An Improved LBP Algorithm for Avatar Face Recognition

Abdallah A. Mohamed, Roman V. Yampolskiy
Computer Engineering and Computer Science
University of Louisville
Louisville, USA

***Abstract*—This paper presents a novel avatar face recognition algorithm based on Discrete Wavelet Transform and LBP descriptor. The 2-D Discrete Wavelet Transform has been used to process the avatar face dataset by extracting the low frequency components and then forming the low frequency sub-images. Then the LBP operator is used to extract the characterizations of these sub-images. Finally, the Chi-Square distance is used to connect each image to its subject. Experimental results show that the proposed method can be used effectively in avatar face recognition with a single training sample per avatar. The performance of the proposed algorithm on a dataset of 581 avatar face images shows that the proposed algorithm performs better than PCA and Traditional (single scale) LBP method with respect to the recognition rate.**

***Index Terms*—Avatar; face recognition; LBP; second life; wavelet transform**

I. Introduction

Face recognition became a very active area of research during the past few decades and a large number of novel face recognition techniques have been developed in the last few years. They have a wide range of practical applications such as access control, surveillance systems and bankcard identification [3]. However, even after all this progress in human face recognition techniques; identification of non-human agents (avatars) in the virtual worlds is still very limited.

Virtual worlds such as Second Life amongst its millions of users have been known to contain different types of terrorist organizations such as al-Qaeda and local groups of radicals (such as Second Life Liberation Army) [4, 5]. These terrorist groups have many camps for recruiting and training their new members but since they are prosecuted in most countries where these training camps are in, they have to search for another training option. Virtual worlds offer them such an option. Using avatars in an environment similar to the real one and with weapons that are identical to the real ones terrorist can undergo training in the simulated environment [6, 7].

Avatars are not just virtual creations but they have a great social and psychological correspondence to their creators. It seems that the physical and the virtual worlds are becoming very close to each other. Recent research has reported that security in Second Life is not sufficient and about 40% of people who participate in this research ask for additional security [6]. Just like it is important to identify individuals in the real world it is also important to identify avatars in the virtual worlds [6]. In this paper, we propose a novel face recognition algorithm, called Wavelet Local Binary Pattern (WLBP), to improve the recognition rate for avatar authentication of traditional methods, Local Binary Pattern (LBP) and Principle Component Analysis (PCA). In WLBP, avatar faces have to be detected, then all resulted face images (training and testing) have to be decomposed using the second level wavelet decomposition. Descriptive features will be extracted from approximation face images resulted from the second level of wavelet decomposition and statistic histogram will be obtained using the original LBP operator. At last Chi-Square distance will be used to assign each image to its subject based on a single training image for each subject (avatar).

This paper is organized as following: Section 2 presents an introduction about wavelet transform and its advantages. The definition of Local Binary Pattern (LBP) and its histogram is presented in Section 3. An overview of the proposed method is provided in Section 4. Experiments and results including a comparison between the proposed method and traditional methods are reported in Section 5 and finally concluding summary is given in Section 6.

II. Discrete Wavelet Transform

Wavelet Transform (WT) or Discrete Wavelet Transform (DWT) is a popular tool for image analysis. Its flexibility of choosing bases and its complete theoretical framework allow users to apply it in many image processing and computer vision applications such as image retrieval, detection, compression and recognition. It provides multi-resolution analysis of the image by using coefficient matrices [8]. Many articles have discussed its mathematical background and advantages [9]. WT can be applied in image decomposition for many reasons; we summarized them in the following points [9]:

- Using WT to decompose an image reduces the resolution of the sub-images and then the computational complexity will also be reduced by processing a lower resolution images. Harmon's experiments showed that human faces can be recognized by an image of size 16 x 16 [10].
- Using WT minimizes the computational overhead in the proposed system; because WT decomposes images into sub-bands corresponding to different frequency ranges and these sub-bands can easily meet the input requirements for the next major step.

978-1-4577-0746-9/11/$26.00 ©2011 IEEE

- Using WT allows obtaining the local information in different domains (space and frequency), on the other hand Fourier transform allows obtaining global information only in the frequency domain. Thus, WT supports providing spatial frequency characteristics of the image.

Decomposing an image with the first level of WT provides four sub-bands LL_1, HL_1, HL_1 and HH_1 (see Fig 1.a.) while the subscription is an indication to the level of decomposition.

