

# Artificial Human Face Recognition via Daubechies Wavelet Transform and SVM

Manel Boukhris

Systems and Signal Processing Laboratory  
National Engineering School of Sousse  
Tunisia  
[manelbouk@yahoo.fr](mailto:manelbouk@yahoo.fr)

Abdallah A. Mohamed  
Speed School of Engineering  
Computer Engineering and Computer Science  
University of Louisville, USA  
[aamoha04@louisville.edu](mailto:aamoha04@louisville.edu)

Darryl D'Souza  
Speed School of Engineering  
Computer Engineering and Computer Science  
University of Louisville, USA  
[darryl.dsouza@louisville.edu](mailto:darryl.dsouza@louisville.edu)

Marc Beck

Speed School of Engineering  
Computer Engineering and Computer Science  
University of Louisville, USA  
[mbbeck05@louisville.edu](mailto:mbbeck05@louisville.edu)

Najoua Essoukri Ben Amara  
Systems and Signal Processing Laboratory  
National Engineering School of Sousse  
Tunisia  
[najoua.benamara@eniso.rnu.tn](mailto:najoua.benamara@eniso.rnu.tn)

Roman V. Yampolskiy  
Speed School of Engineering  
Computer Engineering and Computer Science  
University of Louisville, USA  
[roman.yampolskiy@louisville.edu](mailto:roman.yampolskiy@louisville.edu)

**Abstract**—This work presents an approach for applying face recognition to non-biological entities (avatars) in virtual worlds to achieve authentication. Massively multiplayer online games involve virtual worlds which require avatar identification to avoid fraud. First, virtual worlds and avatars are briefly discussed. Next, the concepts of facial biometrics and the face recognition systems are presented. Later, support vector machines and wavelet transforms are introduced as classification tools. Finally, the dataset and the designed biometric system are described with the obtained results.

**Keywords**- *Massively multiplayer online gaming (MMOG), virtual worlds, avatars, face recognition, Support vector machines, Wavelet transforms*

## I. INTRODUCTION

The widespread use of technology has increased the global connectivity of people around the world. The use of virtual worlds for communication is extremely popular [1]. It derives itself from video games widely known as Massively Multiplayer Online Games (MMOG). The virtual world is thus defined as a 2D or 3D environment simulating and emulating the aspects of real life. It offers an environment for business, trade and marketing and contains universities, shops, museums, beaches, etc. Examples of real-world games include Active Worlds [2], Everquest [3], There [4], Sims Online [5], and World of Warcraft [6]. Their use in education [7] has the potential to encourage constructive learning and put students in touch with an immersive environment that improves their competitiveness. The images in Figure 1 present some aspects

of the education evolution in these worlds. The first picture shows a campus of "Kelley School of Business" [8] in Second Life while the second image is a conference within a virtual world [7].



Figure 1. Education in virtual worlds make bigger

Advertisements of world renowned companies such as Coca Cola, IBM, Philips, Toyota, Adidas, etc. are present here as well. Numerous incentives such as advertising, testing and selling of products and services at lesser costs have encouraged businesses to participate in these worlds. These factors have led to the emergence of an economy within the virtual world. Several virtual worlds have created their own currencies that can be exchanged for real money. Their constant growth and progress seem to offer more opportunities for our society in economic, cultural and social development that have been unexplored in the past.

However, these worlds have not escaped the real world criminal activities such as theft, fraud, gambling, money laundering, terrorism, etc. Virtual crimes have become such a critical issue that Second Life [9] displays an electronic bulletin board of crime for the police community. Financial interests of the real world are at stake as deviant acts committed by residents have “real” and disastrous consequences. When residents realize that their purchased virtual goods are either destroyed or stolen they undergo a “real” economic loss [10]. Biometric recognition technologies are the best tools to ensure maximum security in the real world. The evolution of crime has made virtual worlds even more vulnerable than the real world. Virtual crimes may cause real financial damages that will only worsen unless measures are taken to secure authentication and communication within these worlds. It is absolutely necessary to build a recognition system for “avatars”, virtual characters that are graphical representations of users, in virtual worlds. Originally, the word “avatar” comes from Sanskrit and literally means “descent,” however; it is commonly translated into English as “appearance”. The avatar is generally defined as “a physical image or graphic that allows the user to represent themselves in a virtual environment in real time” [11]. It allows a player to visually identify oneself to other players.

