Recognizing Avatar Faces Using Wavelet-based Adaptive Local Binary Patterns 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.

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

1 Introduction

Biometrics research investigates methods and techniques for recognizing humans based on their behavioral and physical characteristics or traits [1]. Face recognition is something that people usually perform effortlessly and routinely in their everyday life and it is the process of identifying individuals from their faces' intrinsic characteristics. Automated face recognition has become one of the main targets of investigation for researchers in biometrics, pattern recognition, computer vision, and machine learning communities. This interest is driven by a wide range of commercial and law enforcement practical applications that require the use of face recognition technologies [2]. These applications include access control, automated crowd surveillance, face reconstruction, mugshot identification, human-computer interaction and multimedia communication.

Face recognition is not limited only to recognizing human faces but it should also work for recognizing faces of non-biological entities such as avatars from virtual worlds. Virtual worlds are populated by millions of avatars. These avatars 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 [3].

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 [3]. 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 [4, 5]. 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 [4, 5]. People often complain about the insufficient security system in the Second Life which motivates our research on security in virtual worlds [4, 6].

Many algorithms were proposed to recognize human faces, such as Principal Component Analysis (PCA) [7], Linear Discriminant Analysis (LDA) [8] and Local Binary Pattern (LBP) [9-12], however recognizing virtual worlds' avatar faces is still very limited. There were some attempts to recognize avatar faces. For example, Boukhris et al. [13] used Daubechies wavelet transform with Support Vector Machines (SVM). Mohamed and Yampolskiy [14] applied the first and the second levels of decomposition with LBP. Mohamed et al. [3] applied hierarchical multi-scale LBP with wavelet transform. Mohamed and Yampolskiy [2] applied different levels of Daubechies wavelet transform on multiscale adaptive LBP with directional features to recognize avatar faces from two different virtual worlds.

In this paper, we propose a new face recognition technique to recognize avatar faces from different virtual worlds. In our technique, we apply different wavelet families on two datasets of avatar faces from two virtual worlds rather than just apply one wavelet family as Mohamed and Yampolskiy applied in [2]. Therefore, we have to select the wavelet family that best describe each dataset. We applied these wavelet families with different numbers of training and testing images. Also, our technique 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. We have to note that during our experiments avatar faces are chosen for training randomly to increase the confidence in our technique. The efficacy of our proposed method is demonstrated by performing experiments on two different avatar datasets from Second Life and Entropia Universe virtual worlds.

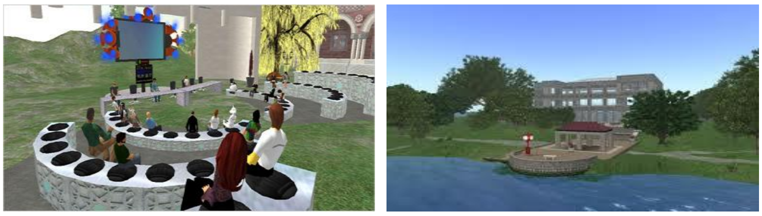
The rest of this paper is organized as follows; Section 2 introduces a background about virtual worlds, avatars and the insecurity of virtual worlds. Section 3 provides an introduction to wavelet decomposition. In Section 4, an overview of LBP with directional statistical features is presented. Section 5, presents the proposed method, Wavelet Adaptive LBP with directional statistical features (WALBPF). In Section 6, experimental results are presented followed by conclusions in Section 7.

2 Background

2.1 Virtual Worlds

Becoming an indispensable part of today's modern life, the internet has added new contexts for daily activities. Specifically, one of the major breakthroughs of the World Wide Web is that it facilitates the creation of interactive web pages that can be accessed worldwide [15]. The roles these web pages play range from facilitating simple communications (e.g., emails, chat, etc.) to more complex ways of communicating including video conferencing and banking. One of the most recent and fast growing applications of these interactive web pages is what has been called three-dimensional virtual worlds. In these virtual worlds (Virtual Reality), computer graphics are manipulated to render simultaneous, interactive, and three-dimensional environments, which mimics real world environments [16]. Designed this way, virtual worlds look realistic to the user to a great extent. This virtual reality thus provides the user with a personal digital space where he or she can perform real world activities. Individuals as well as groups sharing common interests and activities can communicate across the world easily [17]. Accessing these worlds is becoming easier and easier with technology advancement. The presence of virtual worlds and their being easily accessed may lead to transformation of the operation of whole societies. With advancement in building Massively Multiplayer Online Games (MMOG), virtual worlds became even more accessible and popular [15].

