Face Recognition Based on Wavelet Transform and Adaptive Local Binary Pattern

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Abstract. Local Binary Pattern (LBP) is a very efficient local descriptor for describing image texture. In this paper, we propose a novel face recognition technique based on wavelet transform and the least square estimator to enhance the classical LBP. First, Wavelet transform is used to decompose a given image into four kinds of frequency images from which the features of that image can be extracted. Then, the least square estimation of local difference between each image pixel and its neighborhoods is used to build the adaptive LBP. Finally, the classification accuracy is computed using a nearest neighbor classifier with Chi-square as a dissimilarity measure. Experiments conducted on three face image datasets (ORL dataset and two avatar face image datasets); show that the proposed technique performs better than traditional methods (single scale) LBP and PCA, Wavelet Local Binary Pattern (WLBP) and Adaptive Local Binary Pattern (ALBP) in terms of accuracy.

Keywords: Face recognition, avatar, Adaptive Local Binary Pattern (ALBP), wavelet transform.

1 Introduction

Face recognition has become the center of attention of many researchers during the last few decades because of its wide range of practical applications, including access control, surveillance systems and biometric identification. However, after all these years of research to find out proper human face recognition techniques, identification of avatars in virtual worlds is still an open problem [1].

Face recognition techniques can be divided into two categories [2]: holistic matching and local feature-based methods. Local Binary Pattern (LBP) is one of the most popular local feature-based methods.

LBP, first proposed by Ojala et al. [3], is a powerful way for texture description and it was applied to face recognition for the first time by Ahonen et al. [4]. Later, some methods further developed LBP for either recognizing human faces or avatar faces. For example, Yang et al. [5] applied LBP for face recognition with Hamming distance constraint. Chen et al. [2] used Statistical LBP for face recognition. Mohamed et al. [6] applied hierarchical multi-scale LBP with wavelet transform to recognize avatar faces. In this paper, we propose a novel face recognition approach

combining wavelet transform with a new LBP type (adaptive LBP) to recognize both human and avatar faces. The efficacy of the new method is demonstrated by the experiments on ORL dataset and two avatars datasets from Second Life and Entropia virtual worlds.

The remaining of this paper is organized as follows; Section 2 provides an introduction to wavelet decomposition. In Section 3, an overview of the LBP is presented. Section 4, presents the proposed method, Wavelet Adaptive LBP (WALBP). In Section 5, experimental results are presented followed by conclusions in Section 6.

2 Review of Wavelet Transform

Wavelet Transform (WT) is a popular tool for image analysis. It provides multi-resolution analysis of the image by using coefficient matrices [7]. It has many applications in signal and image processing including multi-resolution analysis, computer vision and graphics. Many articles have discussed its mathematical background and advantages [8]. WT can be applied in image decomposition for many reasons [8]:

- Using WT to decompose an image reduces the resolution of the sub-images and then the computational complexity will also be reduced.
- WT decomposes an image into sub-images corresponding to different frequency ranges and this can lead to minimize the computational overhead.
- Using WT allows obtaining the local information in different domains (space and frequency).

Decomposing an image with the first level of WT provides four sub-bands LL1, HL1, HL1 and HH1 (see Fig 1.a.).

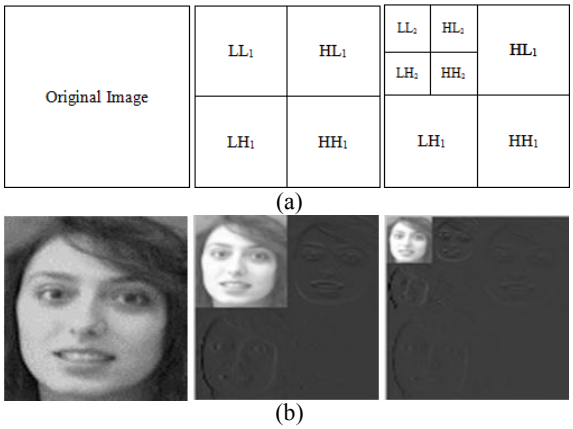


Figure 1. a) Structure of one-level and two-level wavelet decomposition b) an example of decomposing an image using one-level and two-level wavelet decomposition

The sub-band LL represents the approximation coefficient of the wavelet decomposition and it has the low frequency information of the face image [7]. This

information includes the common features of the same class. The other sub-bands represent the detailed coefficients of the wavelet decomposition and they have most of the high frequency information of the face image. This information includes local changes of face image such as illumination and facial expression. To improve recognition performance we have to enhance the common features of the same class and remove changes. So, during our experiments we considered only the approximation images.