This paper demonstrates an approach towards applying the biometric tool of face recognition on non-biological entities (avatars) in virtual worlds to achieve authentication. The images representing the faces of the avatars were collected from the popular virtual world “Second Life” [9] and a biometric face recognition technique commonly applied to human beings was adopted. It is organized as follows. In Section 2 we briefly discuss the aspects of facial biometrics as well as the architecture and concepts of a face recognition system. Section 3 describes the tools adopted to build the system. Section 4 presents our developed application with the basic design and the development of our face recognition system. Section 5 highlights our experimental results. This work was originally presented in [12].

## II. BACKGROUND

### A. Facial Biometrics

Biometrics can be defined as the automatic recognition of a person using his or her distinguishing traits which helps to verify the identity of an individual. It offers greater security than other methods of authentication (identification numbers, passwords and swipe cards) by overcoming some vulnerabilities of the other systems. Numerous such technologies are used in several applications that utilize multiple biometric data such as fingerprint, face, voice, iris, signature, etc. However, the face is the most natural and popular biometric used by humans for identification, making face recognition one of the most preferred technologies. The difficulties encountered in this process vary depending on the acquisition environment. Current methods are efficient only when the conditions are very well

controlled. Variations in lighting or the camera angle causes serious problems for many existing recognition systems. Some interesting work has been carried out in the application of biometric principles on avatars to recognize them for authentication [13-16].

### B. Architecture of the Face Recognition system

The architecture of a face recognition system is comprised of the following modules:

#### *Preprocessing:*

Preprocessing involves applying noise elimination techniques on images to compensate noise caused degradation.

#### *Face detection:*

This is an essential preliminary step to locate and extract the face from the acquired image. It depends on several factors such as variability of the scale, location, orientation, pose (front, profile), etc. Factors such as face occlusions and lighting conditions must also be taken into account and minimized to achieve reliable results.

#### *Analysis or Characterization:*

It involves the extraction and analysis of useful features towards building a face recognition model. Several methods such as PCA (Principal Component Analysis), SVM (Support Vector Machines), etc. are used to accomplish this task.

#### *Identification or Verification:*

This step deals with an image comparison between the acquired image and the database images to identify the feature similarities to recognize the individual. The purpose of this task is to verify the identity of the individual.

The enrollment phase and recognition phase are two essential phases to authenticate an individual’s biometrics. The enrollment phase is where the information related to the person to be identified is gathered and stored in the database. The recognition phase is a comparison of the image descriptors from the acquired and the enrolled images.

#### *Decision making:*

This is where the final decision is made.

Figure 2 illustrates these different stages of face recognition.

The performance of a recognition system can be measured primarily by two factors that represent the error rates in a decision-making system characterizing the performance of the biometric system [17]. The system can yield one of the following four decisions:

- The impostor is accepted (FAR: false acceptance rate): the probability that a biometric system identifies or authenticates an impostor by mistake.
- The impostor is rejected.
- The truth is accepted.
- The truth is rejected (FRR: false rejection rate) the probability that a biometric system fails during the identification or verification of a person enrolled.

Both factors FAR and FRR measure the accuracy of system identification. The comparison of the system performance is

based on a rate called the Equal Error Rate (EER) where the values of FAR and FRR are equal. The FAR and FRR values are minimized for security systems.

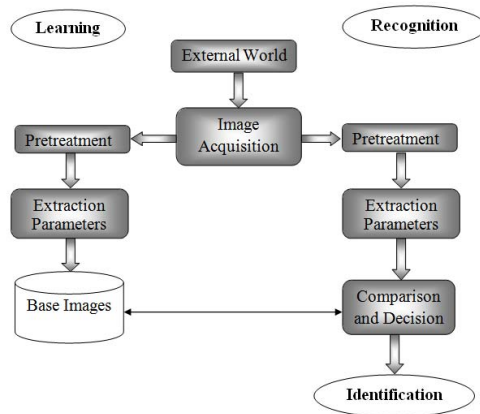


Figure 2. Architecture of a recognition system

Table 1 illustrates some of the face recognition methods while describing the advantages and disadvantages of each of them. We observe that PCA is a popular technique for efficiently representing facial images. The HMM (Hidden Markov Models) approach is not applicable for basic facial images which represent changes in facial expressions as some parts of the face and are relatively invariant in such situations. The last method presented in the table combines the wavelet transform for characterization and SVM for classification. It yields very good results and so it is used here.

