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Face Recognition using Local Binary Patterns (LBP)

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Abstract - The face of a human being conveys a lot of information about identity and emotional state of the person. Face recognition is an interesting and challenging problem, and impacts important applications in many areas such as identification for law enforcement, authentication for banking and security system access, and personal identification among others. In our research work mainly consists of three parts, namely face representation, feature extraction and classification. Face representation represents how to model a face and determines the successive algorithms of detection and recognition. The most useful and unique features of the face image are extracted in the feature extraction phase. In the classification the face image is compared with the images from the database. In our research work, we empirically evaluate face recognition which considers both shape and texture information to represent face images based on Local Binary Patterns for person-independent face recognition. The face area is first divided into small regions from which Local Binary Patterns (LBP), histograms are extracted and concatenated into a single feature vector. This feature vector forms an efficient representation of the face and is used to measure similarities between images.

Keywords : local binary pattern (LBP), feature extraction, classification, pattern recognitin, histogram, feature vector.

GJCST-F Classification: I.4.8

FACE RECOGNITION USING LOCAL BINARY PATTERNS LBP

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Indexterms : local binary pattern (LBP), feature extraction, classification, pattern recognitin, histogram, feature vector.

I. Introduction

Facial expression is one of the most powerful, natural and immediate means for human beings to communicate their emotions and intensions. Face recognition is an interesting and challenging problem, and impacts important applications in many areas such as identification for law enforcement, authentication for banking and security system access, and also personal identification among others [1]. The face plays a major role in our social intercourse in conveying identity and emotion. The human ability to recognize faces is remarkable. Modern Civilization heavily depends on person authentication for several purposes. Face recognition has always a major focus of research because of its noninvasive nature and because it is peoples primary method of person identification.

a) The Paradigm for Face Recognition

Despite of the fact that at this moment already numerous of commercial face recognition systems are in use, this way of identification continues to be an interesting topic for researchers. This is due to the fact that the current systems perform well under relatively simple and controlled environments, but perform much worse when variations in different factors are present, such as pose, viewpoint, facial expressions, time (when the pictures are made) and illumination (lightening changes)[8]. The goal in this research area is to minimize the influence of these factors and create robust face recognition system. A model for face recognition is shown in Figure-1.1.

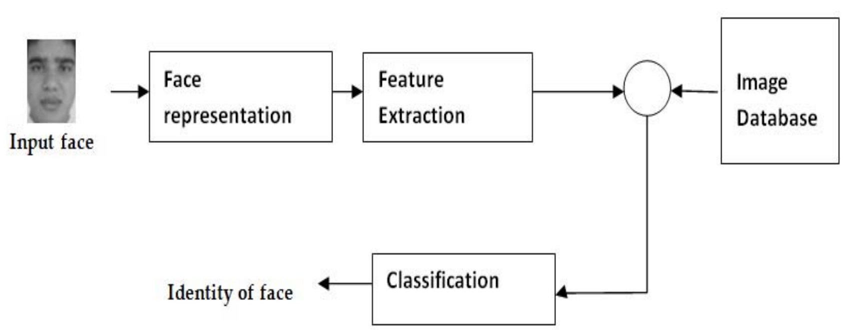

Figure 1.1 : Principle of an identification process with face recognition

The process of person identification by using face recognition can be split into three main phases (figure 1.1). 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

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'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 [7, 9]. 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. 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.

II. Local Binary Patterns

a) *Introduction*

There exist several methods for extracting the most useful features from (preprocessed) face images to perform face recognition. One of these feature extraction methods is the Local Binary Pattern (LBP) method. This relative new approach was introduced in 1996 by Ojala et al. [5]. 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 (figure 1.2).

Figure 1.2 : A preprocessed image divided into 64 regions

These features consist of binary patterns that describe the surroundings of pixels in the regions. The obtained features from the regions are concatenated into a single feature histogram, which forms a representation of the image. Images can then be compared by measuring the similarity (distance) between their histograms. According to several studies [2, 3, 4] face recognition using the LBP method provides very good results, both in terms of speed and discrimination performance. Because of the way the texture and shape of images is described, the method seems to be quite robust against face images with different facial expressions, different lightening conditions, image rotation and aging of persons.

b) *Principles of Local Binary Patterns*

The original LBP operator was introduced by Ojala et al. [15]. This operator works with the eight neighbors of a pixel, using the value of this center pixel as a threshold. If a neighbor pixel has a higher gray value than the center pixel (or the the same gray value) than a one is assigned to that pixel, else it gets a zero. The LBP code for the center pixel is then produced by concatenating the eight ones or zeros to a binary code (figure 1.3).

