Using Discrete Wavelet Transform and Eigenfaces for Recognizing Avatars Faces

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Abstract— **It has been observed that the security of virtual worlds is becoming an important issue for law enforcement agencies. Accurate and automatic tracking of people in the virtual world is an interesting problem for terrorism and security experts. One way to track and recognize the identity of a person in the virtual world is to recognize the face of the avatar that represents this person. To deal with this problem two algorithms capable of recognizing avatar faces with a high degree of accuracy are described in this paper. Experiments conducted on two datasets of avatars from the Second Life and Entropia Universe virtual worlds show the effectiveness of using these algorithms for recognizing avatar faces.**

Keywords-Avatar; eigenfaces; Entropia Universe; PCA; Second Life; virtual world

I. INTRODUCTION

Virtual worlds such as Second Life are populated by millions of computer generated persons such as avatars. These avatars can be used by terrorist organizations for training in a simulated environment using weapons and equipments that are very similar to the real world ones [1, 2]. Terrorist organizations like Al-Qaeda have many military camps for training in Pakistan and Afghanistan but since the presence of the US forces in these countries preventing them from continuing training, they have to find another location [1]. Virtual environments such as Second Life gave them the opportunity to continue training without being worried about detection or prosecution. It has been reported that Al-Qaeda terrorists are using virtual communities, such as Second Life, for recruiting new members and communicating with each other [3]. Also, it was clear that 9/11 terrorists have been trained to fly planes on simulators in their preparation for the deadly attack on the civilian buildings and the Pentagon [1].

The use of computers for stealing identities, committing fraud and other crimes, has grown in prominence as the computer has become central to commerce, entertainment, and e-government [1]. U.S. intelligence officials are concerned with the growth of internet services that enable terrorists to take on new identities as avatars to recruit new members online, rehearse terrorist acts and engage in money laundering operations [4]. The increasing concern of the U.S. government may lead to targeting of online virtual worlds for improved security based on data collection and analysis [5].

Avatars are not just virtual creations as their social, and psychological behaviors in most cases are very similar to those their creators exhibit in the real world [1, 6]. Virtual world agents or avatars are becoming part of our life. Just like it is important and essential to authenticate the human beings identity in the real life, it is also necessary to authenticate the identity of avatars in the virtual world [6]. The more people join the virtual worlds and create avatars, the harder it is to authenticate the identity of the avatars and consequently more difficult to identify their creators [1].

People often complain about the insufficient security system in the Second Life which motivates our research on security in virtual worlds [6, 7]. But how can we identify avatars in the virtual worlds?

To address the need for a decentralized, affordable, automatic, fast, secure, reliable, and accurate means of identity authentication for avatars the concept of Artimetrics – 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 – has emerged [6, 8].

One way to recognize the identity of avatars is to identify the avatar's face automatically. In this paper we describe two face recognition algorithms for avatars based on the idea of wavelet transform, eigenface and eigenvector.

The rest of this paper is organized as follows: discrete wavelet transform is presented in section 2, an overview of the methodology used in the Principal Component Analysis (PCA) and eigenface technique is given in section 3, section 4 presented how to use wavelet transform with PCA for recognizing avatar faces, experiments and discussion are presented in section 5 and finally conclusion and future work are provided in section 6.

II. DISCRETE WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) is a widely used tool for image compression and texture classification because it has an effective ability for multi-resolution decomposition analysis. It was also used to extract the essential features for avatar face recognition [9, 10]. Many articles have discussed its mathematical background and advantages. In the proposed system, DWT is used to decompose images because [11]:

- The computational complexity of the proposed system will be reduced as decomposing images using DWT will reduce the images resolution into sub-band images with lower resolutions. As a result for that the computational complexity will be reduced dramatically.

- The computational overhead in the proposed system will be reduced as DWT will decompose images into sub-bands relating to different frequency ranges and these sub-bands can easily meet the input requirements for the next major step.
- DWT supports providing spatial frequency characteristics of the image as it allows obtaining the local information in different domains (space and frequency).

In case of images we have to apply WT in two directions (row or horizontal direction and column or vertical direction) using four different filters [11]:

$$
\begin{aligned}
&\varphi(n_1,n_2)=\varphi(n_1)\varphi(n_2)\\
&\psi^{H}(n_1,n_2)=\psi(n_1)\varphi(n_2)\\
&\psi^{V}(n_1,n_2)=\varphi(n_1)\psi(n_2)\\
&\psi^{D}(n_1,n_2)=\psi(n_1)\psi(n_2)
\end{aligned}
\tag{1}
$$

where n_1 is the horizontal direction and n_2 is the vertical direction, φ is the scaling function which is essentially a low pass filter, ψ is the wavelet function which is essentially a high pass filter, the product $\varphi(n_1)$ $\psi(n_2)$ means applying the low pass filter in the horizontal direction and applying the high pass filter in the vertical direction, by the same way we can understand the meanings of all the four filters. In the second filter there is a super script H since there is a high pass filter applied on the horizontal direction, by the same way we can understand the superscripts V and D.

