Internal Model Control to Characterize Human Handwriting Motion

Ines Chihi, Afef Abdelkrim, and Mohamed Benrejeb
National School of Engineers of Tunisia, Tunis El Manar University, Tunisia

Abstract: *The main purpose of this paper is to consider the human handwriting process as an Internal Model Control structure (IMC). The proposed approach allows characterizing the biological process from two muscles activities of the forearm, named ElectroMyoGraphy signals (EMG). For this, an experimental approach was used to record the coordinates of a pen-tip moving on (x,y) plane and EMG signals during the handwriting act. In this sense direct and inverse handwriting models are proposed to establish the relationship between the muscles activities of the forearm and the velocity of the pen-tip. Recursive Least Squares algorithm (RLS) is used to estimate the parameters of both models (direct and inverse). Simulations show good agreement between the proposed approach results and the recorded data.*

Keywords: *Human handwriting process; IMC; the muscular activities; direct and inverse handwriting models; velocity of the pen-tip; RLS algorithm.*

Received January 6, 2015; accepted September 22, 2015

1. Introduction

Handwriting is an individual activity, as well as the language. It is also classified as a means of communication and expression of thought. Therefore, writing becomes not only advantageous but actually indispensable in daily life.

The characterization of the handwriting process has been the subject of several investigations. Considering the handwriting motion as a mass moving in a viscous environment, Mc-Donald proposed in [12], an electronic version of a mathematical model proposed by Van Der Gon *et al.* [17]. Yasuhara proposed non-linear differential equations to describe the studied process [18]. The velocity measurements of the handwriting act have attracted the attention of other researches who considered it as a means of distinguishing between the different kinds of the graphic traces. Plamondon is the first to confirm that the velocity profiles of this process are approximately bell shaped [14]. Alimi characterize in [1] the on-line velocity profile of some letters by the use of beta-elliptical model. Other handwriting models based on the velocity profile were presented in [3, 10]. Considering the different complexities involved in the handwriting motion, this paper considers Internal Model Control (IMC) technique to model the human handwriting process.

Based on an experimental approach, the corresponding structure contains direct and inverse handwriting models that are based on the relationship between the pen-tip velocity and two muscles activities of the forearm. Indeed, the proposed IMC structure shows that ElectroMyoGraphy (EMG) signals of the forearm muscles contain useful information reflecting the movement of the hand during the writing motion.

Recursive Least Squares algorithm (RLS) allowing is used to estimate parameters of both models.

The remainder of this paper is organized as follows: In section 2, an experimental approach allowing to record Arabic letters, some geometric shapes and EMG signals, is presented. Section 3 emphasizes on presentation of the relationship between the handwriting shapes (letters and geometric forms) and the velocity profile of the pen-tip moving on (x,y) plane. In this section an IMC structure is proposed to mimic the global generalized handwriting model. Simulation results are showed on Section 4. Section 5 presents concluding perspectives.

2. Experimental Handwriting Approach

The study of handwriting movement according to (x,y) plane shows that this last one is mainly based on two EMG signals EMG1 and EMG2, of the most active forearm muscles during the handwriting motion, namely the “Abductor Pollicis Longus” and “Extensor Capri Ulnaris” [4, 5]. The first muscle is responsible of the vertical displacement and the second is responsible of the horizontal motions, as shown in Figure 1.

a) Abductor pollicis longus. b) Extensor capri ulnaris.

Figure 1. Forearm muscles used on the experimental approach.

It is important to note that, generally, when a writer had to produce lines or shapes in a non-preferred writing direction, the performance is less precise and more instable. The handwriting velocity increases in the less curved form and decreases in the most curved. Indeed, all individuals have preferred movement's directions. These preferences influence the production of the graphic form. Meulenbroek proved that there is a preference to produce vertical traces, from up to down, and horizontal traces to the right, for the Latin script, and to the left, for the Arabic script. He also showed that vertical lines are faster and more accurate than horizontal lines [13].

Using these analysis and in order to construct an experimental basis to characterize handwriting process, students from Hiroshima City University wrote a variety of shapes (horizontal, vertical, complexes, rapid and slow movements, Arabic cursive letters) several times. Table 1 presents the different considered shapes. It's important to note that these students are not used to write cursive Arabic letters, this makes the characterization of this biological process more difficult.

