



Wavelet-Local binary pattern based face recognition

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ABSTRACT

Over the last twenty years face recognition has made immense progress based on statistical learning or subspace discriminant analysis. This paper investigates a technique to reduce features necessary for face recognition based on local binary pattern, which is constructed by applying wavelet transform into local binary pattern. The approach is evaluated in two ways: wavelet transform applied to the LBP features and wavelet transform applied twice on the original image and LBP features. The resultant data are compared to the results obtained without applying wavelet transform, revealing that the reduction base one wavelet achieves the same or sometimes improved accuracy. The proposed algorithm is experimented on the Cambridge ORL Face database.

Keywords

Face recognition, Local Binary Pattern, wavelet transform, support vector machine, K nearest number.

INTRODUCTION

Face recognition is a very problematic issue when it is under uncontrolled conditions (Ahonen, Face description with local binary patterns: Application to face recognition, 2006). To solve this problem, the current research on face recognition has motivated better demonstration of face images and effective feature extraction from these image representations with the objective of obtaining feature vectors that are less sensitive to differences in facial appearance. Local binary pattern based face recognition has been currently proposed as a tough face recognition technique (Ahonen, Face description with local binary patterns: Application to face recognition, 2006). In this technique the image is denoted by local binary patterns (LBP) in which a pattern that reflects the relationships between the intensity values of the neighboring pixels is used, instead of using raw intensity values of pixels. The statistical distributions of the local patterns are utilized as features to be applied in classification. The technique has inspired many other algorithms on face recognition (Ekenel, 2008) (Ekenel, 2008). In [4], LBP is implemented on Gabor filtered images and the obtained features that used for face recognition the same way as in (Nguyen, 2009). In (Lajevardi, 2009), a latest, "symmetry" based approach was used to apply discrimination to downgrade the feature dimensionality. In (Ahonen, Face description with local binary patterns: Application to face recognition, 2006), LBP was used for face verification. In (Zhang, 2005), a boosting algorithm was used to obtain discriminative LBPs, and the found patterns were used for classification. Moreover, face recognition with LBPs has been proven to be a robust algorithm, but it suffers from heavy computational load due to the very high dimensional feature vectors extracted by concatenating the LBP histograms obtained from each local region. Considering these facts, this paper proposes a face recognition algorithm that benefits from both the LBPs' better image representation capability (Burrus, 1997) compared to directly using the intensity values of the pixels, and the wavelet transform's compact representation capability. The proposed algorithm is tested on the face images from ORL databases. The obtained results show that the combined approach performs significantly better than the individual algorithms.

Local binary pattern

The LBP is a non-parametric operator used to define the local spatial structure of an image. At a fixed pixel position the LBP operator is described as an ordered set of binary comparisons of pixel intensities between the center pixel and its neighboring pixels. This operator labels the pixels of the image by considering a neighborhood round every pixel and using the value of the center pixel to threshold the neighborhood. If the neighboring pixel value is less than the center pixel value, this pixel takes 0 (otherwise 1), then a LBP code for a neighborhood is produced. The decimal value of this binary code presents the local structural knowledge around the fixed pixel. The histogram of the LBP image displays how often these 256 different patterns appear in a given texture. The distribution of these patterns denotes the whole structure of the texture. However, it is possible to reduce the number of patterns in an LBP histogram by only using uniform patterns without missing much information. An LBP pattern is a uniform pattern if it includes at most two bitwise switches from 1 to 0 or 0 to 1 at its binary representation when the binary string is measured circularly. For example, 11100000 (with two transitions) is a uniform pattern, however 10110111 (with four transitions) is a non-uniform pattern (Ekenel, 2008).

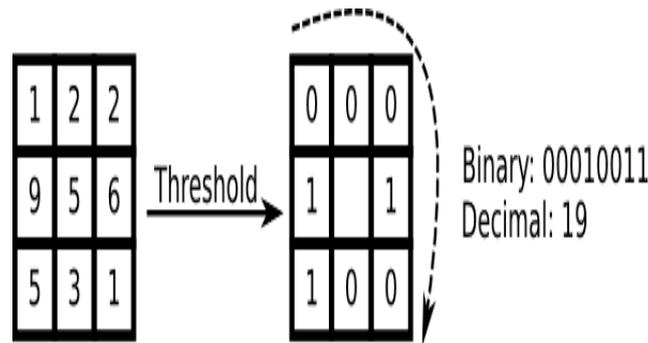


Figure 1 Threshold to Binary

In total there are 58 different uniform patterns at 8-bit LBP representation and 198 different non-uniform patterns, which are assigned with the remaining patterns in one bin. Now, the texture structure can be represented with a 59-bin histogram instead of using 256 bins. Face recognition with LBP is executed as follows. First, the input image is transformed to the LBP-domain. Next, the obtained LBP image is divided into non-overlapping rectangular blocks. On each block, the histogram of LBPs is computed (Ekenel, 2008). The obtained local histograms are then concatenated and used as feature vector for classification (Fig. 2).

