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Handwriting Process Modelling by Artificial Neural Networks

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Abstract: **The handwriting is considered among the fastest and the most complex motor activities of our biological directory. This process also has a side which differentiates it from other human behavior as it is a physical manifestation of a complex cognitive process. Therefore, the modelling of a handwriting system is difficult to implement. Considering the complexity of the biological system involved in this process, several studies have been proposed in the literature based on different approaches. However, the validation results of these models remain unsatisfactory and the basic models have been improved to approach the reality as much as possible. This paper deals with new unconventional handwriting process characterization approaches based on the use of soft computing techniques namely the exploitation of artificial neural networks and more precisely the Radial Basis Function (RBF) neural networks. The obtained simulation results show a satisfactory agreement between responses of the developed RBF neural model and the experimental electromyographic signals (EMG) data for various letters and forms then the efficiency of the proposed approaches.**

Keywords: Handwriting Process, Modelling, Experimental Approach, Electromyographic Signals, Artificial Neural Networks, RBF Neural Networks.

I. Introduction

Considering the complexity of the biological handwriting process, several researches have been conducted to enrich our knowledge on the functioning and organization of this biological system.

At first analysis, Van Der Gon has developed a mathematical model characterizing this phenomenon [1].

An electronic version was then presented by Mc Donald [2], who considered the handwriting system as a mass moving in a viscous environment. The movement of this mass is described by a linear differential second order equation. A model governed by a system of two nonlinear differential equations of the second order was developed by Yasuhara which integrated the effect of the frictional force between the pen tip and the writing surface [3]. He presented then the identification and the decomposition of a fast writing system. In 1987, Edelman and Flash proposed a model based on the study of the hand trajectories [4]. Linear modelling approach derived from experimental data was proposed by Sano and al in 2003 [5].

Using unconventional approaches, several models were proposed for the characterization of the handwriting process. These models are based on the concepts of the artificial neural networks, fuzzy logic, genetic algorithms… [6], [7] and [8]. In this paper, a new model of the handwriting system based on the concepts of RBF neural networks is proposed. First of all, a description of the experimental approach is presented in order to collect experimental measurements for modelling the studied process. Then, a direct neuronal model is suggested allowing the reproduction of the traces of Arab letters and geometric forms starting from experimental measurements of electromyographic signals.

In addition, according to the same principle, an inverse neural model is proposed to reconstruct integrated electromyographic (IEMG) signals from traces of the pen tip along the x-axis and y-axis. Finally, the validation of two neural models is made by cascading them in order to validate the outputs of each proposed model.

II. Experimental Study Description

During the act of writing, the movements performed can be described like displacements in the two-dimensional space of the writing plan. In the literature, multiple researches proved that the natural component of the graphic trace corresponds to space displacements of the pen during the formation of the trajectory. In spite of the complexity of the effector system including the articulations of the shoulder, the elbow, the wrist and the hand, for a total of forty three muscles, the study presented in [3] identified four principal muscles for the hand control. In order to characterize this biological process, an experimental study carried in [5], has recorded electromyograhic signals during the act of writing, figure 1.

Starting from the surface electrodes used per pair and having a common mass, the experimental study allowed recording electromyograhic signals during the writing time. These signals are obtained from the two most active muscles of the forearm, namely the “abductor pollicis longus” and the “extensor capri ulnaris” which are the most active and are opposed in movement; when one contracts the other extends. This experience allowed recording the positions of the pen tip in the plan (x, y), the EMG signals, and the pressure P exerted by the pen on the writing table.

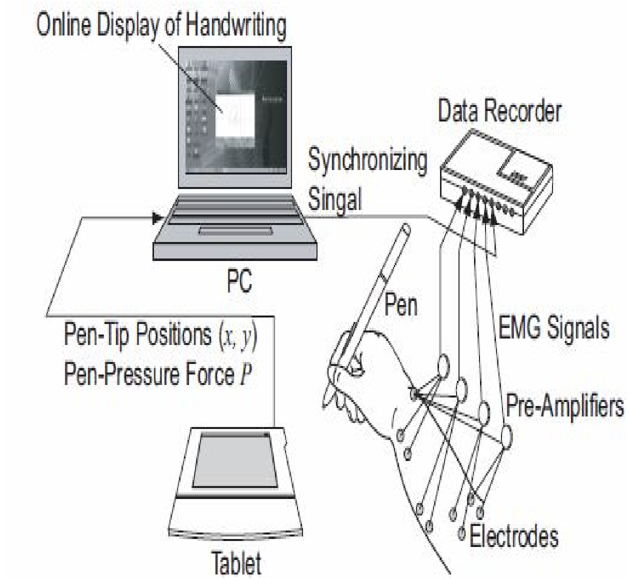


Figure 1. Experimental assembly [5]

The experimental study was carried out by eight writers aged between twenty-two and twenty-three years old in order to obtain a database containing several Arabic letters, namely the letter (SIN), the letter (HA) and letter (AYN), and eight basic geometrical forms, table1.

Table 1. Arabic letters and geometric forms written during the experiment

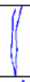
Description	Form	Description	Form
Line left to right and then back to starting point		Closed triangle in a clockwise motion	
Line from right to left and back to starting point		Closed triangle in a movement to the left	
Line from top to bottom then return to the starting point		Arabic letter « AYN »	
Line from bottom to top and back to the starting point		Arabic letter « SIN »	
Circle in a clockwise motion		Arabic letter « HA »	
Circle in a movement to the left			

Figure 2 illustrate an example of the Arabic letter “SIN” and figure 3 shows the pen-tip movements according to x and y directions in addition to the electromyographic signals EMG (CH1) and EMG (CH2) for the same letter.

