

A COMBINED APPROACH USING TEXTURAL AND GEOMETRICAL FEATURES FOR FACE RECOGNITION

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Abstract

Texture feature plays a predominant role in recognizing face images. However different persons can have similar texture features that may degrade the system performance. Hence in this paper, the problem of face similarity is addressed by proposing a solution which combines textural and geometrical features. An algorithm is proposed to combine these two features. Five texture descriptors and few geometrical features are considered to validate the proposed system. Performance evaluations of these features are carried out independently and jointly for three different issues such as expression variation, illumination variation and partial occlusion with objects. It is observed that the combination of textural and geometrical features enhance the accuracy of face recognition. Experimental results on Japanese Female Facial Expression (JAFFE) and ESSEX databases indicate that the texture descriptor Local Binary Pattern achieves better recognition accuracy for all the issues considered.

Keywords:

Face Recognition, Texture Features, Geometric Features, Nearest Neighborhood Classification, Chi-Square Distance Metric

1. INTRODUCTION

Face recognition is an important area in machine vision, which offers potential applications such as surveillance, biometric authentication, computer-human interaction etc. It has received tremendous attention in the field of research because there is a great variability of face images in facial expression, intensity, occlusion, pose and aging [8]. Based on the property of the features extracted, face recognition algorithms are classified into holistic and local feature based [3]. Holistic approaches such as principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), variants of LDA, marginal fisher analysis (MFA), eigenfeature regularization and extraction (ERE) were extensively studied due to their good performance and low computational complexity. Besides the advantages, holistic information of face images is not effective under illumination variation, facial expression and partial occlusion [6]. Feature based techniques are robust to variations in head orientation, scale and location of face in the image. But they are computationally more expensive than holistic approaches [19], [21]. In both methods, it is difficult for a single feature to uniquely describe human face. Hence two or more features can be combined to effectively describe face images [5], [13], [23]. Therefore an idea of combining two features based approaches namely textural and geometry is proposed in this paper.

1.1 MOTIVATION AND JUSTIFICATION FOR THE PROPOSED APPROACH

Textural feature extraction methods have an important role in recognizing objects and scenes. They can be used to determine uniformity, lightness, density, fineness, coarseness, roughness, regularity, etc., of texture patterns as a whole [2], [10]. An ample number of methods have been proposed to extract facial texture features. Ojala et al, [11] developed Local Binary Pattern (LBP) in which a gray scale invariant texture pattern for a local neighborhood of 3×3 is defined. A derivative of the LBP [12] was later introduced by them to describe rotational and gray scale invariant pattern on a circular neighborhood that could represent salient micro-patterns of face images. It is a very powerful method to analyze textures [19], [20]. Suruliandi and Ramar [18] proposed a univariate texture model called Local Texture Patterns (LTP) for image classification and proved that it is robust in terms of gray scale variation and rotational variation. Masily [7] suggested a method called Elliptical Local Binary Template (ELBT) and showed that it works well for face recognition system. Local Line Binary Pattern (LLBP) [1] which was introduced by Amnart and Sanun is more discriminative and insensitive to illumination variation and facial expression. Shengcai et al, [16] introduced Multi-scale Block Local Binary Pattern (MBLBP) for face recognition and proved that their method outperforms other LBP based face recognition systems. All the textural methods discussed above have been applied for face recognition and have produced better results. But the texture descriptors used in this work are not yet been proved to perform better under all the issues in face recognition. Motivated by this, an attempt is made in this paper to investigate the performance of LBP, ELBT, LLBP, LTP and MBLBP under different challenges like expression variation, illumination variation, and variation with spectacles. Also, most of the texture descriptors explained here have not yet been tested for face recognition by combining with geometric features. So in this paper, an effort is made to identify a texture descriptor among the aforesaid descriptors that perform better in combined approach.