Table 1. Examples of methods for face recognition

Method	Benefits	Disadvantages
Principal Component Analysis (PCA)	<ul style="list-style-type: none"> <li>Fast, simple and very popular</li> <li>Smaller learning time</li> </ul>	<ul style="list-style-type: none"> <li>Unoptimized for class separability</li> <li>Very sensitive to lighting or changes</li> </ul>
Hidden Markov Model (HMM)	<ul style="list-style-type: none"> <li>Very simple</li> <li>Noise avoidance by the hair, glasses, etc.</li> <li>Peculiarities of the face taken into account</li> </ul>	<ul style="list-style-type: none"> <li>Lack of precision</li> <li>Difficulty when considering several facial measures</li> </ul>
Neural Networks	<ul style="list-style-type: none"> <li>Considerable time saving</li> </ul>	<ul style="list-style-type: none"> <li>Maybe unable to resolve situations already encountered in learning</li> </ul>
Elastic Bunch Graph Matching (EBGM)	<ul style="list-style-type: none"> <li>Ease of adding new data (new face)</li> <li>Robustness</li> <li>Insensitive to light and pose variations</li> </ul>	<ul style="list-style-type: none"> <li>Many calculations involved</li> <li>Requested a larger image</li> </ul>
Support Vector Machine (SVM)-Wavelet	<ul style="list-style-type: none"> <li>Good selection</li> <li>SVM configuration easy and inexpensive</li> <li>Very successful and well used especially in face recognition.</li> </ul>	<ul style="list-style-type: none"> <li>Storage of information extracted during learning</li> </ul>

### III. ALGORITHMS

#### A. Concept of optimal hyperplane and separators

A Support Vector Machine (SVM) is a set of supervised learning techniques to solve problems of discrimination and regression. SVMs are a generalization of linear classifiers, to which the hyperplane belongs. The goal of the SVM is to find a classifier for two classes of data, to separate copies of this data, and to maximize the distance between these two classes. In order to have the properties of an SVM, it has to be an optimal hyperplane, which means the hyperplane needs to pass through the centre points of two classes of examples. The goal is now to find the maximum hyperplane that maximizes the distance to the training examples or margin.

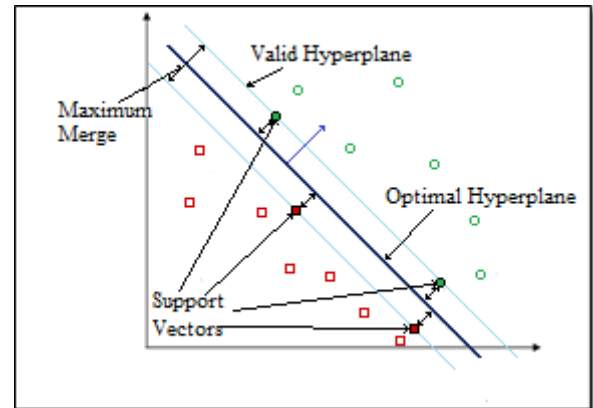


Figure 3. Optimal Hyperplane [18]

#### B. Linear, nonlinear and multi-class classification

There are two models of SVMs, one where the examples are linearly separable and one where they are non-linearly separable. The first case is simpler because it is easy to find a linear classifier. In this case it is possible to use the maximum margin classifiers. The margin between the positive and negative is defined by two hyperplanes  $(w \cdot x) + b = \pm 1$ . In addition, none of the points is lying between these hyperplanes and has a margin width of  $\frac{2}{\|w\|}$ . The algorithm is trying to maximize the margin by minimizing  $\|w\|$  to achieve an optimal solution with a maximum spread. Data points on the separating hyperplanes with maximum margin are called support vectors.