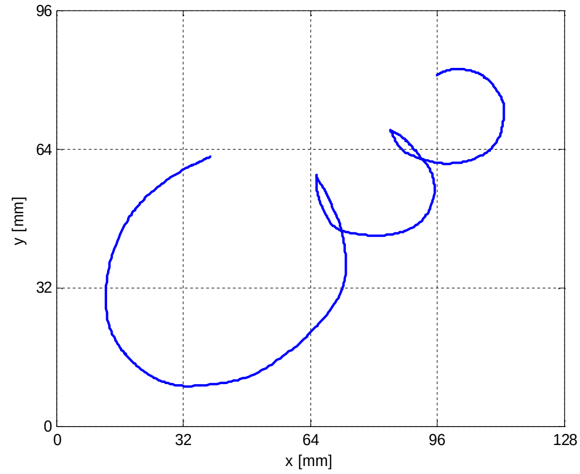


Figure 2. Form of the Arabic letter “SIN”

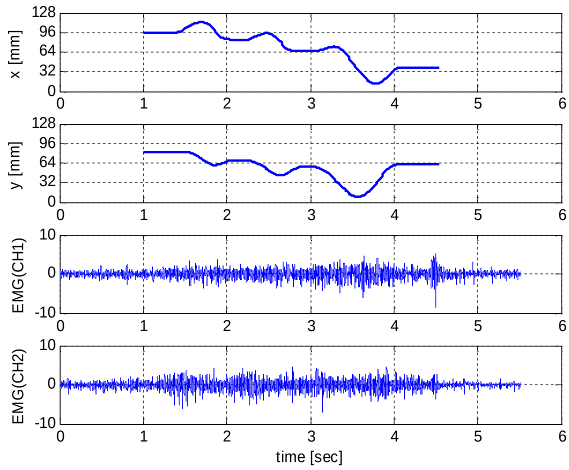


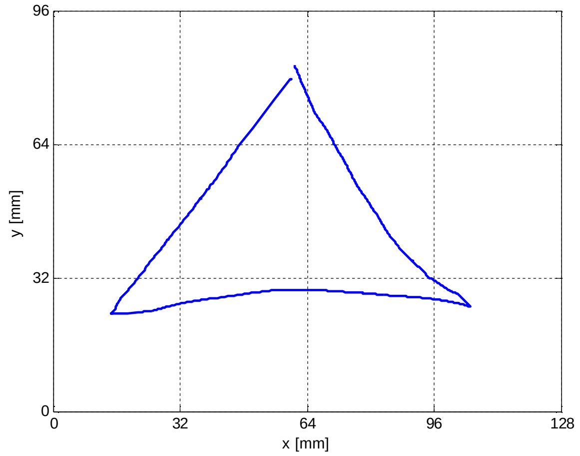
Figure 3. Movements according to x and y directions and EMG signals of the Arabic letter “SIN”

Parasites due to noise are one of the most harmful factors to acquire as much information as possible of the EMG signal. Indeed, the EMG signals recorded during the experimental protocol correspond to the spatial-temporal summation of action’s potentials emitted during muscle contraction.

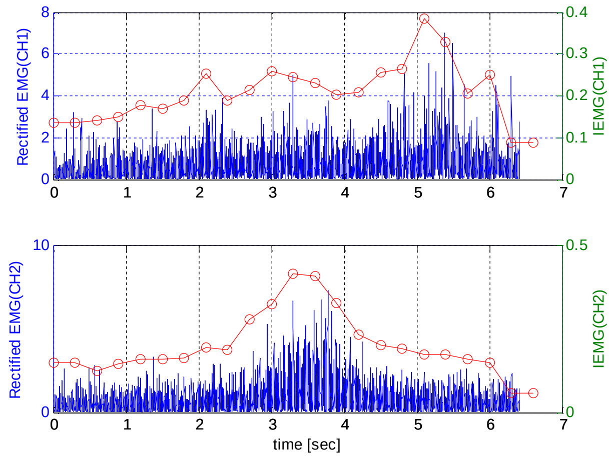
These signals present transitory phenomena or disturbed segments and other disturbing signals due to various sources such as electromagnetic phenomena of the sector and the parasites associated with electrodes and measurement uncertainties [9]. This requires the introduction of the biomedical signal processing approaches to obtain a signal easy to study which is the Integrated Electromyographic signal (IEMG).

After the recovery of the EMG signal’s full wave (Full Wave Rectification) calculating the absolute value of the EMG signal, the obtained signal is then divided into time intervals of fixed duration, and then integrated for each interval [5]. An interpolation is finally carried out between the various values in order to obtain the curve noted IEMG.

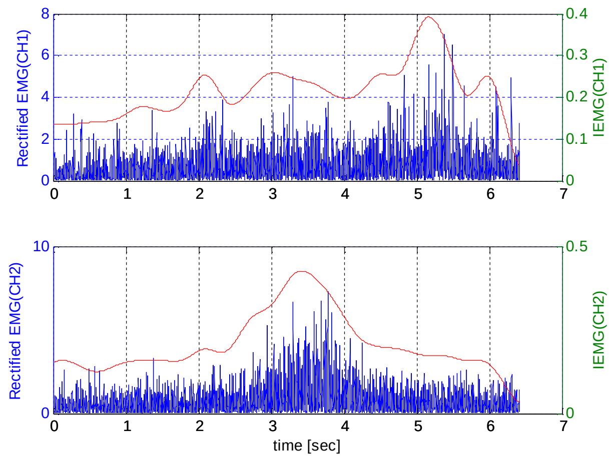
Figure 4 illustrates an example of the geometric form “triangle” (a) and the full-wave rectified EMG and IEMG for (CH1) and (CH2) (b), in addition to the wave form of integred electromyographic signals IEMG (CH1) and IEMG (CH2) (c).



(a)



(b)



(c)

Figure 4. The geometric form (triangle)
(a) Form,
(b) Full-wave rectified EMG and IEMG,
(c) Wave form of integred EMG signals (IEMG)

III. RBF Neural Network Proposed Models

The functions approximation is one of the main uses of multilayer neural networks and namely radial basis function neural networks. For a set of input/output data, the problem is to find a relationship between these two sets of variables. It is a question of developing an approximator of this often unknown relation by choosing its structure and by calibrating it properly so that it best represents the dependence between its inputs and outputs.

A. Design of artificial neural networks

One of the most difficult tasks is to design an artificial neural network able to solve complex problems, because there is no approach that provides an optimized and ideal architecture. Indeed, a too large neural network can lead to a good learning without obtaining a capacity of generalization, this is due to the over fitting problem. On the other hand, a too small neural network even optimized may have unsatisfactory results.

The construction algorithms have as a basic principle to start from a small network, usually containing a single neuron. The neurons are then added successively one by one or in groups to achieve the desired performance [10], [11], [12] and [13]. A repetition of the network learning is necessary after each neuron add operation since the neural network structure changes each time. The convergence of such a type of algorithm depends mainly on the universal approximation properties of the network structure.

However, the implementation of this type of algorithm remains very expensive in computing times as well as storage space if the size of the network reaches important dimensions. Two solutions have been proposed in order to reduce the learning time: the first, known as the method of allocating resources, combines the global adjustment process of the network weights with the storage of the obtained structure weight at the previous iteration.

