Implementation of Face Recognition System Using LBP

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Abstract-In this research, we implemented face recognition algorithmic approach which consist of both frame and texture information to represent face images. The whole area of face is partitioned into small blocks from which Local Binary Pattern (LBP) histograms of size (8x8) are extracted and concatenated into a single image histogram. The extracted enhanced feature histograms represents the given face image. On the basis of extracted features of face, classification is performed by using nearest neighbor techniques. Analysis of results seemingly shows the perfection of the implemented scheme over all considered methods (PCA and Local Binary Pattern) on ORL database which include testing the efficiency of the implemented approach against lighting, aging and different facial expressions of the faces. In addition to its simplicity and efficiency, the scheme requires less than 50% time for feature extraction.

Keywords- LBP, PCA, recognition,Eigen

1. Introduction

Face recognition has been on hype over the last years because of its vast applications in various domains, and it presents a challenging problem in the field of image analysis and computer vision research. Most of the proposed methods for face recognition tasks perform well when the images are in controlled environment but return quite worse results when real environments are considered, where variations of different factors such as illumination and pose are present. In other words, current systems are still far away from the capability of the human perception system. Biometrics-based authentication systems are becoming a popular option in recent years, changing the authentication based on Personal Identification Numbers, passwords or cards to an authentication based on physiological characteristics. Passwords and cards impose an obligation on the user to remember them or to carry them wherever in the wallet, and moreover, they can be stolen. In the age of comfort, this authentication method fall short and new biometrics-based systems have started to pop up, systems which do not require the user any effort and in addition, cannot be misplaced, forgotten or stolen. Most common biometrics-based technologies include identification using face, finger geometry, palm, iris, retina or voice, but most of them require some voluntary action by the user, as placing his hand or finger on some machine or standing in a fixed position in front of a camera for its iris identification. Face recognition, on the other hand, can be done without any effort by the user, just acquiring his face image from a distance by a camera [1], [4].

Face recognition techniques can be grouped into two main groups: feature-based and holistic methods [3]. Feature-based methods process the face image to extract the relevant features like eyes, mouth or nose and compute the geometrical relationship among them to reduce the original image to a vector of geometrical features. One of those methods is the one carried out by Kanade [7], where a simple image processing is used to extract a vector of 16 parameters of the face image (including size of eyes, distances and angles) and used a simple Euclidean distance measure for matching. Holistic methods, conversely, try to represent a face using global descriptors instead of local feature and within them the most commonly used one is PCA [8], which was first used by Sirovich and Kirby. In face recognition, PCA is more commonly named as Eigen face method, and reduces the original image space to an orthogonal Eigen space with reduced dimensionality. In this work, we implement an approach for face recognition which consist of both texture information and shape to represent the face images. In second section of paper all the related work is discussed, third section is about the implementation of algorithm. Fourth section is about display of result. Finally, last section concludes the implemented scheme.

2. RELATED WORK

PCA Algorithm

Principal Component Analysis (PCA, also known as “Eigen faces”), is one of the most known global face recognition algorithm. The main idea is to decorrelating data in order to highlight differences and similarities by finding the principal directions (i.e. the eigenvectors) of the covariance matrix of a multidimensional data. Applying the PCA technique to face recognition, enveloped a well-known Eigen faces method, where the Eigen faces correspond to the eigenvectors associated with the largest eigenvalues of the face covariance matrix. The Eigen faces thus define a feature space, or “face space,” which drastically reduces the dimensionality of the original space, and face detection and recognition are then carried out in the reduced space. Based on PCA, a host of face recognition methods have been developed to improve classification accuracy and generalization performance.

The PCA technique, however, encodes only for second order statistics, namely, the variances and the covariance. As these second order statistics provide only partial information on the statistics of both natural images and human faces, it might become necessary to incorporate higher order statistics as well. Toward that end, PCA is extended to a nonlinear form by mapping nonlinearly the input space to a feature space, where PCA is ultimately implemented. Due to the nonlinear mapping between the input space and the feature space, this form of PCA is nonlinear, and naturally called nonlinear PCA. Applying different mappings, nonlinear PCA can encode arbitrary higher-order correlations among the input variables. The underlying justification of nonlinear PCA comes from Cover's theorem on the separability of patterns, which states that nonlinearly separable patterns in an input space are linearly separable with high probability if the input space is transformed nonlinearly to a high dimensional feature space. While the Hebbian networks, the replicator networks, and the principal curves are all capable of implementing nonlinear PCA, kernel PCA enjoys simple implementation by means of kernel functions. The nonlinear mapping between the input space and the feature space, with a possibly prohibitive computational cost, is never implemented explicitly by kernel PCA. Rather, kernel PCA applies kernel functions in the input space to achieve the same effect of the expensive nonlinear mapping. Specifically, kernel PCA takes advantage of the Mercer equivalence condition and is feasible because the dot products in the high-dimensional feature space is replaced by those in the input space, while computation is related to the number of training examples rather than the dimension of the feature space.

