

NOVEL WEIGHTED LBP APPROACH FOR FACE RECOGNITION SYSTEM

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Abstract- In this research, we propose a novel face recognition 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 are extracted and concatenated into a single image, the extracted enhanced feature histograms representing the given face image. On the bases of extracted features of face, give more weight of main part of face (like eyes, ear, and nose) on which recognition is performed by using nearest neighbour techniques. Analysis of results seemingly shows the perfection of the proposed scheme over all considered methods (PCA and Local Binary Pattern) on ORL database which include testing the efficiency of the proposed approach against lighting and aging of the faces. In addition to its simplicity and efficiency, the scheme requires very less time for feature extraction.

Keywords- Eigen, Fisher face, Conventional LBP, Binarization

Introduction

Texture analysis is a very important part in image processing and computer vision and crucial for many applications such as remote sensing, scene recognition, biomedical image analysis, image recognition and retrieval [1]. There is a large number of algorithm present for texture recognition. But, there are some challenges like rotation, spatial resolution, illumination, and viewpoint in texture. Texture algorithms helps us to extract the distinguish effective and compact features to describe and characterize texture. They can be divided into four major categories [1]: statistical methods, structural methods, model based methods and signal processing methods. Statistical approaches extract information from pixel positions and their values and outturn impersonations of textures as smooth, coarse, grainy, and so on. For texture description Local binary pattern operator [4] is one of the most popular statistical approaches. Model-based texture methods are based on constructing a parametric generative model captured form specific textures [2]. Signal Processing methods, also called multichannel filtering methods [4], are based on spatial or frequency domain filtering [5].

In this work, we implement an approach for face recognition which consist of both texture information and shape to represent the face images using statistical methods and their comparison. 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.

Related Work

PCA

PCA conjointly referred to as principal element analysis that could be a powerful approach to extract the structural data from high dimensional data, that results in the extraction of Eigen vectors that connected with larger vectors from the input distribution. This eigenvector analysis has already been wide employed in face process [2], [1]. A kernel PCA, recently projected as a nonlinear extension of a PCA [4]– [2] computes the principal elements during a high-dimensional feature space, that is nonlinearly associated with the input space. A kernel PCA is predicated on the principle that since a PCA in will be developed in terms of the dot product in, this same formulation also can be performed mistreatment kernel functions while not expressly operating in. A kernel PCA has already been shown to produce a higher performance than a linear PCA in many applications [6]. This letter adopts a kernel PCA [9] as a mechanism for extracting facial data. Through the employment of a polynomial kernel, higher order correlations will be used between input pixels within the analysis of facial pictures. This amounts to characteristic the principal elements inside the merchandise house of the input pixels creating up a facial image. supported these options, face recognition will then be performed mistreatment linear support vector machines (SVMs). Experimental results and comparisons with alternative face recognition ways together with linear PCA show the effectiveness of the projected technique.

LDA

In this section, we have a tendency to concisely review the standard LDA face recognition approach” Fisher face”. Fisher faces technique [10] derives from Fisher’s linear discriminant analysis (FLD or LDA); it works on similar principle as the Eigen faces technique for appearance-based face recognition, a 2nd dimensional face image is viewed as a vector with length N within the high dimensional image space. The coaching set contains M samples $\{X_i\}_{i=1}^M$ associating to C individual categories $\{x_j\}_{j=1}^C$. LDA tries to seek out a group of jutting vectors w best discriminating totally different categories. In line with the Fisher criteria, it will be achieved by increasing the quantitative relation of determinant of the between-class scatter matrix S_b and therefore the determinant of the within-class scatter matrix [13]. The objective of LDA is to perform spatiality reduction whereas protective the maximum amount of the category discriminatory info as attainable by finding direction on that the categories area unit best separated. within the Fisher face technique [9], the face knowledge is 1st projected to a PCA topological space spanned by M-C largest Eigen faces.