This method is mainly used in the case of the RBF neural network construction; it consists in adding a new neuron to the network only if the presented vector for the training is regarded as sufficiently new; that means: whether the effective network output differs from the desired output by an amount greater than a certain fixed value. If not, that means: if the presented vector is introduced close enough to the center of the radial function characterizing a neuron network, the weights of this neuron are adjusted to take account of this vector [14], [15]. The algorithm RAN "Resource Allocating Network" of radial basis function neural network construction presents a typical example of this method [16]. The second solution consists in adjusting only the weights of the last added neuron. This method leads to the assumption that each neuron models the function to be approximated over an interval. In this case, if learning is performed for this interval, it is unnecessary to repeat it with each addition of a new neuron. Therefore, only the learning of this last neuron weights is necessary, the connection weights of the other neurons are maintained fixed. This is repeated until we no longer observe significant changes in the performances of the network under construction. Such an approach may not lead to an optimal set of weights for the entire network. At the end of construction, a last learning should generally be made to finely adjust the whole of the weights [14], [15].

B. Radial basis function neural networks

The RBF network architecture consists of only three layers, an input layer ensuring the transmission of the entries without distortion, a hidden layer which contains the neurons with radial basis functions and an output layer which is a simple layer containing one neuron with linear function. Each layer is completely connected to the next, figure 5.

Each neuron in the hidden layer performs a nonlinear transformation of the input space; these neurons provide the calculation of the internal states of activation. The output layer computes a linear combination of the neurons' outputs in the hidden layer, balanced by the synaptic weights w_i connecting the hidden layer neurons to the output layer neuron [14].

The equation characterizing such a network is described as follows:

$$y_i = \sum_{i=1}^{N} w_i \varphi(\|x-c_i\|)+w_0 \quad (1)$$

with:

c_i : The activation function center φ ,

$w_i \ (i=1,2,...,n)$: The synaptic weights of the network,

$x = [x_1, x_2, ..., x_n]$: The inputs vector,

w_0 : The bias.

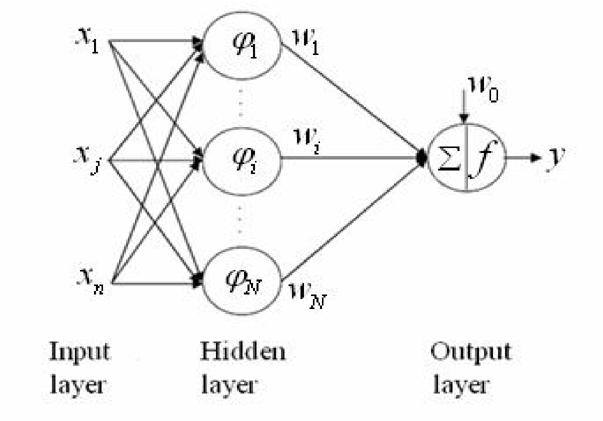


Figure 5. Structure of RBF neural network

$\varphi(\|x-c_i\|)$ are the activation functions of the hidden neurons, defined from IR to IR^+ . The denomination of neurons with radial basis functions is relative to the activation functions which are symmetrical compared to a point.

In the literature, there's whole panoply of radial functions among which we can quote, [17]:

Multi-quadratic kernel : $\varphi(v) = \sqrt{(v^2-\sigma^2)}$ (2)

Thin plate kernel : $\varphi(v) = v^2 \log(v)$ (3)

Gaussian kernel : $\varphi(v) = \exp\left(-\frac{v^2}{2\sigma^2}\right)$ (4)

with: v is the non-negative value of the distance between the input vector x and the center of radial basis function c_i .

Among the various radial functions, the Gaussian kernel is the most widespread and most commonly used in the design of RBF neural networks. The value of its output is more important as the entry is closer to the center, whereas it tends to zero when the distance between the entry-center becomes important. The parameter σ can control the speed of the function φ ; it is related to the width of the core factor of Gaussian activation function that should be chosen judiciously, figure 6.

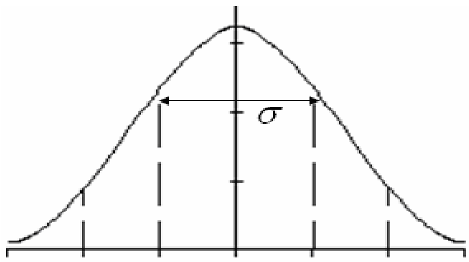


Figure 6. Structure of a Gaussian kernel

The output of a neuron i with a Gaussian kernel is given by the following expression:

$$\varphi_i(x) = \exp\left(-\frac{\|x-c_i\|}{2\sigma^2}\right) \quad (5)$$

The network output is simply a linear combination of the outputs of neurons with radial basis functions multiplied by the weight of their respective connections, figure 7.

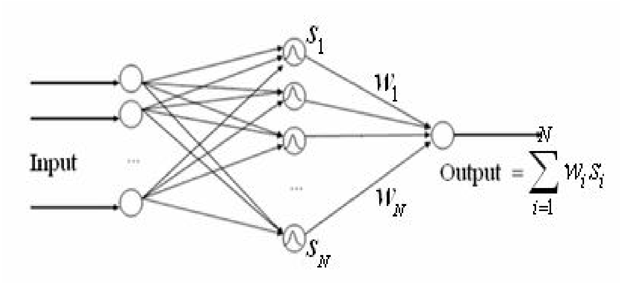


Figure 7. Illustration of the output of RBF neural network

If the general form of the activation function is chosen, the learning of numerical parameters of RBF neural network can be achieved. In RBF neural network, the parameters to adjust are:

- The number and positions of the centers c_i of each neuron Gaussians.
- The width factors σ_i of the Gaussians.
- The synaptic weights w_N of connections between hidden neurons and output neuron.

Any change in one of these parameters involves directly a change in the behavior of the network, hence the need for learning [18].

C. *Direct modelling*

The objective of this part is the modeling of the direct model generating a graphic trace, as response to the electromyographic signals. The inputs of the proposed model are the IEMG1 and IEMG2 signals. Its outputs x and y are respectively the positions of the pen tip according to the x-axis and y-axis.

The proposed model is based on an unconventional approach namely RBF neural networks [19]. Its structure is a closed loop network with one hidden Gaussian kernels layer. The inputs of the neural model are the IEMG signals of the two considered muscles, delayed at times: k, k-1, k-2 and k-3 as well as the x and y positions at: k, k-1, k-2 and k-3. The outputs are the x and y position at time k+1, figure 8.

The direct experimental model was built basing on the principle of construction algorithms of artificial neural networks. Indeed, starting from a small network with five Gaussian kernels neurons, network construction is then completed by adding at each step of building five new neurons in the hidden layer until reaching the desired performance. After several experimental tests, the choice was fixed on the addition of five neurons at each new step of construction and not less in order to avoid the slow learning and especially the overlearning of the network [14], [20], [21] and [22].

