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FACE RECOGNITION BASED ON TEXTURE ANALYSIS USING ROBUST LOCAL BINARY PATTERN

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Abstract- In this paper, we proposed a technique for face Recognition based on texture analysis using Robust Local Binary Pattern (RLBP). The major demerits of original Local Binary Pattern (LBP) based face recognition methods is that they are sensitive to noise and two different structural patterns produce same LBP code. In order to overcome these demerits, we proposed to adapt RLBP for face recognition, in which the value of each centre pixel in a 3x3 local area of the image is replaced by its average local gray level. Compared to gray value, average local gray level is more robust to noise and illumination variants. The experiments are conducted on face images of two popular face databases such as ORL and Yale. Support vector machine (SVM) classifier is used for classification. The proposed method can achieve good results on ORL and Yale database of face.

Keywords- Robust Local Binary Pattern, Local Binary Pattern, Face Recognition, Support vector machine

Introduction

In past three decades, face recognition and texture analysis has most active research areas in the fields of image processing, pattern recognition and computer vision, because it spans numerous applications [1,2]. Face recognition has many applications like biometrics, access control, surveillance, security, internet and intranet access, credit-card verification, and content-based video retrieval. There are mainly two approaches are used for face recognition, one is geometry based approach and second one is the appearance based approach. In geometry based approach [3-6], change in scale, location and in-plane rotation of the face as well as rotation in depth, geometry is difficult to measure with any accuracy, particularly from a single still image, but it provides more robustness against aging and disguises. Whereas, Appearance based approaches [7-10], have shown promising recognition accuracy against changes of facial expression; personal appearance i.e. glasses, make-up, facial hair, hairstyle, but still optimal accuracy is not achieved due to various challenges posed by face recognition problem. Most promising appearance-based methods are based on Local binary pattern (LBP) and its variants features, because the important properties of the LBP features are their tolerance against illumination changes and their computational simplicity.

LBP operator was mainly used for texture description [11,12], image classification [13], and object recognition. The researchers have explored to adopt LBP for face recognition because of its power to extract robust facial features against challenges of face recognition in uncontrolled environment. In face recognition, it achieved a good performance than Eigen face and Bayesian methods. Discriminative feature extraction is an important step prior to face recognition. Extraction of a Discriminative feature set can greatly enhance the performance of any face recognition system. Local Binary Pattern is known to be a powerful discriminative feature extractor for face representation [13]. The success of LBP face description due to its computation simplicity and discriminative power of the operator and its robustness to monotonic gray scale changes caused by illumination variations.

Recently many authors have proposed algorithms for face recognition using LBP variants, Nguyen and Caplier [14] proposed Elliptical Local Binary Patterns (ELBP) for face recognition. In this approach, horizontal and vertical ellipse patterns to capture micro facial feature of face images in both horizontal and vertical directions. Jun, et al. [15] proposed Compact LBP (CLBP) for face analysis. This method having three stages to extract features, in the first stage, reduced the dimensionality of the training images by using mutual information, the selected LBP feature vectors are the most discriminative. In the second stage, the dimensionality reduced training images were transformed into histograms of LBP by the histogram transformation. In third stage, several LBP code frequency vectors are selected using maximization of mutual information based code. Liao, et al. [16] proposed Multi-scale Block Local Binary Patterns (MB-LBP) for face recognition uses sub-region average gray-values for comparison instead of single pixels. MB-LBP encodes both microstructures and macrostructures for better representation of image patterns and it can be computed very efficiently using integral images. Tan and Triggs [17] present a new method for face recognition under uncontrolled lighting based on robust pre-processing and extension of the LBP called Local ternary pattern (LTP). Ren, et al. [18] proposed method Relaxed Local Ternary Patterns for face recognition. Local binary pattern (LBP) is sensitive to noise. Local ternary pattern (LTP) partially solves this problem by encoding the small pixel difference into a third state. The ternary code is split into a positive LBP code and negative LBP code, it may result in a significant information loss. The positive and negative LBP histograms are strongly correlated, and hence a lot of redundant information may reside in those two histograms. The main drawback of LTP is that computationally it is more expensive than LBP. Pu, et al. [19] proposed a method for face recognition based on multi-resolution with multi-scale LBP features. The facial image pyramid is constructed and each facial image is divided into regions from which partial and holistic LBP histograms are extracted. All LBP features of each image are concatenated to a single LBP vector with different resolutions.

