Int. J. Appl. Math. Comput. Sci., 2000, Vol.10, No.4, 877–904

EXPLORING THE HUMAN HANDWRITING PROCESS

FAOUZI BOUSLAMA*, MOHAMED BENREJEB**

The study of human handwriting movements is of great interest to researchers and biologists. It can lead to an understanding of the properties of the biological system that generates the human handwriting movements. With the identification of a dynamical system that exhibits characteristics similar to the biological one, it is possible to study handwriting movements, to identify their driving motor signals and to try to reproduce by machine the handwriting motion. In this paper, we give an analysis of modeling techniques for the handwriting process proposed in the literature. We show that either mathematical models based on the trajectories of handwritten objects or physical models obtained from the dynamic motion of the human hand can be used for modeling the handwriting process. We study the handwriting movements using these approaches and we give an analysis and synthesis of the driving motor signals. We apply the results to the generation of handwritten Arabic letters. We then propose a new synthesis technique where a more promising and realistic model can be obtained. We present the basic idea and expect that some improvement over the previous techniques can be obtained. The technique is based on Feedback Error Learning neural networks.

Keywords: human handwriting, hand-muscle system, EMG signals, Van der Gon dynamic models, feedback error learning

1. Introduction

The benefits of studying the human handwriting process are numerous. Human handwriting movements characterize people and their study can explain any neurologic disorder or malfunction. They also play a major role in human communication. To analyze the hand movements, several representations of the hand-muscle system were proposed in the literature. The muscles in the hand receive their driving (motor) signals from the nerve system and move the hand to generate desired shapes and characters. The human hand performs a supervised learning action where the desired movement trajectory is known, but not the motor command. The goal of the movement is to move the hand to draw an exact image.

* Zayed University, College of Arts and Sciences, P.O. Box 4783, Abu Dhabi, United Arab Emirates, e-mail: `faouzi_bouslama@zu.ac.ae`

** Laboratoire de Recherche en Automatique, Ecole Nationale d'Ingénieurs de Tunis BP 37, Le Belvédere 1002 Tunis, Tunisia, e-mail: `mohamed.benrejeb@enit.rnu.tn`

In the literature, the study of the hand movements was based on proposed models. Several modeling techniques were used to derive motor driving signals and to simulate the handwriting process. Van der Gon and Thuring (1962) proposed a simple second-order linear system where the human hand was considered as a mass in a viscous medium. Van der Gon and his co-workers simulated samples of handwriting movements. The results were fairly good. However, the simulated versions differ in detail from the original ones. MacDonald (1966) proposed an electronic version of the simulator proposed by Van der Gon. He assumed that the acceleration of the hand movements could be expressed as a trapezoidal waveform. The friction force between the pen and the writing surface was ignored. Yasuhara (1975) proposed a refined version of Van der Gon's model including the effects on physical properties of the handwriting signals. The sliding friction force term between the pen and the writing surface was added. Yasuhara designed and constructed a handwriting analyzer by which measurements of the pen displacements, its velocity and acceleration, the writing pressure and the muscle forces were made. Yasuhara's model was used in the identification and decomposition of a fast handwriting system (Yasuhara, 1983). The automatic handwriting recognition and writer verification was carried out based on real-time signals. The model was then used to recognize cursively handwritten Arabic characters (Iguider and Yasuhara, 1996). The handwriting process was modeled by an autoregressive moving average model. The control pulses were extracted by a model reference adaptive control system. The method recognized well the actively handwritten characters. Edelman and Flash (1987) proposed a mathematical model based on the trajectories of the hand. Polynomial interpolation with cubic spline functions was used to generate the handwritten trajectories. Benrejeb *et al.* (2000) used the refined model of Yasuhara to determine the driving motor pulses of the handwriting movements obtained when Arabic characters were drawn. The global system of the hand and muscle is modeled. A stability analysis using the arrow-form matrix (Benrejeb, 1980) of the ensemble confirmed the stability of the hand-pen combination.

All these models, although succeeded in synthesizing the control pulses that drive the muscles, are rather simplified representations of the real physical model of the hand-muscle system. They are used under some assumptions and certain conditions. In this paper, a study of these approaches is given and an attempt to construct a model with more realistic features of the hand-muscle system is proposed. Bouslama *et al.* (1999) proposed to use the error feedback learning neural network in 1999. The new approach attempts to identify the inverse model of the handwriting process. The idea is based on Feedback Error Learning (FEL) techniques (Kawato *et al.*, 1987) which were proposed by Kawato (1990). Real-time data are used to train an FEL network in order to reproduce a specific handwriting dynamics. The trained system can then be used to identify characters stemming specifically from a particular user. The system can re-learn by adjusting its weights when presented with new data. Hence it is possible to produce any particular handwriting dynamics at the output.

2. Analysis of the Human Forearm Muscle

Hand movements result from the flexion and extension of the forearm muscles. Flexors are muscles that bring one body part closer to another. Extensors are muscles that extend a body part moving it further away. The flexors and extensors that generate the movements of the hand and fingers are located in the forearm. The flexors are on the inside of the forearm and the extensors are on the outside or back of the forearm. Any movement of the hand involves the use of a combination of several muscles of the forearm. Figure 1 shows the front and back muscles in the human arm.

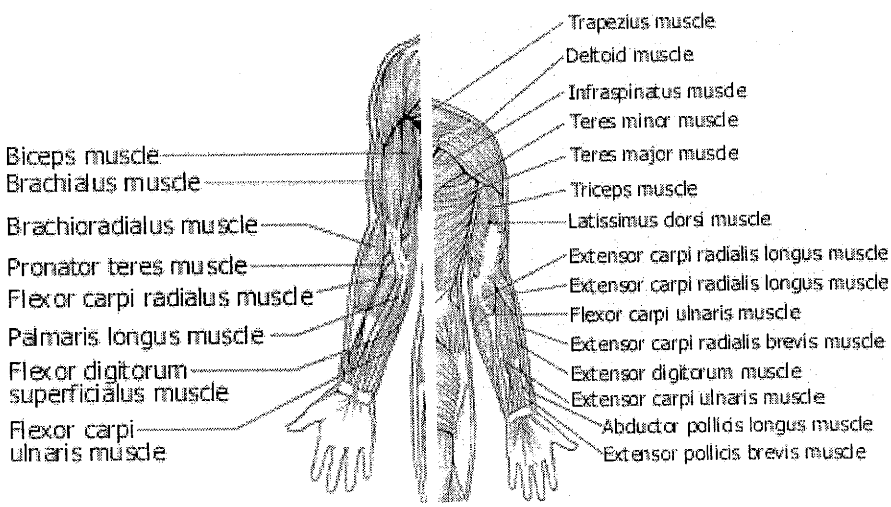


Fig. 1. Front and back muscles of the human arm.

There are two types of muscles in the forearm that perform the hand movements: the flexion muscles and the extension muscles. For the execution of the horizontal movements on a plane, the muscular activity is performed by the following muscles: the extension muscle or Carpi Ulnaris, and the abduction muscle or Pollicis Longus. For the vertical movements executed within the same plane, they are the results of the efforts provided by the flexion muscle or Digitorum Superficialis and the extension muscle or Digitorum Communis.

All these muscles play a major role in the execution of the movements related to the handwriting process. It is difficult to analyze the hand movements based on all these muscles. For simplification, the motion of the hand is formulated about the wrist joint. The movements at the wrist joint are those derived from the forearm and the hand. They can be decomposed into either an extension or a contraction of the arm or an abduction of the hand and the fingers.

During the handwriting process, the hand movements are complicated and cannot be interpreted in a simple model. However, if the hand movements are resolved into two principal and independent ones, and if the wrist joint is assumed fixed during those movements, then a simplified model that can interpret the movements can be formed.

3. Analysis of the Hand Muscles

The human hand is the most skilful part of the body. There are so many muscles involved in the complicated motion of the hand that an attempt to interpret it in terms of a simplified model does not lead to the right representation. Figure 2 shows the muscles of the hand.

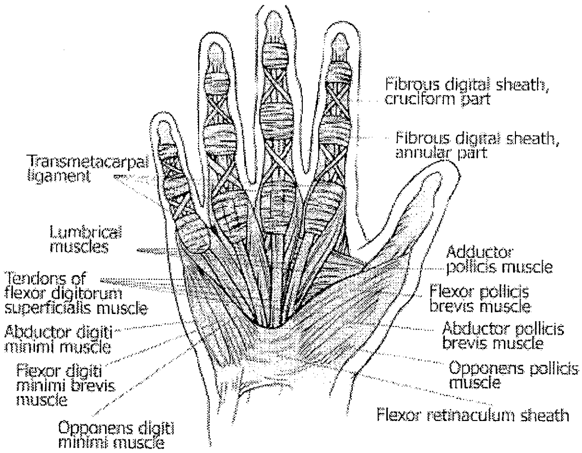


Fig. 2. Muscles of the hand.

To study the hand movements, many assumptions have to be made. In (Yasuhara, 1975), a simplified prototype model of the hand was presented where basic assumptions such as the independence of the radial-ulnar and volar-dorsal abductions were made. This means that the hand movements are resolved into two principal movements. Other assumptions such as the existence of a fixed point in the wrist joint of the hand during movements help in the development of a simplified model.

To study hand movements, a space coordinate system denoted by (x', y', z') is fixed in the space and coincides with the fixed point of the wrist joint. Another system of coordinates, called the body system, (x, y, z) is fixed on the hand and its origin is chosen so as to coincide with that of the space coordinate system as shown in Fig. 3.

The rotary movements around the x'-axis correspond to the volar-dorsal adbuction of the hand. The angular velocities are given by

$$\omega_x = \dot{\theta}, \quad \omega_z = \dot{\phi}\cos\theta, \tag{1}$$

where it has been noticed that the rotation angles θ are between -85 and 85 degrees. The rotary movements around the z'-axis represent the radial-ulnar abduction of the hand where the rotation angles ϕ are between -27 and 27 degrees.