At the present time, there are several well-known virtual world online applications such as Second Life [18], Entropia Universe [19], Active Worlds [20] and Sims Online [21]. Second Life for instance is a multi-user online three-dimensional virtual world, which includes up to 20 million registered users. It facilitates education, socializing, shopping, starting small businesses and enterprises as well as making money [18]. The diversity of interests that can exist in a virtual world is clearly shown in the activities that are facilitated by second life as well as other worlds. Thus, real businesses can exist and actually flourish in virtual worlds. Realizing how popular these sites are becoming, well know companies, TV and radio channels as well as prestigious schools are using them. Reuters for instance has built a virtual headquarters in second life so that it would be able to broadcast news not only in the real world but to the virtual one as well. News broadcast sessions have been broadcast by the National Public Radio through second life as well. IBM arranged for a gathering of its employees also in Second Life. Universities are building islands in virtual worlds where classes can be offered. For instance, Harvard Law School offers a CyberOne course partly on Berkman Island in Second Life [22]. Indiana University's Kelly school of business has established a presence also in Second Life virtual world [13, 23]. Companies like Dell, Cisco, Xerox and Nissan have stores within Second Life. Virtual worlds thus host and offer different activities for its residents. They have been used as environments for games and adventure. For example in Everquest and World of Craft which are examples of Massively Multiplayer Online Role Playing Games (MMORPGs) the main activity that the virtual world establishes is the creation of an entertaining virtual world for games. Unlike games, adventure based virtual worlds, offer computer mediated environment so that the residents would interact free of a dictated plot or a specific story or adventure line. Music Television (aka MTV) established a virtual world (i.e., MTV's Virtual Laguna Beach) where users can have access to the MTV Laguna Beach television and can interact live with family and friends. MTV future plans include holding virtual music concerts as well [24].



(a) (b)

Fig. 1. a) Harvard Law School lecture in Second Life [22] b) and Indiana University Kelly School of business in second Life [23]

2.2 Avatars

Originally, the word avatar comes from a religious Hindu expression meaning the appearance or the manifestation of a god in human or super human form [25]. An avatar is simply a digital identity of a user. An avatar is a representation of the user that enables interaction in 3D or in 2D contexts. Users usually prefer to have social presence in these worlds by creating distinct and different avatars. The created avatars sometimes refer to user's own personality or to a made-up identity. Although the avatar is a representation of a user identity, it is still not authentic. Users have the choice of how they would look like as well as how they can express themselves via such chosen appearance. Some users might make decisions to disclose facts about themselves with their choice of the appearance of an avatar. Others might use a popular image as their avatar. The same avatar can be used by a user in different online sessions. Some of the avatars mirror a user's role in virtual world which is reflected by an outfit or a specific appearance. Some users avatars are given a realistic look that resembles a human being. Users who tend to make such realistic choice of avatar appearance believe this would help them create a closer connection with their avatars. Some online websites restrict avatar identities to one per a single user. This requirement would avoid problems of trust, as a user will not be able to use alternative identities. Avatars have different aspects that include animations, emotions, gestures, speech, and voice. Virtual world service providers require that a user gives up his or her rights of the avatar they created or chose to the providers. Subsequently, this agreement makes ownership of an avatar a debatable issue. Virtual world service providers also have the right to terminate an avatar as well as its user's account [26].

The figures below (Fig. 2) show examples of avatars from Second Life and Entropia Universe. There is a relationship between how an avatar would look like and how the user would behave within virtual worlds. For instance, users who create attractive avatars usually reveal more information to strangers more than users with unattractive avatars. Also, tall avatars correspond to a confident user especially during tasks requiring decision making. Realistic looking avatars show a great deal of positive social interactions.