These Japanese students was comfortably seated in front of a computer monitor and wrote on the pen tablet (WACON, KT-0405-RN) while looking at the computer monitor that displayed the written traces. Two EMG signals, EMG1 and EMG2, were simultaneously recorded by the means of bipolar surface electrodes (MEDICOTEST, Blue Sensor N-00-S), placed on two forearm muscles. The recording of the signals is registered into the data recorder (TEAC, DR-C2) through the pre-amplifiers (TEAC, AR-C2EMGI). To reduce the influence of nose of EMG signals, they wrap their forearms by bandage. Positions of the pen-tip on (x,y) plane and the pressure exerted by this last one on the digital table are also recorded during the time of writing. The measuring data are synchronized by sending a step signal from the parallel interface port on the computer to the data recorder, as shown in Figures 2 and 3.

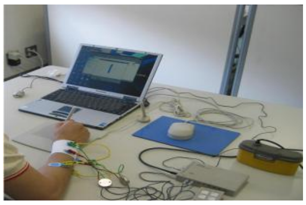


Figure 2. Experimental approach.

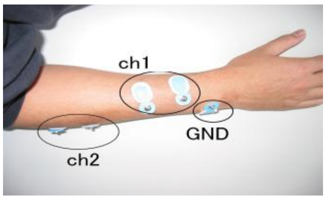
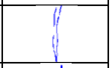
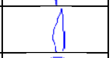
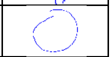
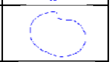
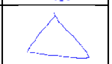
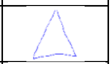
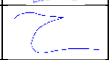
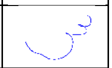
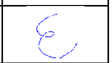
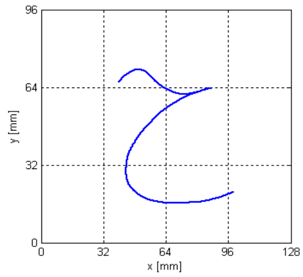


Figure 3. Positions of the surface electrodes ch1 and ch2 to measure EMG1 and EMG2 signals, respectively.

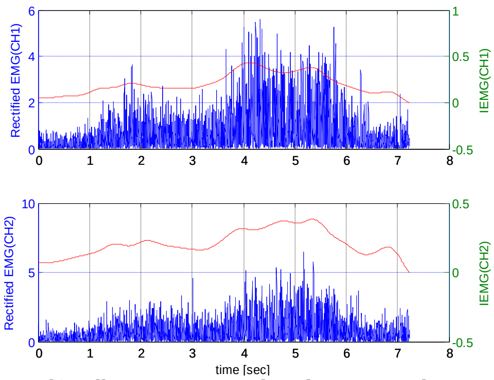
Compared with other biological signals, EMG signals are noisy and contain complicated transient phenomena, disruptive signals resulting from various sources, such as electromagnetic phenomenon sector and noise associated with electrodes and uncertainties of measures, electromagnetic induction, motion artifacts, interaction of different tissues, etc. Although, it is difficult to get the useful information from activities of muscles. For this, a variety of signal processing techniques are used to make EMG waveforms easier to interpret. Indeed, the fluctuation of EMG's magnitudes can be filtered to obtain new curves called Integrated ElectroMyoGraphy (IEMG), as shown in Figure 4.

Table 1. Considered Arabic letters and geometric forms.

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



a) Form.



b) Full wave EMG signals and IEMG signals.

Figure 4. Example of the experimental recordings.

3. Proposed Handwriting IMC

During the human handwriting motion, several factors and elements intervene to generate the graphic traces, such as the system of perception, the brain, the muscles, etc. In this sense, [2] represents a global generalized handwriting model to prove that the pen-tip position is detected by the means of the eyes and transmitted to the brain to be analyzed and compared with the desired position. Finally, forearm muscles activities, named EMG signals, are sent to perform the desired movement on the writing surface. This analysis recalls the principle of the IMC structure.

The proposed approach resumes the relationship between the pen-tip, perception, brain and hand. In this model, the role of the eyes is modelled by a feedback. This approach is presented by Figure 5.

The generalized model of the handwriting motion, given in Figure 5, is similar to the IMC structure, shown in Figure 6. Indeed, this section focuses on the characterization of the control structure of the studied process using IMC technique.

