i,j); & LBP_{P,R}(i,j) = k \\ 0; & otherwise \end{cases} \qquad ......(3)$$

Now find the LBPV histogram. A histogram of the labelled image fl(x, y) can be defined as

$$H_i = \sum_{x,y}\{f_1(x,y) = i\}, i = 0,\ldots..,n-1,$$

in which n is the number of different labels produced by the LBP operator and

$$I\{A\} = \begin{cases} 1, & A \text{ is true} \\ 0, & A \text{ is false} \end{cases}$$

This histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the whole image. For efficient face representation, one should retain also spatial information [5]. For this purpose, the image is divided into regions R0,R1, . . . Rm−1 and the spatially enhanced histogram is defined as

$$H_{i,j} = \sum_{x,y} I\{f_1(x,y) = i\} I\{f_1(x,y) \in R_j\}, i = 0,\ldots,n-1, j = 0,\ldots,m-1.$$

1) LBP Operator: Here we used LBP operator introduced by Ojala et al, where the operator labels the pixels of an image by thresholding the 3x3 neighbourhood of each pixel with the centre value and considering the result as a binary number. Then the histogram of the labels is used as a texture descriptor. Later the operator was extended to use neighbourhoods of different sizes [2]. Using circular neighbourhoods and bilinear interpolating the pixel values allows any radius and number of pixels in the neighbourhood. For neighbourhoods we will use the notation (P,R) which means P sampling points on a circle of radius R.

2) The LBP Equation: gc represents the gray value of the central pixel, gp is the value of its neighbours, P is the number of neighbours and R is the radius of the neighbourhood. Suppose the coordinates of gc are (0,0),then the coordinates of gp are given by (-R sin(2∏p/P),R cos(2∏p/P)). The gray values of neighbours that are not in the centre of grid scan be estimated by interpolation [5].

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

$$s(x) = \begin{cases} 1; & x \geq \\ 0; & x < \end{cases} \quad ....(4)$$

3) Histogram: For the image size of NxM. After identifying the LBP pattern of each pixel (i, j), the whole image is represented by building a histogram.

$$H(k) = \sum_{i=1}^{N} \sum_{j=1}^{M} f(LBP_{P,R}(i,j),k), k \in [0,k]$$

$$f(x,y)= \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases} \quad ....(5)$$

Where, K is the maximal LBP pattern value. The U value of an LBP pattern is defined as the number of spatial transitions (bitwise 0/1 changes) in that pattern [8].

A histogram of the labelled image fl(x, y) can be defined as

$$Hi = \sum_{x,y}\{f_1(x,y) = i\}, i = 0, \ldots.., n-1, \quad ....(6)$$

in which n is the number of different labels produced by the LBP operator and

$$I\{A\} = \begin{cases} 1, & A \text{ is true} \\ 0, & A \text{ is false} \end{cases} \quad ....(7)$$

This histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the whole image. For efficient face representation, one should retain also spatial information. For this purpose, the image is divided into regions R0, R1, . . . Rm−1 and the spatially enhanced histogram is defined as

$$Hi,j= \sum_{x,y} I\{f_1(x,y) = i\} I\{f_1(x,y) \in R_j\}, i = 0, \ldots, n-1, j = 0, \ldots, m-1.$$

4) Calculation Of Rotation Invariant Pattern: The locally rotation invariant pattern is defined as:

$$LBP_{P,R}^{riu2} = \begin{cases} \sum_{p=0}^{p-1} s(g_p - g_c) & ; if\ U(LBP_{P,R}) \leq 2 \\ P+1 & otherwise \end{cases} \quad .....(8)$$

5) Rotation Invariant Variance Measures (VAR)

A rotation invariant measure of the local variance can be defined as -

$$VAR_{P,R} = \frac{1}{P} \sum_{p=0}^{p-1} (g_p - u)^2 \quad .... (9)$$

where,

$$u = \frac{1}{P} \sum_{p=0}^{p-1} g_p.$$

Since LBP P,R and VARP,R are complementary, their joint distribution LBPP,R/VARP,R can better characterize the image local texture than using LBPP,R alone. Although Ojala proposed to use only the joint distribution LBPriu2 P,R =VARP,R of LBPriu2 P,R and VARP,R. other types of patterns, such as LBPu2 P,R, can also be used jointly with VARP,R. However, LBPu2 P,R is not rotation in variant and it has higher dimensions. In practice, the same (P, R) values are used for LBPriu2 P,R and VARP,R [7].