As a result of applying the four filters an image will be decomposed into four sub-bands LL (low pass filter on the horizontal direction and low filter on the vertical one), HL (high pass filter on the horizontal direction and low pass filter on the vertical one), LH and HH (see Fig 1.a.). The band LL represents an approximation to the original image while bands LH and HL represent respectively the changes of the image along the vertical and horizontal directions. The band HH records the high frequency component of the image.

To obtain a higher level of decomposition any one of the previous four sub-bands can be analyzed but since images generally are very rich in the low frequency contents, so we have to decompose the LL sub-band of the previous decomposition level using four different filters as we did before. For example, to obtain the second level of decomposition we have to decompose the LL_1 sub-band. The decomposition has to be carried out for the LL_2 to obtain the third level decomposition and so on.. So, we can say that wavelet decomposition of an image provides an approximation image, which is used to obtain the next decomposition level, and three detailed images in horizontal, vertical and diagonal directions.

The two-dimensional wavelet transform, which is required to deal with images, 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 (see fig. 1.b.).

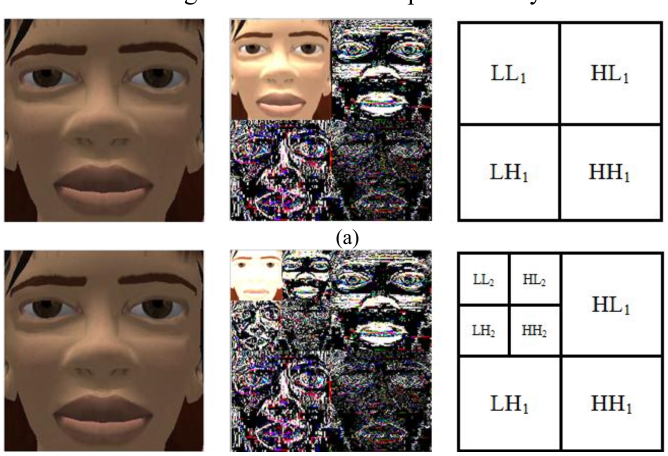


Figure 1. (a) The decomposed face images by one-level (b) The decomposed face images by two-level.

III. USING PCA FOR RECOGNIZING FACES

To build a PCA [13, 14] based system we have to go through two main stages, the first stage is to create the eigenspace and the second is to recognize avatar faces using eigenfaces. As a preparatory step a two dimensional image (from the training dataset) has to be transformed into a vector or a point in high dimensional space. This can be easily done by concatenating the columns of the array that represent this image. For example, if $\Gamma(x, y)$ represents an m by n image then vector $X = [x_1 \ldots x_N]^T$, where $N = m$ x n can represent this image in N dimensional space where each pixel of the image can be seen as a coordinate in this space. We can call such space the image space [15].

Images constituting the training set must be normalized to have the eyes and mouths aligned across all images [13, 14].

Figure 2. Part of manually cropped Second Life avatar faces training dataset used in the experiments

Figure 3. Part of manually cropped Entropia avatar faces training dataset used in the experiments

A. Creating Eigenspace

Suppose that the training dataset has M avatar face images $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M$, we start this stage by computing the mean face image for the training dataset (see Fig. 4). The following equation is used to obtain this image [13-15]:

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \tag{2}$$

Each avatar face image in the training dataset differs from the mean image by vector $\Phi_i = \Gamma_i - \Psi$ where $i = 1$ to M. These vectors are arranged in matrix A of dimension N x M.

We find the covariance matrix of A using the following equation [13-15]:

$$C = A.A^T \tag{3}$$

and compute its eigenvectors and eigenvalues using the following eigenvector decomposition:

$$C.e_i = \lambda_i.e_i \tag{4}$$

where e_i and λ_i respectively represent the eigenvectors and the eigenvalues for the covariance matrix A. We can use the eigenvalue decomposition and get the eigenvalues and eigenvectors of C, since C is real and symmetric.

Next, we sort the obtained eigenvectors based on the associated eigenvalues and eliminate eigenvectors with the smallest eigenvalues and keep the most important eigenvectors based on the highest k eigenvalues. Eigenvectors with the highest eigenvalues describe more characteristic features of a face than those with the least eigenvalues. These eigenvectors are called eigenfaces since each one of them has the same dimensionality or components as a face image and when rearranged and viewed as a picture it will look like a ghost face (see Fig. 5) At the same time they will cover the new M' dimensional face space [13-15].

