A LBP-based Face Recognition Method with Hamming Distance Constraint

Hong Yang Yiding Wang
Graduate University of Chinese Academy of Sciences,
No.95 Zhongguancun East Road, Beijing, 100080
yhong04@mails.gucas.ac.cn ydwang@gucas.ac.cn

Abstract

In this paper, we present a new LBP-based face recognition method with Hamming distance constraint. The traditional LBP operator uses a uniform pattern to describe the local features and assort the other nonuniform patterns to one additional class, for images under expression and illumination condition changes, this method could cause more inaccuracy and instability. By assuming that the illumination, pose or expression changes of a face image are some kinds of "noise", we introduce the widely used Hamming distance in channel coding to LBP so as to decrease the error rate caused by these noise disturbances. Experimental results on FRGC show that our method improves the recognition performance obviously than the traditional LBP-based face recognition methods when face images are under uncontrolled circumstances.

1. Introduction

In the past a few years, a lot of methods have been developed for face recognition, such as Principal Component Analysis(PCA)[1], Liner Discriminant Analysis(LDA) [2], Elastic Graph Matcing(EBGM)[3], They have been making great improvement over the recognition speed and rate day by day. But as we know, there are still many problems concerning illumination, pose, expression, etc, we yet to overcome. The latest proposed algorithms are nearly all designed for solving these challenges.

Among these various types of methods, recognizing human faces with the Local Binary Patterns(LBP) is under particular concern in recent years[4]. The face region is first divided into some small blocks from which the LBP features are extracted, then the histograms of each LBP feature are connected end to end to form a large single feature histogram effectively representing the original image. Experimental results on several well known databases like FERET, ORL have shown that this LBP-based face recognition method outperforms the PCA, LDA and EBGM, etc. methods in recognition rates and it is more robust for facial expression and illumination changes.

The existing LBP algorithms use a so-called *uniform pattern* to describe local features, the other nonuniform patterns are all assorted to one additional class. In many cases, this makes the additional class comparatively large and the histogram of it is much higher than the other patterns. Especially for faces under expression and illumination condition changes, this method could cause more inaccuracy and instability. In this paper we use the Hamming distance constraint to assort each nonuniform pattern to one of the uniform patterns by minimizing their Hamming distance between them so as to get a better description of the local patterns. We did experiments according to the Face Recognition Grand Challenge (FRGC)[7] requirements and found our method outperforms the traditional LBP-based face recognition method when facial expression and illumination are under uncontrolled conditions.

The paper is organized as follows: the original LBP-based face recognition method is explained in Section 2. Then our improvement of pattern description by minimizing Hamming distance between the two patterns is presented in Section 3. In Section 4 we give the experimental results, followed by discussion and conclusion in Section 5.

2. LBP-base Face Recognition

2.1. the LBP Methodology

The original LBP method is introduced by Ojala to be used in texture description [5][6]. It is based on thresholding neighborhood pixel values against the center pixel in a circular order to form a binary pattern. Then these patterns of different pixels are assorted and concatenated into a histogram so that each pattern corresponds to one bin. This histogram is used to

0-7695-2929-1/07 $25.00 © 2007 IEEE
DOI 10.1109/ICIG.2007.144

represent the original image for later classification purpose. Figure 1 gives an illustration of the basic LBP operator.

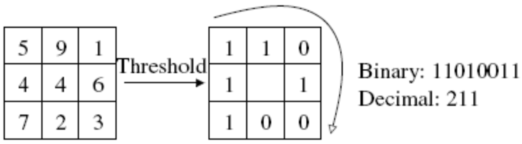

Figure 1. The basic LBP operator

We can use $LBP_{P,R}$ to denote LBP operators with different sizes, in which (*P,R*) means *P* sampling points on a circle of radius *R*. It allows for any value of *P* and *R*, for the gray values of neighbors which do not fall exactly in the center of pixels are estimated by bilinear interpolation. The total 2^P different patterns are concatenated into a histogram by their number of occurrences.

Allowing for that experimental results show certain local binary patterns are fundamental properties of texture images, Ojala proposed an improved LBP operator called *uniform patterns*, which contain at most two 0/1 or1/0 transitions when the binary string is considered circular. We denote it by $LBP_{P,R}^{u2}$, in which u2 reflects the use of rotation invariant uniform patterns with bit transitions at most two. For example, the $LBP_{8,1}^{u2}$ operator quantifies the total 256 LBP values into 59 bins according to uniform strategy (58 uniform patterns and the other patterns are assorted to the 59th pattern). Ojala reported 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[5].

