ISSN:0975-9646

Multi-View Face Recognition Using Local Binary Pattern

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Abstract **- One of the major problems in face authentication systems is to deal with variations in illumination. In a realistic scenario, it is very likely that the lighting condition of the probe image does not correspond to those of the gallery image; hence there is a need to handle such variations. In this paper, we present a novel approach to multi-view face authentication considering both shape and texture information to represent facial image. The face area is divided into small regions, from which local binary pattern (LBP) histogram are extracted and concatenated into a single vector efficiently representing the facial image. The proposed method is compared in terms of classification accuracy, to other commonly used Face recognition systems on ORL,YALE and FERET databases results indicate that the performance of the proposed method is overall superior to those and traditional Face recognition approaches, such as the Eigen faces, Fisher faces, and LDA methods and traditional linear classifier. We obtain the performance of 94.81% by applying Support vector machine (SVM) with LBP features.**

Keywords **– Linear Discriminant Analysis (LDA), Local Binary Pattern (LBP), Block based analysis, Face recognition (FR).**

I. INTRODUCTION

During the past three decades, facial image analysis has received much attention in the computer vision and image processing area, which contain face detection, face recognition, facial expression analysis, and so on. A common problem of the above studies is that face images acquired under controlled conditions are considered, which usually are frontal, occlusion-free, with clean background, consistent lighting, and limited facial expressions. However, in real-world applications, face recognition needs to be performed on real-life face mages captured in unconstrained scenarios; see figure 1. Real-life faces [10]. As can be observed, there are significant appearance variations on real-life faces, which include facial expressions, illumination changes, head pose variations, occlusion or make-up, poor image quality, and so on. Therefore, face recognition in real-life faces is much more challenging compared to the case for faces captured in constrained environments. Up to now, many algorithms have been applied to describe the faces: Principal component analysis (PCA)[1], Linear Discriminate Analysis (LDA)[2], and Independent component Analysis(ICA)[3] have been widely introduced for feature extraction, and recently, representations based on the outputs of Gabor filters at multiple scales, orientations, and locations have achieved superior performance for facial image analysis in [4] and [5]. Nevertheless, it is computationally expensive to convolve the face images with a set of Gabor filters to extract multi-scale and multi-orientation coefficients. It is inefficient in both time and memory for high redundancy of Gabor-wavelet features.

Local Binary Patterns (LBP)[6], a non-parametric method summarizing the local structures of an image efficiently, has received increasing interest for facial representation recently[7],[8].LBP was originally proposed for texture description[6], and has been widely exploited in many applications such as image/video retrieval, aerial image analysis, and visual inspection. The most important properties of LBP features are toleranceagainst the monotonic illumination changes and computational simplicity.

The remainder of this paper is organized as follows. Local binary patterns and LBP-based facial description approach are introduced in section II. In section III brief about support vector machine as a classifier. In section IV experiments and discussion and finally concludes in section V.

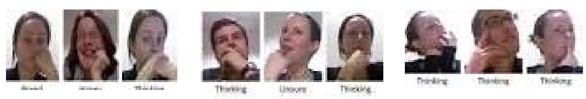


Figure 1: Real life faces

II. LOCAL BINARY PATTERNS

The original LBP operator labels the pixels of an image by threshold a 3x3 neighborhood of each pixel with the center value and considering the results as a binary number, of which the corresponding decimal number is used for labeling. Then histogram of the labels can be used as a texture descriptor. The derived binary numbers are called Local Binary patterns or LBP codes. The basic LBP operator is illustrated in figure 2.

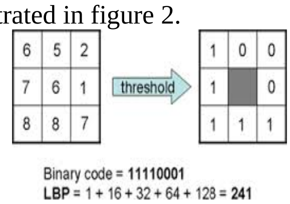


Figure 2. An example of the basic LBP operator.

Formally, the given pixel at location (x_c, y_c) can be expressed in decimal form as :

$$LBP(x_c, y_c) = \sum_{p=0}^{7} s(i_p - i_c)2^p$$

Where P runs over the 8 neighbors of the central pixel, i_p and i_c are gray level values of the central pixel and the surrounding pixels, and the function $s(x)$ is defined as :

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

By the definition above, the LBP operator is invariant to the monotonic gray-scale transformations which preserve the pixel intensity order in local neighborhoods.