The hand movements of rotation can then be described by the following model:

$$\begin{aligned} J_{o/x}\dot{\omega}_x + K'_x\omega_x &= M_x, \\ J_{o/z}\dot{\omega}_z + K'_z\omega_z &= M_z, \end{aligned} \tag{2}$$

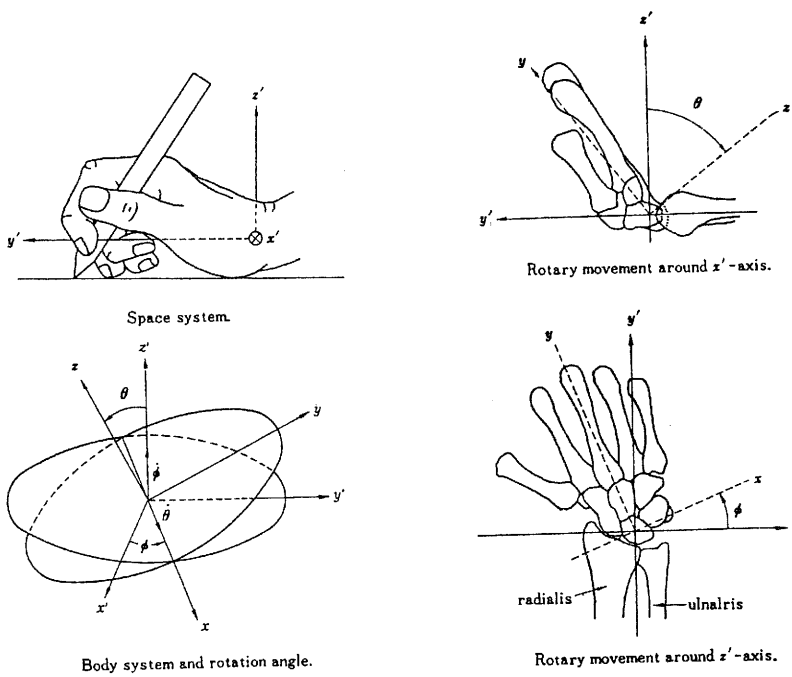


Fig. 3. Space and hand coordinate systems.

where ω_x, and ω_z are the angular velocities of the hand along the x and z axes, respectively. K'_x and K'_z are the intrinsic coefficients of viscosity of the wrist joint, $J_{o/x}$ and $J_{o/z}$ are the moments of inertia with respect to the x and z axes, and m_x, m_z are the moments of rotation around the x and z axes, respectively.

The dynamic model of the hand is then given by the differential equations

$$\begin{aligned} &\ddot{\theta} + k'_x\dot{\theta} = m_x, \\ &\ddot{\phi}\cos\theta + \dot{\phi}\left(k'_z\cos\theta - \dot{\theta}\sin\theta\right) = m_z, \end{aligned} \tag{3}$$

where $k'_x = K'_x/J_{o/x}$, $k'_z = K'_z/J_{o/z}$, $m_{\mathrm{x}} = M_{\mathrm{x}}/J_{o/x}$, $m_{\mathrm{z}} = M_{\mathrm{z}}/J_{o/x}$.

4. Simulation of the Hand Movements

It is difficult to evaluate the moments of inertia of the hand. We take a simplified model where the hand is considered as a rectangle being 6.5 cm across and 12 cm long. The following dynamic model then describes the hand movements:

$$\begin{aligned} &\ddot{\theta} + 4.7\dot{\theta} = m_x, \\ &\ddot{\phi}\cos\theta + \dot{\phi}\left(4.7\cos\theta - \dot{\theta}\sin\theta\right) = m_z. \end{aligned} \tag{4}$$

The hand movements are defined by the angles θ and ϕ. In response to the driving moments m_x and m_z applied to the hand, the hand performs movements as is shown in the simulation results of Figs. 4 and 5. The excitation signals are a unit step function for θ equal to 1.4835 rad that corresponds to an angle of 85 degrees and a unit step function for ϕ equal to 0.4712 rad that corresponds to an angle of 27 degrees.

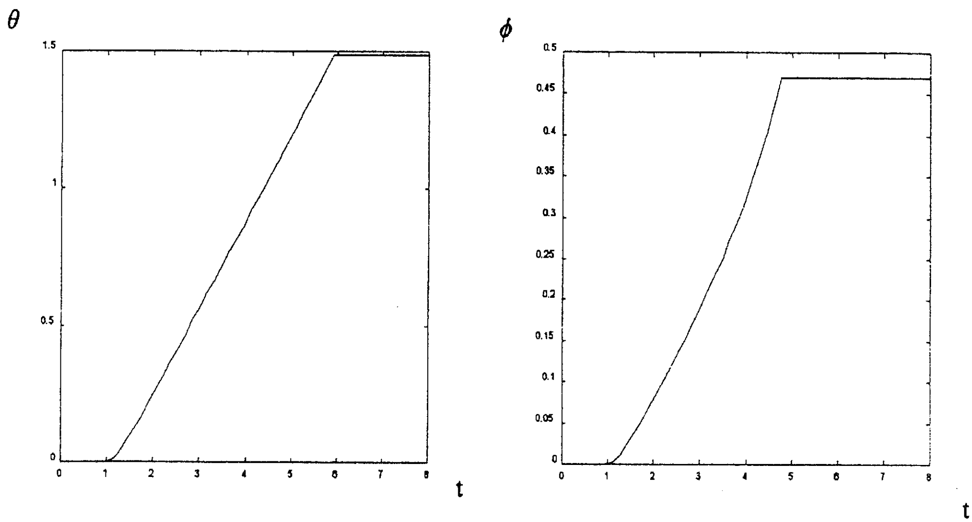


Fig. 4. Hand responses with respect to the x and z axes.

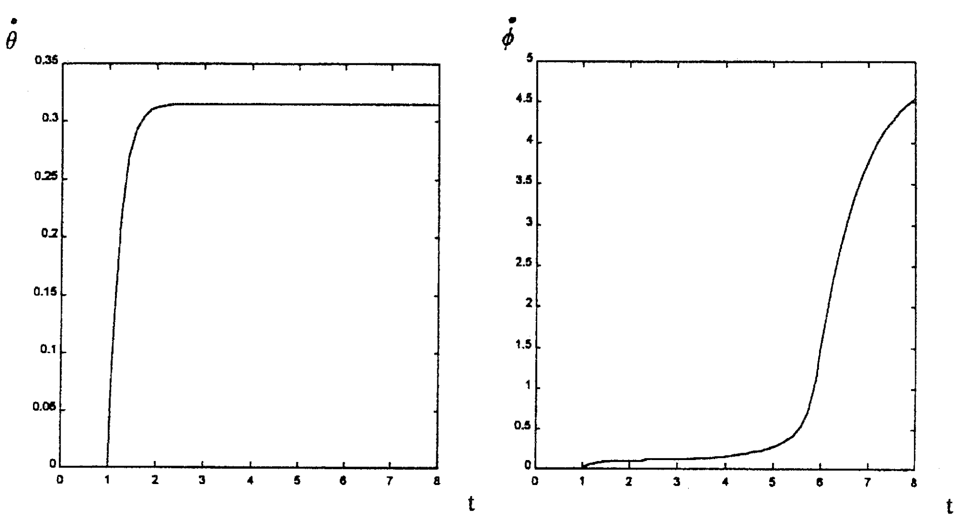


Fig. 5. Angular velocities of the hand along the x and z axes.

These figures show that the variations of the angle θ corresponding to the movements along the x-axis are non-decreasing. During the pen lifting the hand continues its movement at a constant speed up to the maximum value of 85 degrees. For the angle ϕ, the variations depend on those of the angle θ as was explained in (Ayadi, 1999).

5. Measurement of the Muscle Driving Signals

Figure 6 shows the experimental setup used in the handwriting process and signal measurements. An object is drawn on a graphic tablet using a special pen that emits the coordinates of the plotted points at a constant frequency. The graphic tablet has an x-y dimension of 12800 by 9600 with a resolution of 2540 lines per inch. An object is represented by a sequence of points separated by signs indicating when the pen has been lifted from the tablet surface. While the shapes of objects are drawn on the tablet, an electromyographic (EMG) device, a TEAC DR-C2 signal recorder, is used to detect and record the EMG signals.

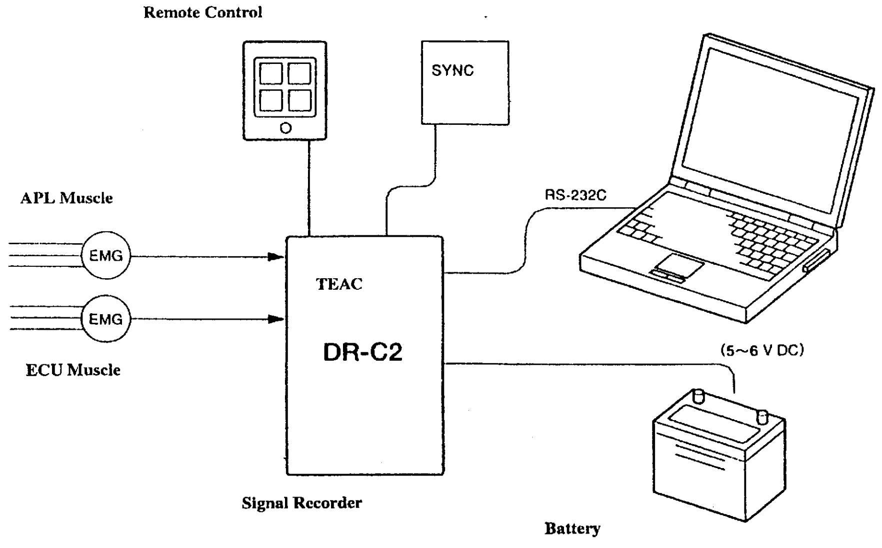


Fig. 6. Experimental setup.

The muscles to be studied are fairly large in size and located just under the forearm skin. We have selected two forearm muscles which have a well-defined response, and are relatively isolated from other muscles. One muscle was selected in the middle of the front forearm and the other on the back of the forearm. We use the surface type of electrodes having small silver discs at their ends. The electrodes are used in pairs with a common ground where the positive and negative electrodes are placed about 2 cm apart. Recording electrodes are placed over the belly of the muscle to be studied. The recorded signals, electrical changes, are amplified where the maximum voltage is set to 500 mV and the signals are later sampled at a rate of 2000 pulses per second. An aluminum sheet of foil covers the subject's hand and the electrodes so as to minimize the effects of noise and surrounding disturbances.

The Arabic handwriting system was used as an example. Three Arabic characters are chosen for testing. A subject was asked to follow in his handwriting the prototypes for the Arabic letters AYN, SIN and HE shown in Fig. 7. The subject writes the letters at a regular writing speed while fixing his hand wrist and only moving his hand. Figure 8 shows the handwritten sample of the letter AYN. We denote the first sample by AYN_1. Figure 9 presents the x and y displacements of the drawn letter AYN_1, whereas Fig. 10 shows the recorded EMG signals corresponding to AYN_1. In (Yasuhara, 1975), the author proposed a method of estimating the muscular force. The EMG bursts were rectified and the average was calculated.