Decomposing an image with two scales will give us seven sub-bands [8]: LL2, HL2, LH2, HH2, HL1, LH1 and HH1 as in Fig. 1.

3 Local Binary Pattern (LBP)

3.1 LBP Operator

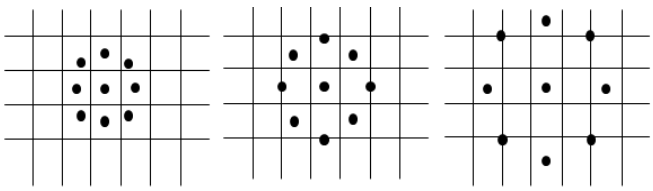
The local binary pattern (LBP) operator was proposed by Ojala et al. [3], to describe local textural patterns. It works by thresholding the pixels in a certain block of an image with its center, multiplied by powers of two and then added together to form the new value (label) for the center pixel [9]. The output value of the LBP operator for a block of 3x3 pixels can be defined as follows [9]:

$$LBP(x_c, y_c) = \sum_{i=0}^{7} 2^i S(g_i - g_c) \tag{1}$$

where g_c corresponds to the gray value of the central pixel, (x_c, y_c) are its coordinates, g_i (i = 0,1,2,..,7) are the gray values of its surrounding 8 pixels and $S(g_i - g_c)$ can be defined as follows:

$$S(g_i - g_c) = \begin{cases} 1, & g_i \geq g_c \\ 0, & otherwise \end{cases} \tag{2}$$

The LBP operator was extended to use neighborhoods of different sizes to be able to deal with large scale structures that may be the representative features of some types of textures [4, 10]. In the following the notation (P, R) will be used as indication of neighborhood configurations. P represents the number of pixels in the neighborhood and R represents the radius of the neighborhood. The neighborhood can be either in a circular or square pattern (Fig. 2 gives an example of a circular neighborhood for the same neighbor set of pixels but with different values of the radius).



(P=8, R=1) (P= 8, R=1.5) (P=8, R=2)

Figure 2. Three different LBP operators [4, 6]

LBP operator can also be extended to other definitions and patterns. One of the most important and successful extensions to the basic LBP operator is called uniform LBP (ULBP). An LBP is called uniform if the binary pattern contains at most two different conversions from 0 to 1 or 1 to 0 when the binary string is viewed as a circular bit string [4]. For example, 11000011, 00111110 and 10000011 are uniform patterns. The results of statistical analysis indicated that most of patterns in images are uniform patterns. Ojala reported that with (8, 1) neighborhood, uniform patterns account for a little less than 90% of all patterns and with (16, 2) neighborhood, uniform patterns account for around 70% of all patterns [4].

3.2 LBP Histogram

After labeling an image with the LBP the histogram of the labeled image can be defined as follows [10]:

$$H_i = \sum_{x,y} I(f(x,y) = i), i = 0,1,..,n-1 \quad (3)$$

where 'n' is the number of different labels produced by the LBP operator, $f(x, y)$ is the labeled image and $I(A)$ is a decision function with value 1 if the event A is true and 0 otherwise.

To form the LBP histogram, the image has to be divided into sub-regions. Then, the LBP histogram for each sub-region has to be computed and then all sub-regions histograms have to be combined to form the feature histogram of the whole image [11].

4 Wavelet Adaptive LBP (WALBP)

We propose an algorithm to work with gray scale images. These images can be either from the real world (human images) or from virtual worlds (e.g. Second Life and Entropia). Our algorithm has three steps: preprocessing datasets, extracting features and classifying each image to its subject.

4.1 Preprocessing Datasets

For the two virtual world datasets (Second Life and Entropia datasets), we have to get rid of the background in each image if it is present. The presence of the background of an image has an effect of identifying that image. To remove the background of an image we manually cropped the facial portion of that image on the bases that the new facial image should have two eyes, nose and mouth in each image.

During our experiments we decomposed all facial images using the first level of decomposition and the low frequency coefficient of decomposition is used in the next step to extract the facial image features.