(a) (b)

Fig. 2. Examples of avatar images from:
a) Enrtopia Universe virtual world [19], b) Second Life virtual world [18]

It has been noticed that users would treat avatars warmly if the avatar looks similar to them [27]. Within virtual worlds, an avatar has the ability to move within its 3D or 2D environment to execute a task. Important characteristics of this society is sharing and trading which maintain and increase the unity within avatar groups. Communication is a very essential characteristic of an avatar as it maintains interactions with other users in the virtual world. Communication can take different forms. It could be 1) Verbal, 2) non-Verbal, 3) Asynchronous, 4) Synchronous, 5) direct and 6) indirect. Users can communicate using instant messages, message boards, emails, Voice over Internet Protocol (VoIP) as well as text chat.

2.3 The lack of security of Virtual Worlds

Because of their becoming part of our society, determining the identity of avatars is indispensable. Determining the identity of these artificial entities is as important as authenticating human beings. Mostly, an avatar would bear resemblance to its real life owner. There is a high demand for an affordable, fast, reliable means to authenticate avatars [4].

Terrorist activities as well as cybercrimes are increasing in virtual worlds. For instance, it has been reported that terrorists recruit within virtual communities such as Second Life [28]. Authorities such as U.S. government's Intelligence Advanced Research Projects Activity (IARPA) believe that they may use virtual worlds for illegal activities. They issue the warning that "avatars" could be used to recruit new members online, transfer untraceable funds and engage in training exercises useful for real-world terrorist operations [28]. Several examples of terrorist activities have been reported within Second Life like flying a helicopter into Nissan Building or the bombing of ABC's headquarters. Another example is where armed militants forced their way into an American Apparel store and shot several customers and then plant a bomb outside a store [29].

Regrettably, these wrong doers cannot be prosecuted for their criminal behavior because these crimes were committed in a virtual world where laws do not exist. Anonymity as well as global access in an online virtual world where there are ease of access banking services that allow for transactions away from the normal routs has made virtual worlds a convenient environment for terrorists [30].

Expressing concern over the consequences of leaving virtual worlds in such a state, researchers in IARPA note that "The virtual world is the next great frontier and is still a very much a Wild West environment [31]. It provides many opportunities to exchange messages in the clear without drawing unnecessary attention. Additionally, there are many private channels that can be employed to exchange secret messages". Virtual world has all the activities that the real world has and therefore, possible scenarios of these activities should be thought about [30].

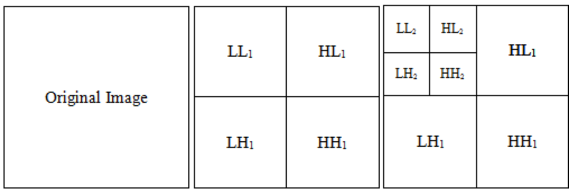
Virtual world environments pose a challenge as communication as well as commercial service between avatars is not recorded. Due to the set-up of the system, companies cannot monitor the creation and use of virtual buildings as well as training centers. Although some of them have been protected by what is described as unbreakable passwords, there have been reports of fraud and other virtual crimes. The situation is getting gloomier as companies in other countries are starting to establish their own virtual worlds. This shows urgency in addressing the issue of the security of virtual worlds. For instance, the founders of the Chinese virtual world HiPiHi [32] which houses prestigious companies such as IBM and Intel aim to create ways to enable avatars to move freely from their virtual world and other virtual environments such as Second Life or Entropia. This in turn would make it difficult to identify avatar or real users behind avatars. The underground activities associated with real world criminals and terrorists will increase in these environments due to accessibility and secrecy they offer.

3 Decomposing an image using Wavelet Transform

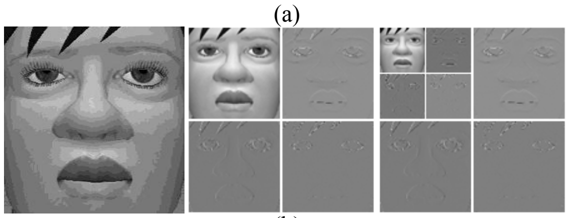
Wavelet Transform (WT) or Discrete wavelet Transform (DWT) is a popular tool for analyzing images in a variety of signal and image processing applications including multi-resolution analysis, computer vision and graphics. It provides multi-resolution representation of the image which can analyze image variation at different scales. Many articles have discussed its mathematical background and advantages [2, 33]. WT can be applied in image decomposition for many reasons [2, 33]: WT reduces the computational complexity of the system, reduces the computational overhead of the system and supports both spatial and frequency characteristics of images.