2.2. Using LBP in Face Recognition

The histogram of LBP contains information about the distribution of local micropatterns. For face recognition, the original images are always too big to use LBP directly, so we spatially divide the image into *m* small regions $R_0, R_1, ...R_{m-1}$. The histogram of each region R_j is defined as

$$H_{i,j} = \sum_{x,y} I\{f_l(x,y) = i\} I\{(x,y) \in R_j\}$$

$$i=0,...,n\text{-}1, j=0,...m\text{-}1 \quad (1)$$

in which n is the number of different labels produced by LBP operator, m is the number of rectangular blocks of the image and I(A) is 1 or 0 depending on whether A is true or false.

As we know, the human face has its particular characteristics distinguished from other images, some of the face regions such as eyes and mouth contain more information for recognition purpose. So we can train and allocate different weights for different face regions. Then the regional histograms are concatenated end to end to build a global description of the face. By this way we can collect local pattern information with spatial information of the whole image together.

The task of face recognition needs to calculate two face images' similarity score to judge whether they are one person or not. Chi square statistic similarity measure is usually used for calculate the similarity of two histograms. It is defined as

$$\chi_w^2(S,M) = \sum_{i,j} w_j \frac{(S_{i,j} - M_{i,j})^2}{S_{i,j} + M_{i,j}}$$

$$i=0,1,...,n\text{-}1, j=0,1,...m\text{-}1 \quad (2)$$

in which w_j is the weight for region *j, S* and *M* are histograms of the target and query face images respectively.

3. LBP Face Recognition Using Hamming Distance Constraint

3.1. Introduction of Hamming Distance

Hamming distance is widely used in channel coding for the purpose of minimizing errors caused in code transmission and the error probability in decoding[8]. A good channel code is designed so that, if a few errors occur in transmission, the output can still be identified with the correct input. This is possible because although incorrect, the output is sufficiently similar to the input to be recognizable. The idea of similarity is made more firmly by the definition of a Hamming distance. Let *x* and *y* be two binary sequences of the same length. The Hamming distance between these two codes is the number of symbols that disagree.

$$D(x,y) = \sum_i |(x_i - y_i)| \quad (3)$$

Supposing the code *x* is transmitted over the channel , due to errors, *y* is received. The decoder will assign to *y* the code *x* that minimizes the Hamming distance between them. For example, if the transmitter sends $(10000)_2$ but there is a single bit error and the receiver gets $(10001)_2$, it can be seen that the "nearest" codeword is in fact $(10000)_2$ and so the correct codeword is found.

3.2. Link Hamming Distance to LBP

As we know, for the uniform LBP algorithm all nonuniform patterns are assorted to one additional class. Take the $LBP_{8,1}^{u2}$ for example, there is 58 uniform patterns and the other 198 nonuniform patterns are labeled as the 59th pattern. Ojala's experiment is done with texture images which are much more different from ordinary human face images. We did many experiments and found that for a lot of face regions, especially the images affected by noises, illumination or expressions changes, the 59th pattern accounts for a much larger percentage compared with the other 58 patterns. If we use only one pattern to depict the properties of so many distinct patterns, it may be inaccurate or improper for face recognition. So we try to classify these patterns in a new way.

We can assume that the illumination, pose or expression changes of face images are some kinds of "noise", just for their existence causes the recognition much more difficult than the "formal" faces. So we can urge these changes to be more like their original images by recombining their LBP histograms.

Taking into account the above considerations and that the Hamming distance is often used in correcting some coding errors caused by noises, we propose a new LBP-based face recognition method using Hamming distance constraints. We incorporate nonuniform patterns into uniform patterns by minimizing the Hamming distance between them. For example, the nonuniform pattern $(10001110)_2$ is converted into the uniform pattern $(10001111)_2$ with their Hamming distance being one. If several uniform patterns have the same Hamming distance with a nonuniform pattern, we choose the one that has the minimum Euclidian distance between them. For instance, $(01011001)_2$ is converted to $(01111000)_2$ with their Hamming distance two and minimum Euclidian distance.