The signal command, u_c, generated by the Controller C is applied simultaneously to the Process P and to its Model M placed on parallel [8, 9, 15].

Independently of the process P, Equation (1), shows clearly that if the controller C is chosen as the inverse of the model, the feedback of the IMC realizes a perfect transfer between the reference y_c and the output of the process, y_p. In this case, the controller can realize a good pursuit.

The new proposed handwriting IMC is shown in Figure 7.

$$y_p = \frac{C.P}{1+C(P-M)} y_c \tag{1}$$

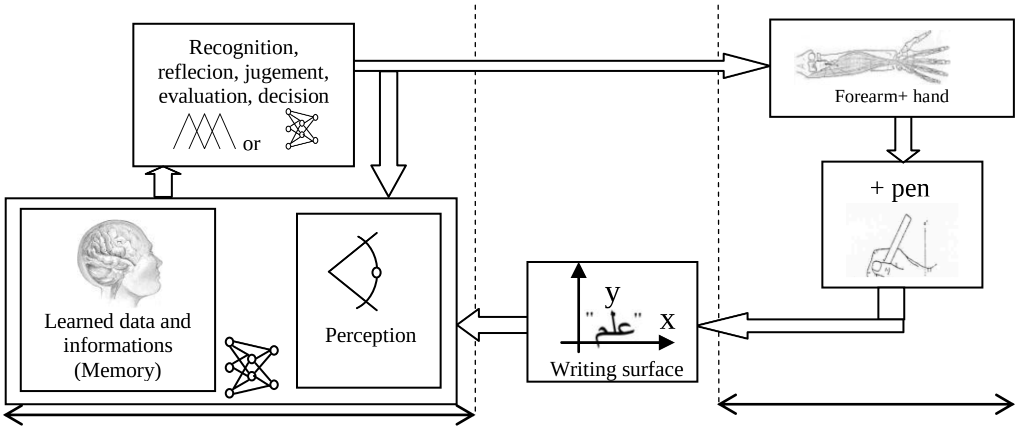


Figure 5. Global generalized handwriting process model.

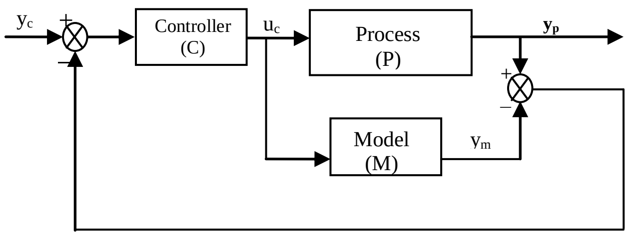


Figure 6. Structure of the IMC.

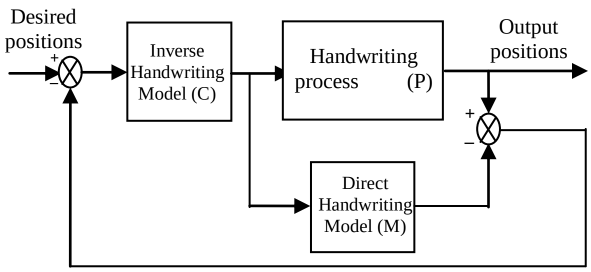


Figure 7. Handwriting IMC.

3.1. Handwriting Process (P)

We propose a linear fourth order model to generate the movements of the pen-tip in (*x*, *y*) plane, from two IEMG signals, IEMG1 and IEMG2, and from the positions of the pen-tip moving on the digital tablet at delayed moments. The model's inputs are *x* and *y* coordinates delayed at the instants: *k-1*, *k-2*, *k-3* and *k-4* and two IEMG calculated muscular signals at the instants: *k*, *k-1*, *k-2*, *k-3* and *k-4*. The outputs are *x* and *y* coordinates at *k* instant. The handwriting models have the following forms:

$$\begin{aligned} x_e(k) = &-\sum_{i=1}^{4}(a_{ix}\, y_e(k-i) - b_{ix}\, x_e(k-i)) + \\ &\sum_{i=1}^{5}(c_{ix} e_1(k-i+1) + d_{ix}\, e_2(k-i+1)) \end{aligned} \tag{2}$$