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 best level of decomposition describing the dataset of images that we have.

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 [34]. 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 [33]: LL_2, HL_2, LH_2, HH_2, HL_1, LH_1 and HH_1 as in Fig. 3.



(a)



(b)

Fig. 3. a) Structure of one-level and two-level wavelet decomposition [34]
b) An example of decomposing an image using one-level and two-level wavelet decomposition

4 Local Binary Pattern (LBP) with Directional Statistical Features

4.1 LBP Operator

The local binary pattern (LBP) is a very simple and efficient descriptor proposed by Ojala et al. [35] to describe local textural patterns. LBP has gained a wide range of popularity in describing images' texture [36]. It labels each pixel in an image by thresholding its neighbors with the central pixel value of that neighborhood, multiplied by powers of two and then added together to form the new value (label) for the center pixel (see Fig. 4) by using [11]:

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

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

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

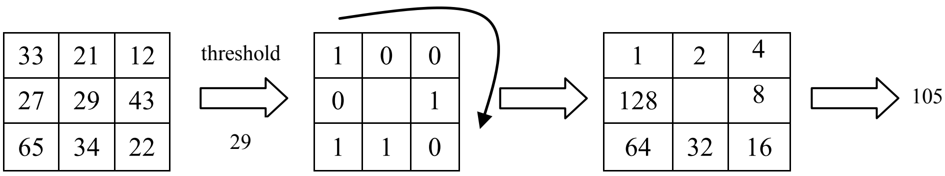
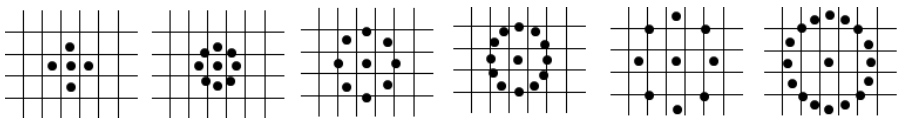


Fig. 4. The Original LBP operator [35, 36]

There are many extensions for the LBP operator. One of these extensions is to use neighborhood of different sizes to be able to deal with large scale structures that may be the representative features of some types of textures [9, 37]. Fig. 5 displays different LBP operators where the notation (P, R) is used as indication of neighborhood configurations in which P represents the number of pixels in the neighborhood and R represents the radius of the neighborhood.



(P=4, R=1) (P= 8, R=1) (P=8, R=1.5) (P=12, R=1.5) (P=8, R=2) (P=16, R=2)

Fig. 5. Different LBP operators [2, 9, 36]

LBP operator can also be extended to other definitions and patterns. One of the most important extensions to the basic LBP operator is called uniform LBP (ULBP). An LBP is called uniform if the binary pattern representation 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 [9]. For example, 10000001, 10111111 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 [35].

4.2 LBP Histogram

After labeling an image with the LBP the histogram of the labeled image can be defined as follows [35]:

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

where '$n=2^P$' is the number of different labels produced by the LBP operator, $f(x, y)$ 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 [12].

4.3 LBP with Directional Statistical Features

For any given image of size N x M, let g_c is its central pixel and g_p is its circular neighbors, where p = 0,1,…,P-1. The local difference $|g_c - g_p|$ has the mean (μ_p) and the standard deviation (σ_p) that can be computed using:

$$\mu_p = \sum_{i=1}^{N}\sum_{j=1}^{M}\left|g_c(i,j) - g_p(i,j)\right| /(M*N) \quad (4)$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M}(\left|g_c(i,j) - g_p(i,j)\right| - \mu_p)^2 /(M*N)} \quad (5)$$

where 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 $2\pi p/P$ [38]. 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:

$$d_\mu = \sum_{p=0}^{P-1}\left|\vec{\mu}_X(p) - \vec{\mu}_Y(p)\right| /(P*e_\mu), \quad d_\sigma = \sum_{p=0}^{P-1}\left|\vec{\sigma}_X(p) - \vec{\sigma}_Y(p)\right| /(P*e_\sigma) \quad (6)$$

where e_μ and e_σ are the standard deviations of $\vec{\mu}$ and $\vec{\sigma}$ respectively from training samples images [38, 39].

