

RADIUS BASED BLOCK LOCAL BINARY PATTERN ON T-ZONE FACE AREA FOR FACE RECOGNITION

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ABSTRACT

This study presents a comparison of recognition performance between feature extraction on the T-Zone face area and Radius based block on the critical point. A T-Zone face image is first divided into small regions where Local Binary Pattern (LBP) histograms are extracted and then concatenated into a single feature vector. This feature vector will further reduce the dimensionality scope by using the well established Principle Component Analysis (PCA) technique. On the other hand, while the original LBP techniques focus in dividing the whole image into certain regions, we proposed a new scheme, which focuses on critical region, which gives more impact to the recognition performance. This technique is known as Radius Based Block Local Binary Pattern (RBB-LBP). Here we focus on three main area which is eye (including eyebrow), mouth and nose. We defined four critical point represent left eye, right eye, nose and mouth, from this four main point we derived the next nine point. This approach will automatically create the redundancy in various regions and for every radius size window a robust histogram with all possible labels constructed. Experiments have been carried out on the different sets of the Olivetti Research Laboratory (ORL) database. RBB-LBP obtained high recognition rates when compared to standard LBP, LBP+PCA and also on T-Zone area. Our result shows of 16% improvement compared with LBP+PCA and 6% improvement compared with LBP. Our studies proves that the RBB-LBP method, reduce the length of the feature vector, while the recognition performance is improved.

Keywords: Principle Component Analysis, Local Binary Pattern, Face Recognition, ORL, RBB-LBP

1. INTRODUCTION

Face recognition is one of the few biometric methods that possess the merits of both high accuracy and low intrusiveness. Since the early 70's, face recognition has drawn the attention of researchers in various fields, which include security, psychology, image processing and computer vision. A face recognition system can be used in two modes: Authentication (or verification) and identification. An authentication system involves confirming or denying the identity claimed by an individual. On the other hand, an identification system attempts to establish the identity of a given person out of a pool of different people. Identification generally

operates on a closed-set scenario (the individual to identify is present in the database), while authentication operates on an open-set scenario, where people's face not present in the database could try to fool the system. Although these tasks are slightly different, both modes usually share the same classification algorithms. In this study, the focus is on the face authentication task.

Existing face recognition algorithms are often divided into two categories: Holistic matching method and local matching method, depending on the way the face image is processed. In holistic matching method, the whole face image is represented as a high-dimensional vector. Due to the size of dimensionality, such vectors cannot be compared directly. Hence, holistic methods use

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dimensionality reduction techniques to resolve this problem and thus derive lower-dimensional vectors for subsequent classification. The most popular examples among such approaches are based on Principal Component Analysis (PCA) (Turk and Pentland, 1991) and on Linear Discriminant Analysis (LDA) (Etemad and Chellappa, 1997). The general idea behind this global approach is to extract the main information in the training set as represented by some template images that capture most of the variability in the data. This is done by calculating the vectors which is the eigenvectors of the covariance matrix for the training set, that best represent this small region of image space. By using only the eigenvectors with eigenvalues (that is above some threshold defined) a new data set is obtained with less dimensions, but still with the most important characteristics of the original data. So the main idea of PCA, used for face recognition, is that the original data is transformed to a different space, with fewer dimensions, in which it is easier to measure the relevant differences and similarities between them.

On the other hand, local matching methods are typically employs a set of local observations obtained from the face image to derive a model of an individual, which is subsequently used for recognition. One of the most representative systems in this family is the Local Binary Patterns (LBP) (Ahonen *et al.*, 2006; Rodriguez and Marcel, 2006), where the face is represented by a set of concatenated LBP histograms, each one being computed in a different block of pixels along the image. Recognition is then performed by measuring the similarity between histograms.

The main objective of this is paper to present a 'significant facial region' in human face area and hybrid techniques of holistic and local based feature extraction method in face authentication. The eye and nose region was providing high accuracy compared to the mouth region as tested independently (Zou *et al.*, 2007). In traditional pattern recognition systems, global feature extraction method such as PCA is widely used to reduce the dimensionality. The use of Principle Component PCA for face recognition has been described by several research groups (Turk and Pentland, 1991; Etemad and Chellappa, 1997; Chan *et al.*, 2010) in the last decade. While on the pixel level or local feature extraction the LBP had emerge into the new dimension in Face recognition study.

1.1. Principles of Local Binary Pattern

The original LBP operator was introduced by (Ojala *et al.*, 1996). This operator works with the

eight neighbors of a pixel, using the value of the center pixel as a threshold in which extensive studies have been done regarding the threshold value (Meng *et al.*, 2010). All neighbors that have values higher than the value of the central pixel are given value 1 and all those that have values lower or equal to the value of the central pixel are given value 0. The eight binary numbers associated with the eight neighbors are then read sequentially in the clockwise direction to form a binary number. This binary number or its equivalent in the decimal system may be assigned to the central pixel and it may be used to characterize the local texture. The process is shown in **Fig. 1**.