To simplify the calculation, the problem is formulated in a Lagrangian framework. This leads to the maximization of the Lagrangian:

$$L_D = \sum_{i=1}^l \alpha_i - \frac{1}{2} \sum_{ij} \alpha_i \alpha_j y_i y_j x_i \cdot x_j \quad (1)$$

Note that  $\alpha_i$  are all equal to zero except those corresponding to support vectors. New examples can be classified by simply using the decision function. In many cases the data cannot be completely separated due to outliers. This can be resolved by introducing the constant  $\zeta_i > 0$  as follows:

$$y_i(x_i \cdot w + b) \geq (1 - \zeta_i) \quad (2)$$

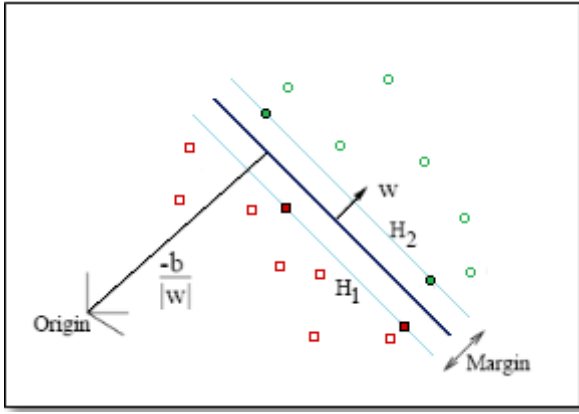


Figure 4. Linear Classification into two classes [19]

It is also possible to construct a nonlinear SVM to classify nonlinearly separable data.

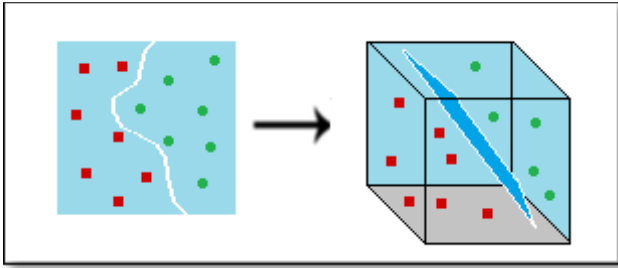


Figure 5. Principle of non-linear classification [18]

To use the nonlinear decision function, the above formulas can be easily generalized. The basic idea is that the kernel method is based primarily on data preprocessing by a transformation function  $\phi$ , and then apply the same linear algorithm as before, but on the image space of  $\phi$ .

$$\phi : \mathbb{R}^d \rightarrow \mathcal{F}, \text{ with } \text{card}(\mathcal{F}) > d \quad (3)$$

This requires solving the following set:

$$\begin{cases} \max \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j \phi(x_i) \cdot \phi(x_j) \\ \forall i, 0 \leq \alpha_i \leq C \\ \sum_{i=1}^n \alpha_i y_i = 0 \end{cases} \quad (4)$$

It results in the following solution:

$$f(x) = \sum_{i=1}^n \alpha_i y_i \phi(x_i) \cdot \phi(x) + b \quad (5)$$

The problem and its solution depend only on the scalar product  $\phi(x) \cdot \phi(x')$ .

Rather than choosing the non-linear transformation  $\phi(x)$ , the kernel function  $K: x * x \rightarrow \mathbb{R}$  is chosen. This function represents a scalar product in the intermediate space.

There are ways to extend the SVM method to more than two classes. Among these approaches is a method of forming a classifier for each class that distinguishes examples of this class from examples of all other classes.

Another approach involves SVM for each pair of classes. It consists of using a classifier for each pair of categories. The classifier indexed by the pair  $(k, l)$  with  $(1 \leq k < l \leq Q)$  is intended to distinguish the category of index  $k$  of the index  $l$ . To assign one example, this therefore  $C_Q^2$  classifiers and the decision usually is obtained by performing a majority vote. The votes of each classifier may be weighted by a function of the output value. The number of classifiers needed in this approach is  $n(n-1) / 2$ , which is more complex than the first approach.

### C. The wavelet transformation

The wavelet transform can be compared to the Fourier transform. The great disadvantage of the Fourier transform is that it only has the frequency and not the time resolution. To overcome this problem several solutions have been developed that are more or less able to represent a concurrent signal in both the time and the frequency domain. The idea behind these time-frequency joint representations is to cut the signal into several parts and analyze them separately. It is clear that the analysis of a signal in this way provides more information on the timing and location of the frequencies of different components.

