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Artificial Face Recognition using Wavelet Adaptive LBP with Directional Statistical Features

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***Abstract*— In this paper, a novel face recognition technique based on discrete wavelet transform and Adaptive Local Binary Pattern (ALBP) with directional statistical features is proposed. The proposed technique consists of three stages: preprocessing, feature extraction and recognition. In preprocessing and feature extraction stages, wavelet decomposition is used to enhance the common features of the same subject of images and the ALBP is used to extract representative features from each facial image. Then, the mean and the standard deviation of the local absolute difference between each pixel and its neighbors are used within ALBP and the nearest neighbor classifier to improve the classification accuracy of the LBP. Experiments conducted on two virtual world avatar face image datasets show that our technique performs better than LBP, PCA, multi-scale Local Binary Pattern, ALBP and ALBP with directional statistical features (ALBPF) in terms of accuracy and the time required to classify each facial image to its subject.**

***Index Terms*— Avatar, face recognition, LBP, LBPF, wavelet transform**

I. Introduction

Biometrics is the study of methods of recognizing humans based on their behavioral and physical characteristics or traits [1]. Face recognition is one of the biometrics traits that received a great attention of many researchers during the past few decades because of its potential applications in a variety of civil and government-regulated domains. It usually involves: initial image normalization, preparing an image for feature extraction by detecting the face in that image, extracting facial features from appearance or facial geometry, and finally classifying facial images based on extracted features.

Face recognition however is not only concerned with recognizing human faces, but also with recognizing faces of non-biological entities or avatars. An avatar is the user's virtual identity within virtual worlds whose appearance can be changed by the user's choice.

Virtual worlds are populated by millions of avatars. Virtual worlds have the ability to do a lot of good and bad things. These bad and destructive purposes include traditional crimes like identity theft, fraud, tax evasion and terrorist activities [2].

Second Life is one of the virtual worlds that are populated by numerous terrorist organizations associated with Al-Qaeda who can train in such environments similar to the real ones. These criminal activities emerged the interest of the law enforcement experts in accurate and automatic tracking of users and their avatars [2]. 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 [3, 4]. 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 [3, 4]. People often complain about the insufficient security system in the Second Life which motivates our research on security in virtual worlds [3, 5].

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 in the past to extract features, such as principal component analysis (PCA) [6], linear discriminant analysis (LDA) [7] and local binary pattern (LBP) [8-11]. Among all these algorithms, LBP method has shown its superiority in recognizing faces [1]. LBP is one of the most popular local feature-based methods. It was first proposed by Ojala et al. [12] as a powerful method for describing textures and it was applied to face recognition for the first time by Ahonen et al. [13]. But the original LBP method worked as a local descriptor to capture only local information [8]. All this work is done to recognize human faces but recognizing virtual worlds' avatars is still very limited. Some methods further developed LBP for either recognizing human faces or avatar faces. For example, Yang et al. [11] applied LBP for face recognition with Hamming distance constraint. Chen et al. [9] used Statistical LBP for face recognition. Mohamed et al. [2] applied hierarchical multi-scale LBP with wavelet transform to recognize avatar faces.

In this paper, we propose a new face recognition technique to recognize avatar faces. This technique uses discrete wavelet transform to enhance the common features of the same class of facial images to improve the recognition performance. Also, it computes the mean and the standard deviation of the local absolute difference between each pixel and its neighbors (in a specific block of pixels) within the Adaptive Local Binary Pattern (ALBP) operator and the nearest neighbor classifier to improve the accuracy rate. The efficacy of our proposed method is demonstrated by the 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 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 with statistical features (WALBP). In Section 5, experimental results are presented followed by conclusions in Section 6.