Qian, et al. [20] proposed another variant of LBP called pyramid transform domain LBP. Cascading the LBP (PLBP) information of hierarchical spatial pyramids, PLBP descriptors take texture resolution variations into account. PLBP descriptors show their effectiveness for texture representation. Gao, et al. [21] presented a face description with single sample by Adaptively Weighted Extended Local Binary Pattern Pyramid (AWELBPP). AWELBPP feature is extracted from the fusion of the Sub-Extended LBP pyramid extracted from local pyramid images and the Adaptively Weighting Map (AWM) according to the contribution of each sub-image to the final face feature description. Maturana, et al. [22] proposed algorithm for face recognition. They extracted descriptors based on histograms of LBP, finally perform descriptor matching with spatial pyramid matching and Naive Bayes Nearest Neighbor. The drawback of Naive Bayes Nearest Neighbor is increase the computational cost relative to the original LBP based algorithm. Anusha Bamini and Kavitha [23] presented a method for face detection using Dominant Local Binary Patterns. In their experiments demonstrate that the Dominant Local Binary Pattern features are discriminative and robust over a range of facial image resolutions.

Shan [24] proposed a method for gender classification using learn discriminative LBP-Histogram bins as compact facial representation, support vector machine is used to classification and achieve the classification rate of 94.81% on the LFW database. Pujol and Garcia [25] present a method Principal Local Binary Patterns to reducing the dimensions of the feature vectors to perform the face recognition task. The feature vector contains relevant information required to recognize a face; they designed a 9-region mask, belonging to the most important face areas related to face recognition, such as the eyes, the nose or the mouth; for face recognition the weights are assigned to each face region using data mining tools.

The face recognition methods described above based on LBP and its variants have two important drawbacks. The first drawback is that, different structural patterns produce same binary patterns. For example, the two different vectors (55, 85, 80, 85, 45, 50, 35, 30) and (150, 230, 235, 240, 10, 100, 150, 150) have produced same binary vector (0, 1, 1, 1, 0, 0, 0, 0). However, it is hard to say they have similar local structure. The second drawback is that, they are sensitive to noise. This is because, in LBP, the value of central pixel in 3×3 local area is subtracted by its neighbors and result yields LBP code. For instance, the value of central pixel is changed due to occurrence of noise, this leads to different binary code than its original binary code. In order to overcome incorrect matches due to same binary code generated for different structural patterns, CLBP (Completed LBP) was introduced by Guo, et al. for texture classification [26]. However, the CLBP method is sensitive to noise because in order to generate binary code, the value of central pixel value is still used as threshold directly. In order to make LBP robust against noise, Zhao, et al. [27] have extended CLBP method called as CRLBP (Completed Robust LBP) for texture classification. The value of every central pixel in a 3x3 local block is replaced by its average local gray level. Compared to gray value, average local gray level is more robust to noise and illumination variants. However, compared to original LBP, the computation time of CRLBP is very high due to computation of three components such as sign, magnitude and central component, whereas original LBP computes only sign component. Therefore, original LBP reduces computation time to half of the CRLBP. In this paper, we proposed a technique for face recognition using Robust Local Binary Pattern (RLBP). Instead of computing three components such as sign, magnitude and central component, we compute only sign component using average local gray value of 3×3 local area. This makes our method insensitive to noise and to avoid the problem of generating same binary code for two different patterns, we considered neighbours of each neighbour pixel for computing the binary code. The rest of the paper is organized as follows, Section II describes the original LBP, Section III introduces the RLBP, which is proposed to adapt for face recognition. Section IV describes the SVM Classifier. In section V, we present experimental results. Finally, we conclude the paper.