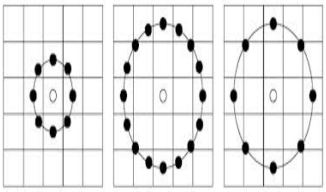
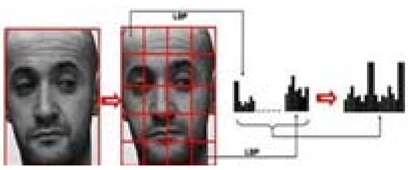


Figure 3. Circular (8,1),(16,2) and(8,2) neighborhood

The i_p correspond to the gray values of P equally spaced pixels on a circle of radius R (R>0) that form a circularly symmetric set of neighbors, figure illustrates three circularly symmetric neighbor sets for different values of P and R. A binomial weight 2p is assigned to each sign S (x_c, y_c)transforming the difference in neighborhood into a unique LBP code: The most prominent limitation of the LBP operator is its small spatial support area. Features calculated in a local 3x3 neighborhood cannot capture large scale structure that may be the dominant features of some textures. Later the operator was extended to use neighborhoods of different sizes [6]. Using circular neighborhoods and bilinear interpolating the pixel values allow any radius and number of pixels in the neighborhood. Examples of these kinds of extended LBP are shown in figure 3.



Face image | Face image divided into blocks | Histogram of the blocks

Figure 4: A face image divided into sub-regions from which LBP histograms are extracted and concatenated into a single, spatially enhanced feature histogram.

The LBP operator $LBP_{(P,R)}$ produces 2^P different output values, corresponding to 2^Pdifferent binary patterns formed by the P pixels in the neighborhood. It has been shown that certain patterns contain more information than the other [6]. It is possible to use only a subset of the 2^Pbinary patterns to describe the texture of the images. Patterns are denoted as $LBP^{u2}_{(P,R)}$.

A local binary is defined uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa when the binary string is considered circular. For example, 00000000 (0 transition), 00011111(2 transition), and 10101010 (6 transition) are uniform patterns [6]. noticed that in their experiments with texture images, uniform patterns account for a bit less than 90% of all patterns when using the (8,1) neighborhood and for 70% in (16,2) neighborhood.

After labeling an image with a LBP operator, a histogram of the labeled image can be used as texture descriptor. Each face image can be seen as composition of micro-patterns which can be effectively described by LBP. In the existing studies [10] to consider the shape information, Face images are divided into non-overlapping sub-regions as shown in figure 4. The LBP histograms extracted from sub-regions are concatenated into a single, spatially enhanced feature histogram the extracted feature histogram describes the local texture and global shape of face images.

A histogram of the labeled image $f_l(x)$ can be defined as:

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

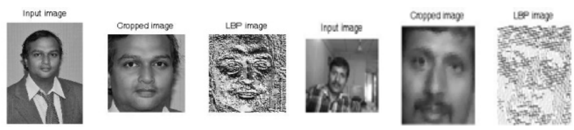
This histogram contains information about the distribution of the local micro patterns over the whole image, such as edges, spots and flat areas. For efficient face representation, one should retain also spatial information. For this purpose, the image is divided into R0, R1,…,Rm-1, as shown Figure.4 and the spatially enhanced

histogram is defined as.

$$H_i = \sum_{x,y} I\{f_l(x,y) = i\}, I\{(x,y) \in R_j\}, \quad (1)$$

Where $i = 0,1, \ldots, n-1$ and $j = 0,1, \ldots, m-1.$

The process of feature extraction for face classification is illustrated in fig an original image is processed by locating eye positions, geometric normalization, cropping and histogram normalization and a so called LBP face is obtained by performing LBP operator on the preprocessed facial image. K x K equal size blocks are divided from the LBP face with a grid on it and their histogram fitted together from a vector that will be fed into the support vector machine (classifier). Figure 5 shows some of multi-view samples and their corresponding LBP faces from the face database.



(a) (b)

Figure 5: Feature extraction. LBP transformation is done after locating eye positions from original images, normalization, and cropping.