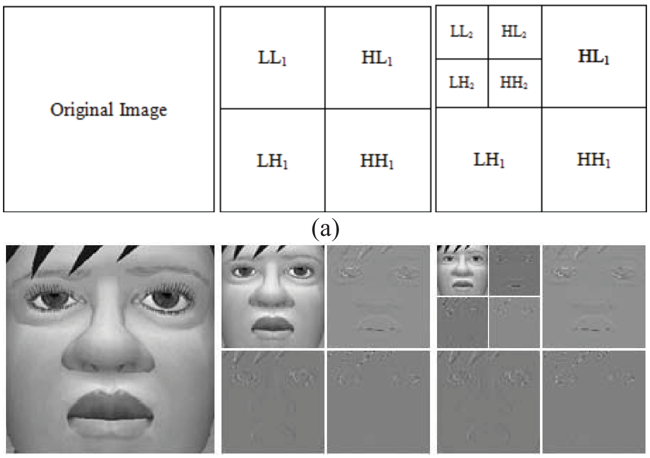


Figure 1. (a) The structure of one level and two level wavelet decomposition (b) Face image with one-level and two-level wavelet decomposition

The *LL* band at any level provides the approximation to the original image. *HL* and *LH* bands respectively provide changes of the image along the horizontal and vertical directions. The *HH* band provides the high frequency component of the image [11]. So we can say that wavelet decomposition of an image provides an approximation image and three detailed images in horizontal, vertical and diagonal directions.

The approximation image, obtained by a low-pass filter, contains the low-frequency information of the face image and it is used for the next level of decomposition. The detail images contain most of the high frequency information of the face image such as illumination and facial expressions which are called the local changes of the face image [11]. The original image is thus represented by a set of sub-images at several scales.

Wavelet decomposition has a linear computational complexity (O (N)) for a number N of computed coefficients. Other transformations have $N \log_2 (N)$ complexity in their fast implementation [8].

The basic function of wavelet transform can be obtained from a single prototype wavelet by dilation and translation as follows [12]:

$$\psi_{x,y}(t) = \frac{1}{\sqrt{x}} \psi(\frac{t-y}{x}) \quad (1)$$

where x and y are real numbers used to determine the scaling and translation operations.

The two-dimensional wavelet transform can be obtained by applying a one-dimensional wavelet transform to the rows and columns of the two-dimensional data [12]. Decomposing an image with two scales will give us seven sub-bands: LL_2, HL_2, LH_2, HH_2, HL_1, LH_1 and HH_1.

Fig. 1 gives an idea about the structure of the wavelet coefficient and the first and the second level of wavelet decomposition for one of the avatar face images used in the experiments.

III. Local Binary Pattern

The local binary pattern (LBP) operator was proposed by Ojala et al. [13], to describe image texture. It works by comparing the gray value of the central pixel with its surrounding 8 pixels (for a given size of 3 x 3 pixels neighborhood for each central pixel) a binary value can be obtained [14]. So LBP operator can be seen as an ordered set of binary comparisons between the gray values of the central pixels and their surrounding pixels and how many comparisons are there depends on the number of pixels in the chosen neighborhood. The binary value will be converted to the decimal value to get the LBP value. The output value of the LBP operator can be defined as follows [14]:

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

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:

$$S(g_i - g_c) = \begin{cases} 1, g_i \geq g_c \\ 0, otherwise \end{cases} \quad (3)$$

See Fig. 2 for an example of basic LBP operator and how to compute the LBP value.

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 [1, 2]. 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 order See Fig. 3 for an example of a circular neighborhood for the same neighbor set of pixels but with different values of the radius.