6) LBP Variance (LPV):

LBPP,R/VARP,R is powerful because it exploits the complementary information of local spatial pattern and local contrast. However, VARP,R has continuous values and it has to be quantized. This is done by first calculating feature distributions from all training images to get a total distribution and then, to guarantee the highest quantization resolution, some 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. There are three particular limitations to this quantization procedure. First, it requires to determine the threshold value for each bin. Second, because different classes of textures may have very different contrasts, the quantization is dependent on the training samples. Last, there is an important parameter, i.e. the number of bins, to be preset [6]. Too few bins will fail to provide enough discriminative information while too many bins may lead to sparse and unstable histograms and make the feature size too large. Although there are some rules to guide selection, it is hard to obtain an optimal number of bins in terms of accuracy and feature size. The LPBV descriptor proposed in this section offers a solution to the above problems of LBPP,R/VARP,R descriptor. The LBPV is a simplified but efficient joint LBP and contrast distribution method. As can be seen in Eq.(2), calculation of the LBP histogram H does not involve the information of variance VARP,R. That is to say, no matter what the LBP variance of the local region, histogram calculation assigns the same weight 1 to each LBP pattern. Actually, the variance is related to the texture feature. Usually the high frequency texture regions will have higher variances and they contribute more to the discrimination of texture images. Therefore, the variance VARP,R can be used as an adaptive weight to adjust the contribution of the LBP code in histogram calculation [3]. The LBPV histogram is computed as,

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

w(LBPP,R(i,j),k)= $\begin{cases} VAR_{P,R}(i,j); & LBP_{P,R}(i,j)=k \\ 0; & otherwise \end{cases}$ ……(10)

7) Rotation Invariant Matching

When an image is rotated in plane, the neighbourhoods, gp around the centre pixel, gc, will be rotated in the same direction. This rotation effect will result in different LBPP,R value. To remove a rotation effect, a circular bit-wise right shift operator, ROR(:), is applied to iterate P times in order to find the minimal decimal value of the binary pattern [4]. The rotation invariant LBP operator, LBPri P,R, mentioned is defined as,

$$LBP_{P,R}^{ri}(x,y) = \min\{ROR\left(LBP_{P,R}(x,y),i\right) \quad | \, i \in [0,P-1]\,\}$$

Traditionally, LBP histogram calculation achieves rotation invariance by clustering each row into one bin. Such an operation loses the global information, and hence two different images may have the same number of locally rotation invariant patterns. In Fig. 4.11, each column in the first seven rows is a 450or -450 rotation of its adjacent column. Fig. 4.10 shows another example. Suppose an image contains 256 (i.e. P=8) possible LBP patterns and the frequency with which each pattern occurs in the image is represented by the number in the pattern, as shown in Fig. 4.11(a). If the image is rotated 900 clockwise, then a new LBP histogram will be created, and Fig. 4.11(a) becomes (b) [6].

This observation suggests the feasibility of designing a rotation invariant matching scheme using rotation variant LBP patterns. This could be done by exhaustively searching for the minimal distance from all candidate orientations but that would be computationally prohibitive. Rather, our proposed global matching scheme first uses the extracted LBP features to estimate the principal orientations, and then aligns the features to the principal orientations to compute the matching distance. Further feature dimension reduction can be achieved by reducing less important patterns [4].