Local Binary Pattern (LBP)

The LBP operator was first introduced by Ojala, et al. [11]. LBPs by the definition are invariant with respect to any monotonic transformation of the gray scale. This is achieved by considering only the signs of differences instead of the exact values of the gray scale. Consider texture T,

$$T \approx t(s(g_o - g_c), s(g_1 - g_c), \dots, s(g_{p-1} - g_c)), \qquad (1)$$

in a local neighborhood with gray levels of P $(P > 1)$ image pixels. Where g_p $(p=0,\dots,P-1)$ gray values, g_c being the centre gray value and

$$s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases}, \qquad (2)$$

the sign is 1 if positive and 0 if negative. The above is transformed into a unique P-bit pattern code by assigning binomial coefficient 2^p to each sign $s\,(g_{p-1}-g_c)$ example shown in [Fig-1].

$$LBP_{P,R} = \sum_{p=0}^{p-1} s(g_{p-1} - g_c)2^p. \qquad (3)$$

Later the operator was extended to use neighborhoods of different sizes [12]. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods, we use the notation (P, R) which means P sampling points on a circle of radius of R.

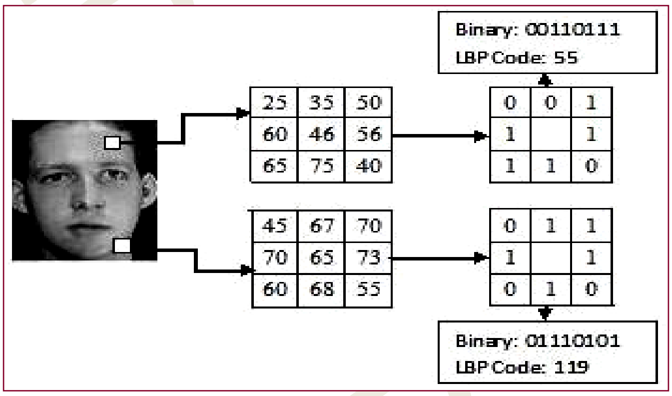

Fig. 1- Basic LBP operator

Robust Local Binary Pattern (RLBP)

Y. Zhao et al. [27] recently proposed Completed robust local binary pattern (CRLBP), finding a threshold which is insensitive to noise and invariant to monotonic gray scale transformation; define the Average Local Gray Level (ALG) as follows

$$ALG = \frac{\sum_{i=1}^{8} g_i + g}{9} \qquad (4)$$

Where g represents the gray value of the centre pixel and g_i (i=0,...,8) denotes the gray value of the neighbor pixel. ALG represents the average gray level of local texture, which is obviously more robust to noise than the gray value of the central pixel. Then the LBP process is applied by using ALG as the threshold instead of the gray value, named Robust Local Binary Pattern (RLBP). This can be defining as follows:

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - ALG)2^p = \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + g_c}{9} \right) 2^p, \qquad (5)$$

where g_c represents the gray value of the centre pixel and gp *(p=0, …., P-1)* denotes the gray value of the neighbor pixel on a circle of radius R, P is the total number of the neighbors and g_{ci} (i=0,...,8) denotes the gray value of the neighbor pixel of g_c. It is obviously that RLBP is insensitive to noise since average local gray level of pixel is used as a threshold. Besides, two different patterns with the same LBP code may have different RLBP code because that the neighbors of each neighbor pixel are also considered. Thus RLBP can overcome the two demerits of the original LBP.