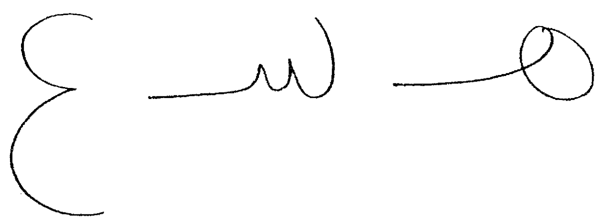


Fig. 7. Original samples of handwritten Arabic characters.

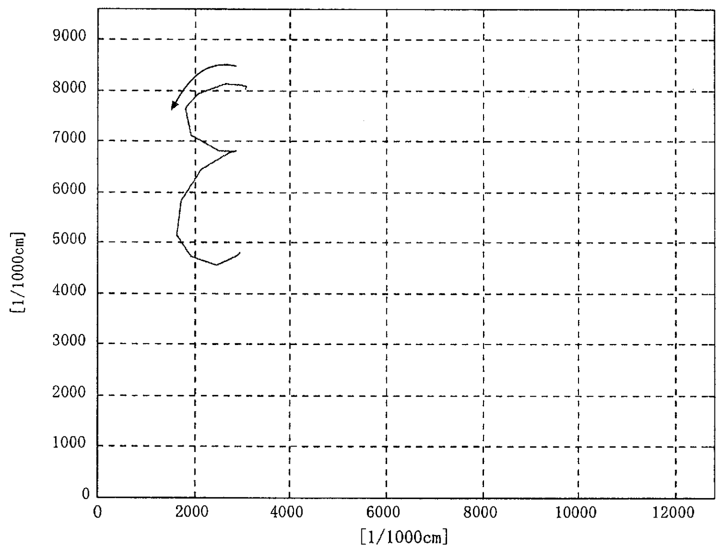


Fig. 8. A handwritten sample: AYN_1.

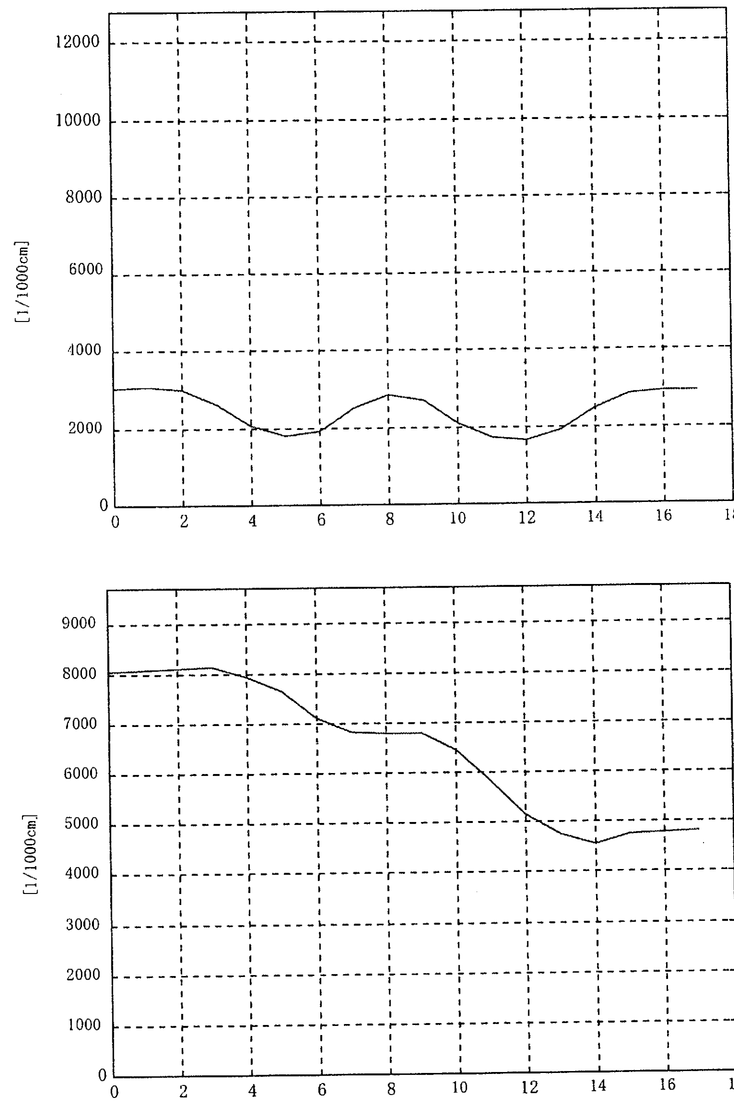


Fig. 9. The x and y displacements of AYN_1.

Now, we take another handwritten sample of the letter AYN. We test the repeatability of the recorded EMG signals. Figure 11 shows the handwritten sample and Fig. 12 gives the corresponding x and y displacements. The EMG signals are displayed in Fig. 13. In fact, we obtained the results shown in Fig. 13, which are in accordance with those obtained in Fig. 10.

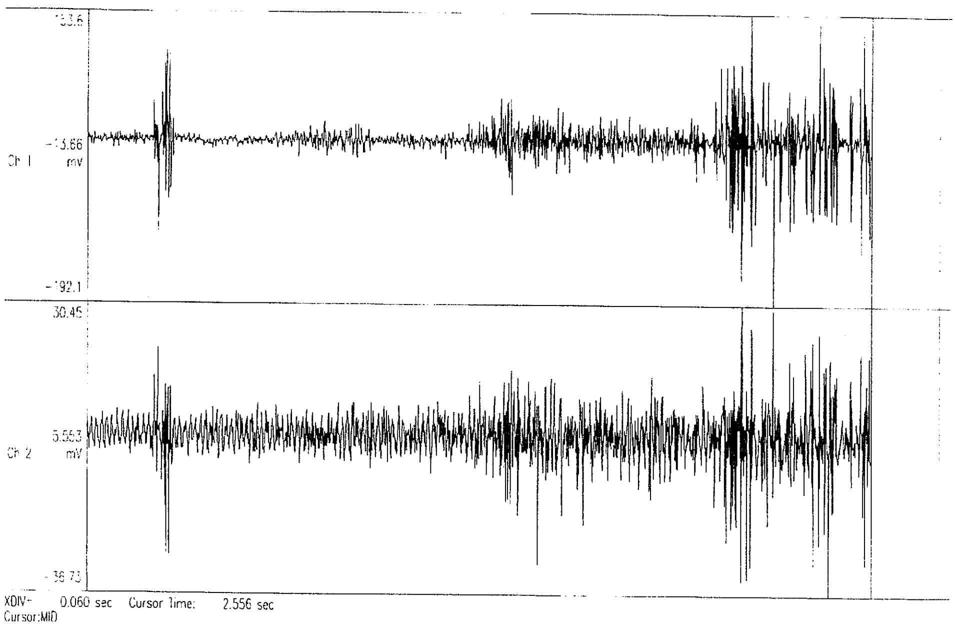


Fig. 10. EMG signals for the letter AYN_1.

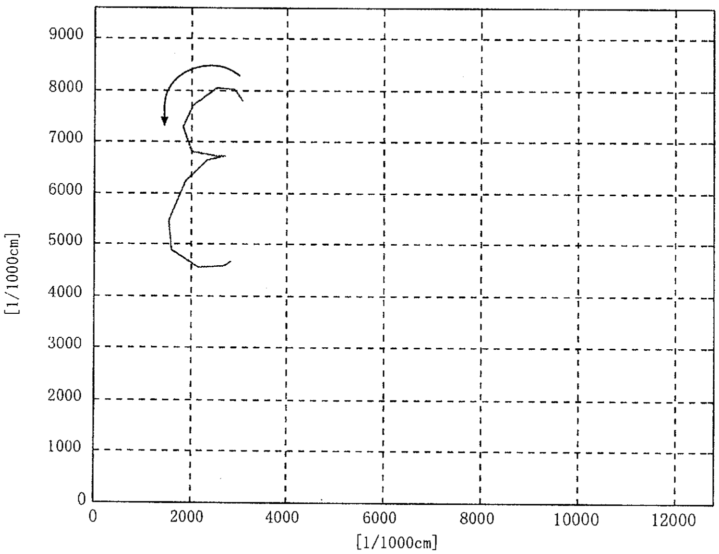


Fig. 11. Another handwritten sample: AYN_2.

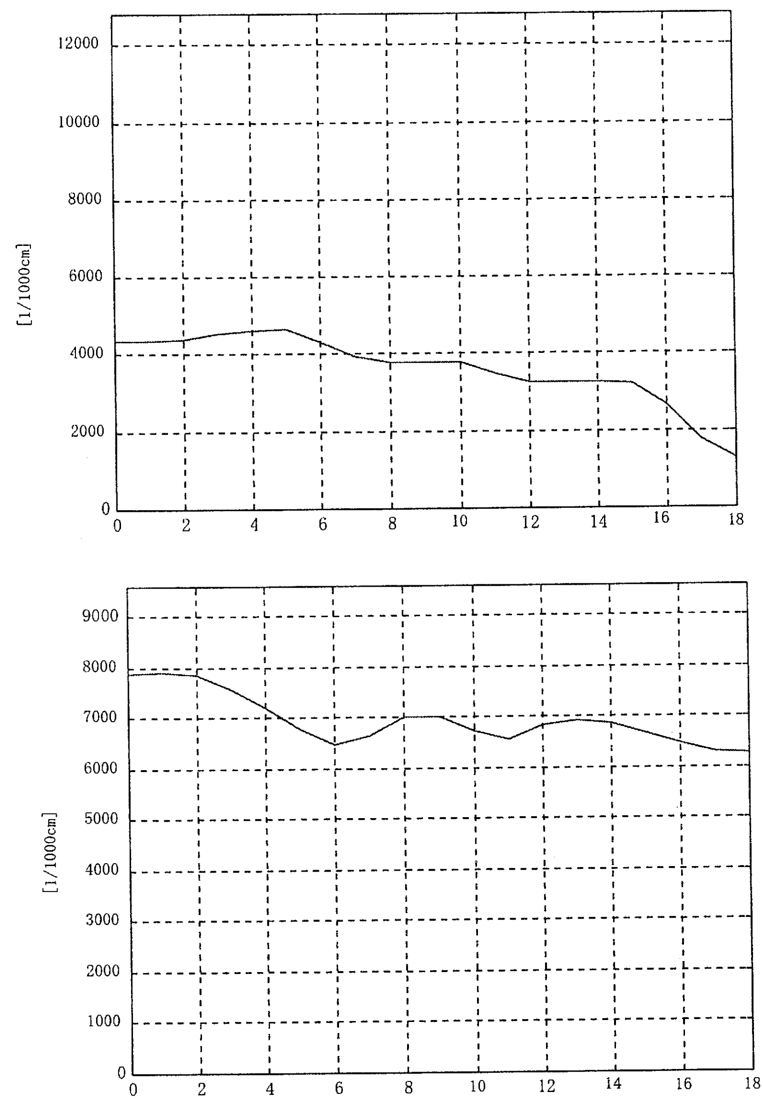


Fig. 12. The x and y displacements of AYN_2

In both the EMG records, except for the starting part with no muscle activity and the noisy ending part, we have noticed the presence of three active regions corresponding to the activation of the forearm muscles. From these results, we notice that the chosen muscles exhibit the same number of major peaks. In other words, they are related to similar types of the hand motion. As for the Arabic letter AYN, we can characterize it by the presence of three major activation regions related to the chosen muscles.