4. Experimental Results

4.1 Introduction to FRGC Database

We use the FRGC (Face Recognition Grand Challenge) ver2.0 database to conduct our experiments. The FRGC data corpus consists of 50,000 recordings divided into training and validation partitions. The data corpus contains high resolution still images taken under controlled lighting conditions and with unstructured illumination, 3D scans, and contemporaneously collected still images. It consists of six experiments and we did the experiment 1 and experiment 4, which are both two dimensional gray-scale images. Some examples of the experimental images are shown below, the first row is sample images of Experiment 1 and the second row of Experiment 4 with same person in one column.

Figure 2. Sample Images of FRGC Experiment 1 and Experiment 4

Experiment 1 measures performance on the classic face recognition problem: recognition from frontal facial images taken under controlled illumination. The query and the target class both consist of 943 images from 275 individuals.

Recognizing faces under uncontrolled circumstances has numerous applications and is one of the most difficult problems in face recognition. Experiment 4 is designed to measure the face recognition performance from uncontrolled frontal still images. In Experiment 4, the target set consists of single controlled still images, and the query set consists of single uncontrolled still images. The query and the target class both consist of 943 images from 275 individuals the same as Experiment 1.

4.2 Experimental Design and Results

We construct our experimental process as follows: first, the face region is cropped from the original image using eye coordinates. All these face regions are 120*142 pixel sizes and histogram equalized for further processing. Then we divided the face region into 7*7 rectangular blocks and train their weights respectively. $LBP_{8,1}^{u2}$, $LBP_{8,2}^{u2}$ and $LBP_{16,2}^{u2}$ operators are used to test their classification ability. We calculate the LBP histogram with our proposed method of each block and connect them end to end to form a large single feature histogram. The weighted Chi square statistic measures are calculated for each pair of histograms to produce a distance matrix. Finally the ROC graph is deduced from this matrix to measure our experimental performance. The experimental results show that our improved LBP-based method using Hamming distance constraint outperforms the existing method for all LBP operator with different *P* and *R*.

The two figures below show the ROC graphs of the traditional $LBP_{8,2}^{u2}$-based face recognition and our new $LBP_{8,2}^{u2}$-based face recognition with Hamming distance constraints methods for FRGC experiment 1 and experiment 4 respectively. We can see from the figures that our method performs almost the same as or slightly better than the traditional LBP-based face recognition method in experiment 1, but for the experiment 4, in which the faces are influenced by expression or illumination changes, our new method outperform the existing method obviously.