IV.RESULT & DISCUSSION

A. Image Database

Following images were captured and used as database (figure.03)

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Figure.03 Image Database

Figure.04 shows the recognized image stored in database. Image given as an input to the system is matched with the actual database and the Euclidean distance is matched. The command window of MATLAB in figure.04 shows that the third match (in database images-top side) is shown where the Euclidean distance is zero in case of the pixel to pixel matching. The histogram also represents the similarity between both the images.

Figure.05 shows the unrecognized image which is different from the images of the database. Also the Euclidean distance of that image is not matched with any of the database images which can be seen in its respective command window.

Figure.06 shows the rotation variant matching feature which is done with the help of LBPV pattern. The image is tilted at 90 degrees; the image still can be recognized because of rotation variant matching technique. Likewise the images related to the database rotated at any angle can be recognized by this algorithm.

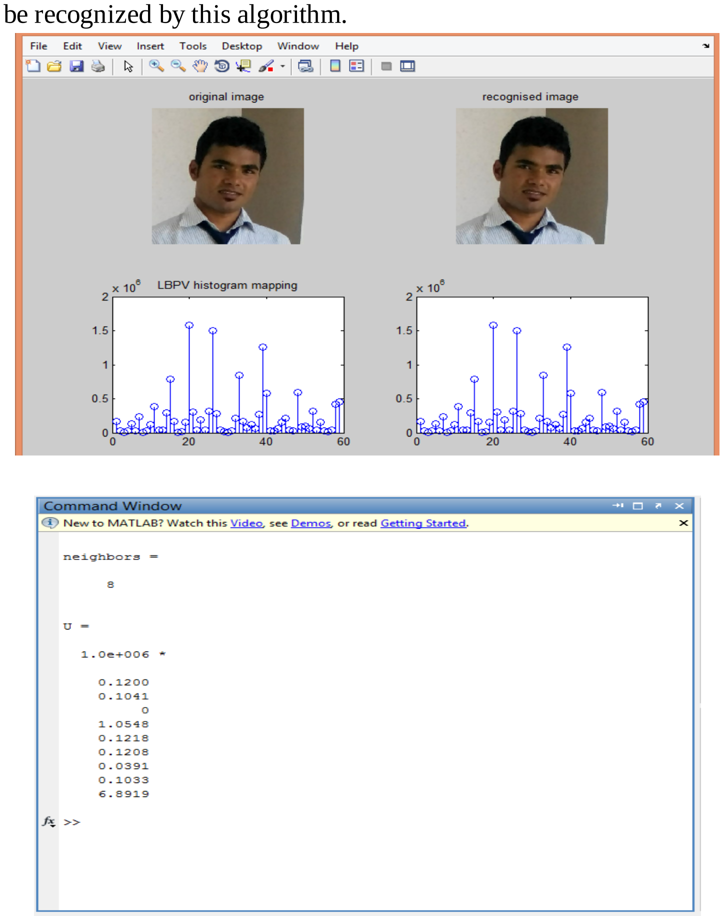
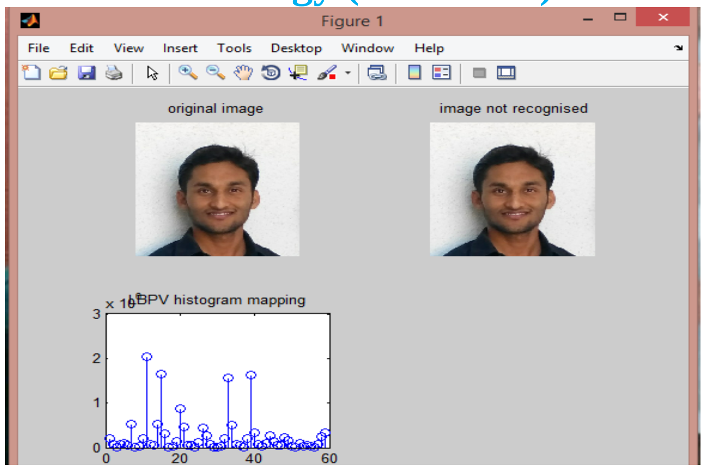