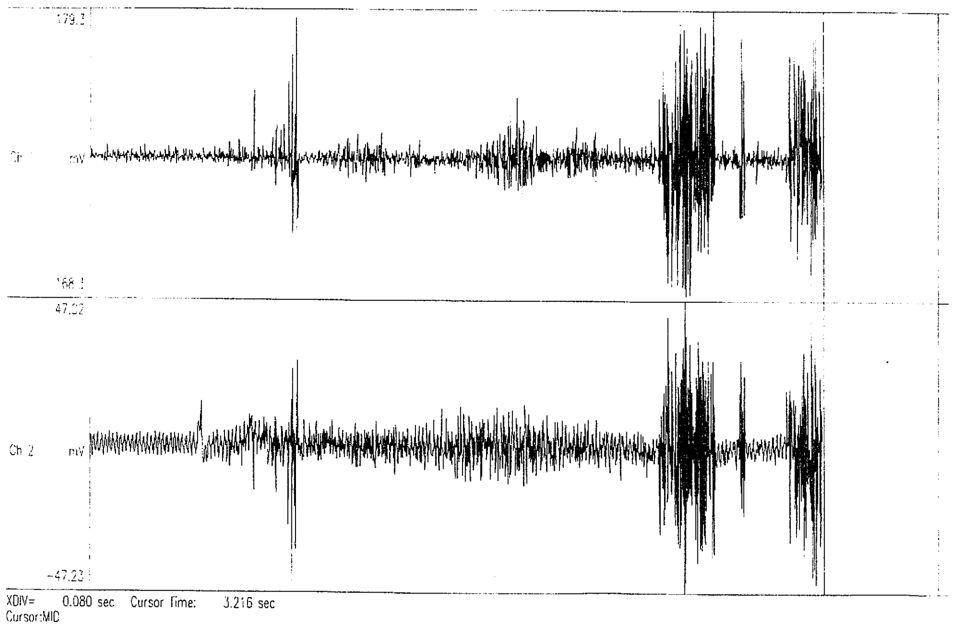


Fig. 13. The EMG signals of AYN_2.

We have conducted feature detection tests on other Arabic samples. Figure 14 shows the x-y plot of the letter SIN that was handwritten by the same subject. Figure 15 shows the corresponding x and y displacements. The EMG signals are depicted in Fig. 16. The starting and ending parts of the record are noisy. Here, we can observe the presence of three major activity regions related to the three cusps of the letter SIN.

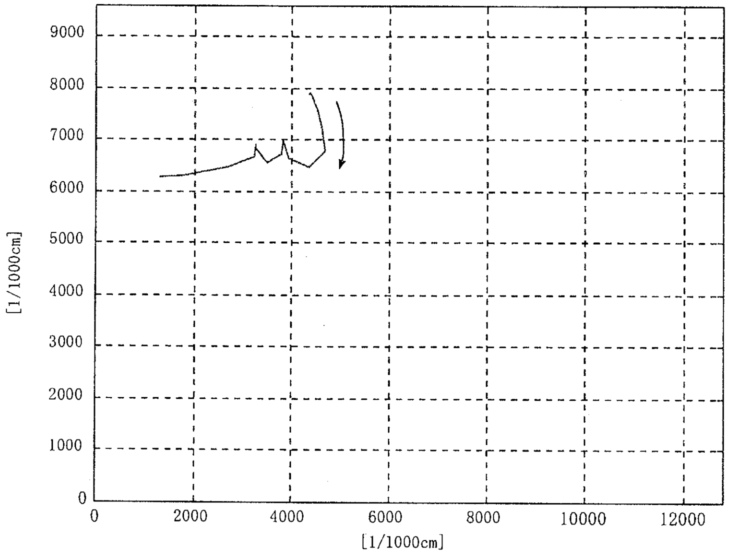


Fig. 14. A handwritten sample of the letter SIN.

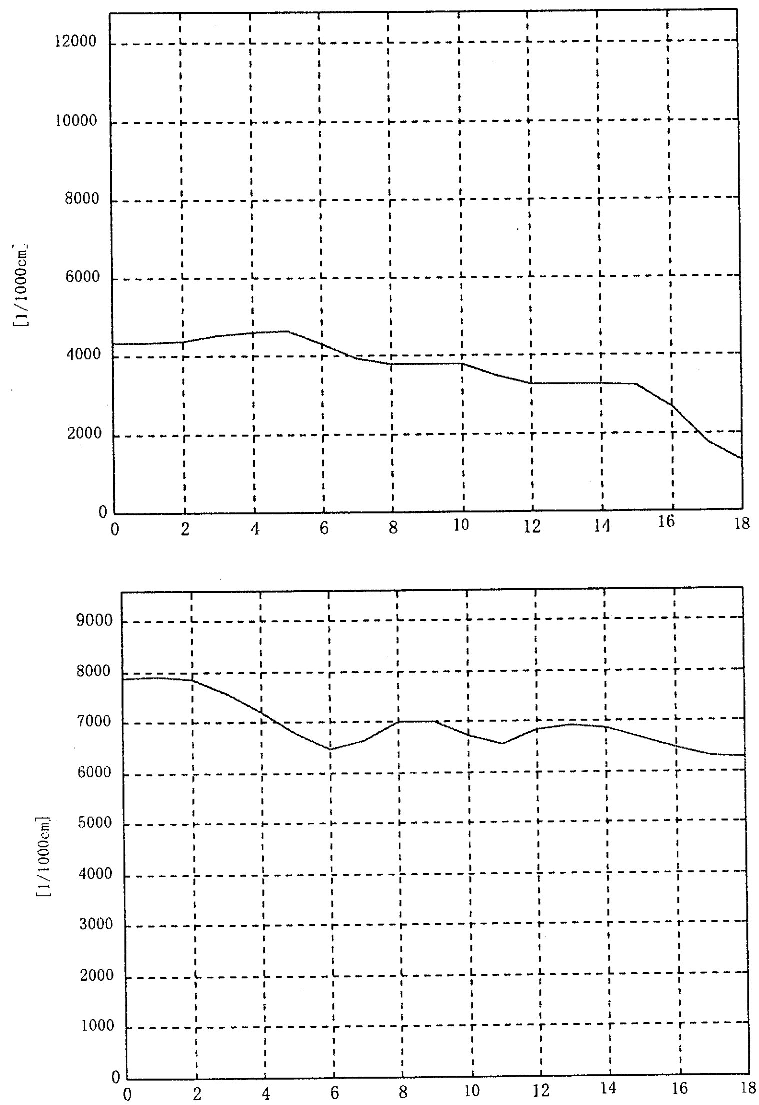


Fig. 15. The x and y displacements of the letter SIN.

The next EMG record was conducted on the letter HE. This Arabic character has geometrical features that differ from those of the letters AYN and SIN. Figure 17 shows the x-y plot recorded on the graphic tablet by the same subject when using the prototype of Fig. 7. Figure 18 gives the corresponding x and y displacements. The EMG signals corresponding to the letter HE are shown in Fig. 19. Here, we can observe the presence of two different regions of activity. The first region on the left corresponds to the circular displacement of the pen and the second part showing no muscle activity depicts the ending horizontal line of the letter HE.

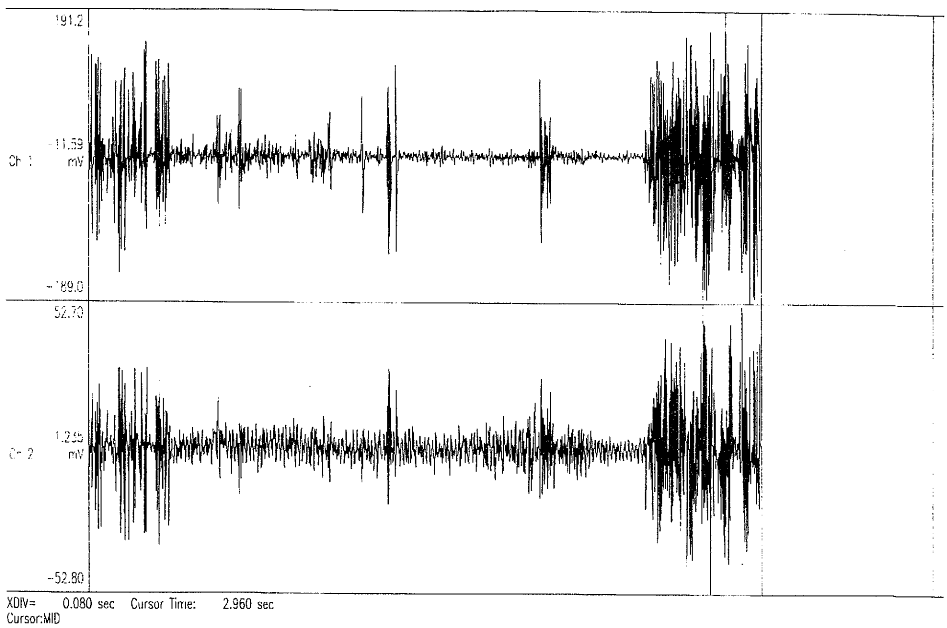


Fig. 16. The EMG signals of the letter SIN.