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

$$D_{LBP}^{F}(X,Y) = D_{LBP}(X,Y)*(1 + c_1 - c_1 * \exp(-d_\mu / c_2))*(1 + c_1 - c_1 * \exp(-d_\sigma / c_2)) \quad (7)$$

where D_{LBP} (X, Y) is the LBP histogram dissimilarity, c_1 and c_2 are two control parameters for the weights[38].

5 Wavelet Adaptive LBP with Directional Statistical Features (WALBPF)

5.1 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 different levels of decomposition and with different wavelet families to decide which will be the best family for the accuracy rate and inside this family which level of decomposition will be better for both accuracy rate and processing time.

5.2 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 [38]. 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 [38, 40]:

$$ALBP_{P,R} = \sum_{p=0}^{P-1} 2^p S(g_p * w_p - g_c) \qquad (8)$$

where the objective function to compute the weight w_p is as follows:

$$J = \sum_{i=1}^{N}\sum_{j=1}^{M} (g_c(i,j) - w.g_p(i,j))^2 \qquad (9)$$

The target of the objective function is to minimize the directional difference $|g_c\text{-}w_p{*}g_p|$. To this end we have to derive equation 9 with respect to w and assign the derivation to zero as follows:

$$\frac{\partial J}{\partial w} = -2\sum_{i=1}^{N}\sum_{j=1}^{M} (g_p(i,j)(g_c(i,j) - wg_p(i,j))) = 0 \qquad (10)$$

So we get:

$$w\sum_{i=1}^{N}\sum_{j=1}^{M} g_p(i,j)g_p(i,j) = \sum_{i=1}^{N}\sum_{j=1}^{M} g_p(i,j)g_c(i,j) \qquad (11)$$

$$w = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} g_p(i,j)g_c(i,j)}{\sum_{i=1}^{N}\sum_{j=1}^{M} g_p(i,j)g_p(i,j)} \qquad (12)$$

From equation 12 we get:

$$w_p = \vec{g}_p^{\,T}\vec{g}_c / (\vec{g}_p^{\,T}\vec{g}_p) \qquad (13)$$

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

Let $\vec{w} = [w_0, w_1, \ldots, w_{P-1}]$ 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.

5.3 ALBP with Directional Statistical Features (ALBPF)

By using the ALBP weight the directional statistics equations (4) and (5) can be changed to [38]:

$$\mu_p = \sum_{i=1}^{N}\sum_{j=1}^{M}\left|g_c(i,j) - g_p(i,j) * w_p\right| / (M * N) \tag{14}$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{M}(\left|g_c(i,j) - g_p(i,j) * w_p\right| - \mu_p)^2 / (M * N)} \tag{15}$$

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:

$$d_w = \sum_{p=0}^{P-1}\left|\vec{w}_X(p) - \vec{w}_Y(p)\right| / (P * e_w) \tag{16}$$

where e_w is the standard deviation of $\vec{w}$ from training samples images [38, 39].

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

$$\begin{aligned} D_{ALBP}^{F}(X,Y) = D_{ALBP}(X,Y) * (1 + c_1 - c_1 * \exp(-d_\mu / c_2)) \\ * (1 + c_1 - c_1 * \exp(-d_\sigma / c_2)) * (1 + c_1 - c_1 * \exp(-d_w / c_2)) \end{aligned} \tag{17}$$

where $D_{ALBP}(X, Y)$ is the ALBP histogram dissimilarity [38].

6 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. 6 displays an example of two subjects from each dataset. The proposed method is compared with PCA [7], 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).

6.1 Experimental Setup

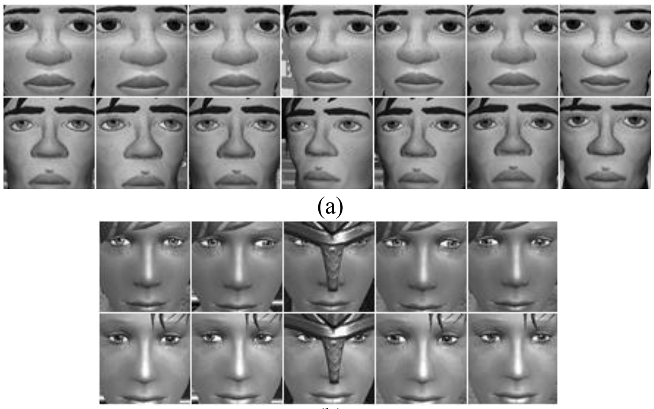
To evaluate the robustness of our proposed technique, we have to apply our system on different datasets of virtual characters and then compare the performance of our technique with others. During these experiments we collected two different datasets of avatars.