III. SUPPORT VECTOR MACHINE

Given a labeled set of M training samples (x_i, y_i) where $x_i \epsilon R^N$ and y_i is the associated label $(y_i \epsilon \{-1,1\})$, 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:

$$f(x) = \sum_{i=1}^{M} y_i \alpha_i . k(x, x_i) + b$$

Where $k(.,.)$ is 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 (QP) 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 higher dimensions feature space via a nonlinear mapping function:

$$\Phi: R^N \rightarrow F^M,$$

Where $M \gg N$, and then constructs a hyper-plane in F. By using mercer's theorem [10], the projecting samples into the high-dimensional feature space can be replaced by a simpler kernel function satisfying the condition

$$k(x, x_i) = \Phi(x). \Phi(x_i)$$

Where Φ is the nonlinear projection function? Several kernel functions, such as, polynomials and radial basis function (RBF), have been shown to satisfy mercer's theorem and have used successfully in nonlinear SVMs:

$$k(x, x_i) = ((x. x_i) + 1)^d$$
$$k(x, x_i) = \exp(-\gamma |x - x_i|^2)$$

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

IV. EXPERIMENTS AND DISCUSSION

To validate the accuracy of the proposed algorithm, we have used three different databases: ORL, YALE, and FERET. The ORL database contains ten different images of 40 distinct subjects in up-right, frontal position with tolerance for some tilting and rotation of up to 20%. Moreover, the most variation of some image scale is close to 10%. Therefore, it is expected that this is a more difficult database to with. 5 face images per person are chosen randomly as training images while the remaining 5 images are set as test images. Figure 4 depicts some sample images from the ORL database.

The YALE face database consists of 15 individuals, where each individual, there is 11 face images containing variations in illumination and facial expression. From these 11 face images, we use 5 for training, chosen randomly. The remaining 6 images are used for testing. Figure 5 depicts some sample images from the YALE database.

A subset of FERET face database, $fa\ fb$ image set, containing images of 145 individuals is used in our experiments. In this subset, there are four frontal views of each individual: a neutral expression and a change of expression from a second session that occurred three weeks after the first. For each of the individual in the set, three of their images are used for training and the remaining is used for testing purposes. Figure 6 depicts some sample images from the YALE database.

We use $LBP^{u}_{(8,1)}$, in all experiments and 130x150 pixels image is divided into K x K equal size blocks, where K is ranged from 5 to 14. The LBP histogram of blocks are extracted and concatenated into a single, spatially enhanced feature by using equation 1. SVM with linear kernel, polynomial kernel and RBF kernel are chosen to evaluate the performance of our method.

All the images are aligned with respect to the manually detected eye coordinates, scaled to 128x128 pixels resolution.

In order to assess the efficiency of the proposed technique described above, we carried out a series of experiments using all databases separately. In this section, we aim to compare our proposed method to the original PCA LDA, and ICA methods. Table 1 reports the results obtained for all databases. It is clear that the proposed method. Outperform the original PCA, LDA, and ICA algorithms. On the ORL database for instance, improvements of 9.5%, 10.6% and 17.5% have been obtained for the PCA, LDA and ICA methods, respectively. It is also worth mentioning that significant enhancements have been obtained for YALE database: 93.33% for the proposed method against 90% for PCA, 92.22% for LDA and 87.78% for ICA. Finally for the FERET database the improvement is about 15.86%, 18.62% and 17.24% compared with PCA, LDA and ICA respectively.

TABLE 1
RECOGNITION ACCURACY COMPARED WITH HOLISTIC ALGORITHMS

	PCA	LDA	ICA	LBP
ORL	88.5	87.50	80.50	98.00
FERET	75.86	73.10	74.48	90.72
YALE	90.00	92.22	87.78	93.23

SVM classification – we further adopted SVM (RBF kernel) to perform face recognition using the selected LBP histogram bins, and obtained the best recognition rate of 94.81%. As a baseline to compare against, we also applied SVM to raw images, which deliver the best performance on face images acquired in controlled environments. We summarize the results of SVM with raw pixels and standard LBP features in table 2.

TABLE 2 :
EXPERIMENTAL RESULTS OF FACE RECOGNITION

Approach		% of Recognition rate
Raw images	SVM	91.27
Std.LBP	SVM	96.38

V. CONCLUSION

In this paper the multi-view face authentication system a challenging but relatively under studied problem. We learn discriminative LBP histogram bins as compact facial representation for classification. The efficiency and simplicity of LBP allow fast feature extraction, and the regional and global descriptions allow for capturing multi-view information of faces. The SVM allows for learning and classifying faces from large set of multi-view faces. The experimental results show that classification accuracy are highly improved and highest correct rate is 98% and average correct rate 94% for ORL,YALE and FERET databases.

ACKNOWLEDGMENT

I wish to express my sincere gratitude goes to advisor, Prof. K.Karibasappa, for his professional guidance, constant support and trust. coauthor and friend, Prof. B.Sreepathi is well experienced in the areas of image processing, pattern recognition and machine learning. I have obtained numerous valuable ideas from frequent discussions with him.

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