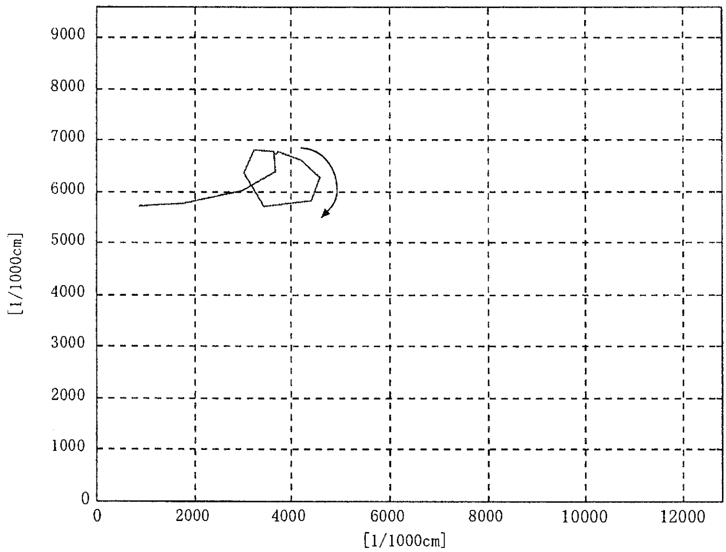


Fig. 17. A handwritten sample of the letter HE.

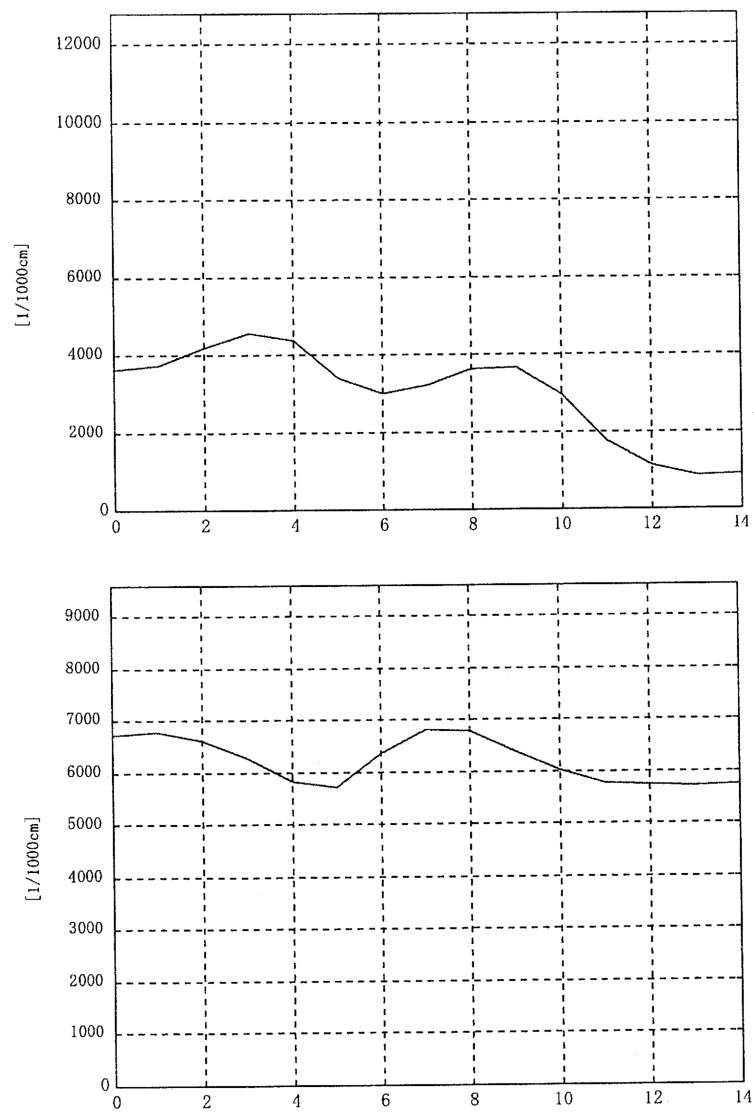


Fig. 18. The x and y displacements of the letter HE.

To identify the relationship between the activity of the chosen muscles and the direction of the hand displacement, we made an EMG record of the hand when it moves in a left-to-right horizontal motion. Figure 20 shows the x-y plot recorded on the graphic tablet by the same subject. Figures 21 and 22 show the corresponding x and y displacements. As shown in Fig. 22, there was no record of any muscle activity. The ending part of the record constitutes just noise.

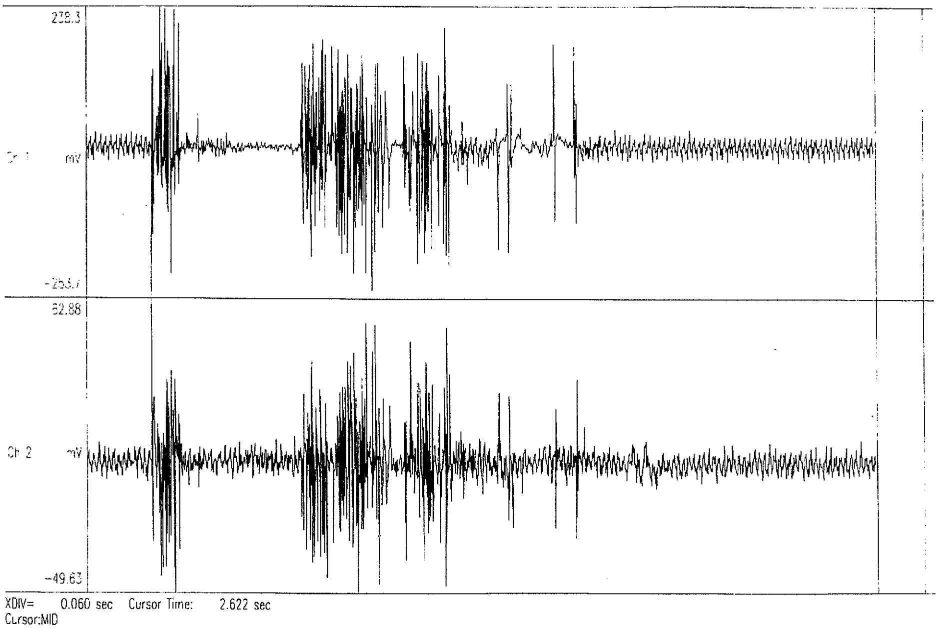


Fig. 19. The EMG signals for the letter HE.

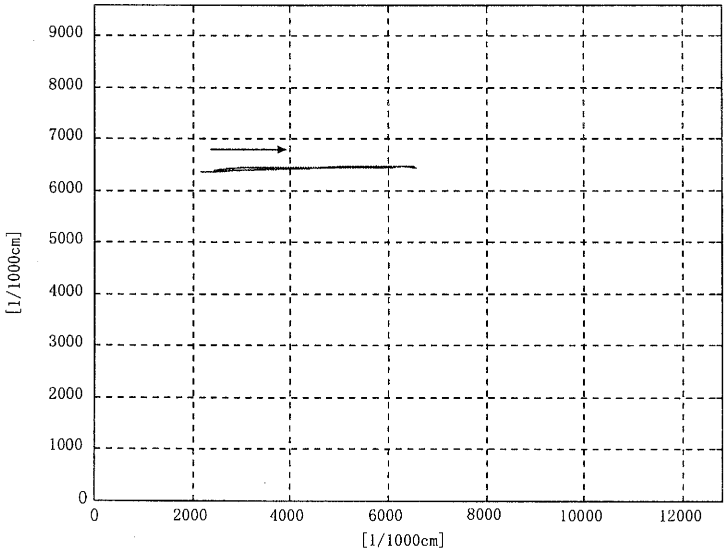


Fig. 20. Left-to-right movements of the hand.

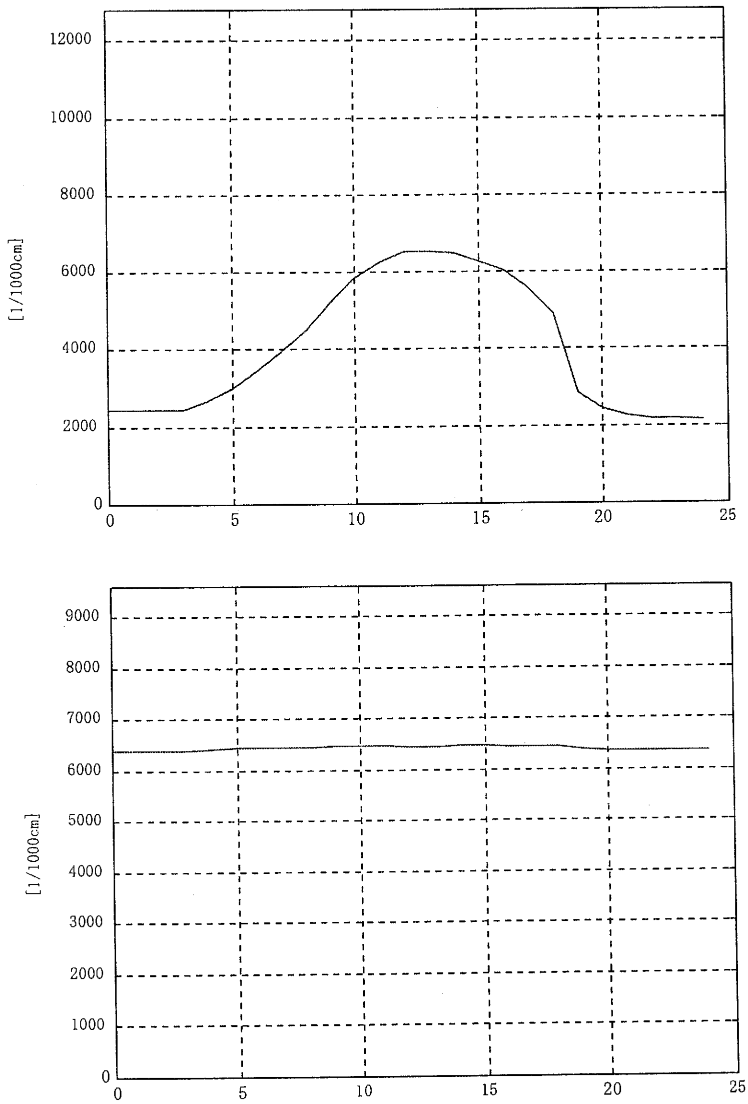


Fig. 21. The x and y displacements of the left-to-right motion.