In the early stages, geometrical features were used for recognizing face images. To determine the feature, certain points in the face are detected to form segments, perimeters and area [17, 22]. Yousra Ben Jemma and Sana Khanfir [21] compared the performance of geometric distances with Gabor coefficients for face recognition and have proved that their combined approach yields better results. Zhengyou et al, [22] have

evaluated the performance of facial expression recognition system using multi layer perceptron by combining geometry based method with Gabor wavelets. In their work they have reported that the combined approach can considerably improve the face recognition. The face images are acquired almost in frontal view in real life situations such as taking photographs in driving license, passport, identity cards etc. In these cases there will be slight expression variation, very less rotation variation, small illumination variation and partial occlusion with spectacle. In such situations, combining texture with geometric measures will be more appropriate. Justified by this, performances of five texture descriptors and seven geometrical measures are analyzed independently and jointly. In our early work [13] the texture descriptors LBP, ELBT and GLCM were combined with geometrical approach and it was proved that it enhances the performance of face recognition under expression variation. In this paper, performance of the approach that combines a few more textural methods with geometrical features has been studied for three different issues.

1.2 OUTLINE OF THE PROPOSED APPROACH

Overall process of the proposed system is depicted in Fig.1. Initially, all the images are preprocessed to align into same canonical pose. In texture based approaches certain region of interest is cropped from the images in order to avoid processing unnecessary detail present in the face. During training, texture and geometrical features are extracted from every image and are stored separately in the database. While testing a probe image, texture and geometrical features are extracted for that image, and are matched against all the images in the database using nearest neighborhood classifier. The dissimilarity measure used to match texture feature is weighted chi-square [7] and geometrical feature is chi-square. The performance of the proposed approach is studied using texture and geometrical features separately and as well as jointly.

1.3 ORGANIZATION OF THE PAPER

Rest of the paper is organized as follows. Section 2 gives a brief review of the texture and geometrical feature extraction

methods used. This section also explains the algorithm proposed for the combined approach. Section 3 focuses on experimental setup, the results, and discussions of the textural, geometrical and the proposed combined approach for three different issues such as expression variation, illumination variation and partial occlusion with spectacle. The conclusions are presented in section 4.

2. FEATURE EXTRACTION

2.1 TEXTURE DESCRIPTORS

Texture is a term that characterizes the contextual property of an image. A texture descriptor can characterize an image as a whole as in GLCM [15]. Alternatively, it can also characterize an image locally at the micro level and by global texture description at the macro level. In local description, the relationship between a pixel and its neighborhood pixels will be expressed in terms of local texture patterns. The occurrence frequency of such patterns will be collected in a histogram which characterizes the global feature of the image. The texture descriptors LBP, ELBT, LLBP, LTP and MBLBP follow the second approach.

2.1.1 Local Binary Pattern (LBP):

Ojala et al, [11] proposed LBP that can be used to label every pixel in the image by thresholding the eight neighbors of the pixel with the center pixel value. If a neighbor pixel value is less than the threshold then a value of 0 is assigned otherwise it is 1. The result of the operation is a binary number as illustrated in Fig.2. Binary number can be formed starting from any position in the neighborhood. The binary number is then converted to decimal value and is assigned as label to the pixel.

In the derivative of original LBP operator [12], the vicinity pixels can be in circularly symmetric neighbor sets of any radius r . The number of vicinity pixels p on the circle with any angle θ may be chosen arbitrarily. The position of vicinity pixels (g_{ix}, g_{iy}) can be computed using Eq.(1) – Eq.(3). In order to determine the coordinates of vicinity pixels, bilinear interpolation can be used.