THE DISCRETE WAVELET TRANSFORM

Wavelets transform one of the important tools in data mining. The wavelet transform is analyzed as a signal in time for its frequency content by dissimilar Fourier analysis,

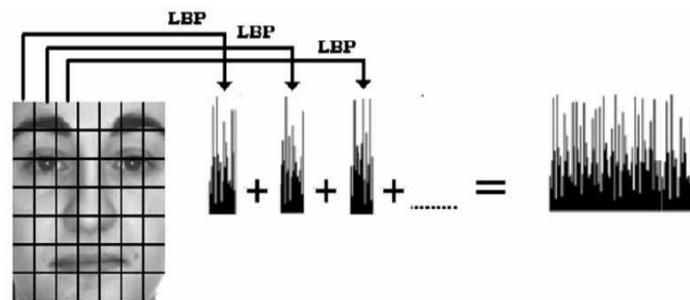


Figure 2 signal to frequency

in which analyzed signals use sines and cosines (Graps, 1995). The image input is converted to LBP domain then discrete wavelet transform is applied to the LBP features obtained from the previous step (Figure). The theory of wavelet transforms is discussed below.

Dilations and translations of the Mother function, $\Phi(x)$ describe an orthogonal root, the wavelet basis is:

$$\Phi(S, \ell)(X) = 2^{-\frac{S}{2}} \Phi(2^{-S} X - 1) \quad 1$$

The variables l and s are integers that denote dilate and scale the mother function Φ to generate wavelets. The location index l gives its position, and the scale index s denotes the wavelet's width. Observe that the mother function has been dilated (or rescaled by the power of two), and transformed by integers (Burrus, 1997). To span the data domain at deferent resolutions, the analyzing wavelet is used in a scaling equation:

$$W(x) = \sum_{k=-1}^{N-2} (-1)^k C_k + 1 \Phi(2x + k) \quad 2$$

Where $W(x)$ is the scaling function for the mother function $\Phi(x)$ and C_k are the wavelet coefficients (Daubechies, 1992). The wavelet coefficients have to gratify quadratic and linear constraints of the formula below:

$$\sum_{k=-1}^{N-2} C_k = 2, \sum_{k=0}^{N-1} C_k C_k + 2\ell = 2\delta 0$$

Where δ is the delta function. One of the most suitable features of wavelets is the ease with which a scientist can choose the defining coefficients for a given wavelet system to be adapted for a given problem. It is helpful to think of the coefficients $\{c_0; \dots; c_n\}$ as a filter placed in a transformation matrix, which is applied to a raw data vector from LPB domain. The coefficients are arranged using two main patterns, one of which works to bring out the data's detail information, and another works as a smoothing filter. Both orderings of the coefficients are called a quadrature mirror filter pair in signal processing parlance. An additional detailed description of the transformation matrix can be found elsewhere (Daubechies, 1992). The wavelet coefficient matrix is applied to the data vector obtained from the output of LBP. The matrix is applied in a hierarchical

algorithm, sometimes named a pyramidal algorithm. The wavelet coefficients are ordered into two groups: first, odd rows include those wavelet coefficients that act as the smoothing filter; and the second even rows include those wavelet coefficients with different signs that act to bring out the data details. In the first the matrix is applied to the original vector, which is then smoothed and decimated by half, and the matrix is applied again, then the smoothed, halved vector is smoothed, and halved again, and the matrix applied once more. This process continues until a small number of "smooth" data remain. The output of the DWT consists the smooth and detail components. The first experimental result is applied for one-dimensional discrete wavelet transform to the LPB, whereby smooth and detailed components are obtained. The second experimental procedure is applied for DWT following the same process described to obtain the first result.