(a) (b)

Figure 4. a) The mean image for the Second Life training dataset b) The mean image for the Entropia training dataset

B. Recognizing the Avatar Faces

We start this stage by feeding to our system an unknown image Γ (unknown avatar face image), subtracting the input image Γ from the mean image Ψ and projecting the result into the new face space using [13-15]:

$$\omega_k = e_k^T(\Gamma - \Psi) \tag{5}$$

where k = 1, …, M'. These values of ω create the vector Ω^T which describes how much each eigenface contributes in representing the input image.

To determine which of the predefined face classes best describes the input face image we have used (5) to compute vector Ω_k which describes the k^{th} face class [13-15]. We have used (6) to determine the Euclidian distance between the input image and each of the predefined face classes.

$$\varepsilon_k = \sqrt{\|\Omega - \Omega_k\|^2} \tag{6}$$

The minimum value of $\mathcal{E}_k$ (the highest score of similarity) is associated with the face class to which the input image belongs. This minimum value must be below a certain threshold and any value of $\mathcal{E}_k$ greater than this threshold is considered to be associated with a class that is not related to avatar face images.

IV. USING WAVELET PCA FOR RECOGNIZING AVATAR FACES

To use discrete wavelet transform with PCA for recognizing avatar faces images, we have to go through two main stages:

A. Preprocessing Face Image Datasets

To emerge the efficiency of extracting face features of the two datasets used in experiments by using PCA and wavelet PCA (WPCA) we have to go through a set of preprocessing operations:

First, to remove the background of the avatar face images which is useless in the recognition operation we manually cropped the two avatar face images datasets. The resulted pure face images datasets are decomposed using the first level of wavelet transform.

Approximation images, resulted from the first level of wavelet decomposition, are the richest type of images with

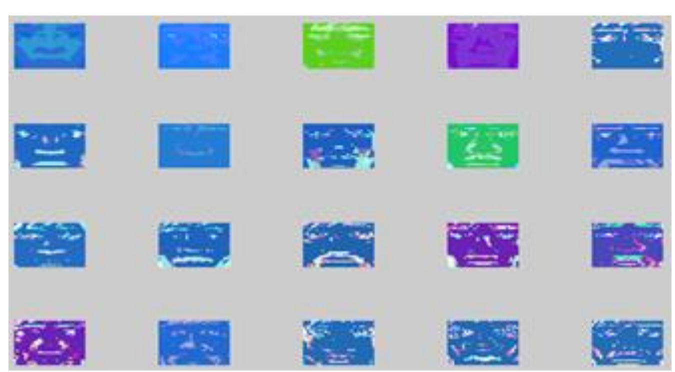


Figure 5. Sample of the PCA Eigenfaces for the Second Life dataset.

respect to the common features of the same class and so we used them in the next step to extract the features of each class of avatar faces [9].

B. Computing Eigenvectors and Classifying Faces to Their Classes

This stage starts by computing the mean image of the training dataset, this mean image can be used to compute the eigenvectors and the eigenvalues for the avatar face images training dataset.

Based on the eigenvalues we sort the eigenvectors and then eliminate the eigenvectors that are less than a predetermined threshold and then we have just created the eigenspace [13-15]. The last step is to build the projection matrix of each one of the tested avatar face images into the new space and to compute the Euclidian distance between each one of these images and the predefined classes. The minimum value of the distance indicates to the best class that can describe the input avatar face image.

V. EXPERIMENTS AND DISCUSSION

To test the efficiency of algorithms presented above, we performed a series of experiments using two datasets of avatar color images. The first one is coming from the Second Life virtual world and the second is coming from Entropia Universe virtual world.

A. Data Preparation

During our experiments we have selected 581 (1280 x 1024 pixels) avatar images from a huge set of Second Life avatar images while we have selected 490 (407 x 549 pixels) avatar images from Entropia Universe virtual world. Avatars faces in both datasets are manually cropped and the resulted 581 (for Second Life dataset) avatar face images (260 x 260 pixels) are organized into 83 classes each of which has 7 images with different angles: front, far left, mid left, far right, mid right, top and bottom (See Fig 6 and Fig 7).

The resulted Entropia avatar face dataset is resized to dimension 180 x 180 and organized into 98 classes each of which has 5 images with different eye angles and facial expressions and one of them is wearing a mask.

After using the first level of wavelet decomposition the resolution of avatar face images in both datasets has changed from 260 x 260 to 130 x 130 for the Second Life dataset and from 180 x 180 to 90 x 90 for Entropia dataset.

The experiments are performed on the condition of three training images per avatar class in both datasets while the other images in each class are used for testing.

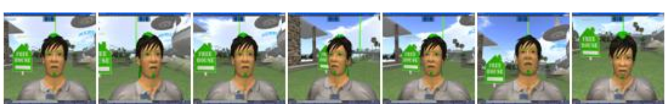
B. Results

For testing we used the two prepared datasets (Second Life and Entropia after preparation) with different number of eigenvectors and compared the PCA with WPCA.