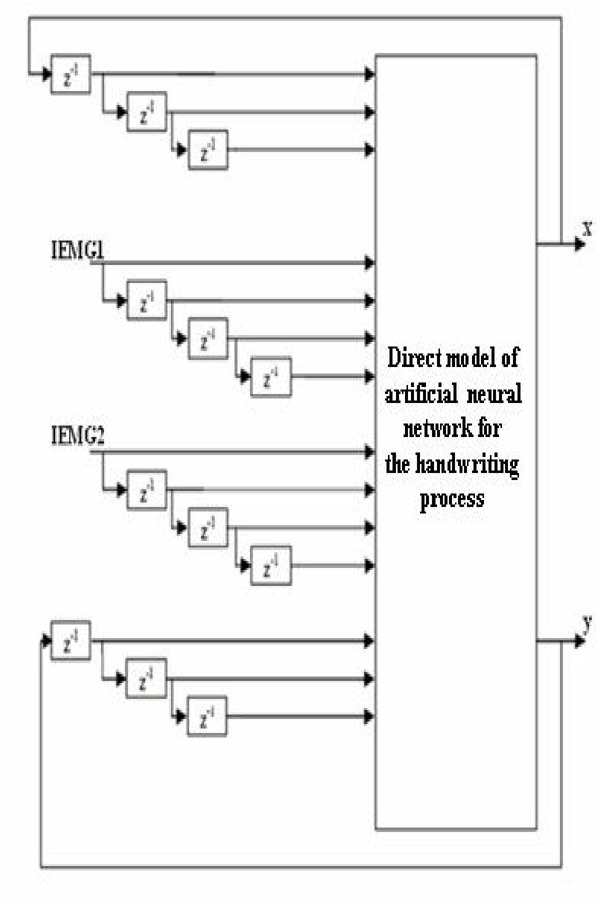


Figure 8. Direct neuronal model structure of the handwriting process

For a given writer, the developed neuronal model synthesizes the writing of Arabic letters or simple geometric forms. Figures 9, 10, 11 and 12 show the learning performance of the neural network developed for example of Arabic letters and geometric forms, as well as the response of the neuronal model to experimental learnt data.

ED is the Experimental Data and NMR is the Neural Model Response.

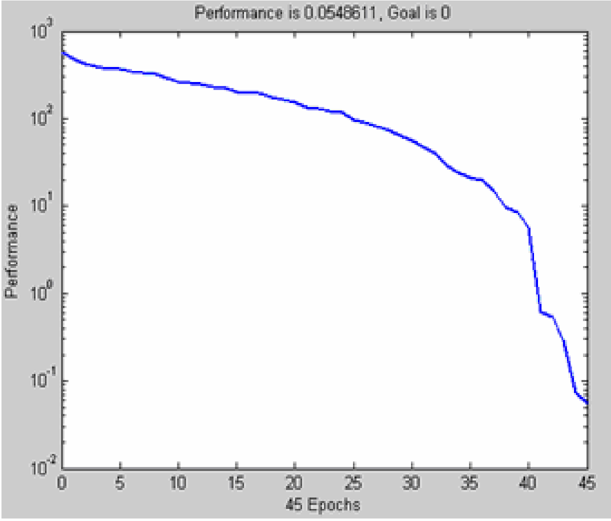


Figure 9. Learning performance of neural model for the Arabic letter "SIN"

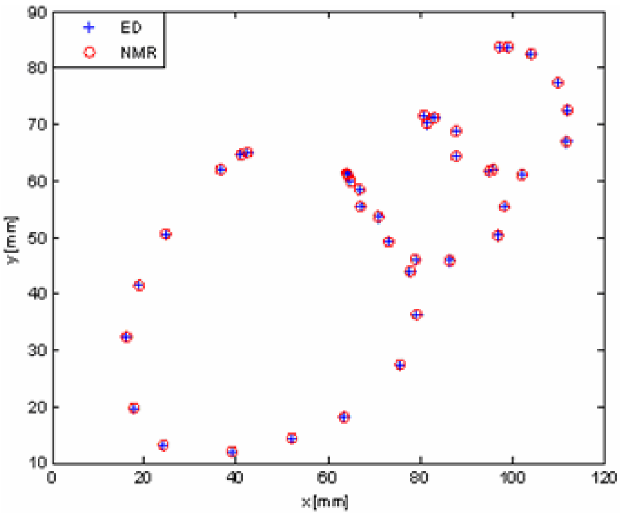


Figure 10. Responses for learnt data of the Arabic letter "SIN"

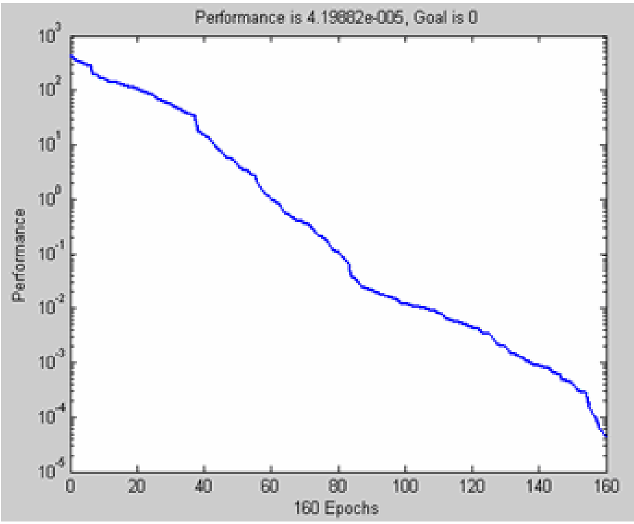


Figure 11. Learning performance of neural model for the geometric form "triangle"

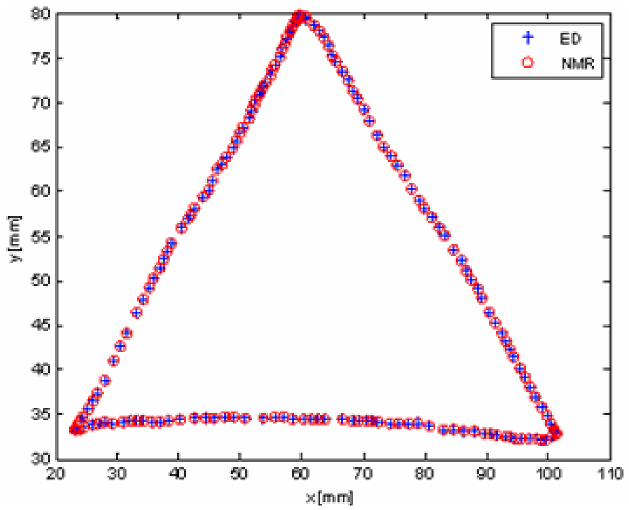


Figure 12. Responses for learnt data of the geometric form "triangle"

The simulation results show a satisfactory agreement between the responses of the developed model and the experimental data for various letters and forms.