Later the LBP operator was extended to use neighborhoods of different sizes (Ojala *et al.*, 2002; Shuicheng *et al.*, 2007). 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 method is necessary. For example, if the coordinates of the center pixel are (x_c, y_c) then the coordinates of its P neighbors (x_p, y_p) on the edge of the circle with radius R can be calculated with the sinus and cosines where P is the stepsize of its circumference Equation 1 and 2:

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

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

From the given formula, **Fig. 2** shows the graphical representations of interpolated pixel calculated for central pixel (4,4).

Ojala *et al.* (2002) also noticed that most of the texture information was contained in a small subset of LBP patterns. These patterns, called uniform patterns, contain at most two bitwise 0 to 1 or 1 to 0 transitions (circular binary code). 11111111, 00000110 or 10000111 are for instance uniform patterns. They represent primitive micro-features such as lines, edges and corners. **Figure 3** shows some texture primitives detected by LBP.

Figure 4 shows an image which is split into an image with only pixels with uniform patterns and its LBP image. These images are created by using the standard LBP operator. From our observation, the image with only pixels from uniform patterns will contains a considerable amount of pixels, with 86% of the original image. Thus, by taking only the pixels with uniform patterns, the background is also preserved.

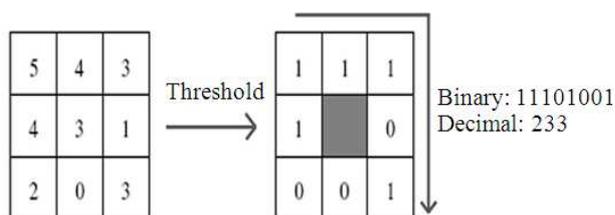


Fig.1. The original LBP Operator

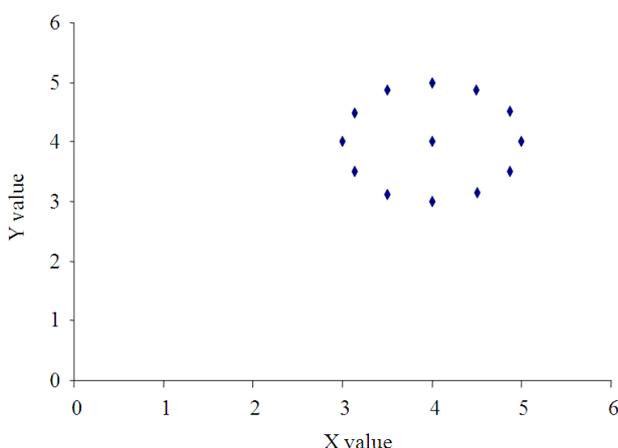


Fig.1. The original LBP operator

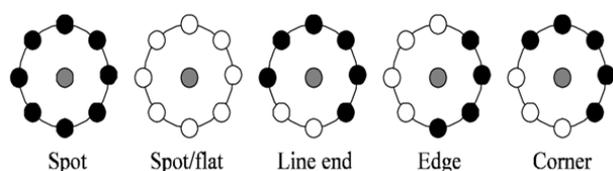


Fig. 3. Texture primitives detected using LBP

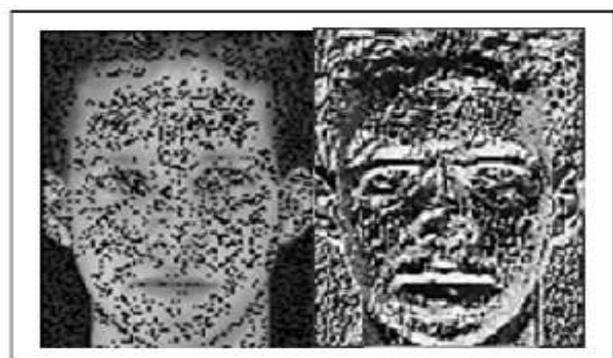


Fig. 4. Uniform image (left), LBP image (left)

This is due to most of the background pixels are having the same color (same gray value) and thus their patterns contain zero transitions. Most of the pixels around the mouth, the nose and the eyes (especially the eyebrows) have uniform patterns.

1.2. Feature Vectors

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 (height×width) image the feature vector is constructed by calculating the LBP code for every pixel (x_c, y_c) with x_c ∈ {R+1, ..., N-R} and y_c ∈ {R+1, ..., M-R}, where R is a radius length. If an image is divided into k×k regions, then the histogram for region (k_x, k_y), with k_x ∈ {1, ..., k} and y_x ∈ {1, ..., k}, can be defined as:

$$H_i(k_x, k_y) = \sum_{x,y} I\{LBP_{p,R}(x, y) = L(i)\}, i = 1, \dots, P(P-1) + 3$$

And L is the label of bin I and P is the number of point selected.