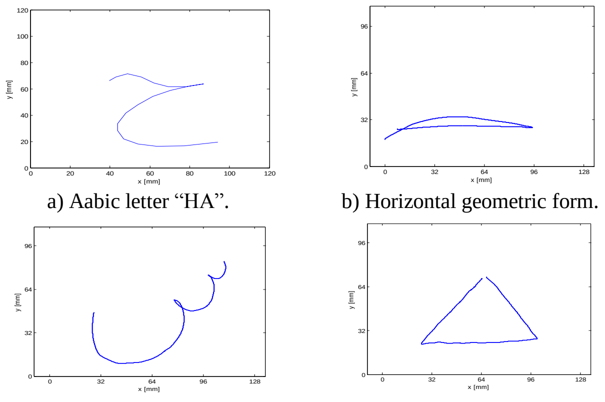
$$\begin{aligned} y_e(k) = &-\sum_{i=1}^{4}(a_{iy}\; x_e(k-i) - b_{iy}\; y_e(k-i)) + \\ &\sum_{i=1}^{5}(c_{iy}\, e_1(k-i+1) + d_{iy}\; e_2(k-i+1)) \end{aligned} \tag{3}$$

x_e and y_e : Estimated position relative to *x* and *y* directions respectively,

e_1 and e_2 : IEMG1 and IEMG2 signals,

$a_{ix}, b_{ix}, c_{ix}, d_{ix}$, $\hat{a}_{iy}, \hat{b}_{iy}, \hat{c}_{iy}, \hat{d}_{iy}$: estimated parameters relative to the estimated coordinates x_e and y_e respectively.

Some simulation results of this model are presented in Figure 8.



a) Aabic letter “HA”. b) Horizontal geometric form.

c) Aabic letter “SIN”. d) Geometric form “Tiangle”.

Figure 8. Handwriting model (P) responses.

3.2. Direct and Inverse Handwriting Velocity Models

Basing on the handwriting velocity analysis and its relationship with IEMG signals to generate the pen-tip movement, in this section, the presented direct and inverse models are used to define IMC for the handwriting process.

In order to minimize the error of prediction, a parametric identification is used to estimate parameters of the direct and inverse models to generate outputs response as close as possible to the real system. We choose Recursive Least Square algorithm, because it has the advantage to be executed on real time and requires less memory resources in terms of calculation.

3.2.1. Correspondence between Trajectory and Velocity of the Pen-Tip

From the described experimental approach considering horizontal, vertical, complexes, rapid and slow movements, the relationship between the velocity of the pen-tip during the handwriting motion and the trajectory of this last one can be analysed.

Velocities of the pen-tip movements according to x and y directions are calculated as follow:

$$\|V(k)\| = \sqrt{V_x(k)^2 + V_y(k)^2} \tag{6}$$

with:

$$V_x(k) = \frac{x(k+1) - x(k)}{t(k+1) - t(k)} \tag{7}$$

$$V_y(k) = \frac{y(k+1) - y(k)}{t(k+1) - t(k)} \tag{8}$$

and:

$V(k)$: Pen-tip velocity,

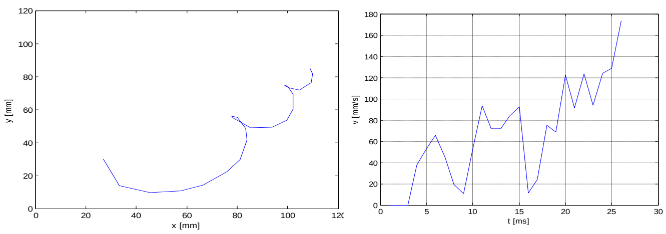
$V_x(k), V_y(k)$: pen-tip speeds according to x and y axis, respectively,

$x(k), y(k)$: pen-tip displacement according to x and y axis, respectively,

$t(k)$: discrete time.

The velocity profiles relative to different measurements of pen-tip displacements are conserved and occur as bell-shaped whatever the kind of movement. Figure 9-a presents an Arabic letter, “SIN”, written according to (x,y) plane. The handwriting velocity of this letter has three main areas, different in durations and amplitudes, formed by a superposition of bell-shaped forms and corresponding to three primitives of the considered letter: two small half circles and a largest third one.

