

Wavelet Based Statistical Adapted Local Binary Patterns for Recognizing Avatar Faces

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Abstract. In this paper, we propose a novel face recognition technique based on discrete wavelet transform and Local Binary Pattern (LBP) with adapted threshold to recognize avatar faces in different virtual worlds. The original LBP operator mainly thresholds pixels in a specific predetermined window based on the gray value of the central pixel of that window. As a result the LBP operator becomes more sensitive to noise especially in near-uniform or flat area regions of an image. To deal with this problem we propose a new definition to the original LBP operator not based only on the value of the central pixel of a certain window, but based on all pixels values in that window. Experiments conducted on two virtual world avatar face image datasets show that our technique performs better than original LBP, wavelet LBP, adaptive LBP and wavelet adaptive LBP in terms of accuracy.

Keywords: Avatar, face recognition, LBP, SALBP, wavelet transform.

1 Introduction

Face recognition is one of the biometric traits that received a great attention from many researchers during the past few decades because of its potential applications in a variety of civil and government-regulated domains [1]. Face recognition however is not only concerned with recognizing human faces, but also with recognizing faces of non-biological entities or avatars. To address the need for a decentralized, affordable, automatic, fast, secure, reliable, and accurate means of identity authentication for avatars, the concept of Artimetrics has emerged [2, 3]. Artimetrics is a new area of study concerned with visual and behavioral recognition and identity verification of intelligent software agents, domestic and industrial robots, virtual world avatars and other non-biological entities [2, 3].

Extracting discriminant information from a facial image is one of the key components for any face recognition system [1]. There are many different algorithms proposed to extract features, such as Principal Component Analysis (PCA) [4], Linear Discriminant Analysis (LDA) [5] and Local Binary Pattern (LBP) [6].

LBP was applied to face recognition for the first time by Ahonen et al. [7]. But the original LBP method worked as a local descriptor to capture only local information [8]. It thresholds all pixels in the neighborhood based on the gray value of the central

pixel. As a result the original LBP becomes more sensitive to noise specially in near uniform or flat areas [9]. One solution to this problem is to threshold all the pixels automatically based on the available data.

Most of the work done so far on face recognition has focused on humans. Research on recognizing virtual world's avatars has not received due attention. Some methods developed LBP further for either recognizing human faces or avatar faces. For example, Yang et al. [10] applied LBP for face recognition with Hamming distance constraint. Chen et al. [11] used Statistical LBP for face recognition. Mohamed et al. [2] applied hierarchical multi-scale LBP with wavelet transform to recognize avatar faces. Mohamed et al. [12] applied wavelet transform as well but with adapted local binary patterns and direction statistical features to recognize avatar faces.

In this paper, we propose a novel LBP face recognition technique to recognize avatar faces from different virtual worlds. In this approach, we combine the idea of discrete wavelet transform with new definition of the original LBP operator, Statistical Adapted Local Binary Pattern (SALBP) operator. The efficiency of our proposed method is demonstrated by experiments on two different avatar datasets from Second Life and Entropia Universe virtual worlds.

The rest of this paper is organized as follows; Section 2 briefly provides an introduction to wavelet decomposition. In Section 3, an overview of the LBP is presented. Section 4 presents SALBP operator. Wavelet Statistical Adapted Local Binary Pattern (WSALBP) operator is described in section 5. Section 6 reports experimental results which followed by conclusions in Section 7.

2 Discrete Wavelet Transform

Wavelet Transform (WT) or Discrete Wavelet Transform (DWT) is a popular tool for analyzing images in a variety of signal and image processing applications including multi-resolution analysis, computer vision and graphics. It provides multi-resolution representation of the image which can analyze image variation at different scales.