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

1.3. Comparing Feature Vectors

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

Histogram intersection Equation 3:

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

Log-likelihood statistic Equation 4:

$$L(S, M) = \sum_{j=1}^{k^2} \left(- \sum_{i=1}^{P(P-1)+3} S_{i,j} \log M_{i,j} \right) \tag{4}$$

Chi square statistic (χ²) Equation 5:

$$\chi^2(S, M) = \sum_{j=1}^{k^2} \left(\sum_{i=1}^{P(P-1)+3} \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}} \right) \tag{5}$$

In these equations $S_{i,j}$ and $M_{i,j}$ 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. Ahonen *et al.* (2004) stated that, the χ^2 (5) performs better than histogram intersection (3) and the log-likelihood statistic (4). This weighted χ^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 χ^2 (also called the 'distance' between the two images), the bigger the similarity.

2. MATERIALS AND METHODS

We have divided our experiment into two section, first section focuses on T-zone face area. In the proposed scheme for each face image is not taken as a whole, but we consider for certain regions, which gives more impact to the recognition. Based on (Zou *et al.*, 2007), the eye and nose regions represent the most important characteristics. This technique is also known as T-Zone based template. **Figure 5** shows the T-Zone face image. As in **Fig. 6**, the T-Zone images are divided into 10 windows to provide more efficient representation of the face region.

The window size is almost an equal size of 18×19 . By dividing the images into m windows, the length of the feature vector becomes m times larger. For every window 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 windows or region. The feature vector is then constructed by concatenating the regional histograms to one big histogram. Once the Local Binary Pattern for every pixel is calculated, the feature vector of the image can be constructed.

For every region all non-uniform patterns (more than two transitions) are labeled with one single label. This means that every regional histograms, it 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 pattern. The total feature vector for an image contains $(P(P-1)+3)$ bins times with the number of region. So, for an image divided into 10 regions (**Fig. 6**) and eight sampling points on the circles, the feature vector has a size of 590 bins. **Figure 7** shows samples on the

individual histogram for each region and **Fig. 8** illustrates the histogram combination of all regions.

In the second section, our experiment is based on the aesthetic values of the face image (Davies *et al.*, 1977; Ellis *et al.*, 1979; Fraser *et al.*, 1990; Young *et al.*, 1985), which shows that the eye, nose, mouth and eyebrow region represents the most important characteristics for a person compared to the cheeks, forehead and chin.

While based on (Javid *et al.*, 2001; Sinha *et al.*, 2006; Keil, 2009) the neurophysiologic study, the eye and eyebrow region are critical followed by mouth and nose region. These study shows the recognition performance using 3 datasets (without eyebrow, eye and normal) that the one without eyebrow drops dramatically as compared to other sets (**Fig. 9**).

As the original LBP techniques focus in dividing the whole image into regions, the proposed scheme focuses on critical region, which gives more impact to the recognition performance as discussed above. This technique is also known as Radius Based Block Local Binary Pattern (RBB-LBP). Here we focus on three main area which is eye (including eyebrow), mouth and nose. We defined four critical points represented as left eye (T_1), right eye (T_2), nose (T_3) and mouth (T_4). From these four main points we derived the next nine point (T_5-T_{13}) as shown in **Fig. 10**.

Based on the points generated, images are divided into T_m windows to provide more efficient representation of the face. The window size is extracted based on the radius from 3 to 10 in size. By dividing the images into m windows, the length of the feature vector becomes m times larger for every radius chosen. **Figure 11a** shows region with radius n_1 from a point and **Fig. 11b** shows region with radius n_2 from a point. This approach will automatically create the redundancy in various regions and for every radius size window, a robust histogram with all possible labels are constructed.

This means that every bin in a histogram represents a pattern and contains the number of its appearance in the windows or region. We also test the combination of various sizes of radius windows as shown in **Fig. 11c**. The feature vector is then constructed by concatenating the regional histograms to one big histogram. Once the LBP for every pixel is calculated, the feature vector of the image can be constructed.

For every region of all non-uniform patterns (more than two transitions) are labeled with one single label. This means that for every regional histograms, it 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 $(P(P-1)+3)$ bins times with the number of region. An image is divided into 13 regions and eight sampling points on the circles, where the feature vector has a size of 767 bins. **Figure 12** shows samples on the individual histogram of each region, **Fig. 13** shows histogram with radius 10 and **Fig. 14** shows histogram with combination of radius 3 and 10.

This study employs the Olivetti Research Laboratory, cambridge (ORL) database (Samaria and Harter, 1994) to obtain and compare the results of proposed method with other similar approaches. It is a relatively small database comprising 400 unregistered images of 40 people with 10 samples for each person. The samples are grey scale and sized at 92×112 pixels. All the images were taken against a dark homogenous background with the subjects in an upright, frontal position, with tolerance for some tilting and rotation of up to about 20° . They contain large within-class variance in lighting, pose and appearance due to the presence/absence of glasses/facial hair and different times of capture.