As part of the validation of developed neural model, unlearnt data were considered for the different neural networks relative to forms and letters, figures 13 and 14.

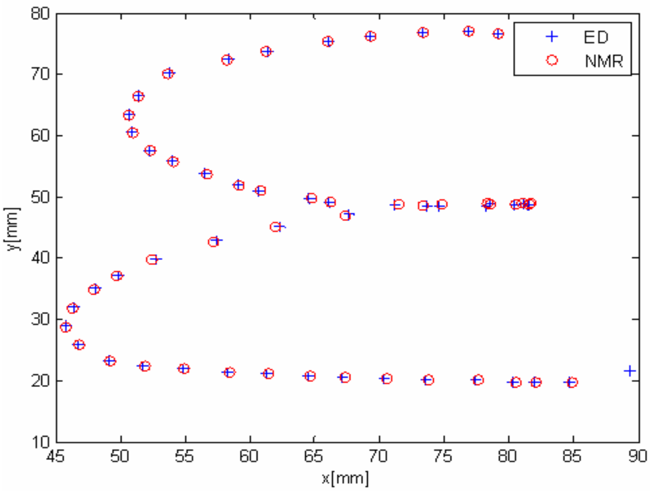


Figure 13. Direct neural model responses to the writing of the unlearned data of the Arabic letter "AYN"

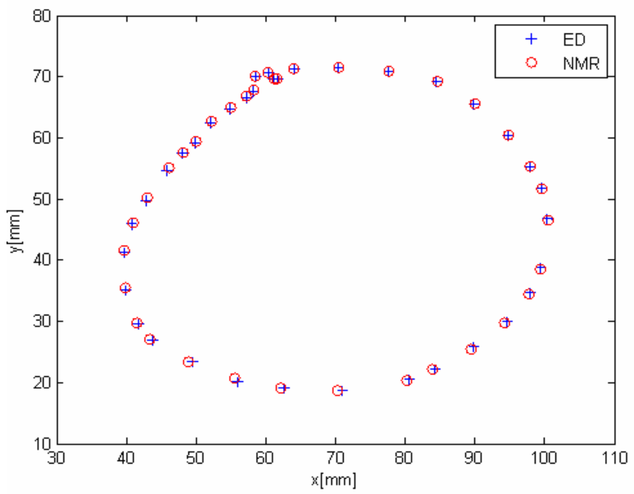


Figure 14. Direct neural model responses to the writing of the unlearned data of the geometric form "circle"

With a few small differences, the simulation results show satisfactory correspondences between the experimental data and the neural model response in the case of handwritten Arabic letters and geometric forms.

D. Inverse modelling

The objective of this part is the reconstitution of the integrated electromyographic waves parting from pen-tip displacements along the x and y-axis. The inputs of the proposed model are x and y positions while the outputs are the IEMG1 and IEMG2 signals.

The same construction principle used in the direct neural modeling approach is considered to build the inverse model [22].

The proposed neural network is a closed loop network with one hidden Gaussian kernels layer. The inputs of the neural model are the x and y positions at: k, k-1, k-2 and k-3 and IEMG signals of the two considered muscles, delayed at times: k, k -1, k-2 and k-3. The outputs are the IEMG1 and IEMG2 waves at time k +1, figure 15.

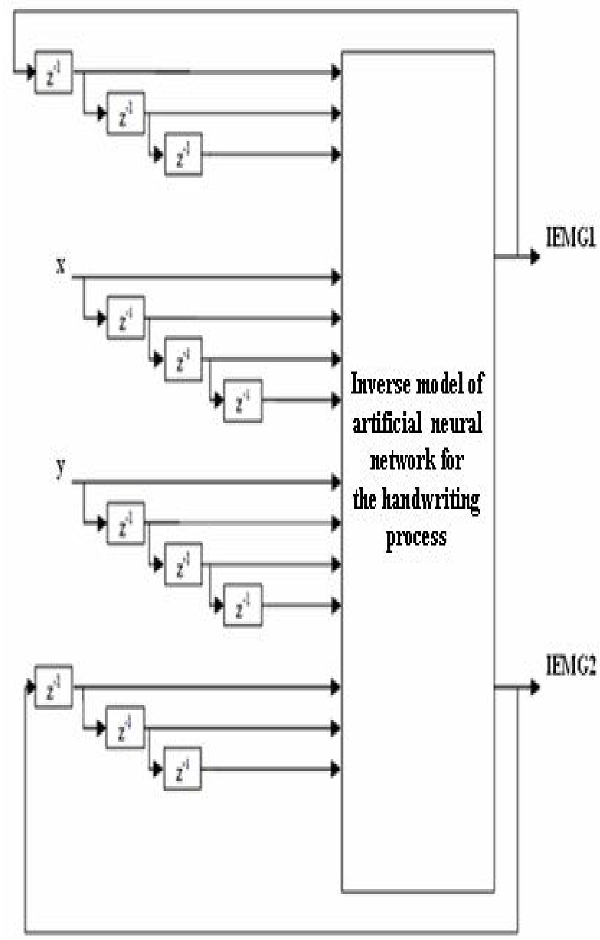


Figure 15. Inverse neural model structure of the handwriting process

Considering a given writer, an inverse neural model is developed to reproduce the IEMG1 and IEMG2 waves, relative to Arabic letters or simple geometric forms.

Figures 16, 17, 18 and 19 show the learning performance of the developed neural network for examples of Arabic letters and geometric forms, as well as its response to learnt experimental data.