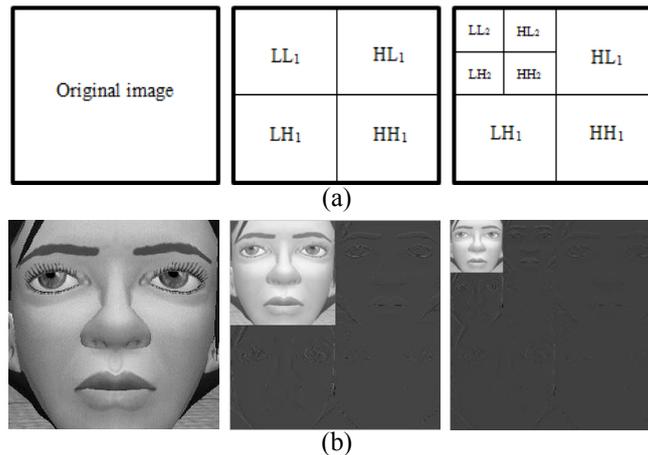


Fig. 1. (a) Wavelet coefficient structure [14] (b) Original image, One and two levels wavelet decomposition for an image

WT was applied in image decomposition for many reasons [13]: it reduces the computational complexity of the system, decomposes images into sub-images corresponding to different frequency ranges and this can lead to reduction in the computational overhead of the system and allows obtaining the local information in different domains (space and frequency). Thus it supports both spatial and frequency characteristics of an image at the same time.

WT decomposes facial images into approximate, horizontal, vertical and diagonal coefficients. Approximate coefficient of one level is repeatedly decomposed into the four coefficients of the next level of decomposition [13]. Decomposing an image with the first level of WT provides four sub-bands LL_1 , HL_1 , LH_1 and HH_1 as in Fig. 1.

3 Local Binary Pattern

LBP operator, proposed by Ojala et al. [6], is a very simple and efficient local descriptor for describing textures. It labels the pixels of an image by thresholding the pixels in a certain neighborhood of each pixel with its center value, multiplied by powers of two and then added together to form the new value (label) for the center pixel [15]. The output value of the LBP operator for a block of 3×3 pixels can be defined as follows [15]:

$$LBP_{p,R} = \sum_{p=0}^7 2^p S(g_p - g_c) \quad (1)$$

where g_c corresponds to the gray value of the central pixel, g_p ($p = 0, 1, 2, \dots, 7$) are the gray values of its surrounding 8 pixels and $S(g_p - g_c)$ can be defined as follows:

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

Later new versions of LBP operator have emerged as an extension to the original one. They used neighborhoods of different sizes to be able to deal with large scale structures that may be the representative features of some types of textures [8, 16]. (Fig. 2 gives examples of different LBP operators where P is the neighborhood size and R is its radius).

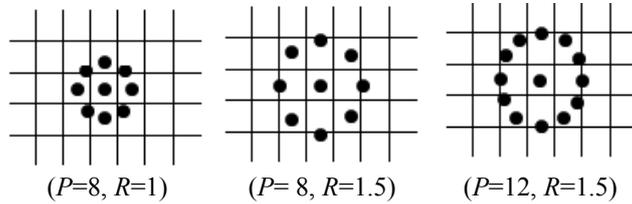


Fig. 2. Three different LBP operators [7, 8]

4 Statistical Adaptive Local Binary Pattern (SALBP)

Using the central pixel value of the neighborhood of any pixel as a threshold has a negative effect on how the LBP method can deal with noise especially in near uniform or flat areas. To obtain good results, we propose a novel LBP operator, SALBP, which overcomes the high sensitivity of LBP to noise. The SALBP's threshold is not fixed but is computed automatically from the available image data using simple statistics. To minimize the effect of noise, we propose the following equation by which differences between the central pixel value of any local patch and its surrounding pixels values can be reduced. The reduction resulting from computing the weight for each pixel in a local patch by using the following equation and then that weight can be used to redefine a new value for each pixel.

$$J = (g_c(i, j) - \sum_{q=1}^P w_q g_q(i, j))^2 \quad (3)$$

where g_c corresponds to the central pixel, g_q to the surrounding pixels, w_q is the weight for any pixel q and $\sum_{q=1}^P w_q = 1$

By deriving both sides of equation 3 with respect to the weight for any pixel p and assign the result to zero we get:

$$\frac{\partial J}{\partial w_p} = -2g_p(i, j)(g_c(i, j) - \sum_{q=1}^P w_q g_q(i, j)) = 0$$

then:

$$g_c(i, j) = \sum_{\substack{q=1 \\ q \neq p}}^P w_q g_q(i, j) + w_p g_p(i, j) \quad (4)$$

From equation 4 we can obtain the value of w_p using the following equation:

$$w_p = \frac{g_c(i, j) - \sum_{\substack{q=1 \\ q \neq p}}^P w_q g_q(i, j)}{g_p(i, j)} \quad (5)$$

where p is any pixel we currently compute its weigh where q is any pixel other than p in the surrounding.