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II. REVIEW OF 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. Many articles have discussed its mathematical background and advantages [14]. WT can be applied in image decomposition for many reasons [14]:

- WT reduces the computational complexity of the system by producing lower resolution images (sub-images) instead of operating on the original images with much higher resolution. For example, applying WT to reduce the resolution of an image from size 128 x 128 to size 32 x 32 will reduce the computational load by a factor of 16.
- WT decomposes images into sub-images corresponding to different frequency ranges and this can lead to reduction in the computational overhead of the system.
- Using WT allows obtaining the local information in different domains (space and frequency) while Fourier decomposition concerns only global information in the frequency domain. Thus it supports both spatial and frequency characteristics of an image at the same time.

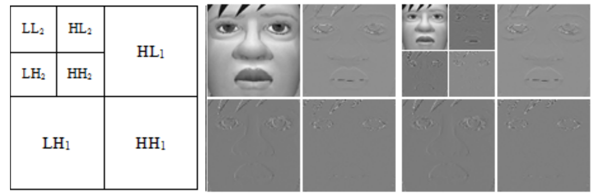
WT decomposes facial images into approximate, horizontal, vertical and diagonal coefficients. Approximate coefficient of one level is repeatedly decomposed into the four coefficients of the next level of decomposition. The process goes on until you find the required level of decomposition. Decomposing an image with the first level of WT provides four sub-bands LL_1, HL_1, HL_1 and HH_1.

The sub-band LL represents the approximation coefficient of the wavelet decomposition and it has the low frequency information of the face image [15]. 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 [14]: LL_2, HL_2, LH_2, HH_2, HL_1, LH_1 and HH_1 as in Fig. 1.

III. LOCAL BINARY PATTERN (LBP) WITH DIRECTIONAL STATISTICAL FEATURES

A. LBP Operator

LBP operator, proposed by Ojala et al. [12], 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



(a) (b) (c)

Figure1. (a) Wavelet coefficient structure [15] (b) One level wavelet decomposition for an image (c) Two levels wavelet decomposition for the same image in b.

multiplied by powers of two and then added together to form the new value (label) for the center pixel [10]. The output value of the LBP operator for a block of 3x3 pixels can be defined as follows [10]:

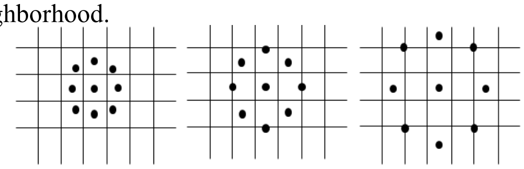
$$LBP_{P,R} = \sum_{p=0}^{7} 2^p S(g_p - g_c) \qquad (1)$$

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

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

Later new versions of LBP operator have been emerged as an extension to the original one and 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].

The neighborhood of each pixel within an image 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). 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.



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

Figure 2. Three different LBP operators [8, 13]

One of the most important and successful extensions to the basic LBP operator is the uniform LBP (ULBP). An LBP is called uniform if the binary pattern contains at most two different transitions from 0 to 1 or 1to 0 when the binary string is viewed as a circular bit string [8]. For example, 11000011, 00111110 and 10000011 are uniform patterns [12].

B. LBP Histogram

Suppose the given image is of size N x M. To represent the whole texture image after computing the LBP pattern value for each pixel in that image, a histogram is built using [16]:

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

where $n=2^P$ is the number of different labels produced by the LBP operator, and $I(A)$ is a decision function with value 1 if the event A is true and 0 otherwise.

The LBP histogram dissimilarity between a test samples X and a class model Y is computed using the chi-square distance:

$$D_{LBP}(X,Y) = \sum_{n=1}^{N} \frac{(X_n - Y_n)^2}{X_n + Y_n} \quad (4)$$

C. LBP with Directional Statistical Features

Suppose that a given image is of size N x M. Let g_c is its central pixel and g_p is its circular neighbors, where $p = 0,1,\dots,P\text{-}1$. The mean (μ_p) and the standard deviation (σ_p) of the local difference $|g_c - g_p|$ can be computed using [17]:

$$\mu_p = \sum_{i=1}^{N}\sum_{j=1}^{M} |g_c(i,j) - g_p(i,j)| / (M*N) \quad (5)$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M} (|g_c(i,j) - g_p(i,j)| - \mu_p)^2 / (M*N)} \quad (6)$$

μ_p and σ_p represent the first-order and the second-order directional statistics of the local difference $|g_c - g_p|$ along orientation $2\pi p/P$ [17]. The vector $\vec{\mu} = [\mu_0, \mu_1, ..., \mu_{P-1}]$ refers to the mean vector and $\vec{\sigma} = [\sigma_0, \sigma_1, ..., \sigma_{P-1}]$ refers to the standard deviation (std) vector.