In wavelet analysis, the use of a fully scalable window solves the problem of cutting the signal. The window is moved along the signal, and the spectrum for each position is calculated. Then, this process is repeated several times with a window slightly shorter (or longer) for each new cycle. Ultimately, the result is a set of time-frequency representation signals with different resolutions (multi resolution).

In the case of wavelets, one usually does not speak of time-frequency representations, but representations of time-scale. The continuous wavelet transform (CWT) is provided by the following equation:

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t) \cdot \Psi^* \left( \frac{t-\tau}{s} \right) dt \quad (6)$$

where  $x(t)$  is the signal to be analyzed and  $\Psi(t)$  is the mother wavelet or basis function. All wavelet functions used in processing are obtained from the mother wavelet through translation and compression. The scale and translation factor is "s," and  $s^{-1/2}$  is the factor for normalization of energy across different scales.

The mother wavelet is used to generate all the basic functions based on some desired characteristics associated with this function. The parameter  $\tau$  is related to the location of the wavelet function. Thus, it corresponds to the temporal information in the transformed wavelet. Note that the wavelet transform performs the convolution operation on the signal and the basic function.

#### D. Properties of wavelets

The most important properties of wavelets are eligibility and regularity

$$\int \frac{|\Psi(w)|^2}{w} dw < +\infty \quad (7)$$

with  $\Psi(w)$  being transformed to Fourier  $\Psi(t)$ .

This condition satisfies the property of eligibility. It can be used first to analyze and then to reconstruct a signal without information loss. The eligibility requirement means that the Fourier transform  $\Psi(t)$  vanishes at a frequency of zero:

$$|\Psi(w)|^2_{w=0} = 0 \quad (8)$$

This means that wavelets must have a band-pass like spectrum. This is a very important observation, which will be used later to build an efficient wavelet transform.

$$\int \Psi(t) dt = 0 \quad (9)$$

#### E. Discrete wavelet transform

A wavelet in the sense of Discrete Wavelet Transform (DWT) is an orthogonal function that can be applied to a finite group of data. Functionally, it is very similar to the discrete Fourier transform.

In the CWT, the signals are analyzed using a set of basic functions that are related by simple translation. In the case of DWT, the representation of the digital signal is obtained using digital filtering techniques. The signal to be analyzed is passed through filters with cut off frequencies at different scales.

The wavelet transform has three more properties that make it difficult to use directly. The first is the redundancy of the CWT, which is removed in most practical applications. The second issue is that even without it there are still an infinite number of wavelets in the transformed pattern that need to be reduced to a manageable number. The third problem is that most functions of the wavelet transform are not analytical solutions and can be calculated only numerically.

The discrete wavelets are translated into a continuous signal by modifying the wavelet representation. The effect of discretizing the wavelet is that the space-time scale is now sampled at discrete intervals. When the discrete wavelet transform is used for a continuous signal, the result will be wavelet series decomposition. It is possible to reconstruct a signal from its wavelet series decomposition under the condition that the energy of the wavelet coefficients lies between two positive terminals:

$$A\|f\|^2 \leq \sum_{j,k} |\langle f, \Psi_{j,k} \rangle|^2 \leq B\|f\|^2 \quad (10)$$

If  $A = B$ , the frame is tight and discrete wavelets behave on an orthonormal basis. If  $A \neq B$ , an exact reconstruction is possible. The last step is to produce discrete orthonormal wavelets. The discrete wavelets can be orthogonal to their own expansion by the choice of the mother wavelet, which means:

$$\int \Psi_{j,k}(t) \Psi_{m,n}^*(t) dt = \begin{cases} 1 & \text{if } j = m \text{ and } k = n \\ 0 & \text{otherwise} \end{cases} \quad (11)$$

An arbitrary signal can be reconstructed by the sum of the basic functions of orthogonal wavelets, weighted by the coefficients of the wavelet transform

$$f(x) = \sum_{j,k} \gamma(j, k) \Psi_{j,k}(t) \quad (12)$$

#### 1) Decomposition of images

For the case of images, the DWT is first applied row by row, then column by column. The image in the centre of the following figure shows the four thumbnails produced by decomposition in DWT level 2. This decomposition gives a detailed image pyramid at different scales and orientations.