Fig. 5. LBP Image (left) and T-Zone LBP Image (right)

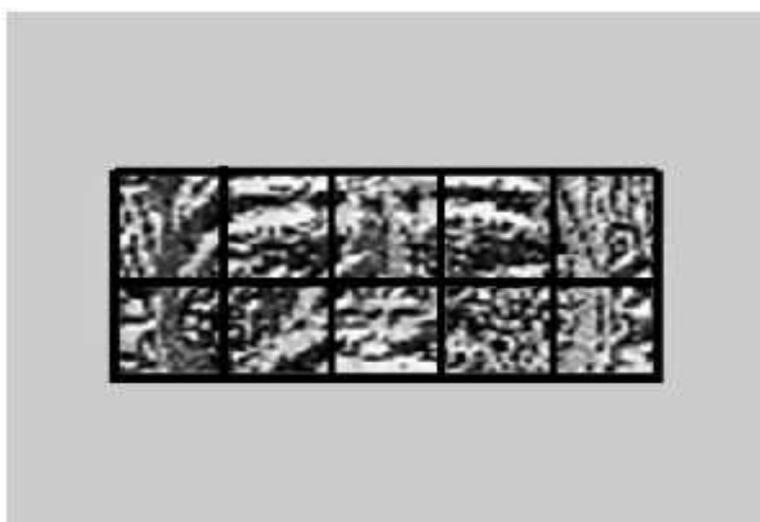


Fig. 6. Face image divided into 10 regions

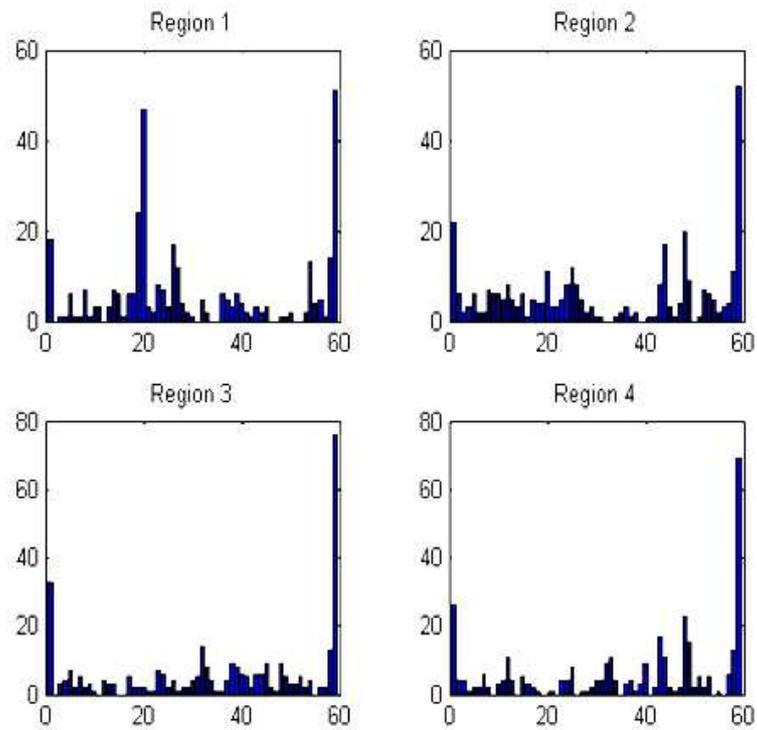


Fig. 7. Individual histogram for every region

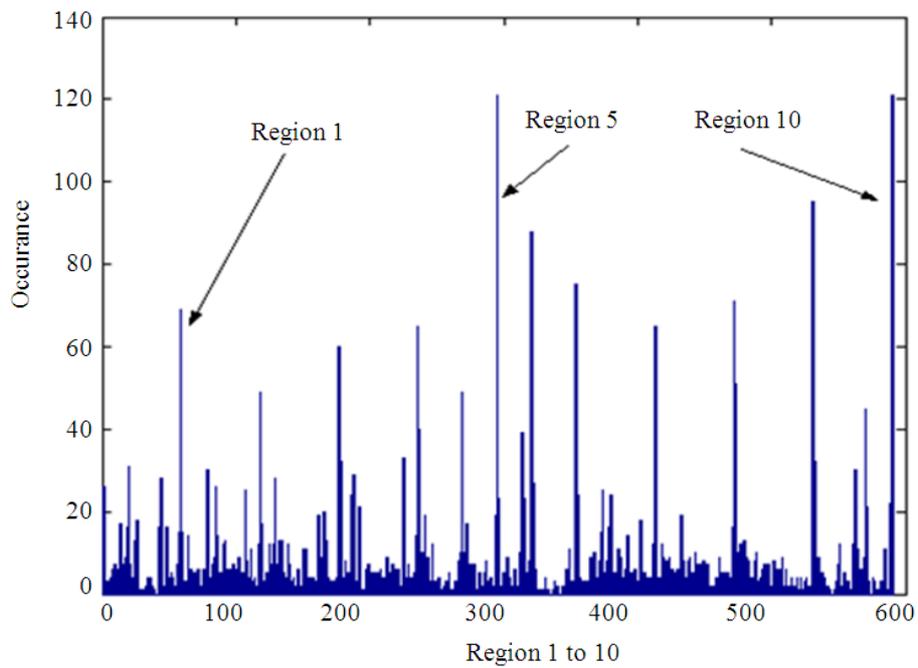


Fig. 8. Combination of all region



Fig. 9. Face Image comparison between non eyebrow and without eyes

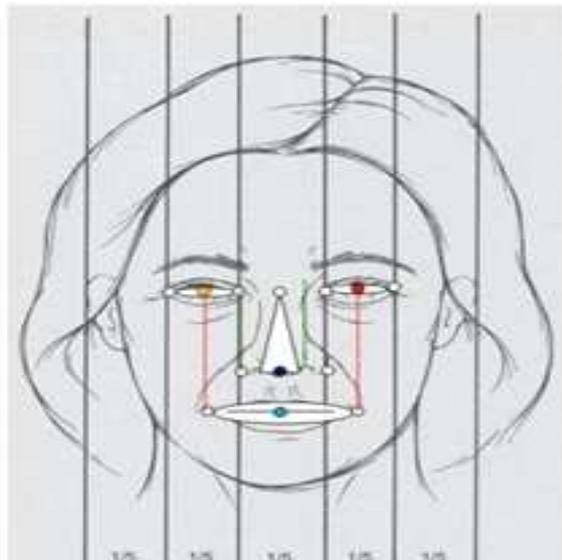


Fig. 10. Critical point derivation from 4 main point

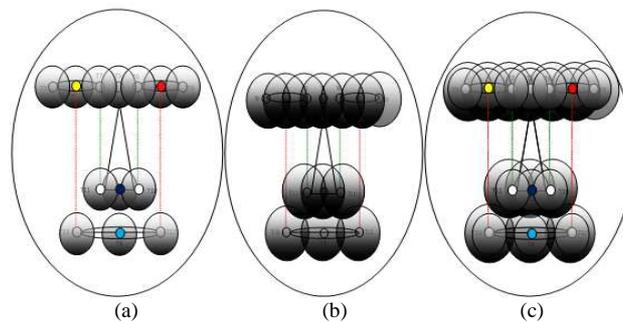


Fig. 11. (a) Region with radius n1 (b) Region with radius n2

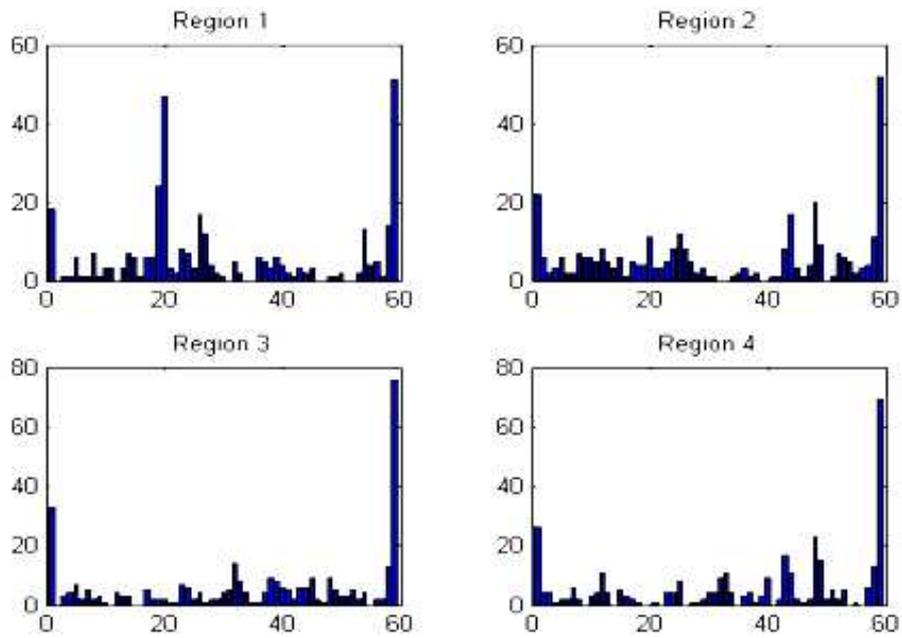


Fig. 12. Individual histogram for every region

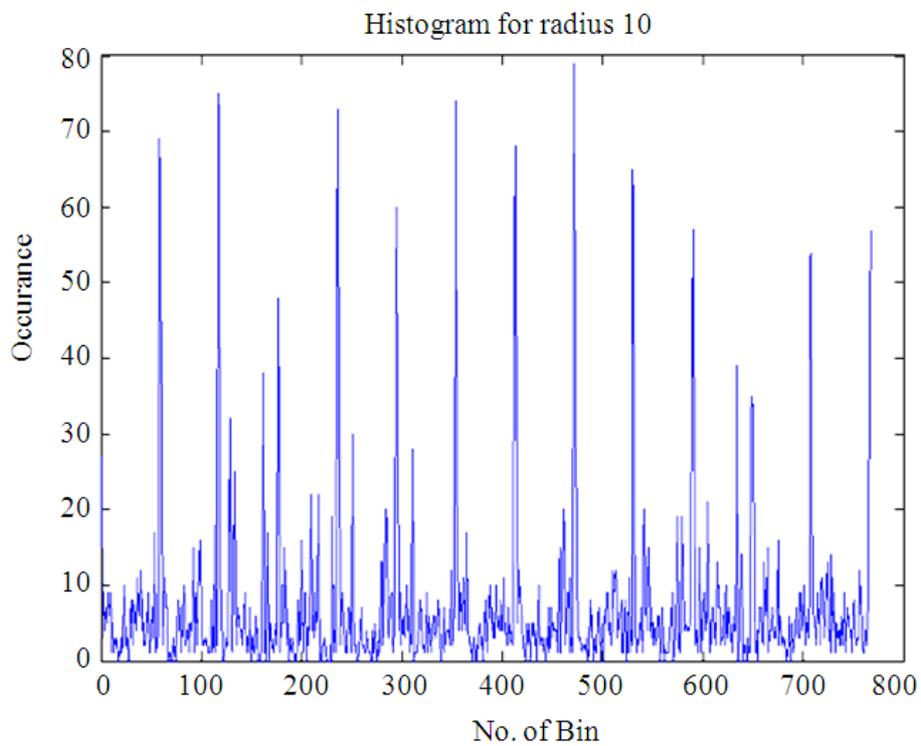


Fig. 13. Histogram with Radius 10

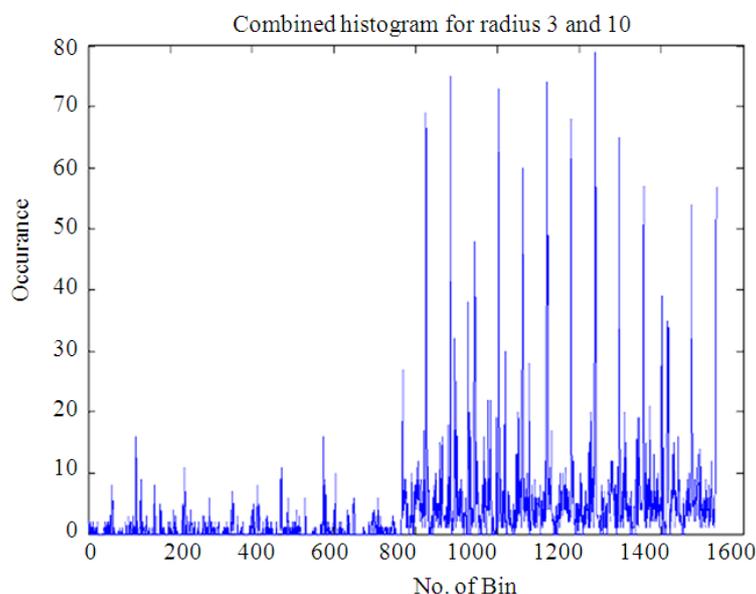


Fig. 14. Combination of histogram with radius 3 and 10