LBP

In this section we briefly review the conventional LBP face recognition process [1], firstly introduced by Ojala et al [7]. The basic idea of LBP is, the operator labels the pixel of an image by setting the centre value of the pixel as the threshold and generate the result for each 3X3-neighborhood of each pixel with the centre value and considering the result as a binary number. After this the histogram of the labels can be used as a texture descriptor. Later the operator was extended to use neighbourhoods of different sizes. Using circular neighbourhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighbourhood. For neighbourhoods, we use the notation (P,R) which means P sampling points on a circle of radius R.

$$LBP(x_c y_c) = \sum_{n=0}^{L-1} s(i_n - i_c) 2^n$$

The LBP texture for centre point can be represented as (x_c, y_c) where i_n denotes the intensity of the n th surrounding pixel and i_c denotes the intensity of the centre pixel, L is the length of the sequence, and $s = 1$ if $i_n \geq i_c$ otherwise, $s = 0$. In the case of a $N \times N$ neighbourhood, there are N^2-1 surrounding pixels, so the big string is of length N^2-1 .

Implementation

ULBP

The dimension of histogram in LBP is 2^P , which is unmanageable while calculating patterns in routine, particularly to more pattern in the neighbourhood. In certain LBPs it was perceived that, it seems to be vital assets of texture spectrum model which gives maximum number of patterns, sometimes over 90%. These LBPs acquire identical attribute: the number of spatial transitions (bitwise 0/1 changes) in their LBP codes is not more than two, which is defined by *ULBP* (where *ULBP* represents Uniform Local Binary Pattern, P is the number of samples and R is the radius of circle) [11]. A local binary pattern is uniform if the binary pattern contains at most two 0-1 or 1-0 transitions. For example, 00000000_2 , 11111111_2 or 00001100_2 contains 2 transitions therefore all are uniform LBPs, but 00001101_2 is not uniform LBP because the number of spatial transitions of bitwise 0/1 changes is 4 (thinking of the code as a circle). ULBP can be described as

$$U(G_p) = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|$$

where, g_c is the pixel of the centre, and g_p is the pixel of the pattern in the neighbourhood. $s(\bullet)$ is signal function whose value is 0 or 1. When $U(G_p) \leq 2$, the LBP code is ULBP. So for P samples, the category of ULBPs is $P(P-1)+2$. Thus the dimension of texture spectrum is shortened from 2^P to $P(P-1)+2$. The texture spectrum features estimated by ULBP are more compact and provide textures description feature according to human vision. At the same time, it provides possibility and basis with block-based and multi-resolution methods.

WLBP

All the possible variations mentioned above can be determined empirically, for instance, the choice of centre point, the base, and the ordering of the neighbours. In this work, we propose to reformulate the problem of LBP encoding by using a learning framework for obtaining the optimal weights. First, we need to reformulate the LBP encoding problem into matrix multiplication. The traditional way of encoding LBP feature is to use a 3×3 window to scan through the entire image. At each 3×3 patch, perform the encoding using Equation 1. However, such formulation is neither efficient, nor provides insight towards an optimal weight learning scheme. Instead of scanning through the entire image using small window and compare the neighbourhood values to its centre point, a simple convolution of the image with 8 difference masks, followed by simple Binarization can achieve the same goal. The traditional LBP is simply a weighted sum of all the bitmaps using the weight vector $w = [2^7, 2^6, 2^5, 2^4, 2^3, 2^2, 2^1, 2^0]$. Therefore, the reformulation of the LBP can be shown as:

$$y = \sum_{i=1}^8 \sigma(h_i * f) \cdot w_i$$

Where $f \in \mathbb{R}^d$ is the original image, h_i are the difference masks, σ is the Binarization operator, and $y \in \mathbb{R}^d$ is the resulting LBP image. Note that only the Binarization is non-linear operation.

Now, we are one step closer towards the formulation of the W-LBP. In the context of N training images from K classes, we re-arrange them in the following way: the N training images are vectorised and becomes one column in the data matrix $F \in \mathbb{R}^{d \times N}$ and for each image in F we apply convolutional mask h_1 to obtain $X_1 \in \mathbb{R}^{8d \times N}$. Then we repeat for h_2 to h_8 to obtain X_2 to X_8 . Stacking all X_i would give us the new bitmap matrix $X \in \mathbb{R}^{8d \times N}$. The weight vector w is now re-written as weight matrix $\Omega \in \mathbb{R}^{8d \times N}$, where $\Omega = [\Omega_1, \Omega_2, \Omega_3, \Omega_4, \Omega_5, \Omega_6, \Omega_7, \Omega_8]$, and $\Omega_i = w_i$. In this way, the LBP image for all the N training images can be found in $Y \in \mathbb{R}^{d \times N}$ using:

$$Y = \Omega X$$

Here, the objective of the optimization is to make the LBP images Y have the best class separation, and thus lead to better classification performance. Fisher ratio is one way to characterize the class separability by simultaneously maximizing the between-class scatter and minimizing the within-class scatter. Note that the only non-linear part within the LBP formulation, Binarization, has been taken care of by stacking all the bitmaps in the matrix X , and a linear method is sufficient to learn an optimal weight matrix. So we are trying to solve for the following optimization:

$$\text{maximize } \frac{|S_b^Y|}{|S_w^Y|} = \text{maximize } \frac{|\Omega S_b^Y \Omega^T|}{|\Omega S_w^Y \Omega^T|}$$

whose optimality can be found by solving the eigenvalue problem:

$$\Omega \Lambda = ((S_w^X)^{-1} S_b^X) \Omega$$

Solving above Equation would give the optimal weight matrix which leads to the highest Fisher ratio for the LBP image matrix Y . The optimal weight matrix can be seen as a linear transformation matrix that reduces the dimensionality from $8d$ to d . Please note that this WLBP learning procedure is different from regular Linear Discriminant Analysis (LDA) because in LDA, a transformation matrix W is learned to reduce the dimensionality of Y from d to d_0 where $d_0 < d$. Whereas in WLBP procedure, the learning is restricted to feature encoding which maps the dimension from $8d$ to d on the bitmap matrix X . In short, we have carried out feature encoding learning in WLBP [3], not subspace learning for images.



Fig. 1. Proposed weight distribution on a face.

In the fig. 1 we proposed weight distribution on a subject face for better texture recognition. We provide most of the weight to naturally unique facial parts like eyes, ears, nose and so on. This helps our algorithm in extraction of facial texture from a subject's face [8].

1. 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. 2. Example faces form ORL Database [10]

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 coding is done 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) and Linear Discriminant Analysis (LDA) 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. Novel weighted LBP face recognition approach gives the better result over than all implemented schemes as shown in fig. 4A and 4B. Recognition rate are increased which beneficial to us for making the face recognition system.