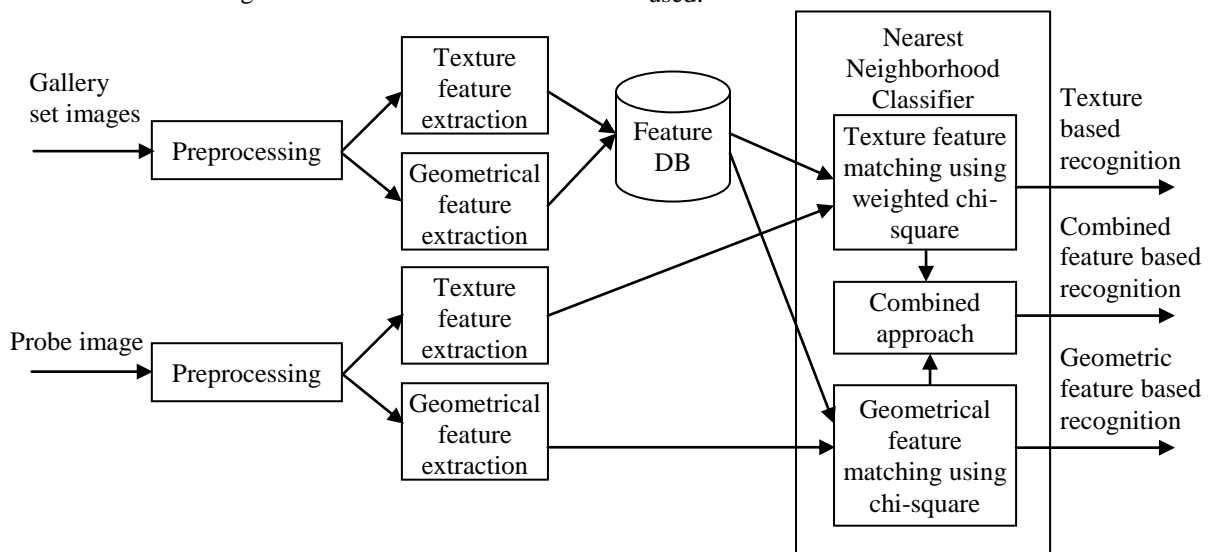
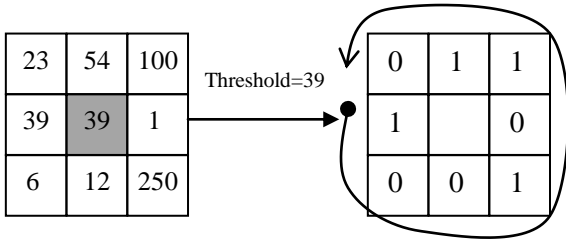


Fig.1. Face recognition process



Pattern: 10010110
 Decimal: $1 \times 2^7 + 0 \times 2^6 + 0 \times 2^5 + 1 \times 2^4 + 0 \times 2^3 + 1 \times 2^2 + 1 \times 2^1 + 0 \times 2^0 = 150$

Fig.2. Computation of label using LBP operator

$$g_{ix} = R_i \cdot \cos \theta_i, g_{iy} = R_i \cdot \sin \theta_i \quad (1)$$

$$R_i = \sqrt{\frac{r^4}{r^2 \sin^2 \theta_i + r^2 \cos^2 \theta_i}}, \quad (2)$$

$$\theta_i = \left[\frac{360}{p} * (i-1) \right]^\circ \quad (3)$$

An LBP can be classified as uniform or non uniform pattern. It is said to be uniform if only it contains at most two transitions from 0 to 1 or vice versa in the binary pattern. Usage of uniform patterns reduces the total number of bins required. Image analysis requires $p(p-1)+2$ bins for uniform pattern and one extra bin for all non uniform patterns thus requires a total of $p(p-1)+3$ bins.