For more explanation about how we can compute w_p for different pixels in the neighborhood we have to follow the following steps:

- 1- Initialization $w_p = 1/P$ for every $p = 1, 2, \dots, P$
- 2- Use the updated equation 5

Repeat

For $p = 1 : P$

Update w_p with the new value and each time when we compute the new value of w_p for any pixel we use this value to compute the w_p for the next pixels.

end

After applying these steps we would have the weights for all pixels in the neighborhood and thus we can define the SALBP operator as following:

$$SALBP = \sum_{p=0}^{P-1} s(g_p * w_p - k * std_p) 2^p \quad (6)$$

And so the obtained binary code can be seen as:

$$s(g_p * w_p - k * std_p) = \begin{cases} 1, & \text{if } g_p * w_p \geq k * std_p \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

where std_p is the standard deviation of all pixels values in an image patch and k is a scaling factor such that $0 < k \leq 1$. For more explanation about how this new LBP operator works see Fig. 3 below shows the result of applying the proposed technique in a local image area with $k = 0.3$.

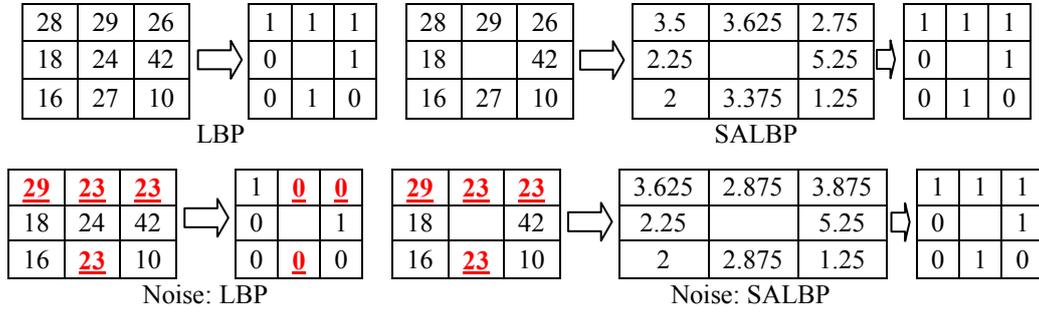


Fig. 3. Comparison of LBP and SALBP operators. First row: original encodings. Second row: encodings with noise. The bold underlined red pixels are changed with noise.

5 Wavelet Statistical Adaptive Local Binary Pattern (WSALBP)

The proposed algorithm has three steps: preprocessing, feature extraction and recognition or classification:

5.1 Preprocessing Facial Images

We followed some of preprocessing operations to improve the efficiency of extracting the face features. First, the input images are manually cropped to pure face images by removing the background which is not useful in recognition. Second, these pure face images have to be normalized and then decomposed using the first level of wavelet decomposition to obtain the pure facial expression images. Detailed images resulting from applying wavelet decomposition contain changes which represent the difference of face images. So considering only the approximation images will enhance the common features of the same class of images and at the same time the differences will be reduced. For this reason, we decomposed only the approximation images resulted from the first level of wavelet decomposition to obtain the second level of decomposition. So, our experiments were concerned only with the approximation

images resulted from the second level of wavelet decomposition and which we used in training and testing to evaluate the performance of the proposed algorithm.

5.2 Extracting Facial Features using SALBP

The choice of the threshold is very important to obtain good results in any face recognition system. One of the best ways for choosing the proper threshold is by automatically computing this threshold using the local statistics of the available images pixels. So, we have used the SALBP operator, defined by equation 6, to provide the new value for each pixel of the approximation facial image obtained from the second level of decomposition.

In order to compute the SALBP binary code for each pixel we have to follow:

- Compute the local weight for each pixel in an image patch by using equation 5 and then multiply this weight by its pixel to produce a new pixel value.
- Compute standard deviation of all old pixels values in the image patch including the central pixel value.
- Choose a scaling factor k which has a value between 0 and 1 and multiply k with the computed standard deviation to obtain new threshold. (there is no fixed value for k but we have to try different values till we obtain a proper one since its value affects the obtained binary code and then affects also the accuracy rate, during our experiments we used $k = 0.3$).