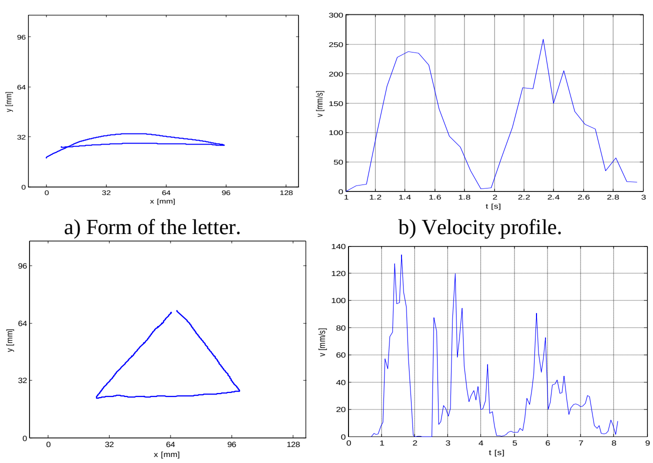
The velocity of writing can be interpreted as a superposition of bells distributed by area with different durations and amplitudes. Each zone corresponds to a primitive of the written letter, Figure 9-b.



a) Form of the letter. b) Velocity profile.

Figure 9. Simple movement (Arabic letter “SIN”).

Figure 10 shows other handwriting shapes. The first form is an horizontal line relative to go and back movement (left/right/left). In this case, the handwriting velocity profile presents two separate bell shapes with different amplitudes and nearly equal during. The first bell shape is the result of left/right movement while the second bell is relative to the right/left movement. The velocity is equal to zero at the beginning, the end of the movement and when the movement according to x axis changes direction.

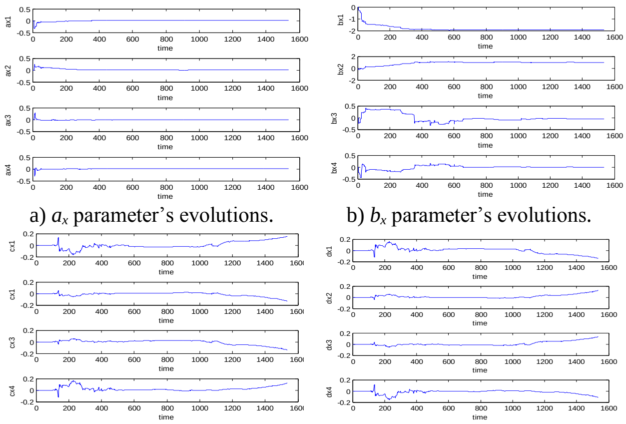


a) Form of the letter. b) Velocity profile.

c) Form of the letter. d) Velocity profile.

Figure 10. Handwriting movements.

The second form shown by Figure 11, allows to present the velocity profile of the geometric form “triangle”. This profile includes three bell shapes corresponding to three segments of the triangle. Therefore, the writing velocity can be interpreted as a superposition of bells distributed by area with different durations and amplitudes. Each zone corresponds to a primitive of the written letter.



a) a_x parameter’s evolutions. b) b_x parameter’s evolutions.

c) c_x parameter’s evolutions. d) d_x parameter’s evolutions.

Figure 11. Parameter’s evolutions relative to the estimated velocity according to x direction.

3.2.2. Direct Handwriting Model (M)

The direct mathematical model consists in generating an Arabic letter or a geometric shape written by a specific writer. The inputs of this model are IEMG signals of the forearm muscle (IEMG1 and IEMG2).

The proposed structure is a third order model. It generates as outputs V_{xe} and V_{ye} at instant k and admitting, as inputs, V_{xe} and V_{ye} delayed at $k-1$, $k-2$, $k-3$ and $k-4$ instances and the EMG signals at k, $k-1$, $k-2$ and $k-3$ instances. The following equations characterize the handwriting velocity direct model:

$$V_{xe}(k)=\sum_{i=1}^{4}-\left[\hat{a}'_{ix}V_{ye}(k-i)+\hat{b}'_{iy}V_{xe}(k-i)\right]+\left[\hat{c}'_{ix}e_1(k-i+1)+\hat{d}'_{ix}e_2(k-i+1)\right] \quad (10)$$

$$V_{ye}(k)=\sum_{i=1}^{4}-\left[\hat{a}'_{iy}V_{xe}(k-i)+\hat{b}'_{iy}V_{ye}(k-i)\right]+\left[\hat{c}'_{iy}e_1(k-i+1)+\hat{d}'_{iy}e_2(k-i+1)\right] \quad (11)$$

with :