A total of 200 images are used for training and another 200 are used for testing. Each training set contains of 5 randomly chosen image from the same class in the training stage. There is no overlap between the training and test set. The preprocessed images and possibly the training data are fed in to the experimental algorithm which performs the feature extraction. We test three types of algorithm which is a standard LBP and the combination of LBP+ PCA and RBB-LBP. In LBP and RBB-LBP we used χ^2 as a distance measure and for LBP-PCA and RBB-LBP+PCA, we applied Euclidean distance to classify. The distance between all pair of Gallery (G) and test (P) image are computed and stored in a distance matrix. To compute a recognition rate, for each test image $p \in P$, sort G by increasing distance d from p, yielding a list of gallery images L_p . Let $L_p(k)$ contain the first k image in this sorted list. An indicator function $r_k(p)$ return 1 if p is recognized at rank k and zero otherwise. Recognition rate for test set P is denoted $R_k(P)$, where:

$$R_k(P) = \frac{\sum_{p \in P} r_k(p)}{n} \text{ where } Ln = |P| \quad (6)$$

By using the (6) the rank curve is calculated. A rank curve is a cumulative matching score for the test images with the trained images.

3. RESULT

The Olivetti Research Laboratory face database was used in our experiments. Each photo is an image of size of 92×112 pixels and quantized to 256 gray levels. We tested 200 images of 40 individuals. In spite of small rotation, orientation, illumination variances, expression and decoration (primarily eyeglass changes) the algorithm works in a fairly robust manner. Distances in the feature space from a template image to every image in the database were calculated. Following to the FERET protocol (Beveridge *et al.*, 2005; Phillips *et al.*, 1998), 5 nearest face images were derived and if there were photos of the query person then the result was considered positive. Each image was tested as a query and compared with others.