2.1.2 Elliptical Local Binary Template (ELBT):

Masily [7] suggested this method which is very similar to that of LBP. The only difference is that vicinity pixels lie on an ellipse relating to the central pixel rather than on a circle. To calculate coordinates of vicinity pixels, vertical radius (vr) as well as horizontal radius (hr) is required. Here R_i is computed as in Eq.(4).

$$R_i = \sqrt{\frac{hr^2 * vr^2}{hr^2 \sin^2 \theta_i + vr^2 \cos^2 \theta_i}}, \quad (4)$$

2.1.3 Local Line Binary Pattern (LLBP):

LLBP researched by Amnart Petpon and Sanun Srisuk [1] differs from LBP in two aspects: 1) Neighborhood pixels considered are those that lie in a straight line either horizontally or vertically. 2) Starting from the adjacent pixel of the center pixel 'c', binary weights are distributed as in Fig.3. Three measures such as LLBP operator for horizontal line (LLBP_h), vertical line (LLBP_v) and its magnitude (LLBP_m) are calculated for every pixel in the image by using Eq.(5) – Eq.(7). The Fig.3 illustrates the operation of LLBP in horizontal direction. Similar operation can be done in vertical direction also.

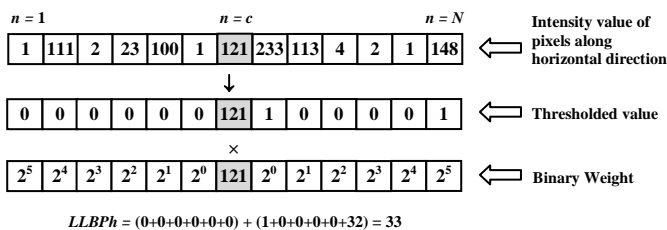


Fig.3. LLBP operator in horizontal direction with line length of 13 pixels

$$LLBP_m = \sqrt{LLBP_h^2 + LLBP_v^2} \quad (5)$$

where,

$$LLBP_h(N, c) = \sum_{n=c-1}^{c-1} s(h_n - h_c) \cdot 2^{(c-n-1)} + \sum_{n=c+1}^N s(h_n - h_c) \cdot 2^{(n-c-1)} \quad (6)$$

$$LLBP_v(N, c) = \sum_{n=c-1}^{c-1} s(v_n - v_c) \cdot 2^{(c-n-1)} + \sum_{n=c+1}^N s(v_n - v_c) \cdot 2^{(n-c-1)} \quad (7)$$

and

$$s(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad (8)$$

In the above equations, c is the position of the center pixel, N is the length of the line and s is as represented in Eq.(8).

2.1.4 Local Texture Pattern (LTP):

Suruliandi and Ramar[18] have proposed LTP. In this, every pixel is assigned with a label that is computed with the pattern units P obtained for its eight neighbors as described below.

$$P(g_i, g_c) = \begin{cases} 0 & \text{if } g_i < (g_c - \Delta g) \\ 1 & \text{if } (g_c - \Delta g) \leq g_i \leq (g_c + \Delta g) \\ 9 & \text{if } g_i > (g_c + \Delta g) \end{cases} \quad i = 1, 2, \dots, 8. \quad (9)$$

In the above equation, g_c is the gray value of center pixel and g_i is the gray value of 3×3 neighbors and Δg is a small positive integer value that has an important role in forming the uniform patterns. A pattern string is then formed by collecting the P values of the eight neighbors starting from any position as described below.

$$LTP = \begin{cases} \sum_{i=1}^8 P(g_i, g_c) & \text{if } U \leq 3 \\ 73 & \text{otherwise} \end{cases} \quad (10)$$

U is the uniformity measure and is defined as,

$$U = s(P(g_8, g_c), P(g_1, g_c)) + \sum_{i=2}^8 s(P(g_i, g_c), P(g_{i-1}, g_c)) \quad (11)$$

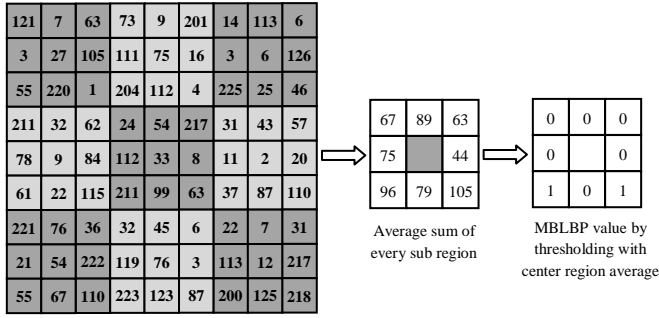
where,

$$s(x, y) = \begin{cases} 1 & \text{if } |x - y| > 0 \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