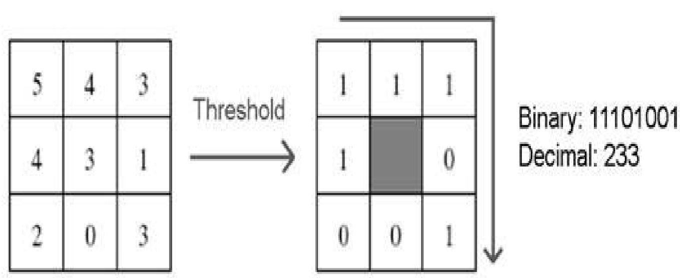

Figure 1.3 : The Original LBP Operator

Later the LBP operator was extended to use neighborhoods of different sizes. In this case a circle is made with radius R from the center pixel. P sampling points on the edge of this circle are taken and compared with the value of the center pixel. To get the values of all sampling points in the neighborhood for any radius and any number of pixels, (bilinear) interpolation is necessary. For neighborhoods the notation (P, R) is used. Figure 1.4 illustrates three neighbor-sets for different values of P and R.

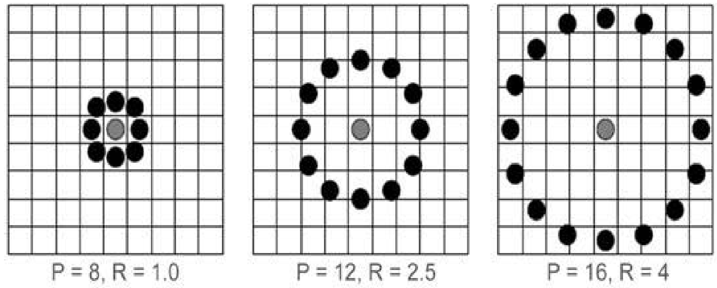

Figure 1.4 : Circularly neighbor-sets for three different values of P and R

If the coordinates of the center pixel are (x_c, y_c) then the coordinates of his P neighbors (x_p, y_p) on the edge of the circle with radius R can be calculated with the sinus and cosines:

$$x_p = x_c + R\cos(2\pi p/P) \quad (1)$$

$$y_p = y_c + R\sin(2\pi p/P) \quad (2)$$

If the gray value of the center pixel is gc and the gray values of his neighbors are g_p, with p = 0, ..., P − 1, than the texture T in the local neighborhood of pixel (x_c, y_c) can be defined as:

$$T = t(g_c, g_0, \ldots, g_{P-1}) \quad (3)$$

Once these values of the points are obtained is it also possible do describe the texture in another way. This is done by subtracting the value of the center pixel from the values of the points on the circle. On this way the local texture is represented as a joint distribution of the value of the center pixel and the differences:

$$T = t(g_c, g_0 - g_c, \ldots, g_{P-1} - g_c) \quad (4)$$

Since $t(g_c)$ describes the overall luminance of an image, which is unrelated to the local image texture, it does not provide useful information for texture analysis. Therefore, much of the information about the textural characteristics in the original joint distribution (Eq. 3) is preserved in the joint difference distribution (Ojala et al. 2001):

$$T \approx (g_0 - g_c, \ldots, g_{P-1} - g_c) \quad (5)$$

Although invariant against gray scale shifts, the differences are affected by scaling. To achieve invariance with respect to any monotonic transformation of the gray scale, only the signs of the differences are considered. This means that in the case a point on the circle has a higher gray value than the center pixel (or the same value), a one is assigned to that point, and else it gets a zero:

$$T \approx (s(g_0 - g_c), \ldots, s(g_{P-1} - g_c)) \quad (6)$$

Where

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

In the last step to produce the LBP for pixel (x_c, y_c) a binomial weight 2^p is assigned to each sign $s(g_p - g_c)$. These binomial weights are summed:

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c) 2^p. \quad (7)$$

The Local Binary Pattern characterizes the local image texture around (x_c, y_c). The original LBP operator in figure 1.3 is very similar to this operator with P = 8 and R = 1, thus $LBP_{8,1}$. The main difference between these operators is that in $LBP_{8,1}$ the pixels first need to be interpolated to get the values of the points on the circle.

c) Uniform Local Binary Patterns

A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa. In a matter of fact this means that a uniform pattern has no transitions or two transitions. Only one transition is not possible, since the binary string needs to be considered circular. The two patterns with zero transitions, with for example eight bits, are 00000000 and 11111111. Examples of uniform patterns with eight bits and two transitions are 00011100 and 11100001. For patterns with two transitions are P(P −1) combinations possible. For uniform patterns with P sampling points and radius R the notion $LBP_{P,R}^{u2}$ is used.

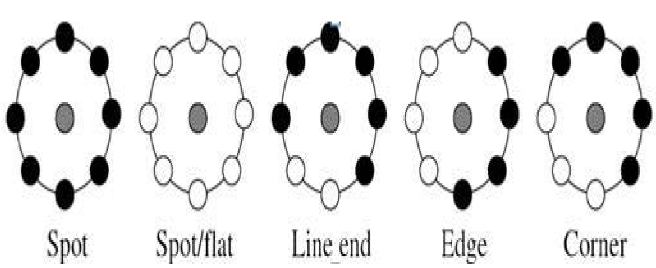

Figure 1.5 : Different texture primitives detected by the $LBP_{P,R}^{u2}$

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Using only uniform Local Binary Patterns has two important benefits. The first one is that it saves memory. With non-uniform patterns there are 2^P possible combinations. With $LBP_{P,R}^{u2}$ there are P (P − 1) + 2 patterns possible. The number of possible patterns for a neighborhood of 16 (interpolated) pixels is 65536 for standard LBP and 242 for LBP^{u2}. The second benefit is that LBP^{u2} detects only the important local textures, like spots, line ends, edges and corners. See figure 1.5 for examples of these texture primitives.

III. Face Recognition Using Local Binary Patterns

We explained how the LBP-method can be applied on images (of faces) to extract features which can be used to get a measure for the similarity between these images. The main idea is that for every pixel of an image the LBP-code is calculated. The occurrence of each possible pattern in the image is kept up. The histogram of these patterns, also called labels, forms a feature vector, and is thus a representation for the texture of the image. These histograms can then be used to measure the similarity between the images, by calculating the distance between the histograms.

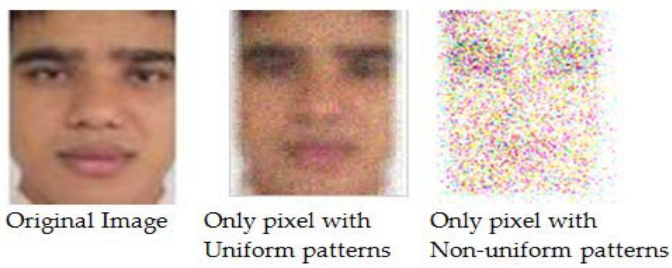

Figure 1.6 : Face image split in an image with only pixels with uniform patterns and in an image with only non-uniform patterns, by using $LBP_{16,2}^{u2}$

Figure 1.6 shows an image which is split in an image with only pixels with uniform patterns and in an image with only non-uniform patterns. These images are created by using the $LBP_{16,2}^{u2}$ operator. It occurs that the image with only pixels with uniform patterns still contains a considerable amount of pixels, namely 99 % of the original image. So, 99% of the pixels of the image have uniform patterns (with LBP this is even 99 %). Another striking thing is the fact that, by taking only the pixels with uniform patterns, the background is also preserved. This is because the background pixels all have the same color (same gray value) and thus their patterns contain zero transitions. It also seems that much of the pixels around the mouth, the noise and the eyes (especially the eyebrows) have uniform patterns.

a) Feature Vectors

Once the Local Binary Pattern for every pixel is calculated, the feature vector of the image can be constructed [10]. For an efficient representation of the face, first the image is divided into K^2 regions. In figure 1.7 a face image is divided into $8^2 = 64$ regions. For every region a histogram with all possible labels is constructed. This means that every bin in a histogram represents a pattern and contains the number of its appearance in the region. The feature vector is then constructed by concatenating the regional histograms to one big histogram.