ALG ignores the specific value of an individual pixel. While sometimes the specific information of the central pixel is needed. To make a balance between anti-noise and information of individual pixel, we define a Weighted Local Gray Level (WLG) as follows:

$$WLG = \frac{\sum_{i=1}^{8} g_i + \alpha g}{8 + \alpha}, \qquad (6)$$

where g and g_i are defined in [Eq-4], α is parameter set by user. It should be notice that WLG is equivalent to the conventional ALG if α is set as 1. Now the RLBP can be calculated as follows:

$$RLBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - WLG_c)2^p = \sum_{p=0}^{P-1} s\left(g_p - \frac{\sum_{i=1}^{8} g_{ci} + \alpha g_c}{8 + \alpha} \right) 2^p, \qquad (7)$$

where g_p, g_c, g_{ci} are defined as in [Eq-5], α is the parameter of WLG.

A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or 1 to 0, when the binary string is considered circular. For example 00000001, 00011111 and 11000111 are uniform patterns. We extend the RLBP to uniform RLBP, the notation used for the RLBP operator: $RLBP^{u2}_{P,R}$ or *U(RLB $P_{P,R}$)* as defined below:

$$U(RLBP_{P,R}) = | s(g_{p-1} - WLG_c) - s(g_0 - WLG_c) | + \sum_{p=1}^{p-1} | s(g_p - WLG_c) - s(g_{p-1} - WLG_c) | \qquad (8)$$

The subscript represents using the operator in a (P, R) neighborhood. Superscript u2 stands for using only uniform patterns and labeling all remaining patterns with a single label.

The $LBP_{P,R}$ operator produces 2P different output values, corresponding to the 2P different binary patterns that can be formed by the P pixels in the neighbor set. When the image is rotated, the gray values g_p will correspondingly move along the perimeter of the circle around g_0. Since g_0 is always assigned to be the gray value of element (0, R) to the right of g_c rotating a particular binary pattern naturally results in a different $LBP_{P,R}$ value. This does not apply to patterns comprising on only 0s (or 1s) which remain constant at all rotation, i.e., to assign a unique identifier to each rotation invariant local binary patterns. We extend the rotation invariant local binary pattern to RLBP as defined below:

$$RLBP^{ri}_{P,R} = min\{ROR(RLBP_{P,R}, i = 0,1,...P-1\} \qquad (9)$$

where *ROR(x,i)* performs a circular bit-wise right shift on the P-bit number x, i times. In terms of pixels, simply corresponds to rotating the neighbour set clockwise so many times that a maximal number of the most significant bits, starting from g_{p-1}, is 0. $RLBP^{ri}_{P,R}$ quantifies the occurrence statistics of individual rotation invariant patterns corresponding to certain micro features in the image:

$$RLBP^{riu2}_{P,R} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - WLG_c) & if \quad U(RLBP_{P,R}) \le 2 \\ P+1 & otherwise \end{cases} \qquad (10)$$

superscript *riu2* reflects the use of rotation invariant uniform patterns.

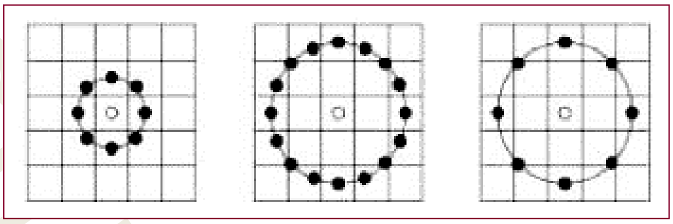

Fig. 2- Extended LBP operators

Support Vector Machine

Support vector machine (SVM) is a learning algorithm for pattern classification, regression and density estimation [28]. The basic training principle behind SVMs is finding the optimal linear hyper plane such that the expected classification error for unseen test samples is minimized. According to the structural risk minimization principle and VC dimension minimization principle, a linear SVM uses a systematic approach to find a linear function with the lowest capacity. For linearly nonseparable data, SVMs can nonlinearly map the input to a high-dimensional feature space where a linear hyper plane can be found.