Figure.04 Recognized Image



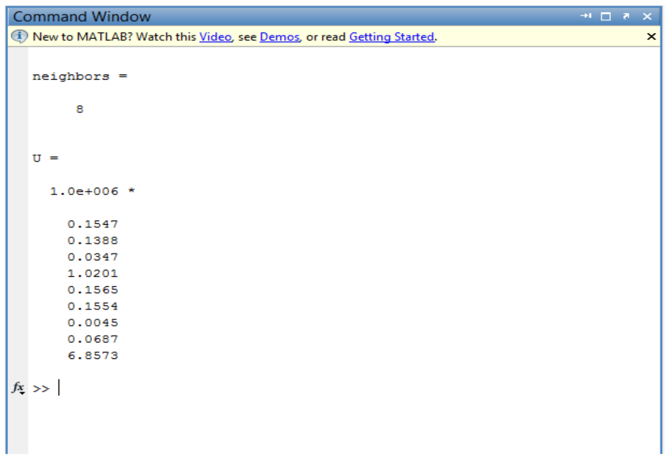
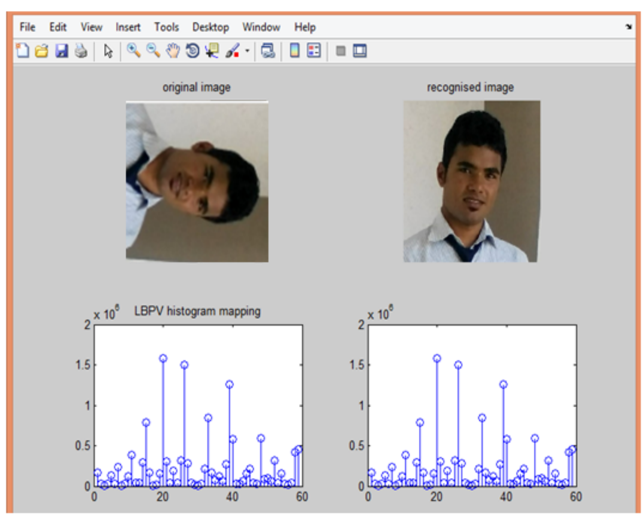


Figure.05 Unrecognized Image



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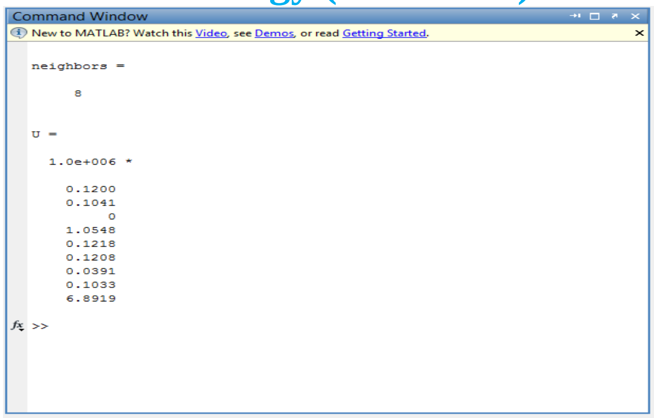

Figure.06 Rotation variant pattern (Image rotated in 90 degrees either wise)

The algorithm has been implemented for determination of face recognition using LBP. It is obvious that the results of this face recognition system are good but there is scope for future improvement. The main improvement will pursue the performances, recognizing the real-time face recognition. Difficulties has been faced when recognizing face images from database such as pose and lighting variations, expression variations, age variations, and facial occlusions. In future to improve the pose correction, quality based frame selection, aging correction, and mark based matching techniques can be combined to build a unified system for video based face recognition. One of the most difficult tasks for modern facial recognition systems is recognizing faces in non-frontal images. Facial recognition systems perform well when all of the images are frontal. But, as a subject becomes more and more off angle (both horizontally and vertically), performance decreases.