The two vectors represent the directional statistical features of the local difference $|g_c - g_p|$ and they carry useful information for image discrimination that can be used to define the weighted LBP dissimilarity. Let $\vec{\mu}_X$ and $\vec{\sigma}_X$ refer to the directional statistical feature vectors for a sample test image X while $\vec{\mu}_Y$ and $\vec{\sigma}_Y$ refer to the two vectors for a class model Y then the normalized distances between $\vec{\mu}_X$ and $\vec{\mu}_Y$, and $\vec{\sigma}_X$ and $\vec{\sigma}_Y$ can be defined as:

$$d_\mu = \sum_{p=0}^{P-1} |\vec{\mu}_X(p) - \vec{\mu}_Y(p)| / (P*e_\mu), d_\sigma = \sum_{p=0}^{P-1} |\vec{\sigma}_X(p) - \vec{\sigma}_Y(p)| / (P*e_\sigma) \quad (7)$$

where e_μ and e_σ are the standard deviations of $\vec{\mu}$ and $\vec{\sigma}$ respectively from training samples images [17, 18].

So the weighted LBP dissimilarity with statistical features using d_μ and d_σ can be defined as:

$$\begin{aligned} D_{LBP}^F(X,Y) = D_{LBP}(X,Y) &* (1 + c_1 - c_1 * \exp(-d_\mu / c_2)) \\ &* (1 + c_1 - c_1 * \exp(-d_\sigma / c_2)) \end{aligned} \quad (8)$$

where $D_{LBP}(X, Y)$ is the LBP histogram dissimilarity, c_1 and c_2 are two control parameters for the weights [17].

IV. Wavelet Adaptive LBP (WALBP) with Directional Statistical Features

A. Preprocessing Datasets

For both types of datasets (Second Life dataset and Entropia Universe dataset) we have to get rid of the background of each image. The presence of the background of an image has an effect on identifying that image. To remove the background of an image we manually cropped this image so that that the new face only image contains two eyes, nose and mouth.

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.

B. Adaptive Local Binary Pattern (ALBP)

The directional statistical feature vectors can be used to improve the classification performance of an image by minimizing the variations of the mean and the std of the directional difference along different orientations. To this end a new version of the LBP was proposed by Guo et al., called Adaptive LBP (ALBP), to reduce the estimation error of local difference between each pixel and its neighbors [17]. A new parameter called weight (w_p) is defined in the LBP equation and so the new definition of the LBP equation will have the following form [17, 19]:

$$ALBP_{P,R} = \sum_{p=0}^{P-1} 2^p S(g_p * w_p - g_c) \quad (9)$$

where the weight w_p can be computed using:

$$w_p = g_p^T g_c / (g_p^T g_p) \quad (10)$$

where $\vec{g}_c = [g_c(1,1); g_c(1,2); \dots; g_c(N,M)]$ 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 $\vec{g}_p = [g_p(1,1); g_p(1,2); \dots; g_p(N,M)]$ is the corresponding vector for all $g_p(i,j)$ pixels.

Let $\vec{w} = [w_0, w_1, ..., w_{P-1}]$ refers to the ALBP weight vector. We have to note that each weight w_p is computed along one orientation $2\pi p/P$ for the whole image.