Now we make an EMG record of the hand when it moves in a downward vertical-type of motion. Figure 23 shows the x-y plot recorded on the graphic tablet by the same subject. Figure 24 gives the corresponding x and y displacements. Now, the muscle activity, as shown in Fig. 25, is very obvious. We conclude that the chosen muscles reflect the movements of the hand in the vertical direction. We also recorded the EMG signals, cf. Fig. 26, when the pen is just pressed against the surface of the table. We took another record of the noise presence.

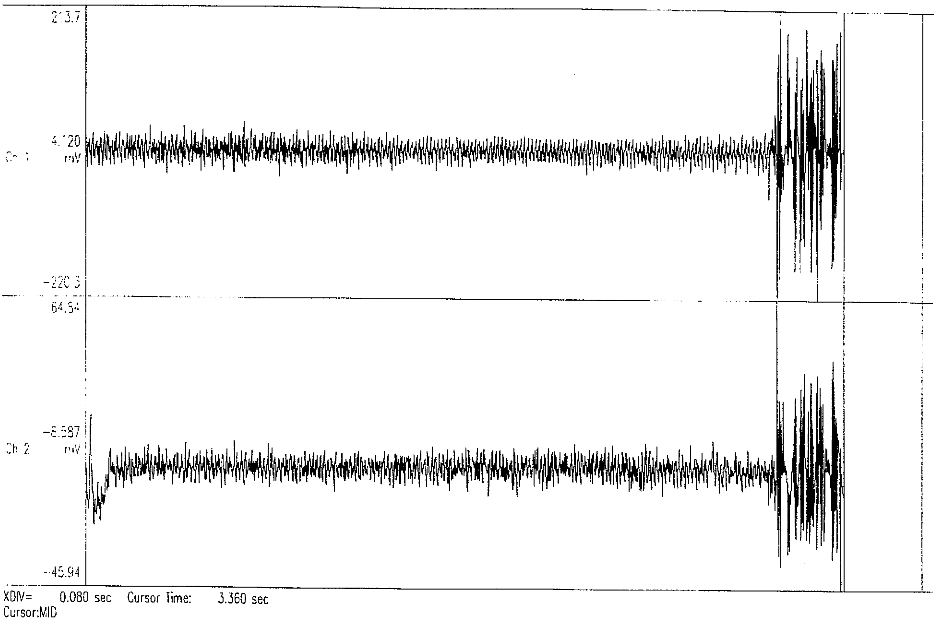


Fig. 22. EMG of the left-to-right motion.

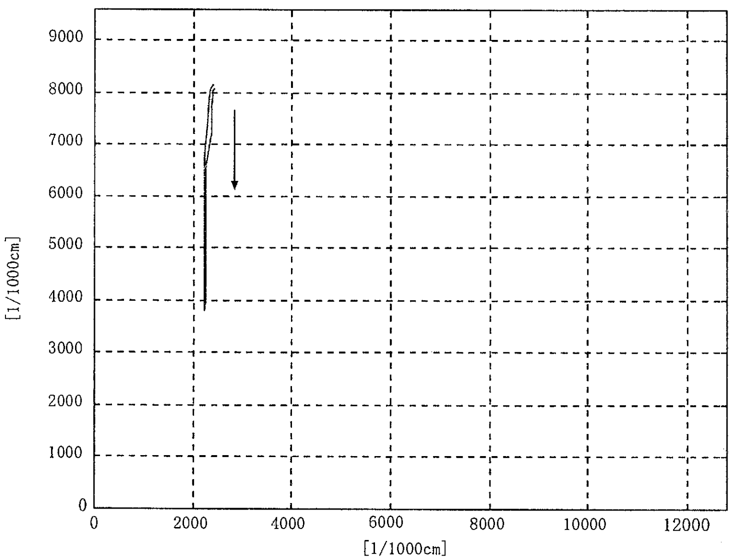
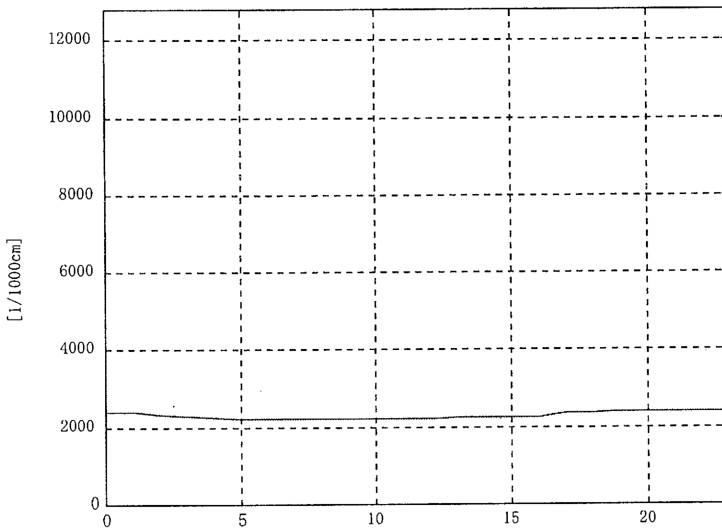


Fig. 23. Upward and downward motions of the hand.



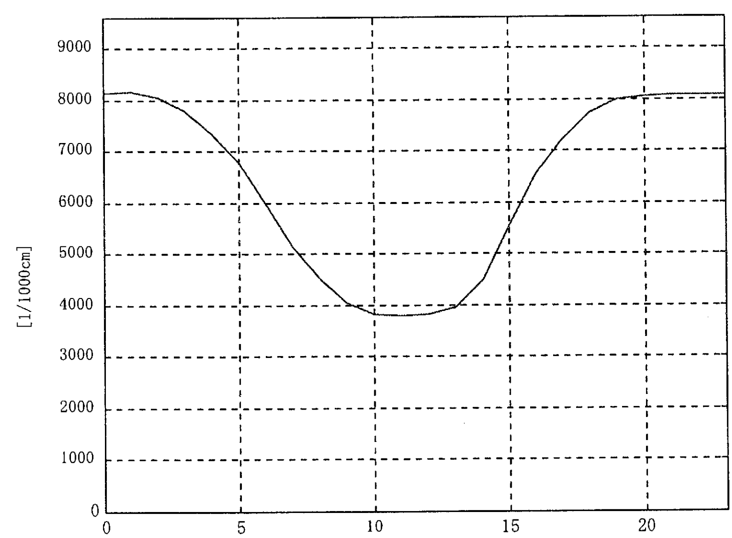


Fig. 24. The x and y displacements of the downward motion.

From all of these measurements, we can very easily relate the muscle activities to that of the hand motion in the vertical direction. In the case of the letter AYN, the y-displacement shown in Fig. 9 reflects three different levels of motion which are interpreted by the three muscle force activities given in Fig. 10. With the letter SIN, the hand movements in the y-direction alternate in three steps separated by two displacements in the x-direction as is shown in Fig. 15. These are interpreted by the three muscle forces of Fig. 16. As for the letter HE, the x-y displacement is more involved. The hand is first moved in a circular motion to draw the first part, and

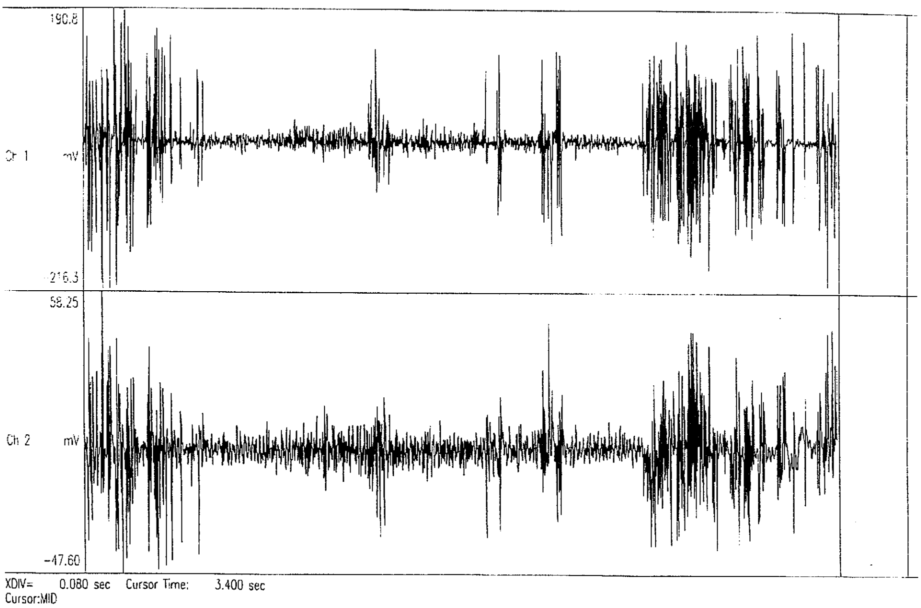


Fig. 25. The EMG of the downward motion.

then it is moved horizontally to the left. The vertical displacement of the hand is shown in Fig. 18. This is interpreted by a very active muscle phase followed by a no-action phase shown in Fig. 19.

In the following sections, we use different modeling techniques to study the handwriting movements.

6. Models for the Handwriting Process

To study and characterize the handwriting process, several models have been proposed in the literature. These models are of two types, either mathematical or physical.

6.1. Mathematical Models

The first modeling technique is based on the trajectories obtained from the handwritten object. The objective is to generate the same trajectories by using the principle of interpolation. These models were proposed by Eldelman and Flash (1987). It has been shown that the minimization of a cost function of the third derivative of the hand position can represent the dynamics of the handwriting:

$$J = \int_0^{t_f} \left[\left(\frac{\mathrm{d}^3 x(t)}{\mathrm{d}t^3} \right)^2 + \left(\frac{\mathrm{d}^3 y(t)}{\mathrm{d}t^3} \right)^2 \right] \mathrm{d}t, \tag{5}$$

where t_f is the final time for writing and $x(t)$, $y(t)$ are the positions of the pen.