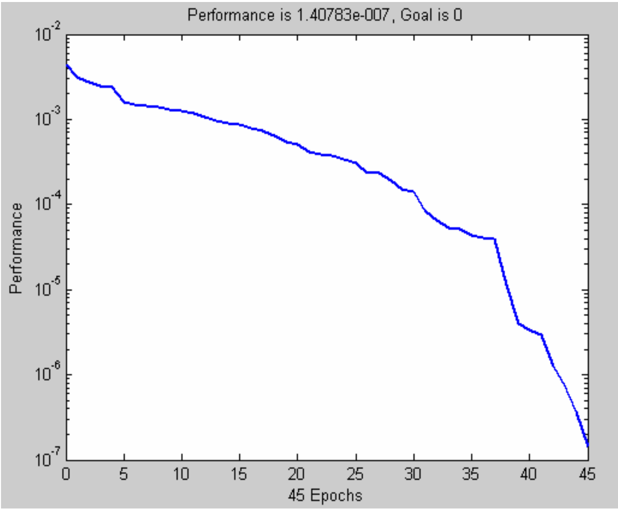
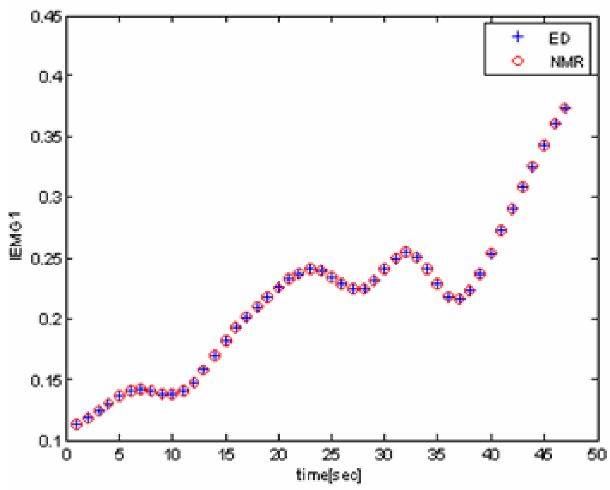
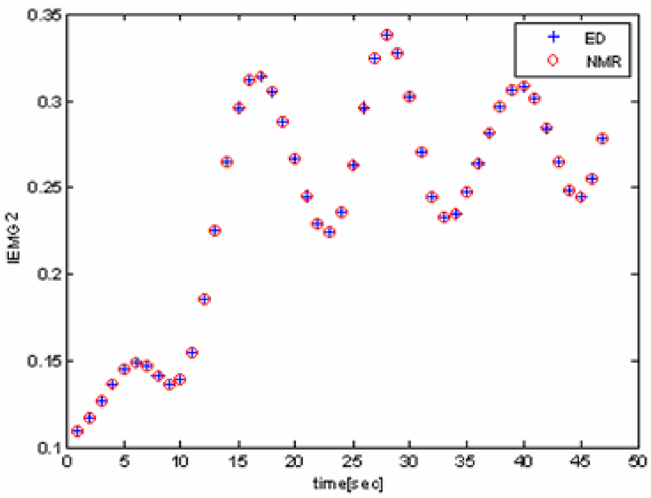


Figure 16. Learning performance of neural model for the Arabic letter "SIN"



(a)



(b)

Figure 17. Experimental data and neural model response corresponding to learnt points of IEMG1 (a) and IEMG2 (b) for the Arabic letter "SIN"

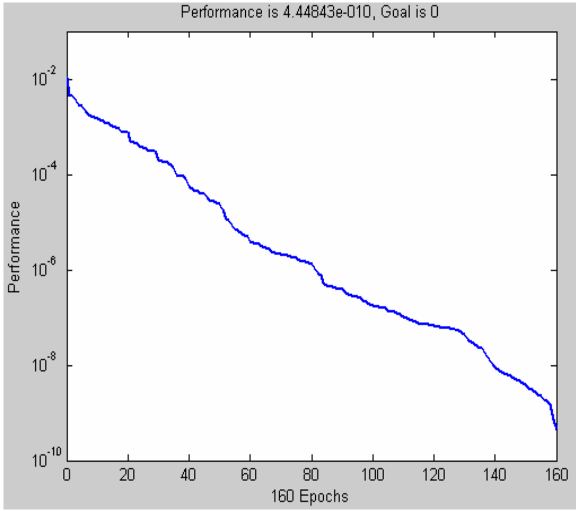
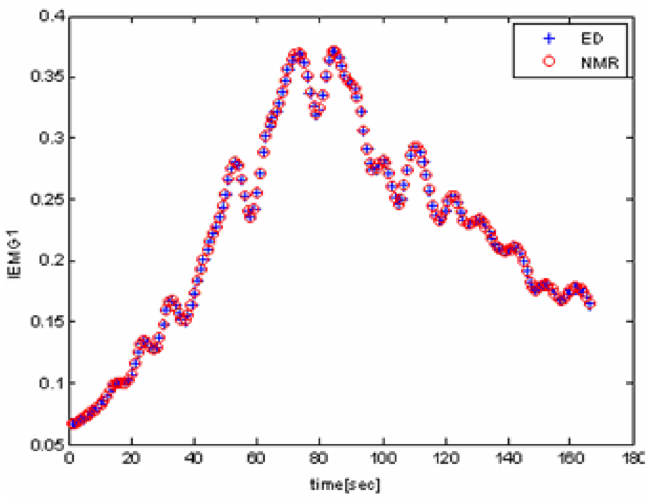
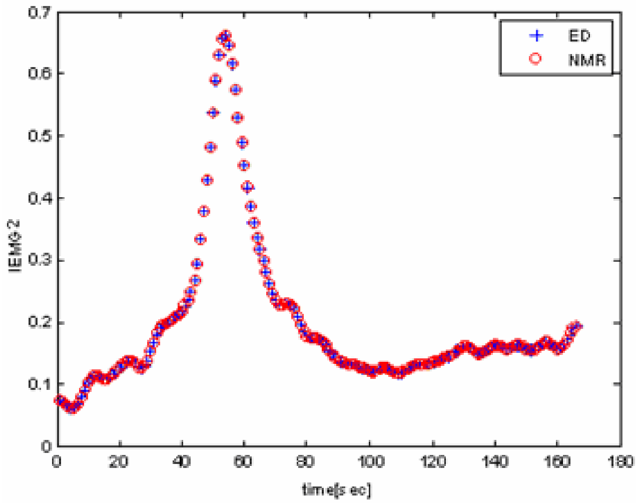


Figure 18. Learning performance of neural model for the geometric shape "triangle"



(a)

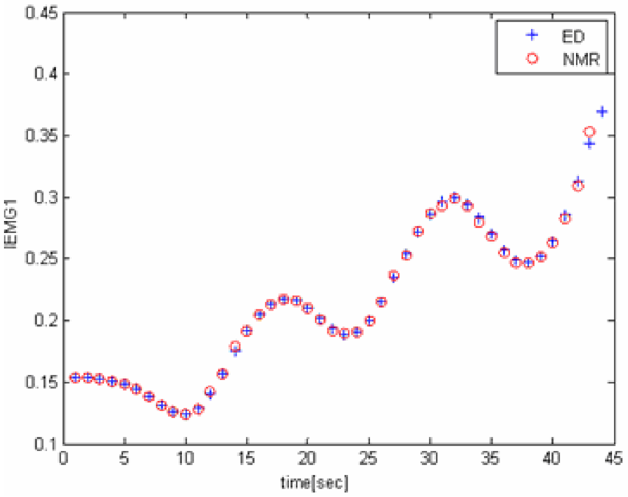


(b)