C. ALBP with Directional Statistical Features

By using the ALBP weight the directional statistics equations (5) and (6) can be changed to [17]:

$$\mu_p = \sum_{i=1}^{N}\sum_{j=1}^{M} |g_c(i,j) - g_p(i,j) * w_p| / (M*N) \quad (11)$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M} (|g_c(i,j) - g_p(i,j) * w_p| - \mu_p)^2 / (M*N)} \quad (12)$$

Based on the ALBP weight w_p, we have three vectors $\vec{\mu}$, $\vec{\sigma}$ and $\vec{w}$. Similar to the normalized distance between $\vec{\mu}_X$ and $\vec{\mu}_Y$, and $\vec{\sigma}_X$ and $\vec{\sigma}_Y$ we can define the normalized distance between $\vec{w}_X$ and $\vec{w}_Y$ as:

$$d_w = \sum_{p=0}^{P-1} \left| \vec{w}_X(p) - \vec{w}_Y(p) \right| / (P * e_w) \quad (13)$$

where e_w is the standard deviation of $\vec{w}$ from training samples images [17, 18].

The weighted ALBP dissimilarity with statistical features using d_μ , d_σ and d_w can be defined as:

$$D^F_{ALBP}(X,Y) = D_{ALBP}(X,Y) * (1 + c_1 - c_1 * \exp(-d_\mu / c_2)) * (1 + c_1 - c_1 * \exp(-d_\sigma / c_2)) * (1 + c_1 - c_1 * \exp(-d_w / c_2)) \quad (14)$$

where D_{ALBP} (X, Y) is the ALBP histogram dissimilarity [17].

V. EXPERIMENTS

In this section, we verify the performance of the proposed algorithm on two different types of datasets: the first type is the Second Life data set and the second is the Entropia Universe dataset. Fig. 3 gives an example of a subject from each dataset. The proposed method is compared with PCA [6], which is one of the most well-known methods in face recognition, single scale LBP, traditional multi-scale LBP, ALBP and ALBP with directional statistical features (ALBPF).

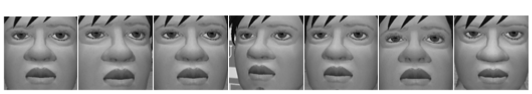
A. Experimental Setup

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

The first dataset was collected from the Second Life (SL) virtual world [20]. This dataset contains 581 gray scale images with size 1280 x 1024 each to represent 83 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 Entropia (ENT) Universe virtual world [21]. ENT dataset contains 490 gray scale images with size 407 x 549 pixels. These images were organized in 98 subjects (avatars). Each subject has different 5 images for the same avatar with different frontal angle and facial details (wearing a mask or no).

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 the size of 180 x 180 pixels. After applying the first level of wavelet decomposition the resolution of each facial image in the SL dataset will be reduced to be 130 x 130 and to 90 x 90 for ENT dataset.



(a)

(b)

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

The intensity of all SL and ENT facial images used in all experiments is normalized to have a mean of 148 and standard deviation of 32 to reduce the variance of illumination.

B. Experimental Results

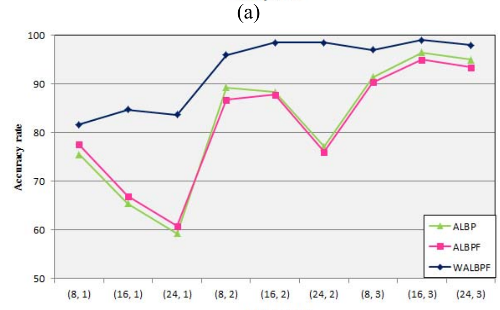
In order to gain better understanding on whether using wavelet transform with ALBPF is advantageous or not we compared WALBPF with ALBPF and ALBP. First we got the performance of WALBP, ALBPF and ALBP with different LBP operator values (see Fig. 4) over the SL and ENT datasets.

In this experiment the training sets were built by selecting the first 4 images from each class of the SL dataset and the first 3 images from each class in ENT dataset.