The first dataset was collected from the Second Life (SL) virtual world [18]. This dataset contains 581 gray scale images with size 1280 x 1024 pixels 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 Universe (ENT) virtual world [19]. 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.

Each one of the two datasets is divided into two independent groups, one for training and the second for testing. The training group images for each dataset are chosen randomly while the rest of images are used for testing. The size of each group differs from one experiment to another as we will explain in sections 6.2 and 6.3.



(a)

(b)

Fig. 6. Samples of two subjects of facial images from:
a) Second Life dataset [18] b) Entropia Universe dataset [19]

6.2 Tests

We performed many tests in order to retain the best mother wavelet family to deal with our datasets and to decide the most efficient decomposition level within this wavelet family describing our datasets. The tests are performed under the condition of randomly selecting 4 images from each SL subject for training (3 images from each subject for testing) and 3 facial images from each ENT subject for training (2 images from each subject for testing). The results obtained from these tests are summarized in table 1.

The results obtained after applying different discrete wavelet families on SL and ENT datasets showed that the recognition rates are alike (ranged between 91.97% and 95.18% for SL dataset and between 91.33% and 95.92% for ENT dataset). The best recognition rate recorded for the SL dataset by two different wavelet families: "Symlet5" and "Db9" and its value is 95.18% while the best recognition rate recorded for ENT dataset by the wavelet family "Symlet9" and its value is 95.92. Once we determined the best wavelet family and its index we have to decide the best level of decomposition of this family. Table 2 summarizes the recognition rates obtained by applying different decomposition levels of the wavelet family "Symlet5" on SL

Table 1. Recognition rate for SL and ENT datasets using tested wavelet families

Wavelet Family		Recognition Rate for SL	Recognition Rate for ENT
Haar		93.98%	93.37%
BiorSplines	Bior1.1	92.37%	92.35%
	Bior2.2	93.17%	94.39%
	Bio3.3	92.77%	91.84%
	Bior5.5	94.38%	91.33%
Daubechies	Db2	93.17%	93.37%
	Db5	94.38%	94.39%
	Db7	94.78%	94.90%
	Db9	**95.18%**	93.88%
	Db13	94.78%	92.35%
Coiflets	Coif1	93.98%	91.33%
	Coif3	94.38%	91.84%
	Coif5	93.17%	93.37%
Symlet	Sym2	94.38%	94.38%
	Sym5	**95.18%**	94.90%
	Sym9	93.57%	**95.92%**
	Sym13	93.17%	94.39%
ReverseBior	Rbio1.1	91.97%	93.37%
	Rbio2.6	93.17%	93.88%
	Rbio3.9	93.57%	94.39%
	Rbio5.5	92.77%	93.37%

dataset and the obtained recognition rates after applying different decomposition levels of “Symlet9” on ENT dataset.

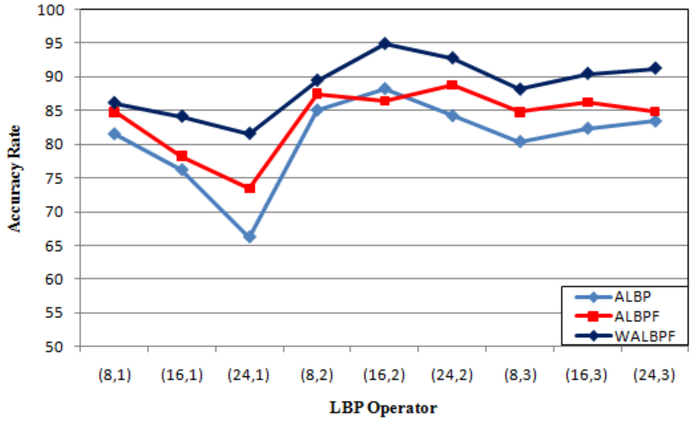
Table 2. Recognition rates of the retained wavelet families with different decomposition levels