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

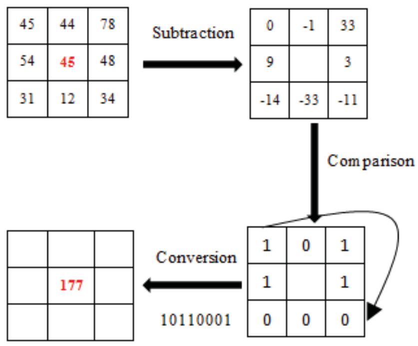


Figure 2. The basic LBP operator [1, 2]

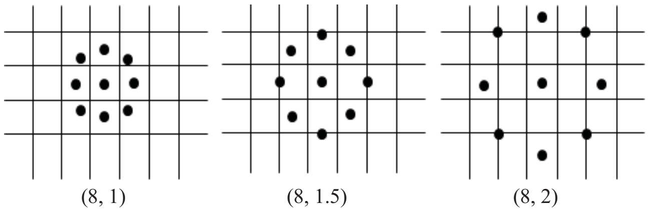


Figure 3. Three different neighborhoods [1]

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 [1]. For example, 11000011, 00111110 and 10000011 are uniform patterns. A large number of statistics have been extracted from images and the results 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 [1].

The LBP is used to label an image and the histogram of the labeled image can be defined as follows [2]:

$$H_i = \sum_{x,y} I(f(x,y) = i), i = 0,1,.., n-1 \tag{4}$$

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 9 sub-regions. Then, the LBP histogram for each sub-region has to be computed [11]. Finally, the nine sub-region histograms have to be combined to form the feature histogram of the image. The LBP histogram of one sub-region contains the local feature of that sub-region and combining the LBP histograms for all sub-regions represent the global characteristics for the whole image [11].

IV. Wavelet Local Binary Pattern (WLBP)

Our proposed algorithm has been designed to work with gray level images and it consists of three stages: preparing dataset for processing, extracting features using LBP and classifying each image to its subject (see Fig. 4).

A. *Dataset Preprocessing*

In this step we manually cropped images in the dataset; we have to remove the background since it is not useful in recognition as we care only about the face features.

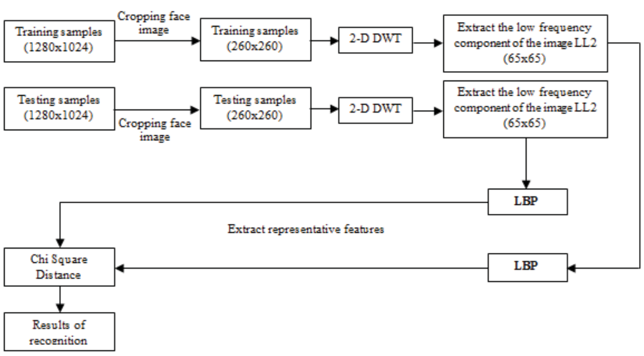


Figure 4. Block diagram of the proposed method

The cropped images have to be decomposed using the first and then the second level of wavelet decomposition and the resulting approximation images from the second level of decomposition are used for feature extraction. We considered only the approximation images since they are produced from low pass filter and this enhances the common features of the same class [11]. See Fig. 5 for an example of image decomposition.

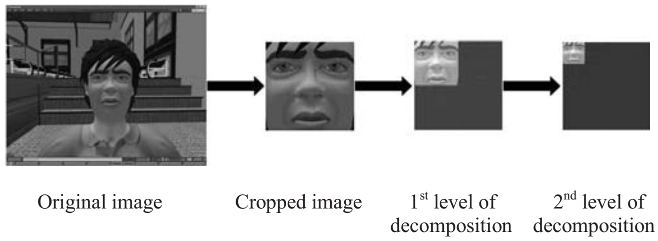


Figure 5. Second level wavelet decomposition of an image

B. *Extracting Features Using LBP*

After decomposing an image with the first level and then the second level of wavelet decomposition, we can obtain seven sub-bands as in Fig. 1. The sub-band LL_2 represents the approximation coefficient of the second level of wavelet decomposition, which contains most of the features that we need to extract to represent the low-frequency information of the image. So each approximation image is divided into 3 x 3 blocks (sub-regions). Next we obtain the statistic histogram for each sub-region and then link all the histograms together to obtain a large histogram sequence as face features for classification.

C. *Classification*

To classify each image to its correct class we used the Chi-Square distance measure of dissimilarity with the condition that only one image is used as a trainer for each class based on the following formula [1]:

$$D(A,B) = \sum_{n=1}^{N} \frac{(A_n - B_n)^2}{A_n + B_n} \tag{5}$$

Where A is the tested image, B is the training sample(s) or image(s).

V. Experiments and Analysis

To ensure its efficiency we have tested the proposed algorithm using a dataset from Second Life virtual world. The tested dataset contains 581 avatar images of 83 different avatars. Also we applied traditional methods of face recognition (PCA and LBP) to recognize avatar faces and compared their result with the result obtained from our proposed algorithm.