The results showed that the recognition rate of using WALBPF is better than the recognition rate of using the other two methods with almost all LBP operators and with all datasets. The recognition rate on average using WALBPF is greater than that of its closest competitor, which is ALBPF for SL datasets and ALBP for ENT dataset, by about 6% with SL dataset where the greatest accuracy is about 96% when LBP operator is (16, 2) and by about 11% with ENT dataset where the greatest accuracy is about 99% when the LBP operator is (16, 3).

The results showed also that not only the recognition rate of using WALBPF is better than that of the other two methods but also the time required to classify each input facial image to its class in case of using WALBPF is less than that in the other two methods with different LBP

(a)



(b)

Figure 4. Recognition rate using ALBP, ALBPF and WALBPF
By: a) SL dataset b) Ent dataset

operators (see table I to recognize the time required for processing the SL dataset). This is an expected result since one of the main reasons of using wavelet decomposition in face recognition systems is that it reduces the computational complexity and overhead of the system and so the system can run faster.

We also compared the performance of our method, WALBPF, with some well-known face recognition algorithms such as PCA, LBP and multi-scale LBP using SL and ENT datasets and based on different number of training and testing images.

For both SL and ENT datasets we performed three experiments for each: for SL dataset, first, we used the first image from each class for training and the rest for testing, then we used the first three images from each class for training and the rest for testing and finally we used the first 5 images from each class for training and the rest for testing (see table II).

For ENT dataset we used the first image from each class for training and the rest for testing, then, we used the first two images from each class for training and the rest for testing and finally we used the first three images from each class for training and the rest for testing (see table III).

It is very clear from Fig. 4, tables I, II and III that our proposed method can achieve better result than the other algorithms in terms of accuracy and classifying time.

VI. CONCLUSION

In this paper, a novel LBP face recognition approach (WALBPF) is proposed based on wavelet transform and adaptive local binary pattern with directional statistical features. The effectiveness of this method is demonstrated on recognizing faces from virtual worlds. Compared with ALBPF and ALBP and with different LBP operators, our proposed technique improved the recognition rate of the SL and ENT datasets by about 6% and 11% respectively. Also the time required by our technique to classify each input facial image to its class is less than the time in case of other methods. Compared with traditional well-known face recognition techniques (PCA, LBP and multi-scale LBP), our technique improved the recognition rate of faces based on different number of training and testing images from each class of datasets used in the experiments.

Applying a multi-scale definition to this approach may lead to better accuracy rate and this is what we intend to try in the future.

Table I. Time in seconds required by different algorithms

Algorithm	LBP operator		
	(8, 1)	(16, 2)	(24, 3)
ALBP	5.40	11.54	179.53
ALBPF	5.50	11.64	179.67
WALBPF	2.03	4.32	167.36

Table II. Accuracy rates on SL dataset with different algorithms

Algorithm	The number of training images		
	1	3	5
PCA	76.71% [22]	82.53%	79.27%
LBP	76.50% [22]	77.41%	80.72%
Multi-scale LBP	78.53%	88.19%	90.56%
WALBPF	81.93%	89.46%	94.58%

Table III. Accuracy rates on ENT dataset with different algorithms

Algorithm	The number of training images		
	1	2	3
PCA	58.16%	69.17%	88.56%
LBP	66.45% [2]	61.56%	90.82%
Multi-scale LBP	70.29%	74.22%	92.46%
WALBPF	73.47%	78.37%	98.98%

REFERENCES

[1] G. Zhenhua, Z. Lei, D. Zhang, and M. Xuanqin, "Hierarchical Multiscale LBP for Face and Palmprint Recognition," *International Conference on Image Processing (ICIP)* Hong Kong, 2010, pp. 4521-4524.

[2] A. A. Mohamed, D. D'Souza, N. Baili, and R. V. Yampolskiy, "Avatar Face Recognition using Wavelet Transform and Hierarchical Multi-scale LBP," *10th International Conference on Machine Learning and Applications (ICMLA'11)*, Honolulu, Hawaii, 2011, pp. 194-199.