Given a labelled set of M training samples (X_i, y_i) where $X_i \in R^N$ and y_i is the associated label ($y_i \in$ {-11}), a SVM classifier finds the optimal hyper plane that correctly separates the training data while maximizing the margin. The discriminant hyper plane is defined by:

$$f(X) = \sum_{i=1}^{M} y_i \alpha_i \cdot k(X, X_i) + b, \qquad (11)$$

where is $k(\cdot,\cdot)$ a kernel function, b is a bias and the sign of *f(X)* determines the class membership of X. To construct an optimal hyper plane is equivalent to finding all the nonzero α_i and is formulated as a quadratic programming problem with constraints.

For a linear SVM, the kernel function is just a simple dot product in the input space while for a nonlinear SVM the kernel function projects the samples to a higher dimension feature space via nonlinear mapping function:

$$\emptyset : R^N \rightarrow F^M, \tag{12}$$

where $M >> N$, and then constructs a hyperplane in F. By using Mercer's theorem, the projecting samples into the high-dimensional feature space can be replaced by a simpler kernel function satisfying the condition

$$K(X,X_i) = \emptyset(X).\emptyset(X_i), \tag{13}$$

where Φ is the nonlinear projection function. Several kernel functions, such as polynomials and radial basis functions have been shown to satisfy Mercer's theorem and have been used successfully in nonlinear SVMs:

$$k(X,X_i) = ((X,X_i)+1)^d, \tag{14}$$

$$k(X,X_i) = exp\,(-\gamma \mid X,X_i \mid^2), \tag{15}$$

where d is the degree in a polynomial kernel and γ is the spread of a Gaussian cluster.

Experimental Results

In this section we present the experimental results obtained from the proposed method using ORL and Yale face database. SVM classifier is used for classification. In order to evaluate the proposed method, recognition result of our method is compared with other popular LBP based face recognition methods. All the experiments were conducted on processor Core 2 duo E8400 @ 3.00 Ghz, 3 GB RAM with Windows XP SP3, the programming environment is Matlab 2010b. For each dataset we use approximately half of the subjects per class as training set and the rest as test. The reported accuracy is the average over 10 runs, with a different training and test set partition used in each run. The experiments are conducted for different combination (neighbourhood=P and radius=R) by varying the value of weighing parameter α in the range 1 to 8. RLBP ($RLBP_{P,R}$) histogram of 255 labels, uniform RLBP $(RLBP^{u2}_{P,R})$ histogram of 59 labels and rotation invariant uniform RLBP $(RLBP^{riu2}_{P,R})$ histogram of 10 labels are calculated. A histogram of the labelled image $f_l\,(x,y)$ is defined as

$$H_i = \sum_{x,y} I\{f_l(x,y) = i\}, i = 0,\ldots,n-1, \tag{16}$$

in which n is the number of different labels produced by the RLBP operator. This histogram contains information about the distribution of the local micropatterns, such as edges, spots and flat areas, over the whole image.

We have conducted several experiments on both the database to identify the optimal value for parameters such as α, R and P for RLBP, uniform RLBP and rotation invariant uniform RLBP. In order to identify the optimal value for each of the parameter, first we fixed the value of $\alpha=1$ and conducted experiments on different combination (P=8, R=1 and P=8, R=2) of uniform and rotation invariant uniform RLBP . After identifying the optimal value for parameters P and R, in the second stage, we vary the α value in the range 1 to 8 to identify the optimal value for α. After conducting several experiments; we conclude that polynomial kernel function with degree 3 for SVM yields highest recognition rate than other kernel functions. Hence, in all the experiments we used SVM with polynomial kernel function (degree 3) for classification.