Number of unique patterns which can be obtained by LTP scheme is 46 in total and they can have values in the range 0 to 73 leaving few holes in between. Therefore patterns are relabeled to form continuous numbers from 1 to 46 by using a lookup table.

2.1.5 Multi-scale Block Local Binary Pattern (MBLBP):

MBLBP introduced by Shengcai Liao et al [16] can be used to obtain texture pattern for every pixel by considering a local region of size $3 \times 3, 9 \times 9, 15 \times 15$ etc. with center pixel. Computation of MBLBP for 3×3 local region is equivalent to the original LBP. Local region of other sizes can be decomposed into equally sized regions. And then the average sum of pixel intensity for every sub regions is calculated, which is then thresholded with the center region average value. Thereafter MBLBP values are computed in a similar manner as in LBP. An example for the calculation of MBLBP is shown in Fig.4.


Fig.4. MB-LBP for 9×9 sub image

2.1.6 Global Texture Description:

Process of forming global texture description is as follows

- For every pixel in the image, select its's neighborhood pixels of predefined size $n \times n$.
- Compute local texture feature for the neighborhood using any one of the local texture descriptor.
- Collect the occurrence frequency of every local texture pattern in a one dimensional histogram that characterizes the global texture description of the image.

2.2 GEOMETRICAL MEASURES

In this approach, important face components and/or feature points are selected in the face images. A feature vector is formed with the distances between those points or the relative sizes or position of the components [17], [22]. In this work, 13 facial points are selected manually and the distances between those points in terms of pixels are computed to identify major face components such as nose width ($p5-p11$), mouth width ($p6-p12$), distance between iris centers ($p3-p9$), distance between the nose and mouth ($p13-p2$), distance between the center point of the line connecting the iris centers and nose ($p2-p8$), face height ($p7-p1$) and face width ($p4-p10$). These geometrical measures have a major role in discriminating different face images because they characterize all the facial components. Performance of face recognition systems may deteriorate if the manual selection is replaced by automatic one [3]. Fig.5. depicts the selection of fiducial points.

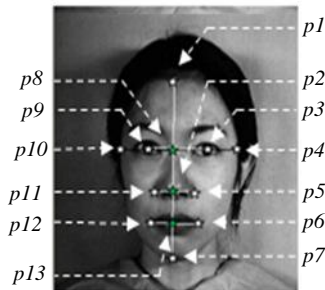


Fig.5. Fiducial points selected for geometrical approach

2.3 PROPOSED TECHNIQUE FOR COMBINING FEATURES

Following procedure is used for combining texture and geometric features.

- 1) Geometric features (**GF**) in the form of vector and texture features (**TF**) in the form of histogram are computed for gallery set images and are stored in a database.
- 2) For every probe image do the following:
 - i. Determine **GF** and **TF** for the image.
 - ii. Find out the dissimilarity between the probe image and every image in the gallery set for **GF** using Chi-square statistic as defined below.

$$\chi^2(O, E) = \sum \frac{(O_i - E_i)^2}{(O_i + E_i)} \quad (13)$$

where, O_i is the i^{th} feature value of the gallery set image and E_i is the i^{th} feature value of the probe one.

- iii. Since certain region in the face have more importance, compute the dissimilarity among the images for **TF** using weighted Chi-square defined in Eq.(14).

$$\chi_w^2(O, E) = w_i \sum_{i,j} \frac{(O_{i,j} - E_{i,j})^2}{(O_{i,j} + E_{i,j})} \quad (14)$$

In the above formula O_{ij} and E_{ij} are the j^{th} feature of i^{th} region in the gallery and probe image respectively. w_i is the weight of i^{th} region as show in Fig.6(c).