Decomposition Level	SL Recognition rate	ENT Recognition Rate
Level 1	92.37%	93.37%
Level 2	93.57%	93.88%
Level 3	**95.58%**	94.39%
Level 4	94.38%	95.41%
Level 5	94.38%	95.41%
Level 6	93.57%	**95.92%**
Level 7	93.17%	94.90%

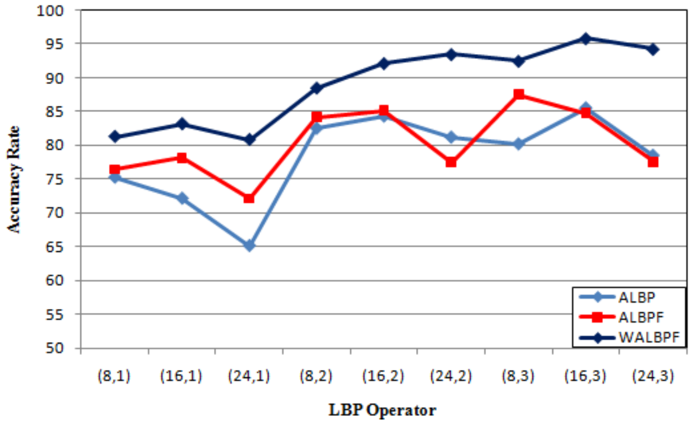
6.3 Experimental Results

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 WALBPF, ALBPF and ALBP with different LBP operator values (see Fig. 7) over the SL and ENT datasets.

In this experiment the training sets were built by randomly selecting 4 images from each class of the SL dataset and 3 images from each class in ENT dataset. The results showed that the recognition rates obtained by WALBPF are better than those obtained by the other two methods with almost all LBP operators and with all datasets. The recognition rate on average obtained by WALBPF is greater than that of its closest competitor, which is ALBPF for both SL and ENT datasets by about 4% with SL dataset where the greatest accuracy is about 95% when LBP operator is (16, 2) and by about 9% with ENT dataset where the greatest accuracy is about 96% when the LBP operator is (16, 3).



(a)



(b)

Fig. 7. Recognition rate using ALBP, ALBPF and WALBPF for:
a) SL dataset b) ENT dataset

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 applying WALBPF is less than that in the other two methods with different LBP operators (see table 3 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.

Table 3. Time in seconds required by different algorithms

Algorithm	LBP operator		
	(8, 1)	(16, 2)	(24, 3)
ALBP	5.34	11.34	178.34
ALBPF	5.55	11.73	179.45
WALBPF	2.12	4.29	166.78

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 SL dataset, we selected one, three and five images from each class for training while the rest is for testing. For ENT dataset we selected one, two and three images from each class for training while the rest is for testing. All training images are selected randomly. We summarize the recognition rates in tables 4 and 5.

Table 4. Accuracy rates for SL dataset obtained by different algorithms

Algorithm	Number of training images		
	1	3	5
PCA	74.70% [14]	79.52%	84.34%
LBP	75.31% [14]	80.96%	89.16%
Multi-scale LBP	77.51%	82.41%	92.17%
WALBPF	80.12%	86.75%	93.98%

Table 5. Accuracy rates for ENT dataset obtained by different algorithms

Algorithm	Number of training images		
	1	2	3
PCA	61.22%	69.73%	85.20%
LBP	65.82% [3]	72.11%	88.27%
Multi-scale LBP	69.39%	75.51%	90.82%
WALBPF	72.19%	79.25%	96.43%

It is very clear from Fig. 7, tables 3, 4 and 5 that our proposed method can achieve better result than the other algorithms in terms of accuracy and classifying time.

7 Conclusion and Future Works

This paper describes a new face feature recognition approach based on applying different discrete wavelet transform families and an adaptive LBP descriptor with directional statistical features on avatar face datasets from different virtual worlds. Selecting the best wavelet family describing each avatar face dataset and deciding the proper level of decomposition within this family has a great effect on the performance of our technique. To evaluate the performance of our technique, we performed many comparisons between our technique and other techniques. 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 4% and 9% 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 the datasets used in the experiments. Applying different classifiers may lead to differentiate between avatar face images and other avatar face images and between avatar face images and human face images and this is what we intend to attempt in the future.

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