3. IMPLEMENTATION OF ALGORITHM

LBP

The original LBP operator [5] is a powerful operator for texture recognition, introduced by Ojala *et al*. the operator labels the pixel of an image by setting the center value of the pixel as the threshold and generate the result for each 3X3-neighborhood of each pixel with the center value and considering the result as a binary number. After this the histogram of the labels can be used as a texture descriptor. See Figure 1 for an illustration of the basic LBP operator.

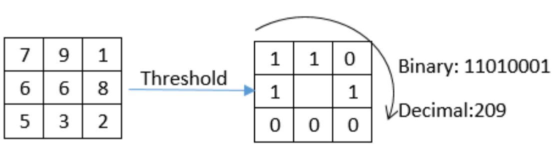


Fig. 1. The basic LBP operator

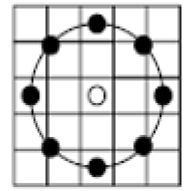


Fig. 2. The circular (8,2) neighborhood. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel.

Later the operator was extended to use neighborhoods of different sizes. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods we will use the notation (P,R) which means P sampling points on a circle of radius of R. See Figure 2 for an example of the circular (8,2) neighborhood.

Another extension to the original operator uses so called *uniform patterns*. A Local Binary Pattern is called 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, 00011110 and 10000011 are uniform patterns. Ojala et al. 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 around 70 % in the (16,2) neighborhood.

We use the following notation for the LBP operator: $LBP^{u2}_{P,R}$. The subscript represents using the operator in a (P,R) neighborhood. Superscript u2 stands for using only uniform patterns and labelling all remaining patterns with a single label.

A histogram of the labelled image fl(x, y) can be defined as

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

in which n is the number of different labels produced by the LBP operator and

$$I(A) = \begin{cases} 1, Aistrue \\ 0, Aisfalse \end{cases}$$

This histogram contains information about the distribution of the local micro patterns, such as edges, spots and flat areas, over the whole image. For efficient face representation, one should retain also spatial information. For this purpose, the image is divided into regions $R_0, R_1, \ldots R_{m-1}$

ULBP

In basic LBP the neighboring pixels are converted in the binary code with respect to the grey scale value of center pixel as threshold and then all these codes form an ordered around the center pixel. Such coding is controlled by the scale of the radius of neighborhoods R and the number of sampling points P, so it is denoted as $LBP_{(P,R)}$. The increase in P will cultivate the indication of texture attribution around pixels. The definite order of such binary codes keeps the direction information of texture around pixels in a way of 2^P kinds of variations. When there exist at most 2 times of 0 to 1 or 1

4. RESULTS AND DISCUSSION

The testing of experiment was done on ORL Face Dataset which consisted of 400 images of 40 people. Each person face covers different expressions and range of poses. The images of faces were in PGM format, 92 x 112 pixels in 256 shades of grey. For some subjects, the images were captured at different facial expressions (smiling / not smiling, open / closed eyes), varying the lighting, different times and facial details (glasses / no glasses). All the images were captured with dark homogeneous background and with frontal pose (consider some side movement).

Experimental Setup

All experiments were captured on the basis cross-validation technique. We have there were 10 different images of single subject. In first experiment, one face of a single subject was for training and other 9 faces of same subject were for matching. This was repeating for all subjects of dataset. In second experiment, two faces of a single subject were for training and other 8 faces of same subject were for matching. This process was repeated for 10 time. In last experiment, 9 faces of a single subject were for training and rest face of same subject is for matching. Results of these experiments are shown in fig. 3.