- iv. Normalize dissimilarity measure for **GF** individually for the images in the gallery set by applying the following equation,

$$N_{GF} = \chi^2(O, E) / (\max \chi^2(O, E) - \min \chi^2(O, E))$$

where, N_{GF} is the normalized dissimilarity measure for every image in the gallery set, $\chi^2(O, E)$ is the dissimilarity measure, $\max \chi^2(O, E)$ and $\min \chi^2(O, E)$ are the maximum and minimum dissimilarity measures among the gallery set images respectively.

- v. Normalize dissimilarity measures for **TF** individually for the images in the training set by applying the following equation,

$$N_{TF} = \chi_w^2(O, E) / (\max \chi_w^2(O, E) - \min \chi_w^2(O, E))$$

where, N_{TF} is the normalized dissimilarity measure for every image in the gallery set, $\chi_w^2(O, E)$ is the dissimilarity measure, $\max \chi_w^2(O, E)$ and $\min \chi_w^2(O, E)$ are the maximum and minimum distance measures among the gallery set images respectively.

- vi. Add the two normalized measures N_{GF} and N_{TF} for every image in the gallery set.
- vii. The gallery image which yields least dissimilarity measure with the probe image is considered as the recognized one.

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

Preprocessing is required since most of the images in the databases are oriented in some direction. Therefore all the images are rotated in such a way that a line connecting iris centers lies in a horizontal line. For textural methods, a subspace is chosen by applying face anthropometric measure (distance between iris centers) as in Fig.6(a) to avoid the computational burden of using entire face. Eq.(15) – Eq.(18) are used to crop the subspace that contains necessary details in the face.

$$x_1 = x - (p/2) \tag{15}$$

$$y_1 = y - p \tag{16}$$

$$x_2 = (x + 3 * p) - (p/2) \tag{17}$$

$$y_2 = (y + 3 * p) - (p/4) \tag{18}$$

where, p is half the distance between two iris centers

Faces can be effectively represented if the subspace is divided into sub regions and matching is done between respective regions in gallery as well as probe image. Therefore only for the textural methods, 49 equally sized sub regions [14, 19] are formed as shown in Fig.6(b). Certain regions cover more important facial features and are assigned different weights as in Fig.6(c).

Following experimental setup and parameter settings are used in the local texture descriptors. With LBP, two experiments are conducted, one with p as 16 (LBP_{16}) and other with p as 8 (LBP_8). For LBP_8 , total number of bins required is $59 [8*(8 - 1) + 3]$ and for LBP_{16} it is $243 [16*(16 - 1) + 3]$. For LTP_8 and LTP_{16} the parameter Δg is set to 5. ELBT operator is applied on 16 neighbor pixels at horizontal radius 3 and vertical radius 2. In LLBP, horizontal and vertical lines with length 13 are considered. In MBLBP, the size of the local region considered is 9×9 . Values assigned to the parameters are the one that have given best results.

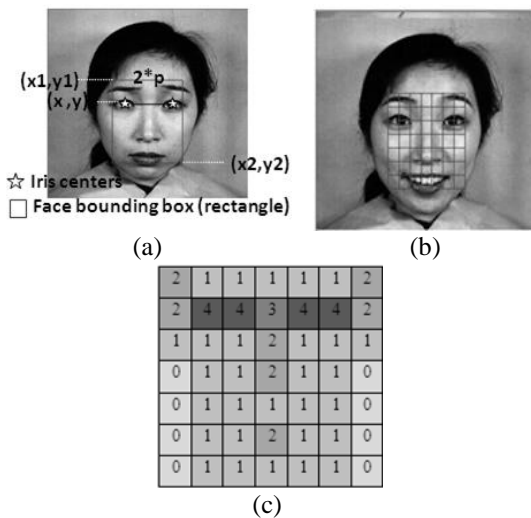


Fig.6. (a). Subspace selection with face anthropometric measure (b). 7×7 regions of face image (c). Weights assigned to every region [7]