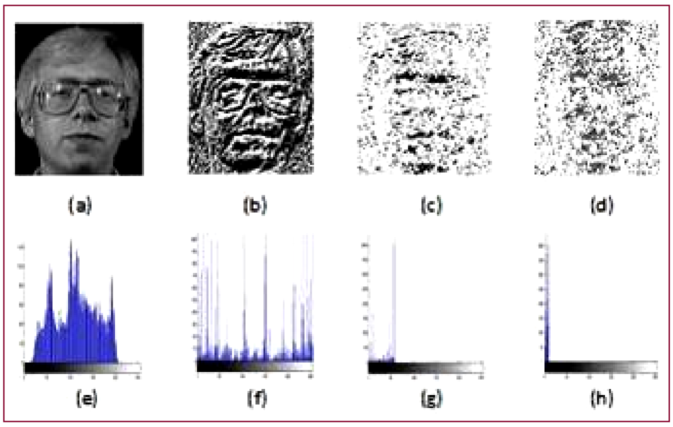

Fig. 3- (a) Original Image **(b)** RLBP image **(c)** $RLBP^{u2}_{P,R}$ image **(d)** $RLBP^{riu2}_{P,R}$ image **(e)** Original image histogram **(f)** RLBP image histogram **(g)** $RLBP^{u2}_{P,R}$ image histogram **(h)** $RLBP^{riu2}_{P,R}$ image histogram

Results on ORL Database

The ORL database contains ten different images of forty distinct subjects, were taken between April 1992 and April 1994 at the AT & T lab [29], Cambridge. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses), All the images were taken against a dark homogeneous background with the subjects in an upright frontal position. The size of each image is 92 x 112 pixels, with 256 grey levels per pixel.

Fig. 4- Sample face images of ORL database

The [Fig-4] shows the sample images of ORL database. We randomly selected five images per subject as a prototype and the rest of the images are used for testing. A ten-fold cross-validation has been performed and average recognition rate is considered. The RLBP features (histograms) are extracted from the face images and SVM classifier with polynomial kernel function of degree 3 is used for face recognition. The [Table-1] shows the recognition rate of proposed method for varying parameter values such as α, P and R. The uniform RLBP (P=8, R=1) with α=8 gives better result than other combinations for RLBP and rotation invariant uniform RLBP.

Table 1- Face Recognition rate (%) of our approach for different combination of RLBP (P, R) on ORL database

Method	Recognition Rate (%)	
	α = 1	α = 8
$RLBP_{8,1}$	89	93
$RLBP_{8,1}^{u2}$	90	98
$RLBP_{8,1}^{riu2}$	85	92
$RLBP_{8,2}$	85	90
$RLBP_{8,2}^{u2}$	89	95
$RLBP_{8,2}^{riu2}$	82	91

Results on Yale Face Database

The Yale database [30] contains 165 greyscale images of size 320 x 243 in GIF format of 15 individuals. There are 11 images per subject, one per different facial expression or configuration: centre-light, glasses, happy, left-light, no glasses, normal, right-light, sad, sleepy, surprised and wink. The images are cropped to size 120 x 170 to extract face subject of the images. The [Fig-5] shows the sample images.

Table 2- Face Recognition rate (%) of our approach for different combination of RLBP (P, R) on Yale database

Method	Recognition Rate (%)	
	α = 1	α = 8
$RLBP_{8,1}$	85	92
$RLBP_{8,1}^{u2}$	89	96
$RLBP_{8,1}^{riu2}$	83	90
$RLBP_{8,2}$	83	92
$RLBP_{8,2}^{u2}$	87	92
$RLBP_{8,2}^{riu2}$	81	90

The Yale database images are cropped to size 120 x 170. As like ORL database, we randomly selected six images per subject as a prototype and the rest of the images are used for testing. A ten-fold cross-validation has been performed and average recognition rate is considered. The RLBP features (histograms) are extracted from the face images and SVM classifier with polynomial kernel function of degree 3 is used for face recognition. The [Table-2] shows the recognition rate of proposed method for varying parameter values such as α, P and R. The uniform RLBP (P=8, R=1) with α=8 gives better result than other combinations for RLBP and rotation invariant uniform RLBP.