V. ACKNOWLEDGMENT

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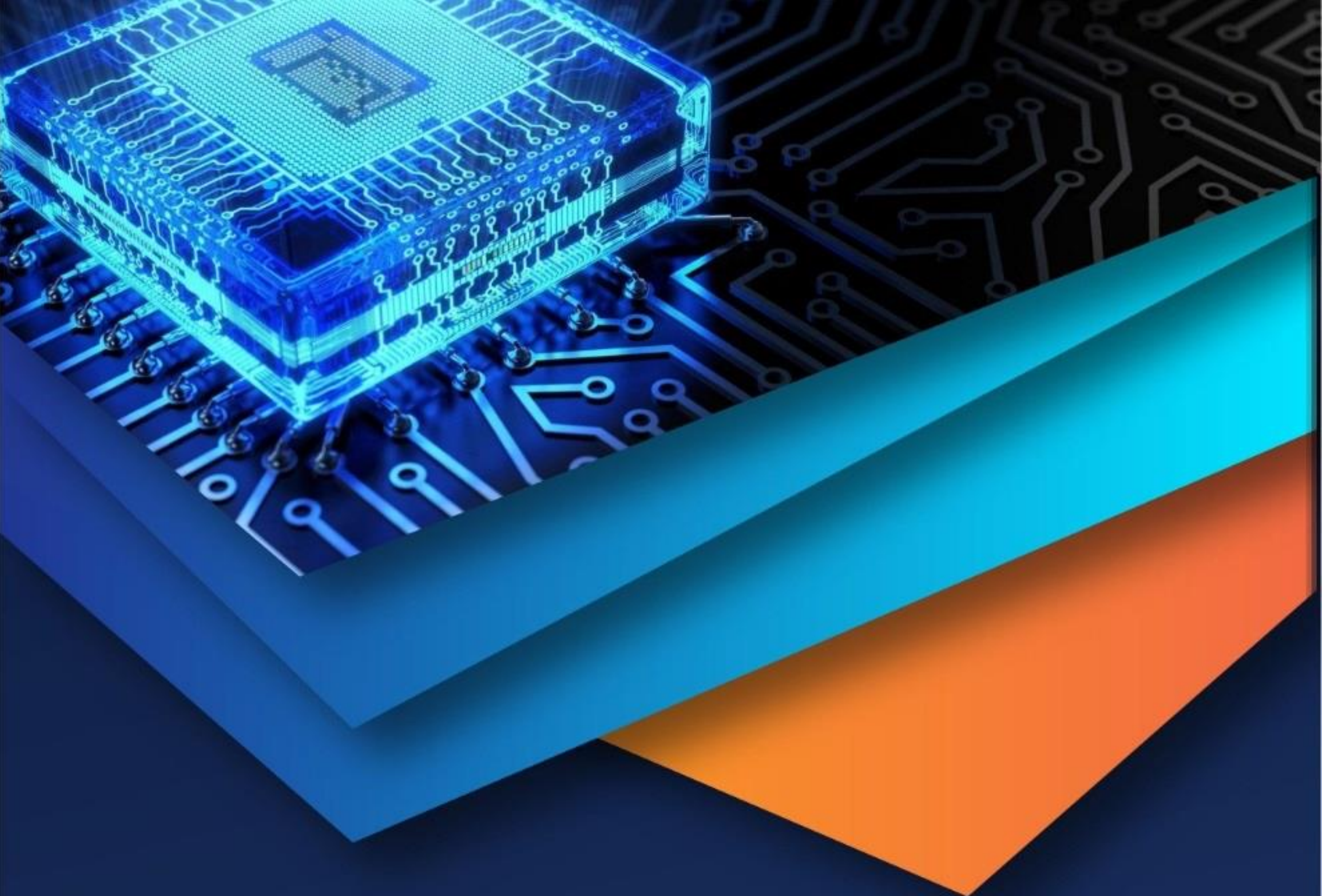

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