3.1 RESULTS ON EXPRESSION VARIATION

Robustness in face recognition under facial expression variations is the most challenging issue. Facial expressions result in temporally deformed facial features that lead to false recognition. Therefore effectiveness of the proposed approach is tested under expression variation by using JAFFE database [9]. The database contains 213 frontal face images of 10 Japanese female models with seven different expressions. Sample images are displayed in Fig.7. Experiment is conducted by setting all the neutral expression images in the gallery set and the rest of the images in the probe set. The results are tabulated in Table.1.

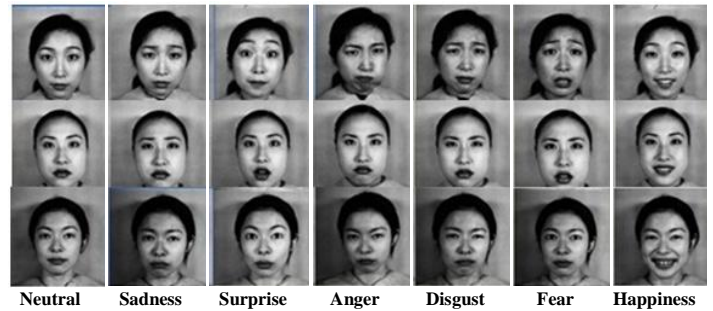


Fig.7. Sample images from JAFFE database

Table.1. Recognition Accuracy under Expression Variation

| Local Texture Descriptors | Recognition in percentage | | |
|---------------------------|---------------------------|-----------------------------|--|
| | Texture based recognition | Geometric based recognition | Combined approach (Texture+ Geometric) |
| LBP_{16} | 90.39 | 51.41 | 92.09 |
| LBP_8 | 68.92 | | 75.14 |
| ELBT | 84.18 | | 86.44 |
| LLBP | 80.79 | | 82.48 |
| LTP_{16} | 78.53 | | 86.44 |
| LTP_8 | 64.40 | | 72.31 |
| MBLBP | 69.49 | | 79.66 |

The results in the table show that among the tested texture methods, LBP_{16} produces better result of 90.39% recognition accuracy. It is noted that this accuracy is 22% greater than that of LBP_8 . Geometrical features fail to produce better results because facial expressions are produced by changes made in the shape of facial components, especially the mouth and eyes. This causes the geometrical measures to produce lower recognition accuracy of 51.41%. It is also observed that the combination of texture and geometrical features produce better results than the individual one for facial expressions.

3.2 RESULTS ON ILLUMINATION VARIATION

Recognition under different lighting condition is a challenging problem in computer vision. This variation in illumination affects the classification greatly. Therefore in this paper, performance of the proposed system is evaluated by conducting an experiment on illumination variation images. Frontal images with controlled illumination variation of 27 persons are taken from ESSEX database [4]. One exemplar per person is kept in the gallery set and 9 images per individual are kept in the probe set. Some of the images used for the

experiment are shown in Fig.8. Experimental results are given in Table.2.



Fig.8. Sample images used for Illumination variation from ESSEX database

texture descriptors perform better in combined approach. For the experiments the regions of eyes with spectacle frame is given more weight. And for different persons those regions are same. Therefore, when two persons wear similar spectacle, that region information can be similar for both. This can be one of the reasons for the texture descriptor not to recognize some images.