Use our threshold with the new pixels values to compute the SALBP binary code for each pixel (see Fig. 3 as an example of how we can use the SALBP operator).

5.3 Dissimilarity Measure

The last stage of our proposed technique is to classify each facial image to its subject. To this end we have used chi-square distance to compute the dissimilarity between each input image and the training model as in the following equation [8]:

$$D_{LBP}(X, Y) = \sum_{n=1}^N \frac{(X_n - Y_n)^2}{X_n + Y_n} \quad (8)$$

where X is the testing image, Y is the training model and N is the number of bins.

6 Experimental Results and Analysis

In this section, we verify the performance of the proposed algorithm on two different types of avatar datasets: the first type is the Second Life (SL) dataset and the second is the Entropia Universe (ENT) dataset (Fig. 5 gives an example of a subject from each dataset). The proposed method is compared with other single scale techniques such as, the original LBP, wavelet LBP (WLBP), adaptive LBP (ALBP) and Wavelet ALBP.

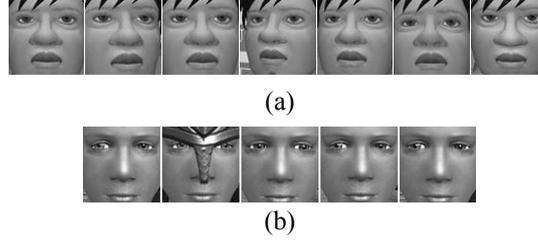


Fig. 5. Samples of one subject of facial images from: a) Second Life dataset
b) Entropia dataset

6.1 Experimental Setup

To evaluate our proposed technique, we have used two facial image datasets.

The first dataset was acquired from a large collection of SL virtual world avatar face dataset [17]. This dataset contains 847 gray scale images with size 1280 x 1024 each to represent 121 different avatars. Each avatar subject has 7 different 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 dataset was collected from ENT virtual world [18]. ENT dataset contains 545 gray scale images with size 407 x 549 pixels. These images were organized in 109 subjects (avatars). Each subject has different 5 images for the same avatar with different frontal angle and facial details (with and without a mask).

In order to compare the performance of our technique against other techniques we added two types of noise to each image in both datasets and then obtain the recognition rate after applying each technique. These two types of noise are noise Gaussian noise and Salt & Pepper noise. We used the default parameters for each one of the two types of noise.

The facial part of each image in SL and ENT datasets was manually cropped from the original images based on the location of the two eyes, mouth and the nose. The new size of each facial image in SL dataset is 260 x 260 pixels while in ENT dataset each facial image was resized to 180 x 180 pixels. After applying the second level of wavelet decomposition the resolution of each facial image was reduced to 65 x 65 pixels and to 45 x 45 pixels for SL dataset and ENT dataset respectively.

Each of the two datasets was split in two independent sets. One set is used for training and the second set for testing. For training we used four image from each subject in the SL dataset and three images from each subject in the ENT dataset. All training images were randomly chosen while the rest were used for testing.

6.2 Experimental Results

To ensure the efficiency of using our new definition of the LBP operator with noisy facial images, we compared WSALBP with the original LBP, ALBP, WLBP and WALBP with several experiments. First we got the performance of WSALBP, LBP, ALBP, WLBP and WALBP with different LBP operators applied on Gaussian noisy

facial images from the two datasets (SL and ENT) and then on Salt & Pepper noisy facial images.

We applied all techniques with $R = 1, 2, 3$ and $P = 8, 16, 24$. It is evident in figures 6 and 7 that changing the LBP operator affects the recognition rate for all techniques. Also the recognition rate for the same technique and LBP operator changes from one dataset to another.

In case of Gaussian noise, the performance of the WSALBP technique is better than the performance of other techniques with most of all LBP operators and with both SL and ENT datasets. In the SL dataset, the WSALBP recognition rate is greater than that of its closest competitor, WALBP, by about 3% in average. The highest recognition rate obtained (when the LBP operator is (16, 3)) is 92.37%. In the ENT dataset, the WSALBP recognition rate is greater than that of its closest competitor, WALBP, by more than 4% in average. The highest recognition rate obtained (when the LBP operator is (16, 2)) is 81.63%.