Fig. 3. Example faces form ORL Database[9]

Results

Experimental setup was placed on work station which was having eight core i3 processor 2.7 GHz, 8 GB ram Memory DDR3 display, keyboard, Logitech (HD 720p) and mouse. Linux (Ubuntu 16.04) operating system with OPNCV (version 3.2.0) library is used and OPENCV algorithm is implemented in C or C++ so that algorithm could be implemented. In this paper, three algorithms have been implemented such as: Basic LBP, Uniform LBP (ULBP) and Principle Component Analysis (PCA). The comparison results are shown in fig. 4A. All the algorithms were implemented on same experimental setup. Principle Component Analysis (PCA) has been implemented. Corresponding results are shown in figure a and fig. 4B bar chart in which it has been shown that when 5 to 9 faces of same subject are trained. Accuracy of algorithm varied between 90 to 95 percent. Secondly Basic LBP and Uniform LBP has been implemented. The results were recorded, like 5 to 9 faces of same subject was trained. Accuracy of the algorithm varied between 94 to 98 percent. Uniform LBP approach gave same results as compared to basic LBP and took less than 50% time in matching and also took less 50% space to store the training dataset histogram.

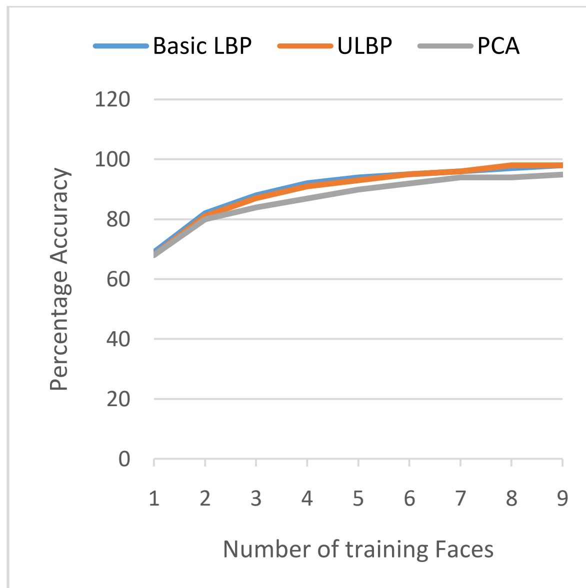
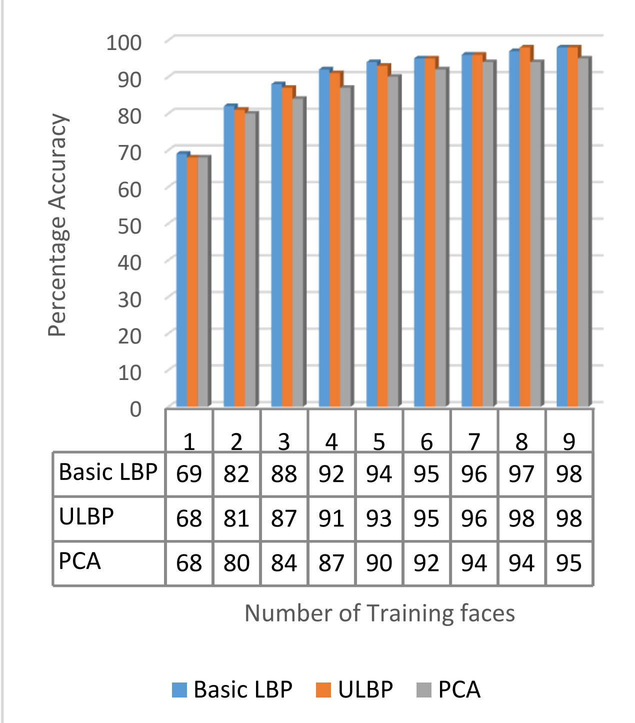


Fig. 4-A.



	1	2	3	4	5	6	7	8	9
Basic LBP	69	82	88	92	94	95	96	97	98
ULBP	68	81	87	91	93	95	96	98	98
PCA	68	80	84	87	90	92	94	94	95

Fig.4-B. Percentage Accuracy vs. Number of training faces chart.

5. CONCLUSION

In this research, robust face recognition algorithms has been implemented which overcome its sensitivity to the visual variations of faces (*e.g.*, pose changes and expressions) of facial images. In this method, the training faces with respect to the test faces were first aligned. Uniform LBP approach gave same result as compared to basic LBP and took less than 50% time in matching and also took less 50% space to store the training dataset histogram. Results were recorded on ORL dataset in terms of the recognition accuracy.

In the future, the authors plan to implement robust recognition approach to enhance performance. The authors are also interested in extending the current work to consider other visual variations of faces such as emotions and corruptions.

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