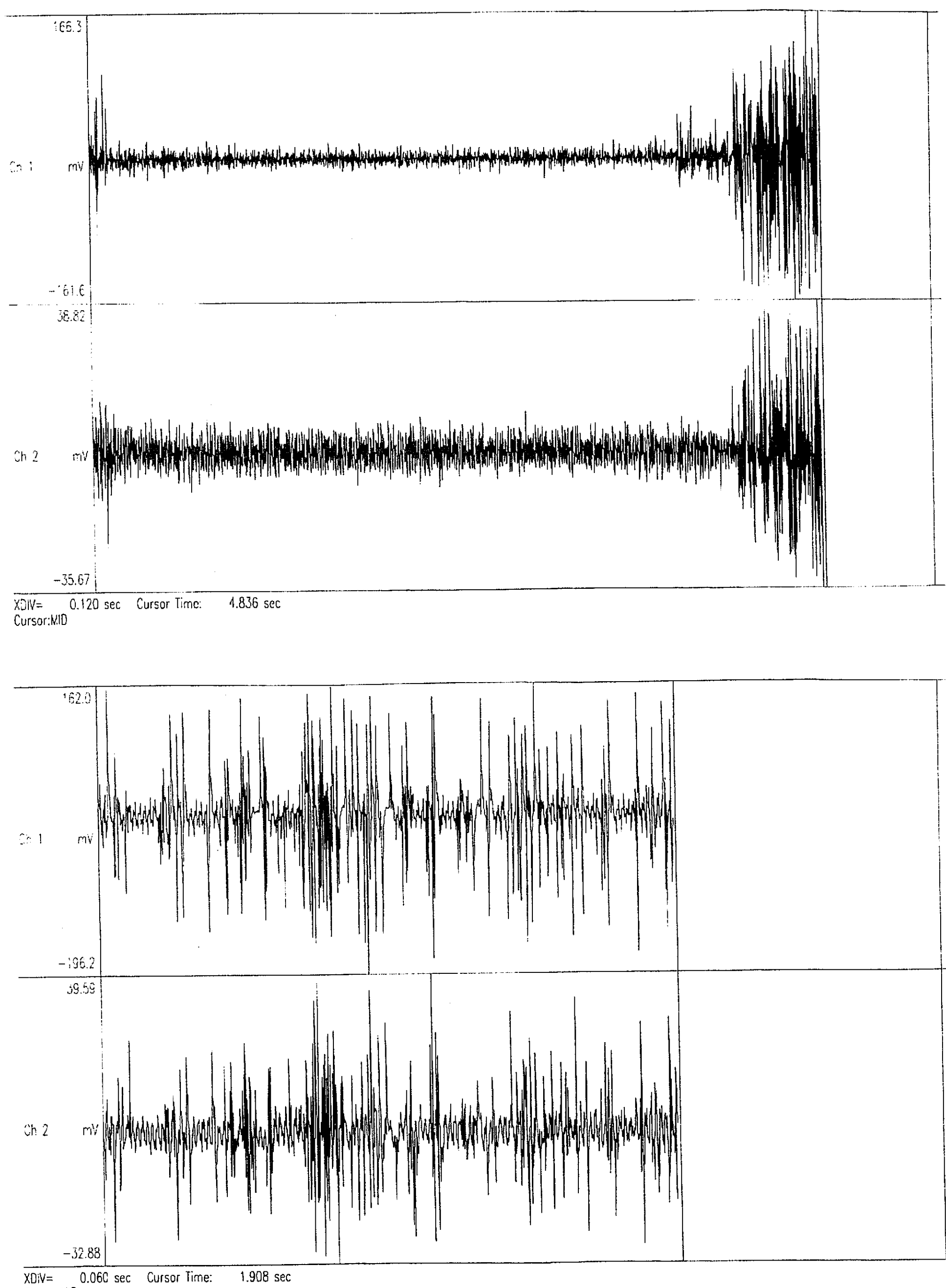


Fig. 26. The EMG of a point (top) and noise (bottom).

The displacements $x(t)$ and $y(t)$ are assumed to be polynomials of the fifth order:

$$x(t) = \sum_{n=0}^{5} a_n t^n, \quad y(t) = \sum_{n=0}^{5} b_n t^n, \tag{6}$$

where the coefficients a_n and b_n are to be determined from the minimization of the cost function J.

6.2. Physical Models

The other type of models is based on the dynamics of the hand and its physical behavior during the handwriting process. The first model was proposed by Van Der Gon and his co-workers in 1962 (Van der Gon and Thuring, 1962), where they suggested to represent the handwriting process by a second-order linear system. The hand-pen combination was modeled as a mass with viscous friction where the mass was attached to a contraction element. The dynamic equations of the pen displacement in the x and y directions are given by

$$M\ddot{d} + k_d\dot{d} = f_d(t), \tag{7}$$

where d is the displacement in the x or the y direction, $f_d(t)$ denotes the driving muscle force, M stands for the mass of the hand, and k_d is the friction constant of the pencil point and the writing surface. The simulation results were fairly good but they did not properly reflect the original samples.

Then in 1975, Yasuhara proposed a more refined and generalized model (Yasuhara, 1975) than the one proposed by Van der Gon. The effects of friction forces appearing between the pen and the writing surface, and the stiffness viscosity of the hand were added leading to the model of Fig. 27.

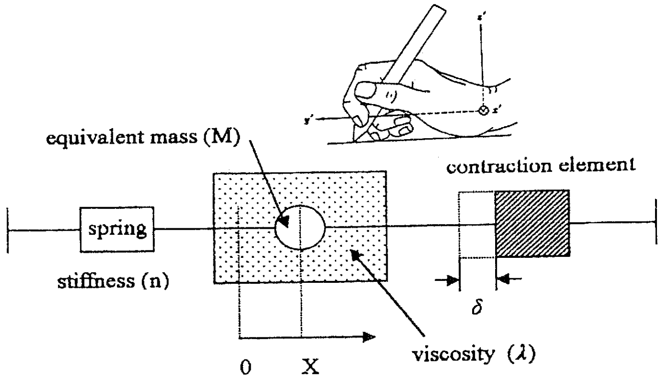


Fig. 27. Representation of the hand-muscle system.

The handwriting movements are resolved into two principal x and y components assuming that the driving forces causing these movements are two pairs of antagonistic groups of muscles. The driving force in the z direction is neglected. In each direction of movements, the muscles generate forces having a determined magnitude and timing. Under these assumptions, Iguider and Yasuhara (1996) introduced the notion of control pulses. They concluded that the shapes of characters are coded only in time, i.e., by the duration and not by the magnitude of the applied muscle force. A dynamic model expressing the motion of the hand is given by

$$M\ddot{d} + k_d\dot{d} + n_d d = f_d(t), \tag{8}$$

where $k_d = \lambda_d + \mu_d p(t)/v(t)$. M is the equivalent mass of the hand-pen system, k_d denotes the equivalent viscosity coefficient, n_d signifies the stiffness coefficient of the hand, $f_d(t)$ stands for the driving force exerted by the muscle along the corresponding axis, $p(t)$ and $v(t)$ are the writing pressure and speed, respectively.

In (Fujiki, 2000; Yasuhara, 1975), the parameters of the dynamic model were estimated. By neglecting the stiffness term and by assuming that the writing speed of the subject and the writing pressure on the tablet surface are made constants, the model (8) can be reduced to a Van der Gon model (7), where $k_d = \lambda_d + \mu_d P/V$ and

$$K_d = \frac{k_d}{M} = \frac{[\lambda_d + \mu_d p/v]}{M} = l_d + \frac{\mu_d P}{v}. \tag{9}$$

The parameters l_d and μ_d specify the model behavior and they have different values for different subjects. In (Fujiki, 2000), their values were determined for the hand motion model in the vertical direction. The results of Section 4 were used. These parameters were given by $l_y = 4$, $\mu_y = 0.5$, $M = 0.45$.

In (Ayadi, 1999), the experimental values of $l_d = 4.7$, $\mu_d = 0.5$ and $M = 0.42\,\text{kg}$ were used to simulate the hand movements and extract the driving motor pulses. The model (8) was used to generate the control pulses for the handwriting of the Arabic characters. Figure 28 shows the results when the letter AYN is simulated.

Accordingly, though it is possible to obtain good results with the above model, the hand movements involved in the handwriting process are more complicated than in the above attempt to interpret them in terms of a simplified model. This might not produce precise motor signals. The basic structure underlying the handwriting process is in fact given in Fig. 29. A desirable trajectory (character shape) in the task-oriented coordinates is first selected from among many possible trajectories. The planar coordinates of the desired trajectory are provided by the visual system (trajectory determination). Then, these coordinates are interpreted in terms of the corresponding set of hand coordinates such as joint angles and muscle lengths (coordinate transformation). Finally, motor commands (e.g., torque) are generated to coordinate the activity of the hand muscles so that the desired trajectory be realized (generation of a motor command). The motor command can be obtained directly from the desired trajectory.

Based on these observations, the following synthesis technique is proposed for future studies on the hand-muscle handwriting system.

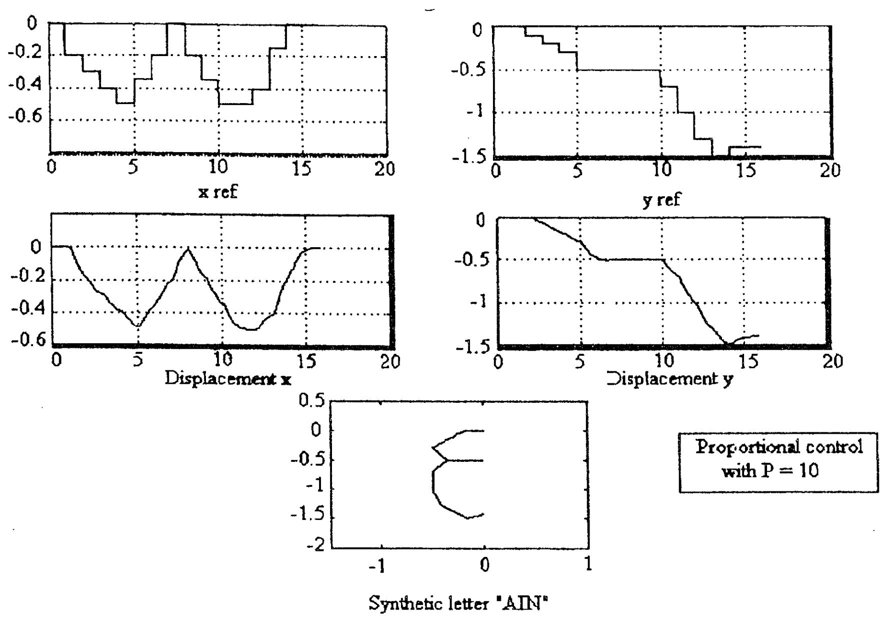


Fig. 28. Simulation of the Arabic letter AYN using Yasuhara's model.