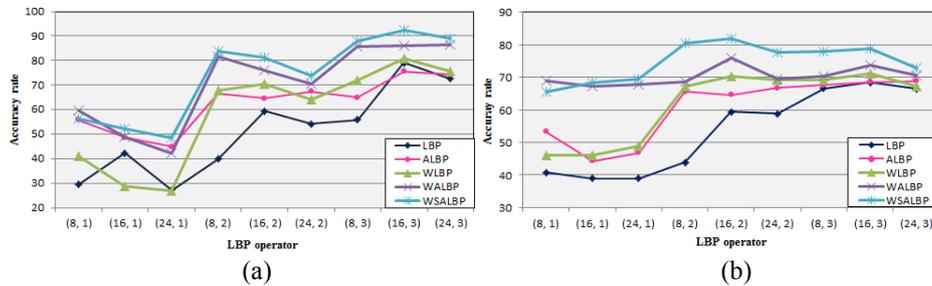


Fig. 6. Recognition rate for the SL dataset and ENT dataset with Gaussian noise:
a) SL dataset b) ENT dataset

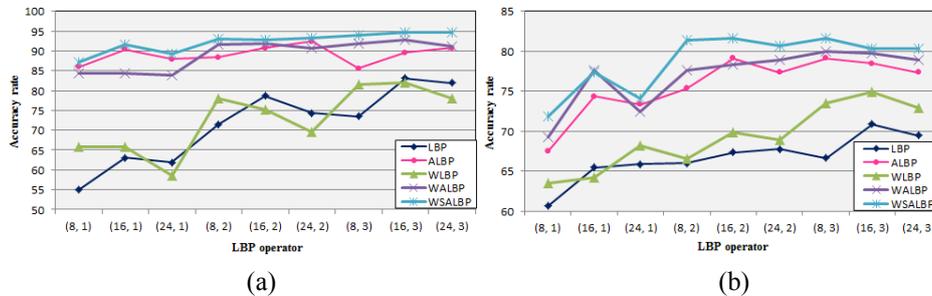


Fig. 7. Recognition rate for the SL dataset and ENT dataset with Salt & Pepper noise:
a) SL dataset b) ENT dataset

There was no great difference in performance of the WSALBP technique on the Gaussian and the Salt & Pepper noisy images. That is, performance of the WSALBP is better if compared to most other techniques. The closest competitor to The WSALBP technique on the Salt & Pepper noisy images is the ALBP technique (in case of the SL dataset). The increase in the recognition rate is 3% in average and the highest recognition rate is 94.77% obtained when the LBP operator is either (16, 3) or (24, 3). In case of the ENT dataset, the closest competitor to the WSALBP technique is the WALBP with difference of about 2% in average to the side of the WSALBP

technique. The highest recognition rate is 81.63% when the LBP operator is either (16, 2) or (8, 3) (see table 1 which shows the average recognition rate for all techniques where SL_G stands for SL dataset with Gaussian noise and SL_{SP} stands for SL dataset with Salt & Pepper noise and the same for ENT_G and ENT_{SP}).

Table 1. Average recognition rate for different algorithms

Dataset	Techniques				
	LBP	ALBP	WLBP	WALBP	WSALBP
SL_G	51.14%	62.56%	58.59%	70.73%	73.92%
SL_{SP}	71.44%	89.29%	72.69%	89.20%	92.29%
ENT_G	53.57%	60.70%	61.67%	70.28%	74.77%
ENT_{SP}	66.68%	75.76%	69.17%	76.97%	78.81%

7 Conclusion

In this paper, a novel LBP face recognition approach (WSALBP) is proposed based on discrete wavelet transform and a new definition to the original LBP operator (SALBP). This proposed approach treats some of the LBP limitations, that is, noise sensitivity. The effectiveness of this method is demonstrated on recognizing faces from two different virtual worlds, Second Life and Entropia Universe. Our proposed technique improved the recognition rate for the SL dataset by about 3% for both Gaussian and Salt & Pepper noise when compared to LBP, ALBP, WLBP and WALBP and different LBP operators. Also, our technique improved the recognition rate for the ENT dataset by about 4% and 2% for Gaussian and Salt & Pepper noise respectively. We intend to use our proposed technique to build a complete recognition system for avatars in the future.

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