Experimental results

The proposed technique is tested extensively on ORL face database, in which there are 10 different images of each of 40 different subjects. The images were captured at different times, with different facial expressions (e.g. open / closed eyes, smiling / not smiling), varying lighting and facial details (glasses / no glasses) (Guo, 2000). Sample images from this database can be seen in Fig. 5.



Figure 3 face database

The experimental result is explained into two parts: working with the original input image and working with the non-original input image.

Working with original input image:

The initial process starts by extracting features from the original images by LBP technique. The wavelet transform is then applied to the LBP features in order to reduce the number of features by half if DWT is taken one time. The smooth coefficients are chosen, which can be called a low frequency in a vector. Through cross-validation the smooth coefficients are chosen, whose "reduction features" are considered in the face recognition system with the application of Support Vector Machine (SVM) and K nearest neighbor (KNN); the results indicate that the former is more accurate: $LBP_8^1 3 * 3$ is better than $LBP_8^1 2 * 2$, as shown in the table below.

Table 1SVM

Accuracy	2*2 Normal		3*3 Normal	
	400*236 Normal	400*118 DWT LOW	400*531 Normal	400*266 DWT LOW
KNN	95	97	99	99.5
SVM	99	99.5	99	99

In addition, the time of recognition is gradually decreased more suitably in SVM, which also enables the face recognition system to obtain better efficiency, as shown in the column chart below.

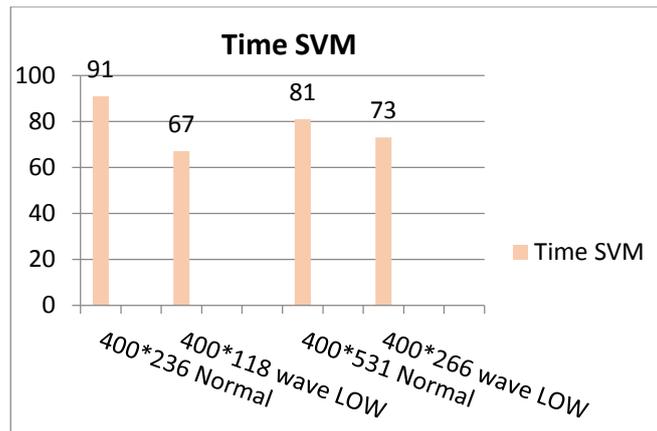


Figure 4 Time SVM

Working with non-original input image:

A non-original input image is one that does not deal with the image directly. The first step is a 2-D discrete wavelet transform for input image in order to obtain approximation coefficients from the whole face image. The approximation coefficients represent the original image. LBP technique is applied to approximation coefficients, the new features in LBP domain that undergo both SVM and KNN classification methods. Moreover single-level discrete wavelet transform is also applied to these features obtained in LBP technique to effect a reduction in the features, resulting in what can be considered new features, with increased accuracy and thus decreased time necessary for recognition. The accuracy is shown in the table below

Table 2 accuracy

Accuracy	2*2 WAVE		3*3 WAVE	
	400*236 Normal	400*118 wave LOW	400*531 Normal	400*266 wave LOW
Knn	97	98	99	99.5
SVM	98	99	99	99.5

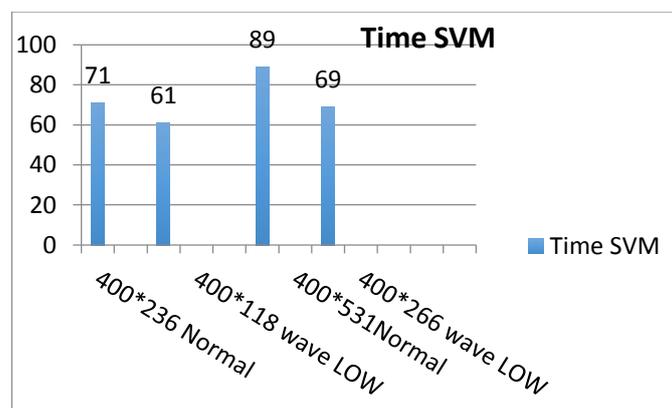


Figure 5 The time of executing SVM

It can be seen that the wavelet transform is useful in both reducing dimensional features and in increasing the accuracy of the face recognition system.

Conclusion

In this paper, a fast and robust face recognition algorithm has been proposed that combines the LBP and discrete wavelet transform. The combined approach benefits from both the robust the low dimensional feature representation capability of wavelet transform coefficients and image representation capability of LBPs. This provides significant improvement in the correct recognition rate compared to each individual.



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