A. *Experimental Setup*

The resolution of each image in the tested dataset is 1280 x 1024 pixels and each image has a background which is not required in the recognition process so to get rid of the background and keep eyes and mouth in each image we manually cropped these images to 260 x 260 pixels resolution. Fig. 6 gives an example of two classes of avatars before and after cropping. The manually cropped dataset is organized into 83 different classes each of which has 7 different face images for the same avatar with different angles (front, far left, mid left, far right, mid right, top and bottom).

By applying the second level of wavelet decomposition on the cropped dataset the resolution of the avatar face images will be changed from 260 x 260 to 65 x 65 pixels.

All experiments are performed based on a single training image condition. In which, each time the Chi-Square uses one of the approximation images as a trainer and computes its dissimilarity with all other approximation images in the dataset. The result will be ordered in an ascending order. The 6 images associated with the least 6 distances will be checked to figure out how many of them are from the same class as the training image.

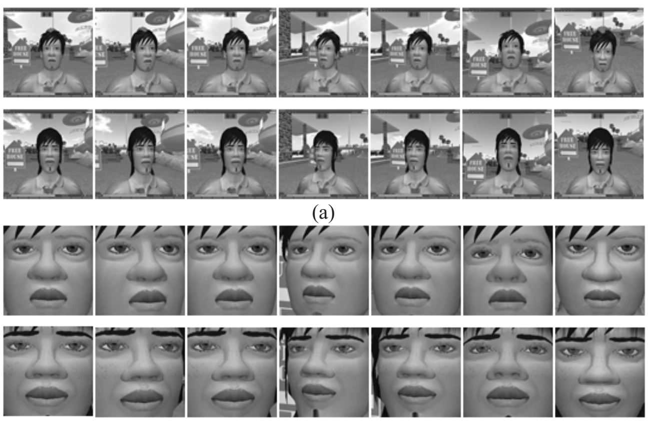
B. *Comparing WLBP with LBP and PCA*

We compared the performance of WLBP with LBP and PCA in order to better understand whether using wavelet transform with LBP is advantageous or not. First we got the performance of WLBP with P = 8 and 16 with different radius values. As we can see in Fig. 7 the performance of WLBP with P = 8 is better than its performance with P = 16 in almost all radius values. So during our comparison we will compare WLBP with LBP based on P = 8 with various values of radius R.

As we can see from Fig. 8 in most of various values of R the recognition rate of using WLBP is better than using LBP. The recognition rate increases 3% to 4% on average and the greatest recognition rate is about 82.32% when R = 4.

We also applied the well-known method PCA on the same dataset and the results were comparable to the average of the recognition rate of WLBP and LBP as can be seen in table I.

The results we obtained demonstrate the quality of our algorithm compared to other algorithms.



(a)

(b)

Figure 6 a). Two classes of unprocessed avatar images b). The same two classes after cropping the avatar faces

VI. CONCLUSION

In this paper we combined the wavelet transform with the LBP to extract useful features from the manually cropped images. The performance of our algorithm has been tested on a dataset of 581 avatar faces from 83 different avatars from the Second Life virtual world. Comparing with the traditional (PCA and LBP) methods, the proposed method improved the recognition rate by at least 3%.

Using Support vector machines or other classifiers in the recognition stage and applying this idea on other datasets from real world and different virtual worlds may lead to better recognition rates and this is what we intend to try in the future.

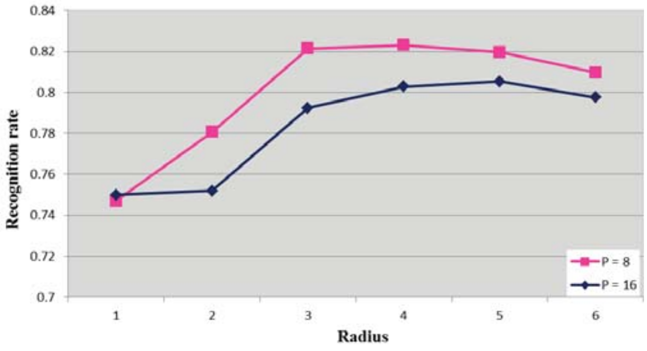


Figure 7. Performance of WLBP with different number of neighborhood pixels and radius values