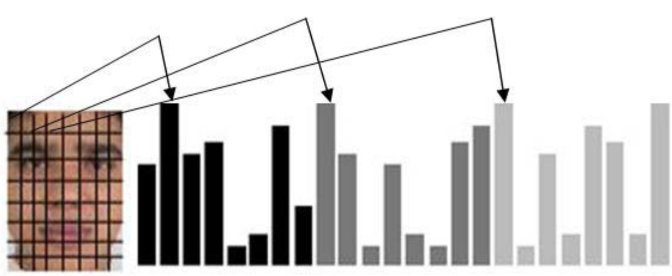

Figure 1.7 : Face image divided into 64 regions, with for every region a histogram

For every region all non-uniform patterns (more than two transitions) are labeled with one single label. This means that every regional histogram consists of P (P − 1) + 3 bins: P (P − 1) bins for the patterns with two transitions, two bins for the patterns with zero transitions and one bin for all non-uniform patterns. The total feature vector for an image contains K2 (P (P − 1) + 3) bins. So, for an image divided into 64 regions and eight sampling points on the circles. The LBP code cannot be calculated for the pixels in the area with a distance R from the edges of the image. This means that, in constructing the feature vector, a small area on the borders of the image is not used. For an N × M image the feature vector is constructed by calculating the LBP code for every pixel (x_c, y_c) with $x_c \in \{R + 1, . . . N - R\}$ and $y_c \in \{R + 1, . . . ,M - R\}$. If an image is divided into k × k regions, then the histogram for region (k_x, k_y), with $k_x \in \{1, . . . , k\}$ and $k_y \in \{1, . . . , k\}$, can be defined as:

$$H_i(K_x, K_y) = \sum_{x,y} I\{LBP_{P,R(x,y)} = L(i)\}, i = 1, \dots\dots\dots. P(P-1)+3 \quad (8)$$

$$x \in \begin{cases} \{R+1, \dots\dots\dots\dots \quad , {}^{N}/_{K}\} & K_x = 1 \\ \{(K_x-1)(N/K\} + 1, \dots, N-R & K_x = K \\ \{(K_x-1)(N/K\} + 1, \dots, \quad K_x(N/K) & else \end{cases}$$

$$y \in \begin{cases} \{R+1, \dots\dots\dots\dots \quad , {}^{M}/_{K}\} & K_y = 1 \\ \{(K_y-1)(M/K\} + 1, \dots, M-R & K_y = K \\ \{(K_y-1)(M/K\} + 1, \dots, \; K_y(M/K) & else \end{cases} \quad (9)$$

In which L is the label of bin i and

$$I(A) = \begin{cases} 1, & A \text{ is true} \\ 0, & A \text{ is false} \end{cases} \quad (10)$$

The feature vector is effectively a description of the face on three different levels of locality: the labels contain information about the patterns on a pixel-level; the regions, in which the different labels are summed, contain information on a small regional level and the concatenated histograms give a global description of the face.

b) Comparing the Feature Vectors

To compare two face images, a sample (S) and a model (M), the difference between the feature vectors has to measure. This can be done with several possible dissimilarity measures for histograms:

- Histogram intersection:

$$D(S,M) = \sum_{j=1}^{k^2} \left(\sum_{i=1}^{P(P-1)+3} \min(S_{i,j}, M_{i,j})\right) \quad (11)$$

- Log-likelihood statistic:

$$L(S,M) = \sum_{j=1}^{k^2} \left(-\sum_{i=1}^{P(P-1)+3} S_{i,j} \log M_{i,j}\right) \quad (12)$$

- Chi square statistic (x^2):

$$x^2(S,M) = \sum_{j=1}^{k^2} \left(\sum_{i=1}^{P(P-1)+3} \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}}\right) \quad (13)$$

In these equations Si,j and Mi,j are the sizes of bin i from region j (number of appearance of pattern L(i) in region j). Because some regions of the face images (for example the regions with the eyes) could contain more useful information than others, a weight can be set for each region based on the importance of the information it contains. According to article [31] the x^2 performs slightly better than histogram intersection and the log-likelihood statistic. By applying a weight w_j to region j, the equation for the weighted x^2 becomes:

$$x_w^2(S,M) = \sum_{j=1}^{k^2} w_j \left(\sum_{i=1}^{P(P-1)+3} \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}}\right) \quad (14)$$

This weighted x^2 for two (face) images, which is calculated from the histograms, is a measure for the similarity between these images. The lower the value of the x^2 (which is also called the 'distance' between the two images), the bigger the similarity.