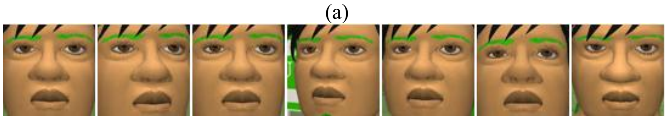
For the Second Life dataset, the experimental results showed that the recognition rate or accuracy of using WPCA is better than the accuracy of using PCA with most of eigenvectors values (see Fig. 8 a) and the greatest accuracy is about 89.5% when number of eigenvectors used is 30. Even if this increase of accuracy is still very limited, the time required for processing and testing the input images by using WPCA is very short (less than quarter) when it is compared to the time required in case of PCA.

For Entropia dataset, the experimental results showed that plus the required testing time in case of using WPCA is less than that in case of PCA the recognition rate increases about 2% to 3% and the greatest accuracy is about 92% when the number of eigenvectors is 70 (see Fig. 8 b).

Using PCA and WPCA methods to recognize avatar faces give near perfect results when the training dataset contains a

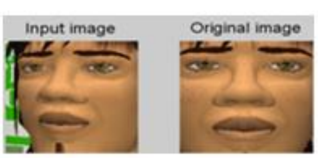


(a)

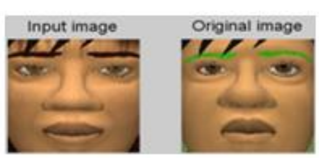


(b)

Figure 6. a) A set of unprocessed images with the same avatar. b) The same set after face detection where the first image to the left (frontal image) is a member in the training dataset while the other images are used for testing.

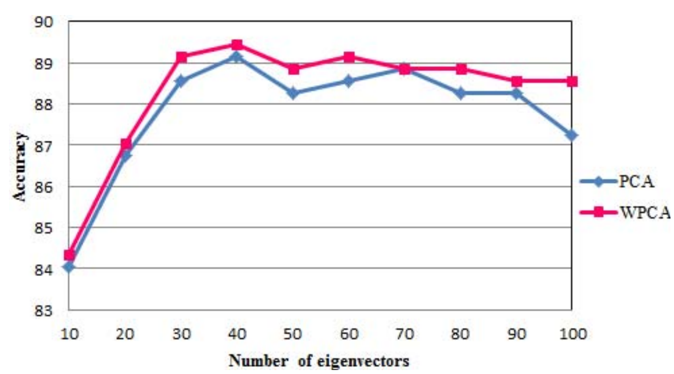


(a)

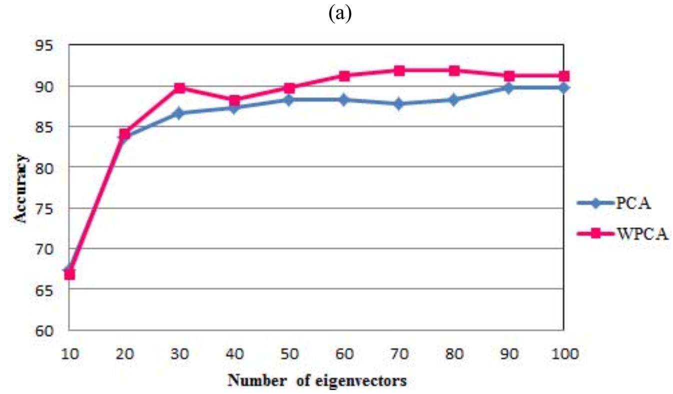


(b)

Figure 7 a) an example of correct identification (input image correctly linked to its original image in the training dataset), b) an example of incorrect identification (input image linked to a wrong image in the training dataset)



(a)



(b)

Figure 8. The accuracy of using PCA and WPCA on: a) Second Life dataset b) Entropia dataset

frontal image of each class. Sometimes these frontal images are not the centered frontal image or a frontal image taken at some angle which will not affect the performance of the class in which these images are in but will also affect the performance of the other classes.

VI. CONCLUSION AND FUTURE WORK

This paper presented two methods of recognizing avatars based on their faces PCA and WPCA. Our experiments were performed on 83 different subjects of avatar color face images from the Second Life virtual world and 98 different subjects of avatar color face images from Entropia Universe virtual world. These experiments were performed with different number of eigenvectors.

The experimental results demonstrate the effectiveness of the two methods we used in experiments.

We are currently in the stage of implementing and testing a fully automated system which first will crop the avatar faces using Haar-like features and then recognize avatar faces using different versions of PCA. We intend to apply this system to recognize avatars from different virtual worlds such as IMVU and Active Worlds.

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