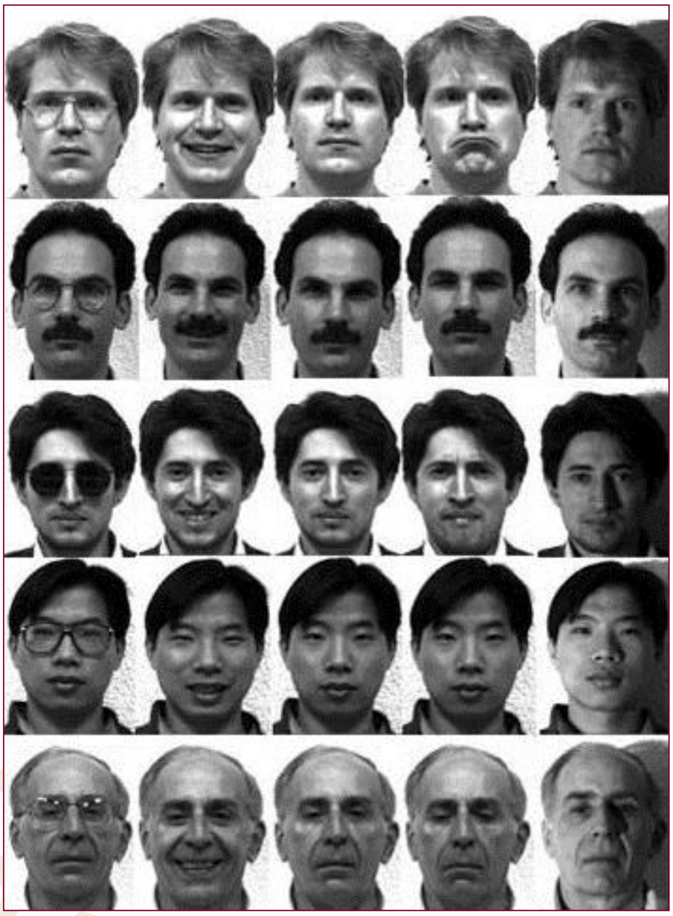

Fig. 5- Sample face images of Yale database

Comparative Study

In sections 5.1 and 5.2, different results of proposed face recognition method on ORL and Yale face database have presented. In order to establish reliability of the proposed method, we have compared results of our method against well established existing standard techniques like LBP [13], CLBP [26], Eigenface [8], LBP+NBNN [22]. Ratio of training and test images for ORL and Yale face database remains as before. Recognition rates reported in [Table-3] are achieved after five-fold cross-validation.

Table 3- Comparison of recognition rate (%) of proposed method with other methods

Method	Recognition Accuracy (%)	
	ORL face images	Yale face images
LBP [13]	95.45	84.05
CLBP [26]	96	89.35
Eigenface [8]	92.6	87
LBP + NBNN [22]	99.35	86.81
Our Approach	98	96

Conclusion

In this paper, we proposed a novel method for face recognition based on texture analysis using RLBP. We extracted the local binary patterns and constructed a global feature histogram that represents the statistics of the facial micro-patterns. These features are in sensitive to noise and robust against illumination variants. Finally, face recognition is performed by using the SVM classifier. Various results presented in sections 5.1 and 5.2 demonstrate that high recognition accuracy can be achieved using RLBP for face recognition. It is observed that for ORL database, recognition rate is 98 %, indicating the robustness of RLBP against extreme expression variation. From the experimental results, it is conclude that our technique has been found to be robust against significant variation in illumination and facial details (present in ORL and Yale). When compared to standard techniques like eigenface and LBP variants, our technique shows promise. It has been found empirically, that in a standard personal computer with Core 2 duo processor @ 3.00 Ghz, and 3 GB RAM, computation time of our method is 19.92 seconds, which is well suited for real time face recognition. Extensive experiments ORL and Yale face databases clearly show the superiority of the proposed method over traditional LBP variants, especially on the robustness of the method against different facial expression, lighting variation and postures of the subjects.

Conflicts of Interest: None declared.

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