V_{xe}, V_{ye} : Outputs vectors, relative to the estimated velocities according to x land y movements respectively,

$\hat{a}'_{ix}, \hat{b}'_{ix}, \hat{c}'_{ix}, \hat{d}'_{ix}$, $\hat{a}'_{iy}, \hat{b}'_{iy}, \hat{c}'_{iy}, \hat{d}'_{iy}$: parameters relative to the estimated velocities V_{xe} and V_{ye}, respectively.

Using the identification technique, RLS presented by Equation (12) to (14), the direct model is based on the computing velocities of the pen-tip, according to x and y coordinates (V_x and V_y). The forgetting factor is equal to 0,95. RLS algorithm performs the following operations to update the parameters of the researched model [6, 7, 11, 16]:

$$\hat{\theta}(k)=\hat{\theta}(k-1)+P(k)\sum_{i=n+1}^{k}y(i)\Psi(i) \quad (12)$$

$$P(k)=P(k-1)-\frac{P(k-1)\Psi(k)\Psi^T(k)P(k-1)}{1+\Psi^T(k)P(k-1)\Psi(k)} \quad (13)$$

$$\varepsilon(k)=y(k)-\hat{\theta}(k-1)\Psi(k) \quad (14)$$

with:

$\hat{\theta}(k)$: Vector of estimated parameters,

$P(k)$: adaptation matrix,

$y(k)$: actual output of the system to identify,

$\psi(k)$: observation matrix,

$\varepsilon(k)$: estimated error.

The model structure used to identify the handwriting system dynamics for multi-inputs-multi-outputs is given as follows:

$$\begin{aligned} V_{xe} &= \psi_x^T\theta_x+\varepsilon_x \\ V_{ye} &= \psi_y^T\theta_y+\varepsilon_y \end{aligned} \quad (15)$$

ε_x and ε_y : Error vectors, relative to the velocities according to x and y movements respectively,

ψ_x^T and ψ_y^T : matrices whish elements are the delayed inputs and outputs components, relative to the velocities according to x and y movements respectively.

$$\hat{\psi}_x^T(k)=\begin{bmatrix} -V_{ye}(k-1) & -V_{ye}(k-2) & -V_{ye}(k-3) & -V_{ye}(k-4) \\ -V_{xe}(k-1) & -V_{xe}(k-2) & -V_{xe}(k-3) & -V_{xe}(k-4) \\ e_1(k) & e_1(k-1) & e_1(k-2) & e_1(k-3) \\ e_2(k) & e_2(k-1) & e_2(k-2) & e_2(k-3) \end{bmatrix} \quad (16)$$

$$\hat{\psi}_y^T(k)=\begin{bmatrix} -V_{xe}(k-1) & -V_{xe}(k-2) & -V_{xe}(k-3) & -V_{xe}(k-4) \\ -V_{ye}(k-1) & -V_{ye}(k-2) & -V_{ye}(k-3) & -V_{ye}(k-4) \\ e_1(k) & e_1(k-1) & e_1(k-2) & e_1(k-3) \\ e_2(k) & e_2(k-1) & e_2(k-2) & e_2(k-3) \end{bmatrix} \quad (17)$$

Variations of parameters in time show that they converge to constant values, characterizing the studied handwriting model, as shown in Figures 11 and 12. The estimated parameters of velocities vectors $\hat{\theta}_x$ and $\hat{\theta}_y$ according to x and y movements, respectively, will take the following forms:

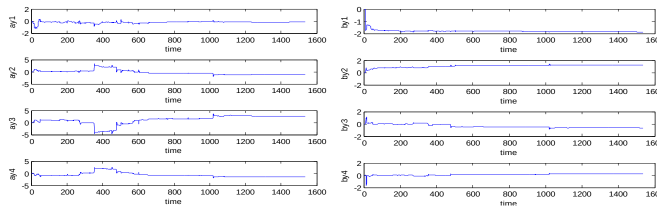
$$\hat{\theta}_x=\begin{bmatrix}\hat{a}_{1x} & \hat{a}_{2x} & \hat{a}_{3x} & \hat{a}_{4x} & \hat{b}_{1x} & \hat{b}_{2x} & \hat{b}_{3x} & \hat{b}_{4x} & \hat{c}_{1x} & \hat{c}_{2x} & \hat{c}_{3x} & \hat{c}_{4x} & \hat{c}_{5x} & \hat{d}_{1x} & \hat{d}_{2x} & \hat{d}_{3x} & \hat{d}_{4x} & \hat{d}_{5x}\end{bmatrix} \quad (18)$$

$$\hat{\theta}_y=\begin{bmatrix}\hat{a}_{1y} & \hat{a}_{2y} & \hat{a}_{3y} & \hat{a}_{4y} & \hat{b}_{1y} & \hat{b}_{2y} & \hat{b}_{3y} & b_{4y} & \hat{c}_{1y} & \hat{c}_{2y} & \hat{c}_{3y} & \hat{c}_{4y} & \hat{c}_{5y} & \hat{d}_{1y} & \hat{d}_{2y} & \hat{d}_{3y} & \hat{d}_{4y} & \hat{d}_{5y}\end{bmatrix} \quad (19)$$

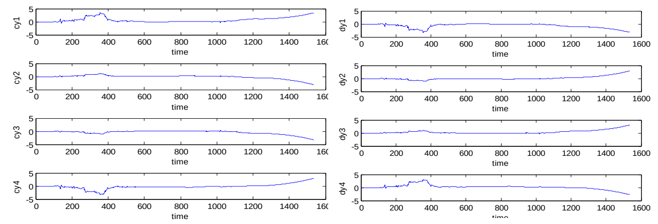
Figure 13 shows some examples of comparison between the real trajectories and the handwriting direct model's outputs. The solid line presents the recorded experimental data and the dotted line is relative to the answer given by the estimated parameters of the obtained model.

The validation of the proposed direct model consists on, integrating parameters of a model characterizing a letter or a geometric form with data saved from another example of the same kind of drawing trace and of the same writer, Figure 14.

Compatibility between the prediction results of pen-tip speed and the experimental data is shown.

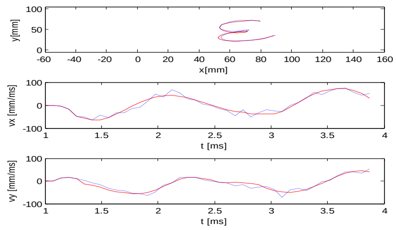


a) a_x parameter's evolutions. b) b_x parameter's evolutions .

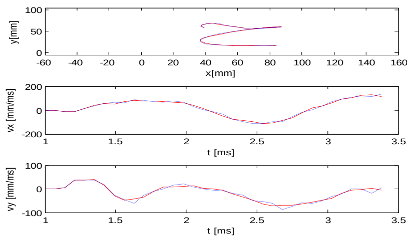


c) c_x parameter's evolutions. d) d_x parameter's evolutions.

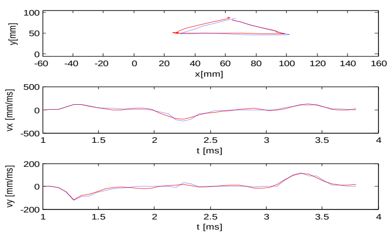
Figure 12. Parameter's evolutions relative to the estimated velocity according to y direction.



a) Data of the arabic letter "AYN".

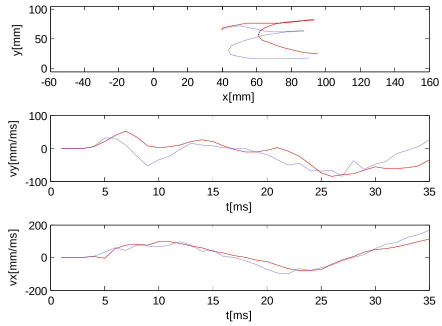


b) Data of the arabic letter "HA".