[3] M. L. Gavrilova and R. V. Yampolskiy, "Applying Biometric Principles to Avatar Recognition," *International Conference on Cyberworlds (CW2010)*, Singapore, 2010, pp. 179-186.

[4] J. N. Oursler, M. Price, and R. V. Yampolskiy, "Parameterized Generation of Avatar Face Dataset," *14th International Conference on Computer Games: AI, Animation, Mobile, Interactive Multimedia, Educational & Serious Games*, Louisville, KY, 2009, pp. 17-22.

[5] D. Nood and J. Attema. (2008). *The Second Life of Virtual Reality*. Available: http://docs.rice.edu/confluence/download/attachments/5111868/EPN-REPORT-The_Secon_Life_of_VR1.pdf?version=1

[6] M. Turk and A. Pentland, "Face Recognition using Eigenfaces," *IEEE Conference on Computer Vision and Pattern Recognition*, Maui, HI, 1991, pp. 586-591.

[7] J. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, "Face Recognition Using LDA Based Algorithms," *IEEE Transactions on Neural Networks,* vol. 14, pp. 195-200, 2003.

[8] T. Ahonen, A. Hadid, and M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence* vol. 28, pp. 2037-2041, 2006 2006.

[9] L. Chen, Y.-H. Wang, Y.-D. Wang, and D. Huang, "Face Recognition with Statistical Local Binary Patterns," *8th International Conference on Machine Learning and Cybernetics*, Baoding, 2009, pp. 2433-2438.

[10] J. Meng, Y. Gao, X. Wang, T. Lin, and J. Zhang, "Face Recognition based on Local Binary Patterns with Threshold," *IEEE International Conference on Granular Computing*, San Jose, CA, 2010, pp. 352-356.

[11] H. Yang and Y. D. Wang, "A LBP-based Face Recognition Method with Hamming Distance Constraint," *4th International Conference on Image and Graphics*, 2007, pp. 645-649.

[12] T. Ojala, M. Pietikainen, and D. Harwood, "A comparative study of texture measures with classification based on feature distributions," *Pattern Recognition,* vol. 29, pp. 51-59, 1996.

[13] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution Gray-Scale and Rotation Invriant Texture Classification with Local Binary Patterns," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 24, pp. 971-987, 2002.

[14] M. Mazloom and S. Ayat, "Combinational Method for Face Recognition: Wavelet, PCA and ANN " *International Conference on Digital Image Computing: Techniques and Applications*, Canberra, 2008, pp. 90-95.

[15] C. Garcia, G. Zikos, and G. Tziritas, "A Wavelet-based Framework for Face Recognition," *5th European Conference on Computer Vision (ECCV'98)*, Freiburg Allemagne, 1998, pp. 84-92.

[16] W. Wang, F. Chang, J. Zhao, and Z. Chen, "Automatic facial expression recognition using local binary pattern," *8th World Congress on Intelligent Control and Automation*, Jinan, China, 2010, pp. 6375-6378.

[17] Z. Guo, L. Zhang, D. Zhang, and S. Zhang, "Rotation Invariant Texture Classification Using Adaptive LBP with Directional Statistical Features," *IEEE 17th International Conference on Image Processing (ICIP)*, Hong Kong, 2010, pp. 285-288.

[18] B. S. Manjunath and W. Y. Ma, "Texture Features for Browsing and Retrieval of Image Data," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 18, pp. 837-842, 1996.

[19] A. A. Mohamed and R. V. Yampolskiy, "Face Recognition based on Wavelet Transform and Adaptive Local Binary Pattern," unpublished.

[20] *Second Life*. Available: www.secondlife.com

[21] *Entropia Universe*. Available: www.entropiauniverse.com

[22] A. A. Mohamed and R. V. Yampolskiy, "An Improved LBP Algorithm for Avatar Face Recognition," *23th International Symposium on Information, Communication and Automation Technologies (ICAT'11)*, Sarajevo, Bosnia & Herzegovina, 2011, pp. 1-5.