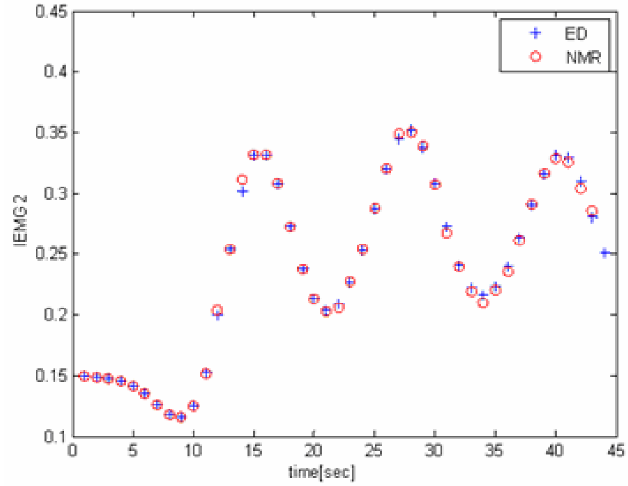
Figure 19. Experimental data and neural model response corresponding to learnt points of IEMG1 (a) and IEMG2 (b) for the geometric shape "triangle"

The responses of the inverse neural model proposed are in satisfactory agreement with the experimental data for traces of two IEMG signals for the various letters and geometric shapes.

As part of the validation of developed neural model, unlearnt data were considered for the different neural networks corresponding to letters and forms, figures 20 and 21.

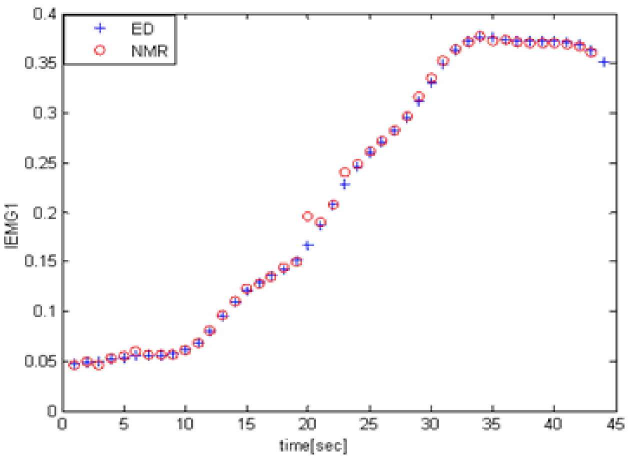


(a)

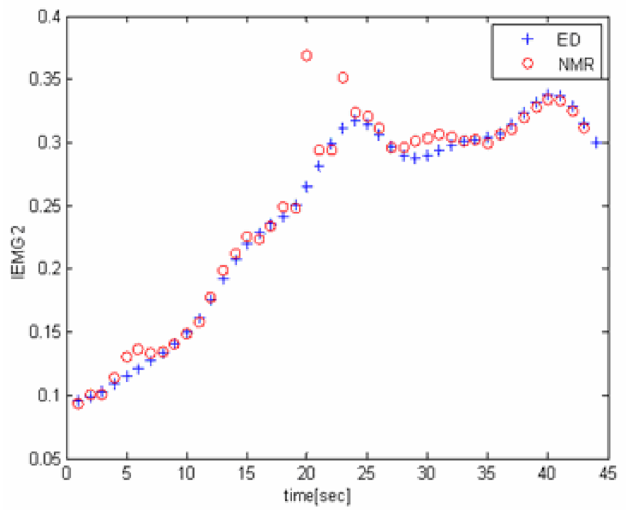


(b)

Figure 20. Inverse neural model responses to the trace of unlearned data from the IEMG1 (a) and IEMG2 (b) waves of the Arabic letter "SIN"



(a)



(b)

Figure 21. Inverse neural model responses to the trace of unlearned data from the IEMG1 (a) and IEMG2 (b) waves of the geometric form "circle"

With a few small differences, the simulation results show a satisfactory agreement between the responses of the developed inverse model and the experimental data for the traces of two IEMG signals of various letters and geometric forms.

IV. Cascading Proposed Models

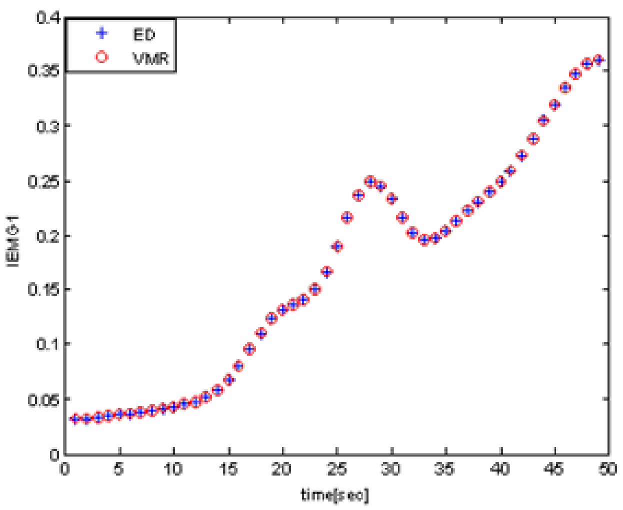
In order to validate the proposed direct and inverse models, two cascading procedures are proposed.

A. Direct model

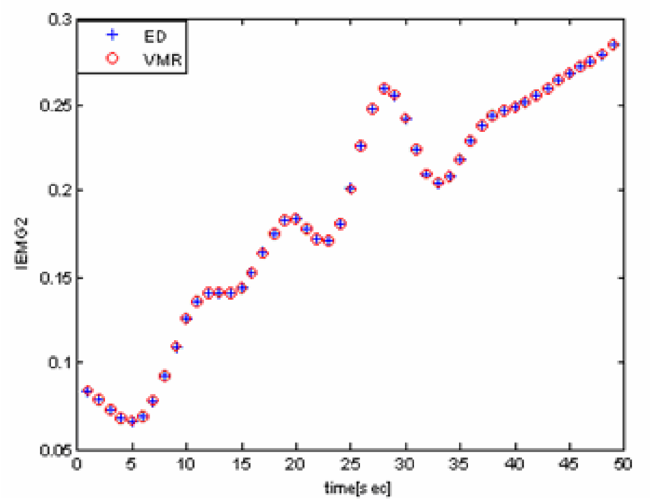
The first cascading procedure consists of applying the outputs of the direct model for a considered written shape as input to the inverse neuronal model already built. The purpose of the direct validation model is the reproduction of IEMG1 and IEMG2 signals starting from x and y positions obtained from the direct model.