Fig.9. Sample images used for Variation with Spectacles from ESSEX database

Table.2. Recognition Accuracy under Illumination Variation

| Local Texture Descriptors | Recognition in percentage | | |
|---------------------------|---------------------------|-----------------------------|--|
| | Texture based recognition | Geometric based recognition | Combined approach (Texture+ Geometric) |
| LBP ₁₆ | 99.58 | 66.66 | 100 |
| LBP ₈ | 96.29 | | 96.70 |
| ELBT | 99.58 | | 100 |
| LLBP | 95.88 | | 97.94 |
| LTP ₁₆ | 97.53 | | 97.94 |
| LTP ₈ | 94.23 | | 95.06 |
| MBLBP | 90.53 | | 91.35 |

Experimental results indicate that, for illumination variant images, LBP₁₆ and ELBT produce 99.58% recognition accuracy for the probe images. This shows the effectiveness of LBP₁₆ and ELBT in recognizing illumination variant images. It is also observed that even with seven geometrical measures the system gains 67% recognition accuracy. This is an evident that shows the efficiency of the seven geometrical measures chosen. In addition, it is noticed that the combined approach yields better results than the individual ones.

3.3 RESULTS ON PARTIAL OCCLUSION WITH OBJECTS

Occlusions appear as local distortion away from a common face representing human population [6]. In order to study the capability of the approaches on recognizing faces occluded with objects, frontal face images of 13 persons with spectacles are collected from ESSEX database [4]. Three images per individuals are chosen in random as gallery set and 10 images per person are kept in the probe set. Sample image used for the experiments are given in Fig.9. Table.3 gives the experimental results.

Experimental results demonstrate that the texture descriptor LBP₁₆ produces higher recognition accuracy of 96.15% for faces partially occluded with spectacles. This shows that LBP₁₆ is more suited than the other tested texture descriptors in recognizing faces partially occluded with spectacles. With the given seven measures, the geometrical method is able to achieve recognition accuracy of 72%. This shows the effectiveness of the geometrical measures chosen. It is also noticed from the test results that except LBP₈, LLBP and MBLBP, all the other

Table.3. Recognition Accuracy under Variation with Spectacles

| Local Texture Descriptors | Recognition in percentage | | |
|---------------------------|---------------------------|-----------------------------|--|
| | Texture based recognition | Geometric based recognition | Combined approach (Texture+ Geometric) |
| LBP ₁₆ | 96.15 | 72.30 | 97.69 |
| LBP ₈ | 94.61 | | 94.61 |
| ELBT | 95.38 | | 96.92 |
| LLBP | 95.38 | | 95.38 |
| LTP ₁₆ | 93.07 | | 94.61 |
| LTP ₈ | 93.07 | | 93.84 |
| MBLBP | 92.30 | | 92.30 |

4. CONCLUSION

Texture features capture the micro primitive patterns present in the face and geometrical features describe the shape details of the facial components. But when they are applied alone, face recognition may not produce good results. Therefore this paper proposes to combine those two features to enhance the accuracy of face recognition. Performances of five texture feature extraction methods LBP, LTP, ELBT, LLBP and MBLBP and geometrical methods are investigated independently and combined together. Face recognition issues such as illumination variation, expression variation and variation with spectacle are addressed in this work.

Experimental results demonstrate that LBP₁₆ provides more accuracy of recognition than the other textural methods for all the issues discussed. This is due to its ability in determining many number of important local texture primitives. Moreover for all the issues concerned, the combined approach of LBP₁₆ with geometrical features produces better recognition accuracy.

LBP₁₆ produces better results at the cost of high computational complexity due to more number of bins. Because of simple computations and less number of bins used, LTP is the one that produces results faster than the other methods tested.

LTP also produces better results with 97.53% accuracy for illumination variation and 93.07% accuracy for variation with spectacle. Face recognition under varying expression requires more attention owing to low results produced by all the methods tested.

In future, the methods experimented here can be used to evaluate the performance of face recognition systems under issues that are not considered in this work such as aging, pose variation, and faces partially occluded with objects other than spectacle. A new texture method that improves recognition accuracy with less number of bins can be evolved from the methods tested. Performance of more number of geometrical measures can be analyzed for the combined approach in future.

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