IV. Implementation

Face recognition is not a simple problem since an unknown face image seen in the extraction phase is usually different from the face image seen in the classification phase. Although local binary features has been extracted from the face image for face recognition that there are several face image uses in the database that compared with the input face image. The face image depends on viewing lighting and environmental conditions. In addition the face image changes according to the expressions. In the research work, which is flexible and efficient, should be solved the problems.

a) Face Recognition Algorithm

To implement the face recognition in this research work, we proposed the Local Binary patterns methodology. Local Binary Pattern works on local features that uses LBP operator which summarizes the local special structure of a face image [11].

LBP is defined as an orders set of binary comparisons of pixels intensities between the center pixels and its eight surrounding pixels. Local Binary Pattern do this comparison by applying the following formula:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c) 2^n \quad (15)$$

Where i_c corresponds to the value of the center pixel (x_c, y_c), i_n to the value of eight surrounding pixels. It is used to determine the local features in the face and also works by using basic LBP operator. Feature extracted matrix originally of size 3 x 3, the values are compared by the value of the centre pixel, then binary pattern code is produced and also LBP code is obtained by converting the binary code into decimal one.

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The Face Recognition Algorithm

Input: Training Image set

Output: Feature extracted from face image and compared with centre pixel and recognition with unknown face image

1. Initialize *temp = 0*
2. FOR each image I in the training image set
3. Initialize the pattern histogram, *H = 0*
4. FOR each center pixel *tc* ∈ *I*
5. Compute the pattern label of *tc*, LBP (1)
6. Increase the corresponding bin by 1
7. END FOR
8. Find the highest LBP feature for each face image and combined into single vector
9. Compare with test face image
10. If it match it most similar face in database then successfully recognized.