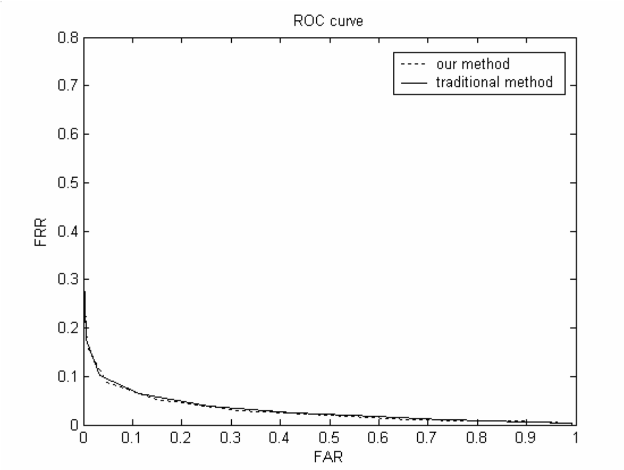

Figure 3.
ROC Graph of FRGC Experimet 1 using $LBP_{8,2}^{u2}$

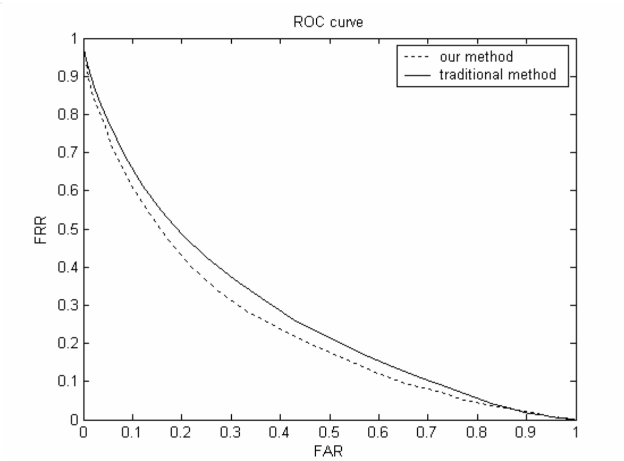

Figure 4.
ROC Graph of FRCE Experimet 4 using $LBP_{8,2}^{u2}$

5. Discussion and Conclusion

In this paper, we proposed a new LBP-based face recognition method with Hamming distance constraint and did our experiments on the FRGC database. We try to introduce the widely used Hamming distance in channel coding to our face recognition problem for considering the illumination, pose or expression changes of the face are some kinds of "noise". The result of Experiment 1 shows that our new method improves only a little better than the original LBP-based method, for the images in Experiment 1 are taken under controlled circumstance and could be seen as the original noise-free images. The images in Experiment 4 are influenced by illumination, pose or expression changes and they can be considered as being changed from the original frontal face images, so in this case our method can improve the recognition performance obviously.

As we know, the original LBP and $LBP_{P,R}^{u2}$ operator are developed for texture image descriptions. The human face is much more different from the ordinary texture images and has its particular characteristics, so the uniform patterns Ojala proposed may be not suitable for human face recognition. How to find the best local binary patterns for human face is a great challenge for us. Some researchers suggested using the Adaboost algorithm to choose the best patterns for face recognition[10]. We currently also concern about how to find some feature training methods to improve the uniform binary patterns.

Although the simplicity and accuracy of LBP-based face recognition method, some improvements are still possible to be made. One drawback of it is the length of the feature vector. The face image is always divided into some blocks, smaller blocks usually mean higher recognition accuracy but cause the overall feature vector too long, so we must find a proper tradeoff between the feature vector length and the computing efficiency. A possible direction is to apply a dimensionality reduction to the face feature vector, for example, reducing the feature vector length by PCA, using the symmetry patterns[9]. Our future research will concentrate on combining LBP with some knowledge in string coding and to work out a better way to reduce the length of feature vector. How to divide and represent the whole face image in a more meaningful and effective way and combining the other image processing methods such as wavelets are also under consideration.

Acknowledgements

This research is supported by National High-Tech Research and Development Program of China (863 Program). Program number is 2006AA01Z133.

References

[1] Tur, M, Pentland, A.: "Eigenfaces for recognition". *Journal of Cognitive Neuroscience*, 1991, pp.71-86.

[2] Etemad, K., Chellappa, R.: "Discriminant analysis for recognition of human face images". *Journal of the Optical Society of America*, vol.14, 1997, pp.1724-1733.
[3] Wiskott, L., Fellous, J.M., Kuiger, N., von der Malsburg, C., "Face recogniton by elastic bunch graph matching". IEEE Trans. *Pattern Analysis and Machine Intelligence*, vol 19, 1997, pp.775-779.
[4] T.Ahonen, A.Hadid, M.Pietikainen, "Face Recognition with Local Binary Patterns", *Computer Vision Proceedings*, ECCV 2004, Lecture Notes in Computer Science 3021, Springer, pp.469-481.
[5] T.Ojala, M.Pietikainen, T.Maeopaa, "Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns", *IEEE transactions on Pattern Analysis and Machine Intelligence*, vol.24, 2002, pp.971-987.
[6] T.Ojala, M.Pietikainen, D.Harwood, "A Comparative Study of Texture Measures with Classification Based on Feature Distributions", *Pattern Recognition*, vol.29, 1996, pp.51-59.
[7] P.Philips, P.Flynn, T.Scruggs, K.Bowyer, "Overview of Face Recognition Grand Challenge", *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol.1, 2005, pp. 947-954.
[8] Robert J. Mc Eliece, *The Theory of Information and Coding (Second Ediation)*, CUP, 2002
[9] O.Lahdenoja, M.Laiho, A.Paasio, "Reducing the Feature Vector Length in Local Binary Patten Based Face Recognition", *IEEE international conference on Image Processing*, vol.2, 2005, pp.11-14.
[10] X.S. Huang, S.Z.Li, Y.S. Wang, "Jensen-Shannon boosting learning for object recognition", *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol.2, 2005, pp.144-149.