4.2 Adaptive Local Binary Pattern (ALBP)

In an image, to improve the classification performance using the LBP by reducing the estimation error of local difference between each pixel and its neighbors a new parameter called weight (w_p) is defined in the LBP equation. We call this new approach Adaptive LBP (ALBP).
So the new definition of the LBP equation will have the following form [12, 13]:

$$ALBP_{P,R} = \sum_{p=0}^{P-1} 2^p S(g_p * w_p - g_c) \tag{4}$$

where the weight w_p can be computed using:

$$w_p = \bar{g}_p^T \bar{g}_c / (\bar{g}_p^T \bar{g}_p) \tag{5}$$

where $\bar{g}_c$ = [$g_c(1,1)$;$g_c(1,2)$;…;$g_c(N,M)$] is a column vector that contains all possible values of any pixel $g_c(i,j)$, N x M is the size of an image and $\bar{g}_p$ = [$g_p(1,1)$;$g_p(1,2)$;…;$g_p(N,M)$] is the corresponding vector for all $g_p(i,j)$ pixels. We have to note that each weight w_p is computed along one orientation $2\pi p/P$ for the whole image.

4.3 Classification

The last step in our algorithm is to classify each face image to its class. We have to build the distance matrix of the training images and the testing ones using the ALBP definition and the definition of the Chi-Square distance. The Chi-Square distance has the following form [4]:

$$D(X,Y) = \sum_{n=1}^{N} \frac{(X_n - Y_n)^2}{X_n + Y_n} \tag{6}$$

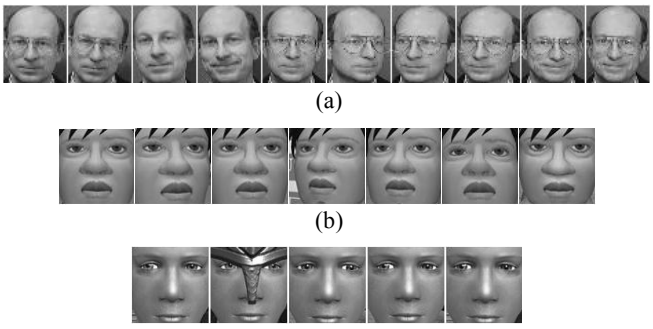
where X is the testing images and Y is the training images.
The distance matrix is used by the definition of the nearest neighbor classifier to compute the accuracy rate

5 Experiments

In this section, we verify the performance of the proposed algorithm on three different datasets: one real world well known human dataset (ORL) and two virtual world agents (avatar) datasets (see Fig. 3). The proposed method is compared with well-known methods of face recognition, PCA, single scale LBP and wavelet LBP.

5.1 Experimental Setup

Three facial image datasets were used to evaluate the proposed WALBP method. The first one is the ORL dataset. The ORL dataset contains 400 images representing 40 distinct subjects [14]. Each subject has 10 different images. These images were taken at different times, with varying lighting, pose angle, facial expressions (open eyes,



(a)

(b)

(c)

Figure 3. Samples of one subject of facial images from: a) ORL dataset b) Second Life dataset c) Entropia dataset

closed eyes, smiling, not smiling) and facial details (wearing glasses or no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position and each is grayscale image with a resolution of 92 x 112 pixels [14]. We have used all images in this dataset during our experiments without cropping the facial portion from each image but we used them as they were in the original dataset. After applying the first level of wavelet decomposition the resolution of each image in the ORL dataset was changed from 92 x 112 to 46 x 56.

For the other two datasets, the first one was collected from the Second Life (SL) virtual world [15]. This dataset contains 581 gray scale images with size 1280 x 1024 each to represent 83 different avatars. Each avatar subject has different 7 images for the same avatar with different frontal pose angle (front, far left, mid left, far right, mid right, top and bottom) and facial expression.

The second virtual world dataset was collected from Entropia (ENT) Universe virtual world [16] and contains 490 frontal images of 98 subjects or avatars (5 images per avatar) with size 407 x 549 pixels each. Each avatar subject's images have different frontal angle and details (wearing a mask or no). The facial part of each virtual world image used in our experiments was manually cropped from the original images (for the second Life dataset the size will be 260 x 260) based on the location of the two eyes, mouth and the nose. Each cropped Entropia facial image was rescaled to the size of 180 x 180 pixels. After applying the first level of wavelet decomposition the resolution of each face image in the Second Life dataset will be reduced to be 130 x 130 and for Entropia dataset the new resolution for each face image becomes 90 x 90.