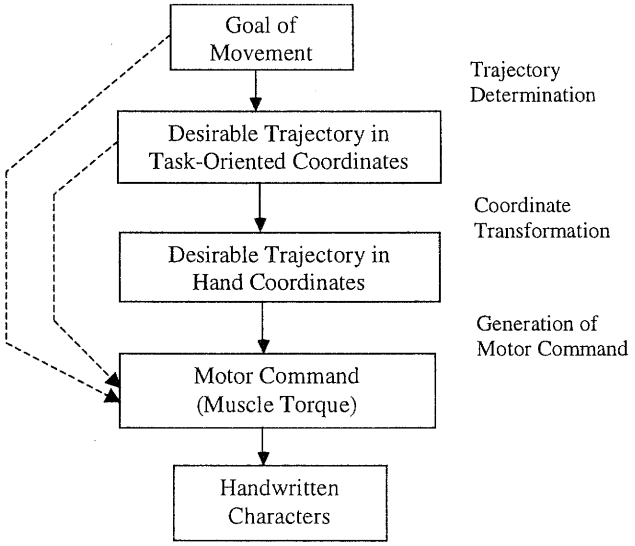


Fig. 29. Human handwriting process.

7. Feedback Error Learning Model

We propose to use the Feedback Error Learning (FEL) neural network (Kawato *et al.*, 1987) which, when trained, learns the inverse dynamics of a controlled plant. Figures 30 and 31 show the basic structure of the identification technique. This method is based on contemporary physiological studies of the human cortex (Kawato, 1990; Miyamoto *et al.*, 1988). The total control effort u applied to the plant (hand-muscle system) is the sum of the feedback control output and the network control output. The ideal configuration of the neural network would correspond to the inverse mathematical model of the plant. The network is given the information of the desired position and its derivatives, and it will calculate the control effort necessary to make the output of the system follow the desired trajectory. If there are no disturbances, the system error will be zero.

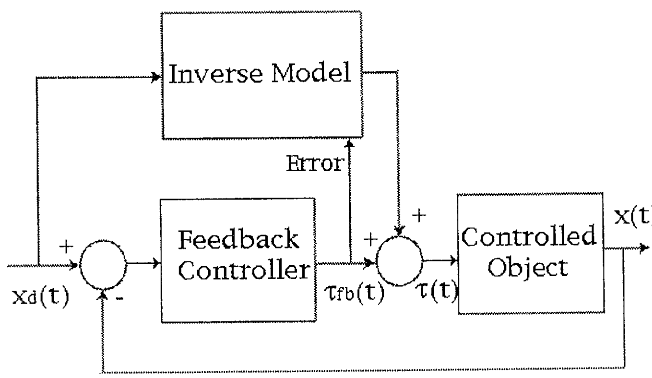


Fig. 30. Inverse modeling.

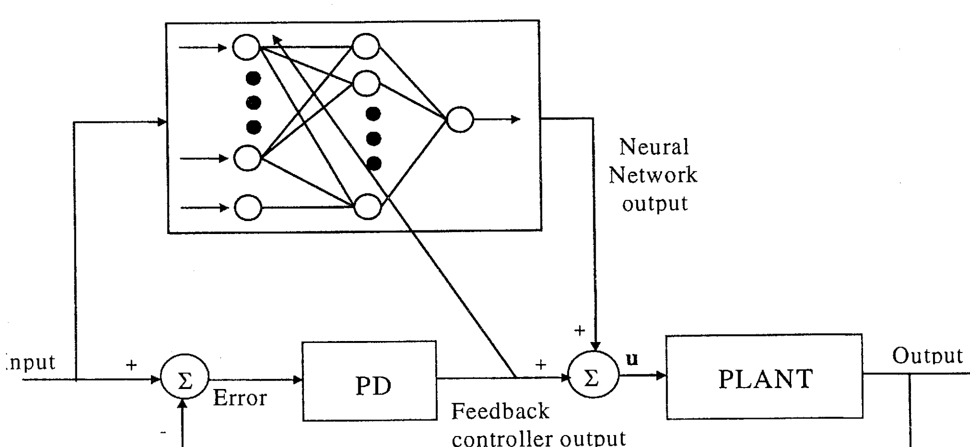


Fig. 31. Structure of the Feedback Error Learning system.

The configuration of the neural network is to represent the inverse dynamics of the hand-muscle system when the training is completed. The proportional-plus-derivative (PD) feedback controller is included to provide stability during the training of the neural network (Kalanovic, 1996). In essence, the output of the feedback controller is an indication of the mismatch between the dynamics of the plant and the inverse-dynamics model obtained by the neural network. If the true inverse-dynamic model is learned, the neural network alone will provide a necessary control signal to achieve the desired trajectory.

In (Kalanovic *et al.*, 1999), the authors applied the FEL technique to the control of a powered trans-femoral prosthesis or an artificial leg. The nonlinearities and the time-variations of the system dynamics made the conventional control methods difficult to apply. The walking process of the human being is achieved by coordinated movements of the body segments employing an interplay of internal and external forces, e.g., muscular, inertial, gravitational and frictional. The effective use of the external forces is learned by the nervous system during the early childhood. The walking patterns are different from one human to another, but there is a well-defined set of trajectories that have been called normal walking. The aim of the FEL implementation was to design a control algorithm that would enable the artificial leg, a simplified version of the human leg, to normally walk. As mentioned in (Kalanovic *et al.*, 1999), the extension of the modeling and control techniques of mechanical plants to human body or biomechanical systems may easily produce results that are in sharp discrepancy with reality. Human extremities are unlike any other plant encountered in control engineering, especially in terms of joints, muscles (actuators), and sensors.

Similarly, we can apply the same reasoning to the identification and modeling of the human hand. We need to know the parameters of the model with sufficient accuracy. In our case, however, though it is possible to determine the parameters of the hand system, it is not possible to use them for real-time control as was proposed in (Kalanovic *et al.*, 1999). Some parameters of the hand model can be estimated and used in an off-line simulation to design elements that can assist in the development of a precise model. The EMG signals can be used to train FEL-based control systems in order to produce a specific handwriting dynamics. Once the system is trained, it can be used to generate characters that vary in their attributes as compared to original training data. This configuration may also be used to identify characters stemming specifically from a particular user. In other words, if an EMG which does not belong to the subject whose data were used for learning is presented to the system after training, then the system will react by attempting to adjust the weights and to re-learn the dynamics. Furthermore, once the system is trained, it is sufficient to remotely pass the subject's EMG to the system in order to produce a particular handwriting dynamics at the output.

8. Conclusions

We have presented an overview study of the modeling techniques representing the handwriting movements. By analyzing the hand-muscle system, we have shown that the handwriting process is achieved by coordinated movements of the hand-muscle and joints. The effective use of the muscle forces is a process learned by a human being since the early childhood. The writing style, speed and legibility of characters vary from person to person, but there is a well-defined set of trajectories that define the average writing. Modeling a human hand writing system differs from the modeling of any other physical system. Simple extension of analytical tools used for the modeling of mechanical plants to biomechanical systems may easily produce results that are in sharp discrepancy with reality. Biomechanical models of the hand require knowing its parameters with sufficient accuracy. We have studied several modeling techniques and provided experimental results that supported them. We have proposed a new approach that can learn the inverse model of the handwriting process. The method is based on FEL, a neural-based strategy that lends itself to inverse model encoding. We expect that, by using this identification technique, it will be possible to generate a more realistic model and to be able to make an elaborate and precise analysis of the characteristics of the handwriting system.

Acknowledgements

The authors wish to thank Dr. D. Kalanovic of the South Dakota School of Mines and Technology, USA, and Prof. M. Sano of Hiroshima City University for their contributions and encouragement.

References

Ayadi M. (1999): *Sur la modélisation et l'identification de processus d'écriture à la main: Application a l'écriture cursive.* — M.Sc. Thesis, Ecole Nationale d'Ingénieurs de Tunis.

Benrejeb M. (1980): *Sur l'analyse et la synthèse de processus complexes hierarchisés.* — These de Doctorat (Ph.D. Thesis) ès Sciences Physiques, Lille.

Benrejeb M., Bouslama F., Ayadi M. and Sano M. (2000): *Studying and modeling handwriting process.* — Proc. Int. Conf. *Artificial and Computational Intelligence for Decision, Control and Automation in Engineering and Industrial Applications, ACIDCA'2000*, Monastir, Tunesia, pp.124–129.

Bouslama F., Kalanovic V. and Benrejeb M. (1999): *Identification of dynamic models for handwriting process: Application to character recognition.* — Proc. Tunisian Interdisciplinary Workshop *Science and Society – TIWSS'99*, Tokyo, Japan, pp.13–15.

Edelman S. and Flash T. (1987): *A model of handwriting.* — Biol. Cybern., Vol.57, pp.25–36.

Fujiki S. (2000): *Handwriting modeling based on biomedical signals.* — B.Sc. Thesis, Hiroshima City University.

Iguider Y. and Yasuhara M. (1996): *An active recognition of handwritten isolated Arabic characters.* — Trans. Soc. Instr. Contr. Eng., Vol.32, No.8, pp.1267–1276.

Kalanovic V.D. (1996): *Total energy extraction from a class of nonlinear systems via feedback error learning.* — Proc. IEEE SMC Conf., Lille, France.

Kalanovic V.D., Popovic D. and Skaug N.T. (1999): *Feedback error learning neural network for trans-femoral prothesis.* — Submitted to IEEE Trans. Contr. Theory (paper under review).

Kawato M., Furukawa K. and Suzuki R.(1987): *A Hierarchical Neural-Network Model for Control and Learning of Voluntary Movement.* — Biol. Cybern., Vol.57, pp.169–185.

Kawato M. (1990): *Computational schemes and neural network models for formation and control of multi-joint arm trajectory,* In: Neural Network for Control (W.T. Miller, R.S. Sutton and P.J. Werbos, Eds.). — MIT Press.

MacDonald J. (1966): *Experimental studies of handwriting signals.* — Tech. Rep. 443, MIT.

Miyamoto H., Kawato M., Setoyama T. and Suzuki R. (1988): *Feedback-Error-Learning Neural Network for Trajectory Control of a Robotic Manipulator.* — Neural Networks, Vol.1, pp.251–265.

Van der Gon D. and Thuring J. (1962): *A handwriting simulator.* — Phys. Med. Biol., Vol.6, pp.407–414.

Yasuhara M. (1975): *Experimental studies of handwriting process.* — Rep. Univ. Electro-Comm. 25–2 (Sci. & Tech. Sect.), Shofn, Tokyo, pp. 233–254.

Yasuhara M. (1983): *Identification and decomposition of fast handwriting system.* — IEEE Trans. Circuits Syst., Vol.CAS–30, No.11, pp.828–832.