The first part of recognition performance is reported in **Table 1 and 2** (for standard LBP and LBP-PCA. **Figure 15** shows the recognition performance of LBP-PCA on T-Zone and whole face region, while in **Table 3**, show the performances of both LBP and LBP-PCA comparing with other methods

In the second section, we compare our result on RBB-LBP ($s_{1,1}$) and RBB-LBP ($s_{2,2}$) with original LBP, PCA, PCA with histogram equalization and combination of RBB-LBP+PCA. **Figure 16 and 17** shows that the performance of RBB-LBP (for 8 sampling point and radius 1 and 2). **Figure 18** compares the performance of RBB-LBP and RBB-LBP+PCA.

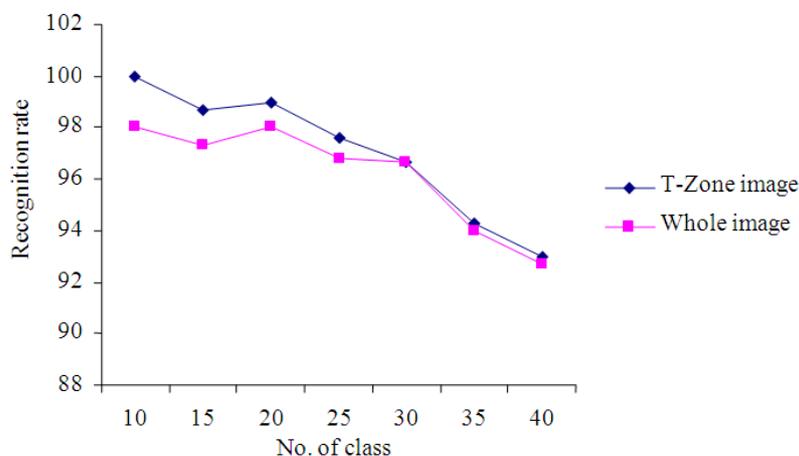


Fig. 15. LBP-PCA-Comparison of recognition rate and number of classes on T-Zone and whole face re

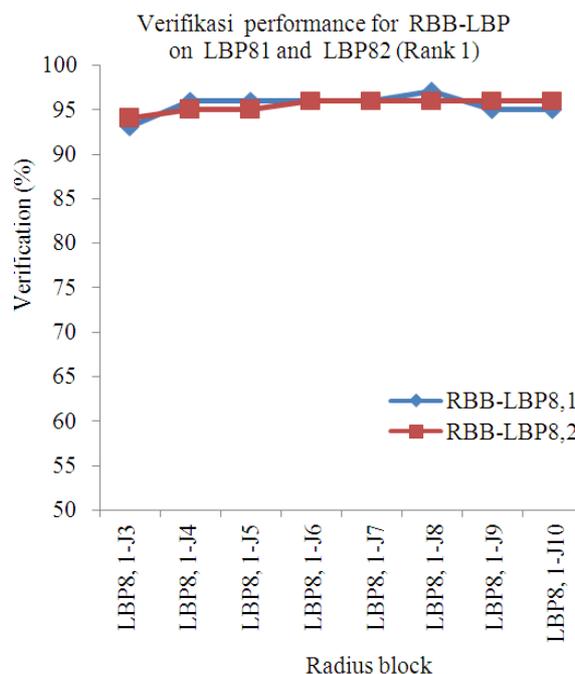


Fig. 16. Verification Performance for RBB-LBP8,1 and RBB-LBP8,2

4. DISCUSSION

Although we are only considering partial area on the face image (T-Zone) and standard LBP operator, the experimental results clearly show a highest recognition rate when the test class size grows bigger and LBP-PCA shows an outstanding recognition rate on a small to medium test class size. The recognition

performance of LBP-PCA on T-Zone and whole face region, It's indicates that T-Zone area gives good recognition rate because of elimination of expressions contains in the whole face region, particularly the mouth region. Both of LBP and LBP-PCA outperformed other methods. These results also indicate a possible direction of applying a dimensionality reduction to the face feature vectors.

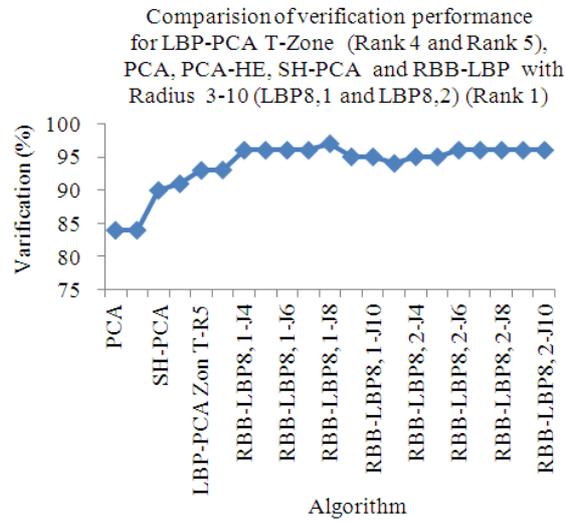


Fig. 17. Verification Performance of Algorithm LBP+PCA on T-Zone, PCA, PCA-HE, SH-PCA and RBB-LBP+PCA Radius 3 to 10 (LBP8, 1 and LBP8, 2)