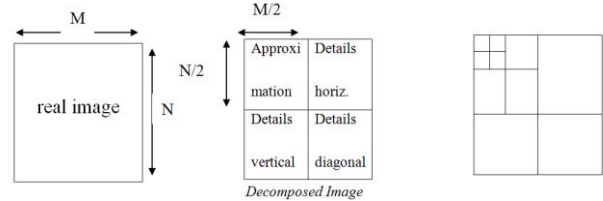


Figure 6. Principle of DWT

#### 2) The scale function

Whenever the wavelet is stretched in time by a factor of 2, its bandwidth is reduced by half. In other words, with each wavelet only half of the remaining spectrum can be covered, which means an infinite number of wavelets is required. The solution to this problem is to not cover the entire spectrum with wavelets, but to use a scaling function instead. Assuming the scaling function is merely a signal spectrum with a low pass which can then be decomposed into wavelet components and is expressed as follows:

$$\varphi(t) = \sum_{j,k} \gamma(j, k) \Psi_{j,k}(t) \quad (13)$$

The scaling function  $\varphi(t)$  was chosen so that its spectrum occupies the space left open by the wavelets, the above formula uses an infinite number of wavelets. This means that if a signal is analyzed using a combination of a scaling function and wavelets, the number of wavelets can be forced to be finite. With the use of a scaling function instead of wavelets, the information is lost, but it is still possible to reconstruct the original signal. The spectrum width of the scaling function is an important parameter in the wavelet transform. As the spectrum is very narrow, wavelet coefficients are needed but their number is limited. Adding a wavelet spectrum to the spectrum of the scaling function doubles the spectrum of the scaling function.

## IV. DESIGNING THE DATASET USED IN EXPERIMENTS

### A. Image Database

In the field of biometrics, image databases are collected and used to evaluate the performance of biometric recognition systems. The image databases are essential elements in the recognition domain. They are required to learn and to test the performance of classification algorithms, detection and localization [20]. There are many factors which affect the performance of face recognition system, including, the resolution of images, the quality of the facial image, the



orientation of the head, facial expressions, lighting conditions and occlusion.

### B. The procedure for collecting images

We will collect images from the virtual world - "Second Life." To get into Second Life, we must first begin by creating an account on its official website, download the software and install it.

In Second Life virtual world there are several agents that can affect the appearance of the avatars, such as the silhouette that defines the set of features and overall appearance of the avatars. These features include the skin color of the avatar, the details (like wrinkles), makeup, hair, eyes, etc. These parts can be changed by buying them as objects that exist in shopping centers in Second Life. Second Life has a camera that can take photos as a snapshot. By default the camera follows the chosen avatar everywhere, but it can be controlled by the keyboard in order to vary the angles of views.

### C. Description of the dataset collected

The dataset we used in experiments contains 10 images collected from each of 100 different subjects. For all subjects, the images were taken at the same time, with different facial expressions (normal, happy, sad, sleepy, and surprised). Lighting is controlled when taking snapshots of each subject. The face occupies about 90% of the width of each image. Figure 7 gives a complete example of different poses of a single subject used in the experiments.



Figure 7. An example of a subject used in the experiments

Almost all images were taken in frontal position with a homogeneous background. Initially the images were taken with screenshots containing a frontal pose of the avatar and the size was minimized by applying a mask that we minimized the background in order to minimize the noise in the image.

## V. THE BIOMETRIC SYSTEM

Recognizing individuals using biometric data requires two phases: enrollment and recognition. The enrollment phase is a learning pattern recognition process, which aims to collect information on whom to identify. The feature extraction and classifier learning are essential to the performance of a face recognition system. Discrimination characteristics and robustness of the classifier are always desirable in recognition applications. The proposed method uses the wavelet transform

combined with SVM. In fact, global features from the wavelet transform are used for SVM learning machine which works as a classifier. During experiments, four images were selected randomly for testing and six images for training from each subject.

### A. Characterization

The wavelet transform is a popular tool in image processing applications, such as compression, detection, and recognition. It represents good characteristics in the localization of the frequency space and multi-resolution. The main reason for its popularity lies in the flexibility of choice of bases and in the simplicity of calculation. We have improved our description of the face by extracting global features from the wavelet transform. The wavelet transform offers features that represent information about the texture of the image. Each image can be represented as four performances: approximation coefficients, diagonal, horizontal and vertical details.