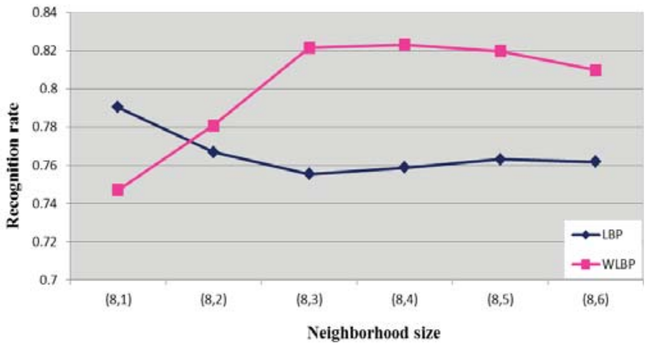


Figure 8. The recognition rate for WLBP and LBP with P = 8 and different radiuses values

TABLE I. RECOGNITION RATE FOR DIFFERENT ALGORITHMS.

Dataset	PCA	LBP	WLBP
Second Life	76.71%	76.50%	79.55%

REFERENCES

1. Ahonen, T., A. Hadid, and M. Pietikainen, *Face Description with Local Binary Patterns: Application to Face Recognition*. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2006. **28**(12): p. 2037-2041.
2. Wang, W., Chang, F., Zhao, J., and Chen, Z., *Automatic facial expression recognition using local binary pattern, in 8th World Congress on Intelligent Control and Automation* 2010: Jinan, China. p. 6375-6378.
3. Tan, N., L. Huang, and C. Liu, *Face Recognition Based on a Single Image and Local Binary Pattern, in Second International Symposium on Intelligent Information Technology Application* 2008. p. 366-370.
4. Klare, B., R.V. Yampolskiy, and A.K. Jain, *Face Recognition in the Virtual World: Recognizing Avatar Faces*, MSU Technical Report, MSU-CSE-11-2, 2011.
5. Ajina, S., R.V. Yampolskiy, and N.E.B. Amara, *Evaluation of SVM Classification of Avatar Facial Recognition, in 8 th International Conference on Advances in Neural Networks* 2011, Springer-Verlag Berlin/Heidelberg. p. 132-142.

6. Gavrilova, M.L. and R.V. Yampolskiy, *Applying Biometric Principles to Avatar Recognition, in International Conference on Cyberworlds (CW)* 2010: Singapore. p. 179-186.
7. Boukhris, M., A.A. Mohamed, D'Souza, D., Beck, M., N.E.B. Amara, and R.V. Yampolskiy, *Artificial Human Face Recognition via Daubechies Wavelet Transform and SVM, in 16th International Conference on Computer Games: AI, Animation, Mobile, Multimedia, Educational and Serious Games* 2011: Louisville, KY, USA. p. 18-25.
8. Garcia, C., G. Zikos, and G. Tziritas, *A Wavelet-based Framework for Face Recognition, in 5th European Conference on Computer Vision (ECCV'98)* 1998: Freiburg Allemagne. p. 84-92.
9. Mazloom, M. and S. Ayat, *Combinational Method for Face Recognition: Wavelet, PCA and ANN in International Conference on Digital Image Computing: Techniques and Applications* 2008: Canberra. p. 90-95.
10. Harmon, L., *The recognition of faces*. Scientific American, 1973. **229**(5): p. 71-82.
11. Liu, X., M. Du, and L. Jin, *Face Features extraction Based on multi-scale LBP, in 2nd international Conference on Signal Processing Systems (ICSPS)* 2010: Dalian. p. 438-441.
12. Liping, N., L.X. Yuan, and D. Yuqiang, *Bayesian Face Recognition Using Wavelet Transform, in International Conference on Intelligent Human-Machine Systems and Cybernetics* 2009: Hangzhou, Zhejiang. p. 312-315.
13. Ojala, T., M. Pietikainen, and D. Harwood, *A comparative study of texture measures with classification based on feature distributions*. Pattern Recognition, 1996. **29**(1): p. 51-59.
14. Meng, J., Gao, Y., Wang, X., Lin, T., and Zhang, J., *Face Recognition based on Local Binary Patterns with Threshold, in IEEE International Conference on Granular Computing* 2010: San Jose, CA. p. 352-356.