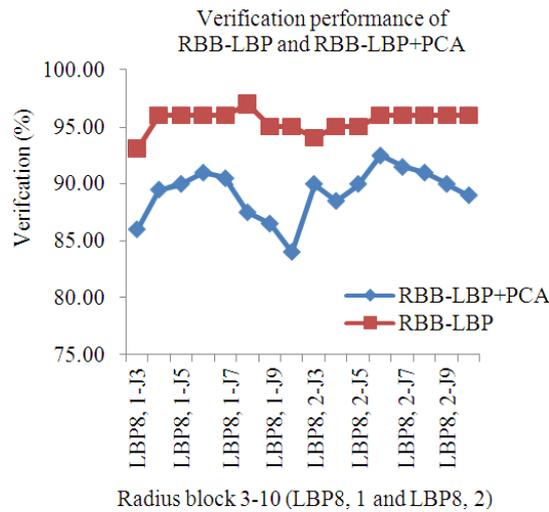


Fig. 18. Performance of RBB-LBP and RBB-LBP+PCA

Table 1. LBP-recognition rate and number of classes

No. of classes	Recognition rate percentage				
	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
10	90.0000	92.0000	92.0000	94.0000	94.0000
15	93.3333	94.6667	94.6667	94.6667	96.0000
20	92.0000	93.0000	96.0000	96.0000	96.0000
25	91.0000	93.6000	96.8000	96.8000	96.8000
30	92.0000	93.3333	96.0000	96.6667	97.3333
35	91.4286	93.1429	95.4286	96.5714	97.1429
40	91.5000	92.0000	94.5000	96.0000	97.0000

Table 2. LBP-PCA-recognition rate and number of classes

No. of Classes	Recognition Rate Percentage				
	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
10	96.0000	96.0000	96.0000	98.0000	100.0000
15	93.3333	94.6667	96.0000	98.6667	98.6667
20	86.0000	89.0000	94.0000	97.0000	99.0000
25	87.0000	89.6000	92.0000	95.2000	97.6000
30	86.0000	89.3333	92.0000	94.0000	96.6667
35	86.8571	90.2857	91.4286	92.5714	94.2857
40	81.0000	85.0000	89.0000	91.0000	93.0000

Table 3. Comparison LBP, LBP-PCA, PCA, PCA with histogram equalization and sh-pca algorithm's correct detection rate for 5 training images of each class

No. of classes	Recognition rate percentage						
	PCA (Khan <i>et al.</i> , 2005)	PCA with HE (Khan <i>et al.</i> , 2005)	Sub Holistic PCA (Khan <i>et al.</i> , 2005)	T-Zone LBP Rank 4	T-Zone LBP Rank 5	T-Zone LBP-PCA Rank 4	T-Zone LBP-PCA Rank 5
10	97	95	99	94.0000	94.0000	98.0000	100.0000
15	97	95	99	94.6667	96.0000	98.6667	98.6667
20	92	92	96	96.0000	96.0000	97.0000	99.0000
25	91	91	95	96.8000	96.8000	95.2000	97.6000
30	89	89	95	96.6667	97.3333	94.0000	96.6667
35	85	86	92	96.5714	97.1429	92.5714	94.2857
40	84	84	90	96.0000	97.0000	91.0000	93.0000

We expect that the combining technique presented here is applicable to several others object recognition tasks. In the second section, we compare our result on RBB-LBP ($_{8,1}$) and RBB-LBP ($_{8,2}$) with original LBP, PCA, PCA with histogram equalization and combination of RBB-LBP+PCA. It's shows that the performance of RBB-LBP (for 8 sampling point and radius 1 and 2) having almost equal performance and also indicates that the RBB-LBP method possesses very high recognition rate (rank1) as compared to other method such as LBP, PCA, LBP T-Zone, PCA with histogram equalization and sub-holistic PCA 5th rank result obtained by (Khan *et al.*, 2005). The performance of RBB-LBP highly outperformed the combinaing technique with PCA.

5. CONCLUSION

In this study, we propose a scheme which focuses on critical region, directly increasing the recognition performance as discussed above. We defined four critical points which represent left eye, right eye, nose and mouth. From this four main points we derived the next nine critical points. Our experimental results clearly

show that our approach outperforms the other methods. RBB-LBP obtained high recognition rates when compared to standard LBP, LBP+PCA and also on T-Zone area. Our studies proves that the RBB-LBP method, reduce the length of the feature vector, while the recognition performance is improved.

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