To reduce the number of wavelet coefficients, we will only consider the mean and standard deviation of approximation coefficients and the standard deviation of the three matrices of the detail coefficients. Figure 8 illustrates the decomposition of an image through the application of wavelet transform.

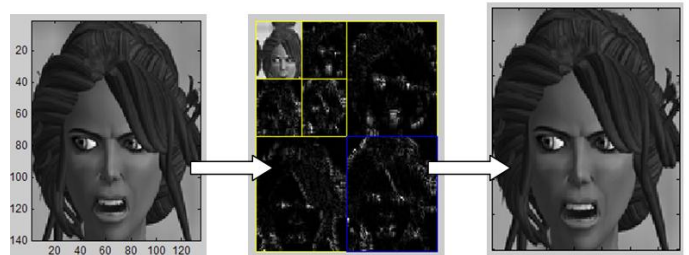


Figure 8. Decomposition of an image

### B. Classification

SVMs have recently been used for a variety of object recognition techniques. In most cases, SVM generalization performance is significantly better than other techniques. During recent years, attempts have been made to apply SVM for classification of facial expressions. The results were among the best ever made, suggesting that SVM is actually a very appropriate approach for classifying facial expressions. For these reasons, we want to test the SVM classifier on our dataset. The extracted global information consists of characteristic vectors of SVM for recognition. SVM rearranges the points according to a mathematical function to transform them into a space that allows its classification. In this algorithm, we use the radial basis function (RBF).

$$K(x, x') = \exp\left(-\frac{\|x-x'\|^2}{2\sigma^2}\right) \quad (13)$$

## VI. RESULTS

The system performance is estimated by measuring two error rates: False Acceptance Rate (FAR) and False Rejection Rate (FRR). It showed that in the DET (Detection Error Trade-off) curve these values are obtained by varying the system parameters, such as the threshold for classification. We

concluded that 4.22% EER was obtained, which means that all the checks carried out have resulted in misclassification.

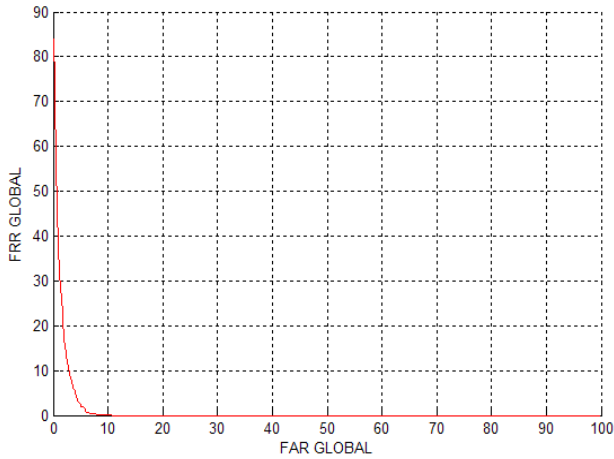


Figure 9. DET curve

For example, for a threshold of 0.8 we notice that the recognition rate varies from 91% to 100% as observed in Table 2.

Table 2. Recognition results

Av. #	R. rate	FRR	FAR	Av.#	R. rate	FRR	FAR
1	91	25	8.83	51	92.5	0	7.57
2	93.75	0	6.31	52	95	0	5.05
3	98	0	2.02	53	94	0	6.06
4	99.5	0	0.50	54	89.25	0	10.8
5	100	0	0	55	100	0	0
6	96.5	0	3.53	56	99.5	0	0.50
7	97	75	2.27	57	94	0	6.06
8	99.5	0	0.50	58	98	0	2.02
9	96.75	0	3.28	59	98	0	2.02
10	98	0	2.02	60	99	0	1.01
11	97.25	0	2.77	61	98.25	0	1.76
12	93.5	0	6.56	62	93.5	0	6.56
13	99.75	25	0	63	96.75	25	3.03
14	93.75	0	6.31	64	99.5	0	0.50
15	94.75	0	5.30	65	98.25	0	1.76
16	98.25	0	1.76	66	100	0	0
17	95	0	5.05	67	97	0	3.03
18	98.25	0	1.76	68	94.25	0	5.80
19	93	0	7.07	69	94.5	25	5.30
20	99	0	1.01	70	99	0	1.01
21	98	0	2.02	71	94.25	50	5.30
22	100	0	0	72	97	0	3.03
23	98.25	0	1.76	73	99.25	0	0.75
24	98.25	0	1.76	74	100	0	0
25	98	0	2.02	75	95.5	0	4.54
26	96.75	0	3.28	76	8.5	0	1.51
27	97.25	0	2.77	77	93.25	50	6.31
28	85.75	25	14.1	78	98	0	2.02
29	99.75	0	0.25	79	97	0	3.03
30	97.25	50	2.27	80	98.75	25	1.01
31	97.5	0	2.52	81	96.25	0	3.78
32	98.75	0	1.26	82	97	0	3.03
33	99.5	0	0.50	83	100	0	0
34	99.25	0	0.7	84	100	0	0
35	99	0	1.01	85	99.5	25	0.25
36	99.75	0	0.25	86	98.25	0	1.76
37	92	0	8.08	87	93	0	7.07
38	98.75	0	1.26	88	100	0	0
39	93.25	0	6.81	89	97.75	0	2.27