Figures 22 and 23 show the response of the validation cascading procedure, corresponding to the Arabic letter "AYN" and the simple geometric shape "triangle".

VMR is the direct Validation Model Response.

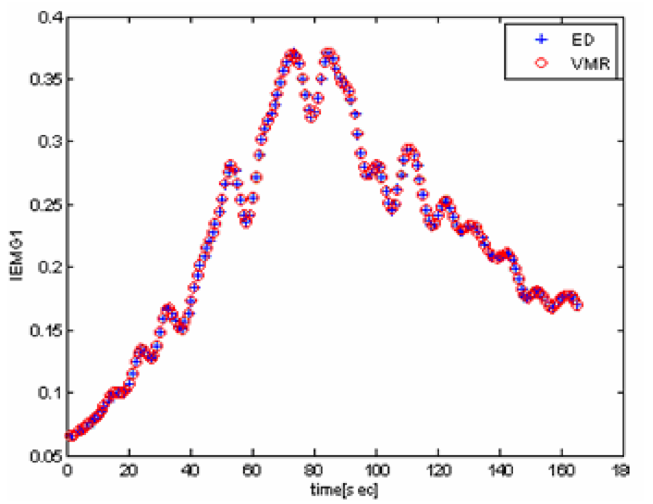


(a)

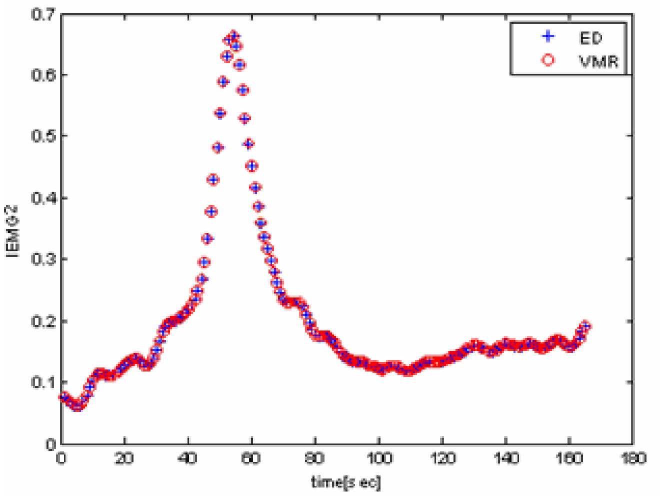


(b)

Figure 22. Responses of the direct validation mode to the trace of waves IEMG1 (a) and IEMG2 (b) of the Arabic letter "AYN"



(a)



(b)

Figure 23. Responses of the direct validation mode to the trace of waves IEMG1 (a) and IEMG2 (b) of the geometric shape "triangle"

Compared to experimental data, the developed cascading procedure leads to satisfactory reconstruction of IEMG signals obtained from x and y reconstructed positions for various Arabic letters and geometric forms.

B. Inverse model

In order to validate the experimental inverse neuronal model for a given writer a second cascading procedure is proposed. The outputs of the inverse neuronal model must be applied as inputs to the direct neuronal model already built.

The purpose of the inverse validation procedure is the reconstruction of the x and y traces of forms or handwritten letters of the experimental approach starting from IEMG signals calculated by inverse neural model.

Figures 24 and 25 show the response of the validation procedure for the inverse neuronal model outputs corresponding to the Arabic letter "HA" and simple geometric form "circle".

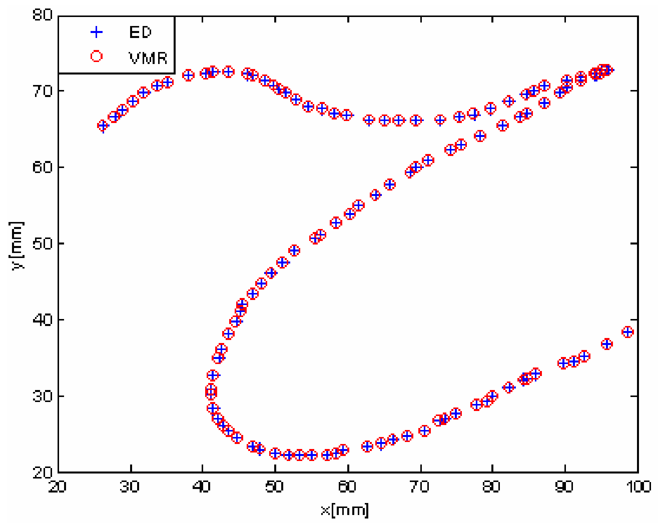


Figure 24. Responses of the inverse validation model with the trace of the Arabic letter "HA"

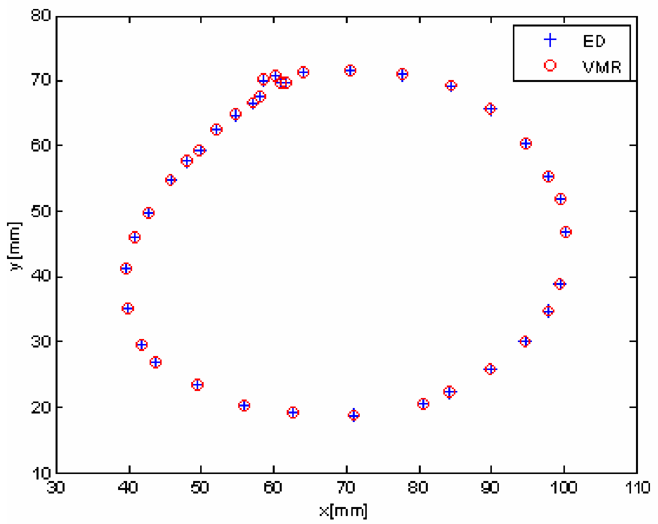


Figure 25. Responses of the inverse validation model with the trace of the geometric form "circle"

According to the experimental data, the proposed cascading procedure permits to well reconstruct x and y displacements parting from IEMG signals obtained from inverse proposed model.

V. Conclusion

The study of the handwriting process and the development of an RBF neural network using electromyographic signals, are the main contributions of this paper.

The proposed experimental approach allowed the acquisition of the muscular stimuli and the coordinates of the pen tip moving over the writing surface, according to time. These experimental measurements constituted a learning base for the development of a direct neuronal model and an inverse neuronal model for the studied process. The simulation results of neural suggested models are satisfactory and their validation for various writers was successful. It is very interesting to apply the study to the medical field to elaborate a system essentially helpful to those who suffer from physical handicaps.

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