b) Flowchart of the LBP

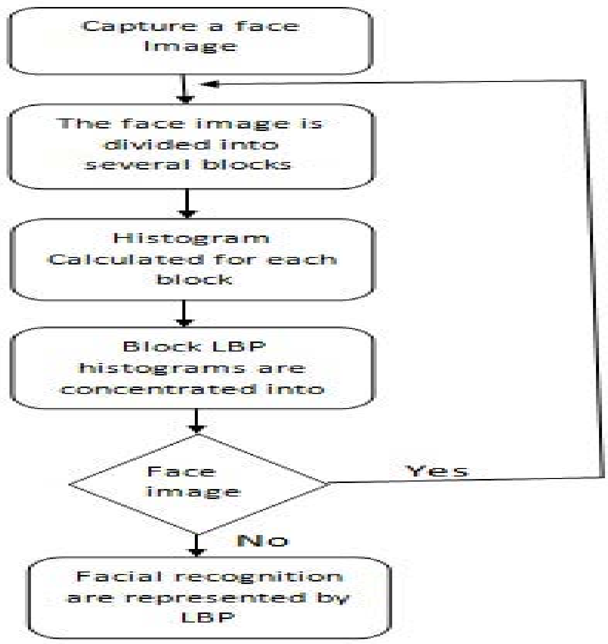


Figure 1.6 : Flow chart of the LBP process

c) Flowchart of the Proposed System

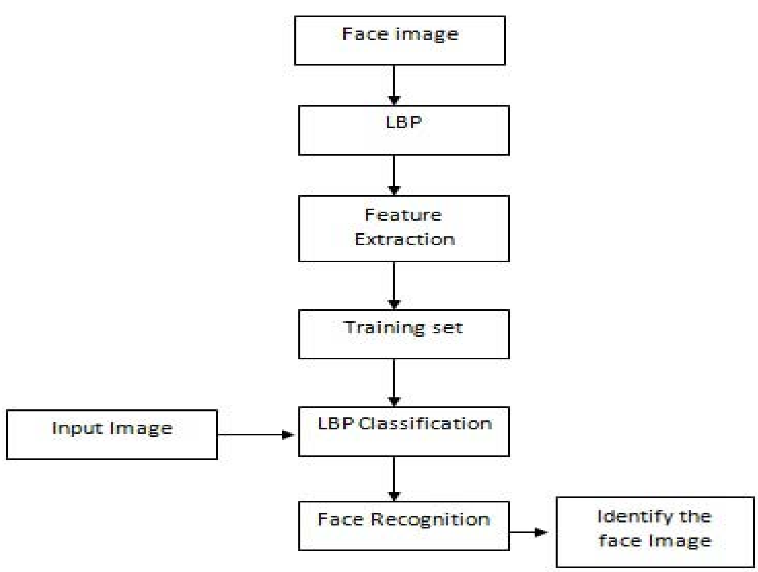


Figure 1.7 : Diagram of the whole system

V. Results and Discussion

This implementation is used to test the performance of the LBP-method on different kind of face images. Several parameters, like the LBP operator (P and R), non-weighted or weighted regions and the dividing of the regions, are varied to see the influence of these parameters on the performance. For this experiment we have collected lots of face images, some of them are collected from photographs taken with a Canon Power shot A610 camera and some are taken from A4Tech webcams. And also collected face images from the face database [14]. In the proposed algorithm, different types of face images have been recognized. Based on algorithm, the face image of an unknown identity is compared with face images of known individuals from a large database. In the figure 1.8 we can see the input facial images used for input for face recognition are given below:

Facial Image 1 Facial Image 2 Facial Image 3

Figure 1.8 : Different input facial images

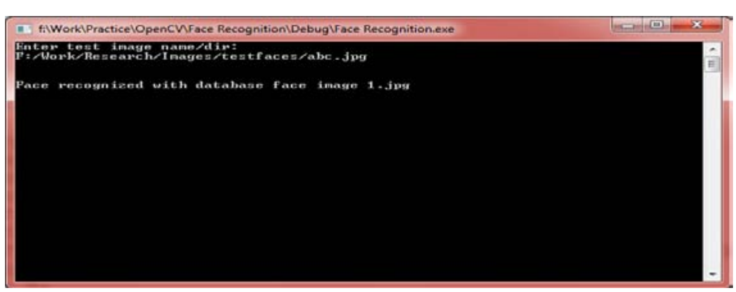
And also in the figure 1.9 we can see the facial images that are stored in the database which compared with the input facial images. If the input face images are found or the more similarities face images are matched in the database then we say the face image is successfully recognized.

Database image 1 Database Image 2 Database Image 3

Figure 1.9 : Facial images from the database

In the experiment we can train the face images in the database. That the facial images are successfully trained shown in the window mode in the bellow:

Based on the algorithm the input face images are compared with database facial images for identification. The face recognition results are shown in below in window mode:



The following table shows overall face recognition rate:

Table 1 : Recognition Rate of the Research

Number of face images stored in database	Number of input face images compared with database	Recognized Image	Unrecognized Image	Recognition Rate
2000	2000	1980	20	99%

In the table 1 the recognition rate is above 100%. We recognize the face images from the database face images by comparing between input face image and database image. From the experimental result, it is seen that the research satisfies all the requirements to recognize the face images.

VI. Conclusion and Future Improvements

a) *Conclusion*

In this research has been done to the performance of a face recognition system by making use of feature extraction with Local Binary Patterns [12]. It mainly consists of three parts, namely face representation, feature extraction and classification. Face representation represents how to model a face and determines the successive algorithms of detection and recognition. The most useful and unique features of the face image are extracted in the feature extraction phase. In the classification the face image is compared with the images from the database. This method represents the local feature of the face and matches it with the most similar face image in database. The accuracy of the system is above 100% by the Local Binary Patterns algorithm.

b) *Future Improvements*

It is obvious that the result of this face recognition system is good but there is scope for future improvement. Due to time constraints we were not able to implement some objectives that should have made the research work a better proposition. The main improvement will pursue the performances, recognizes the real-time face recognition [13]. I would like to improve my code for face image recognition as well as clean up the code in order to improve performance.

Many difficulties has been faced when recognized 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.

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