The intensity of all images used in all experiments is normalized to reduce the variance of illumination.

5.2 Experimental Results

We performed many experiments to proof the superiority of our algorithm over the other methods used in experiments.

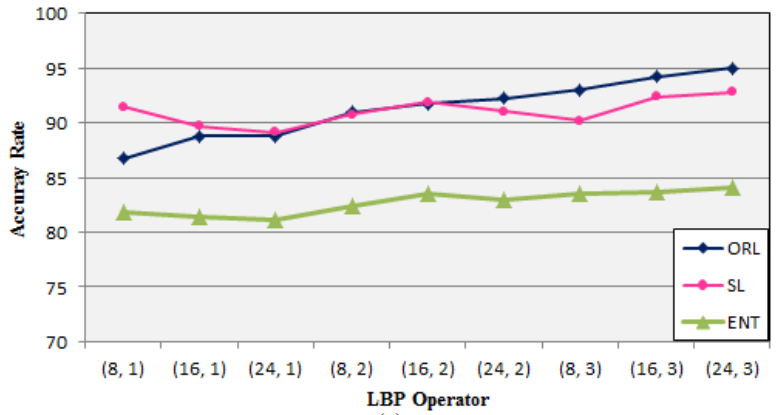
In the first one we compared ALBP with our proposed method WALBP, in this experiment the first 5 images from each subject in the ORL were used for training and

the rest were used for testing and then the training and testing sets were swapped. The average of the two experiments was used as the final accuracy rate. We followed the same protocol with the other two datasets but with different number of training and testing images. In SL dataset the first 4 images were used for training and the rest were used for testing and then the training and testing images were swapped. In ENT dataset the first 3 images were used for training and the rest for testing and then training and testing images were swapped. The result of this experiment using different LBP operators can be seen in Fig. 4.

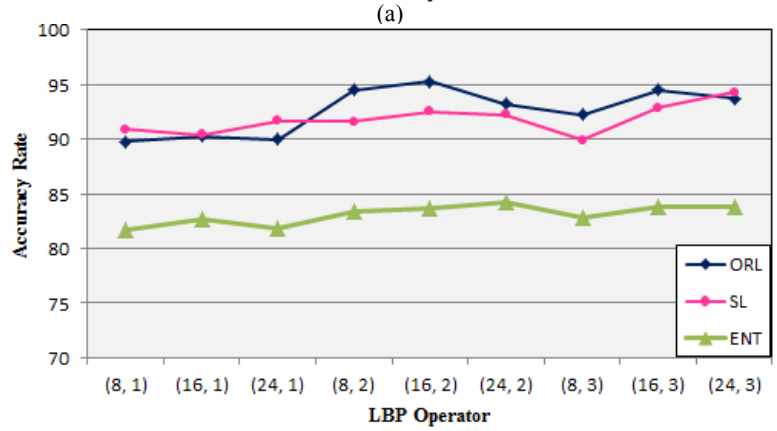
From Fig 4 we can recognize that in most of the cases the accuracy rate of using WALBP is better than that of using ALBP. Also the processing time of using WALBP is less than that of using ALBP.

We also compared WALBP with PCA, Traditional LBP and WLBP using different number of training images from each subject and the result are shown in table I. We did this experiment using only the SL dataset.

It is very clear from Fig 4 and table I that our proposed method can achieve better result than the other algorithms in terms of accuracy.



(a)



(b)

Figure 4. Recognition rate average using:
a) ALBP algorithm b) WALBP algorithm

Table I. Accuracy rates for SL dataset

Algorithm	The number of training images		
	1	3	5
PCA	76.71% [17]	84.29%	87.35%
LBP	76.50% [17]	86.37%	89.23%
WLBP	79.55% [17]	88.19%	90.56%
WALBP	84.96%	90.66%	93.77%

6 Conclusions

In this paper, a novel LBP face recognition approach (WALBP) is proposed based on a new definition of the LBP operator and wavelet transform to increase the recognition rate of facial images. Experimental results show the effectiveness of the WALBP in recognizing faces from both real and virtual worlds. In the future work, we will add statistical features such as mean and standard deviation to the multi-scale version of the adaptive LBP to increase the recognition rate of faces and facial expressions.

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