40	99.5	0	0.50	90	93.25	0	6.81
41	92.5	75	6.81	91	96.25	0	3.78
42	96	100	3.03	92	97.75	0	2.27
43	79.25	0	20.9	93	94.75	0	5.30
44	92.5	0	7.57	94	92.5	0	7.57
45	94	0	6.06	95	97.25	0	2.77
46	96	0	4.04	96	100	0	0
47	95.25	0	4.79	97	91.75	0	8.33
48	99.25	0	0.75	98	98	0	2.02
49	100	0	0	99	98.25	0	1.76
50	100	0	0	100	95.75	25	4.04

\*Av. # means avatar number and R. rate means recognition rate.

## VII. CONCLUSION

This work was originally presented in [12], and is a part of the overall security framework for virtual worlds based on biometric identification systems of avatar faces. The results seem to be promising since we have obtained a good classification performance. Given the need for security in virtual worlds many improvements can be made in this innovative research area. Undoubtedly, it is still necessary to develop our biometric system further and achieve higher recognition rates. Described system was limited to ten images per person as the avatar facial movements are limited as compared to human faces. However, other images can be added by varying the degree of brightness, lighting angles and poses. Moreover, we have also observed that low resolution training images can affect the quality of recognition and should be avoided if at all possible.

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**Abdallah A. Mohamed** received the B.S. and M.S. degrees in Computer Science from Menoufia University, Egypt, in 1997 and 2002, respectively. He received another M.S. degree in Computer Science from Indiana University, Bloomington, Indiana, USA in 2009. Currently, he is working towards the Ph.D. degree at Department of Computer Engineering and Computer Science, University of Louisville, Louisville, USA. His current research interests include statistical pattern recognition, face detection and recognition.



**Darryl D'Souza** received the B.Eng. degree in Computer Engineering from University of Mumbai, India, in 2006 and the M.S. degree in Computer Science from University of Louisville, Louisville, USA, in 2009, respectively. Currently, he is working towards the Ph.D. degree at the Department of Computer Engineering and Computer Science, University of Louisville, Louisville, USA. His current research interests include accessibility in virtual worlds, face detection of non-biological entities, digital forensics.



**Marc Beck** received the B.S. degree in Computer Science from Brescia University, Owensboro, USA and the M.S. degree in Industrial Technology from Morehead State University, Morehead, USA. Currently, he is working towards the Ph.D. degree at the Department of Computer Engineering and Computer Science, University of Louisville, Louisville, USA. His research interests include signal processing and robotics.



**Roman V. Yampolskiy** is the director of the Cybersecurity Research Lab at the CECS department, University of Louisville. Dr. Yampolskiy holds a PhD degree from the Department of Computer Science and Engineering at the University at Buffalo. There he was a recipient of a four year NSF fellowship. After completing his PhD dissertation Dr. Yampolskiy held a position of an Affiliate Academic at the Center for Advanced Spatial Analysis, University of London, College of London. He had previously conducted research at the Laboratory for Applied Computing at the Rochester Institute of Technology and at the Center for Unified Biometrics and Sensors at the University at Buffalo. Dr. Yampolskiy's main area of expertise is biometrics. He has developed new algorithms for action-based person authentication. Dr. Yampolskiy is an author of over 60 publications including multiple journal articles and books.