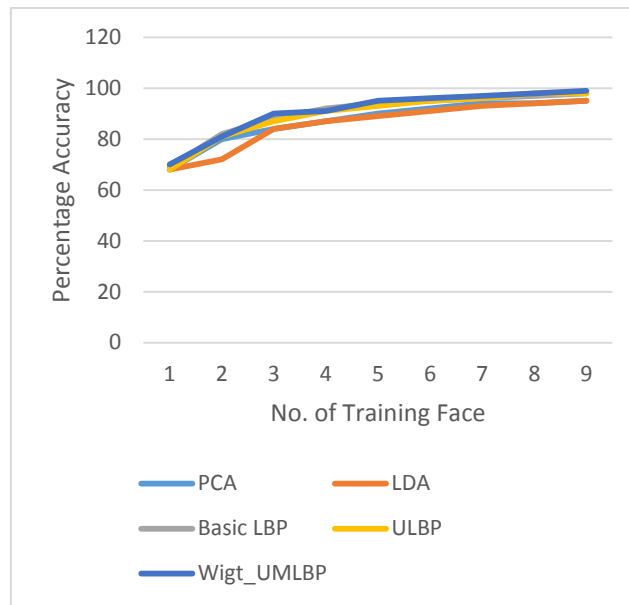


Fig. 3-A. Comparison

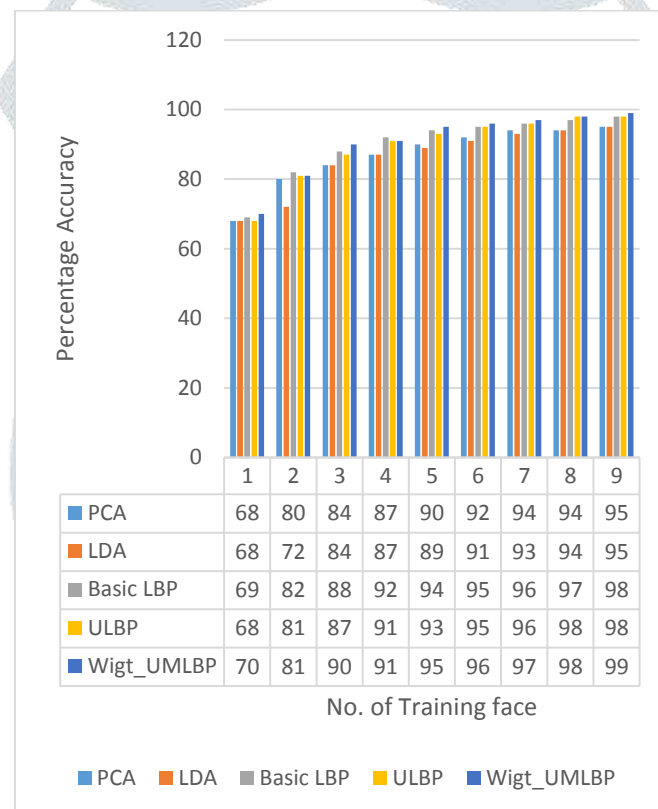


Fig.3-B. Bar chart: Percentage Accuracy vs. Number of training faces chart.

1. CONCLUSION

In this research, robust face recognition algorithms has been proposed which overcome its sensitivity to the visual variations of faces (e.g., pose changes and expressions) of facial images. The training faces with respect to the test faces were matched as there calculated part of face which is more important of the point of uniqueness. The proposed method had taken less time than basic LBP and took more time as compare to uniform LBP approach and gave the better results. Results were recorded on ORL dataset in terms of the recognition accuracy.

In the future, the authors plan to implement robust face recognition system to enhance performance. The authors are also leads to this work 100 percent accuracy consider with visual variations of faces such as emotions and corruptions.

References

[1] June-Young Jung, Seung-Wook Kim, Cheol-Hwan Yoo, Won-Jae Park, and Sung-Jea Ko: LBP-Ferns-Based Feature Extraction for Robust Facial Recognition. In IEEE Transactions on Consumer Electronics, Vol. 62, No. 4, November 2016

[2] Wu Fengxiang “Face Recognition Based on Wavelet Transform and Regional Directional Weighted Local Binary Pattern” in JOURNAL OF MULTIMEDIA, VOL. 9, NO. 8, AUGUST 2014

[3] Felix Juefei-Xu, Marios Savvides ” Weight-Optimal Local Binary Patterns” in Agapito L., Bronstein M., Rother C. (eds) Computer Vision - ECCV 2014 Workshops. ECCV 2014. Lecture Notes in Computer Science, vol 8926. Springer, Cham

- [4] S. Zhao and Y. Gao, "Establishing point correspondence using multidirectional binary pattern for face recognition," Proc. 20th International Conference on Pattern Recognition (2008), pp. 1–4.
- [5] Manish Kumar, Sumit Saini, Abhishek Goel: Enhancement of biometric image by implementing Gabor filter. In IJARD (International Journal of Academic Research and Development) Volume 2(2017) 159.
- [6] T. Ahonen, A. Hadid, and M. Pietikäinen, "Face description with local binary patterns: Application to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.
- [7] Ojala, T., Pietikäinen, M., Mäenpää, T.: Multiresolution gray scale and rotation invariant texture analysis with local binary patterns. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 24(7) (2002) 971-987
- [8] T. Kanade, J. F. Cohn, and Y. Tian, "Comprehensive database for facial expression analysis," in *Automatic Face and Gesture Recognition, 2000. Proceedings. Fourth IEEE International Conference on.* IEEE, 2000, pp. 46–53.
- [9] B. Schölkopf, A. Smola, and K. Müller, "Kernel principal component analysis," in *Advances in Kernel Methods-Support Vector Learning*, B. Schölkopf, C. Burges, and A. Smola, Eds. Cambridge, MA: MIT Press, 1999, pp. 327–352
- [10] The ORL Database of Faces by AT&T Laboratories Cambridge link-<http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html>
- [11] Manish Kumar, Rahul Gupta, Sumit Saini, Abhishek Goel "IMPLEMENTATION OF FACE RECOGNITION SYSTEM USING LBP" in "INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS" Volume 6, Issue 1 January 2018, pp. 1353-1356
- [12] Fatma zohra CHELALI, A. DJERADI and R. DJERADI "Linear Discriminant Analysis for Face Recognition" in "2009 International Conference on Multimedia Computing and Systems" IEEE, 2009, pp. 1-10