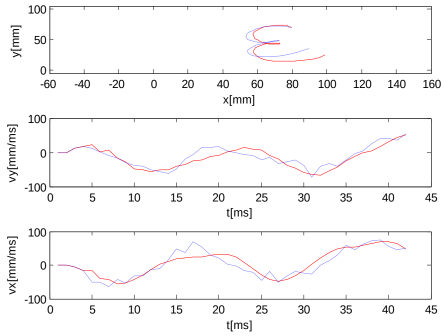


c) Data of the geometric fom "Triangle".

Figure 13. Comparison between experimental recorded data and the direct handwriting velocity model response.



a) Data of the arabic letter "HA".



b) Data of the arabic letter "AYN".

Figure 14. Validation results of the direct handwriting model.

3.2.3. Inverse Handwriting Velocity Model (C)

The inverse handwriting velocity model which allows to reconstruct IEMG signals from the pen-tip velocity, according to x and y coordinates. This new third order model generates the ElectroMyoGraphic signals IEMG at k instance from the velocities, V_x and V_y at k, k-1, k-2 and k-3 instances and from IEMG signals at k-1, k-2 and k-3 instances, relations (20) and (21) .

$$e_1(k) = \sum_{i=1}^{4} -\left[\hat{a}_{i1}\, e_1(k-i) + \hat{b}_{i1} e_2\, V_{xe}(k-i)\right] + \left[\hat{c}_{i1}\, V_x(k-i+1) + \hat{d}_{i1}\, V_y(k-i+1)\right] \tag{20}$$

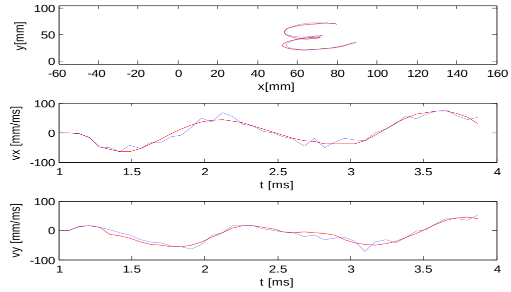
$$e_2(k) = \sum_{i=1}^{4} -\left[\hat{a}_{i2}\, e_2(k-i) + \hat{b}_{i2} e_1\, V_{xe}(k-i)\right] + \left[\hat{c}_{i2}\, V_x(k-i+1) + \hat{d}_{i2}\, V_y(k-i+1)\right] \tag{21}$$

with:

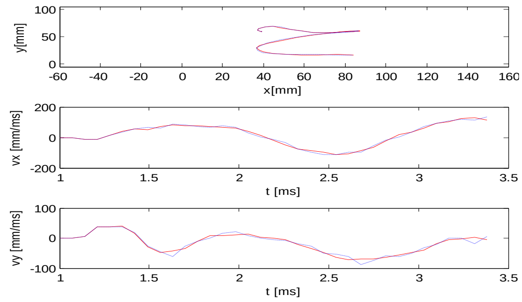
$\hat{a}_{1i},\ \hat{b}_{1i},\ \hat{c}_{1i},\ \hat{d}_{1i},$ $\hat{a}_{2i},\ \hat{b}_{2i},\ \hat{c}_{2i},\ \hat{d}_{2i}$: Estimated parameters relative to the estimated e_1 and $e2$ signals respectively.

Comparisons between the recorded IEMG signals and the reconstructed ones are shown in Figure 15, which illustrates some identification's results for the Arabic letters "HA" and "SIN", written by different persons. For the first shape "HA", an important correspondence is shown between the proposed model outputs and the recorded data. The solid line presents the recorded experimental data and the dotted line is relative to the answer given by the presented model.

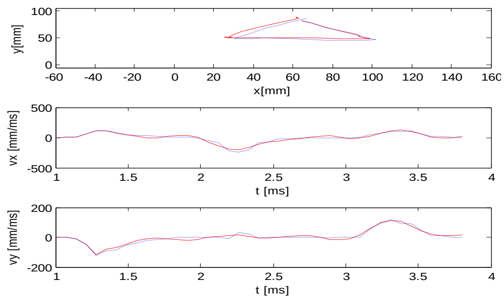
Validation results of the inverse handwriting velocity model in monowriter case, is shown in Figure 16. Indeed, good concordance is observed in this case.



a) Data of the arabic letter "AYN".

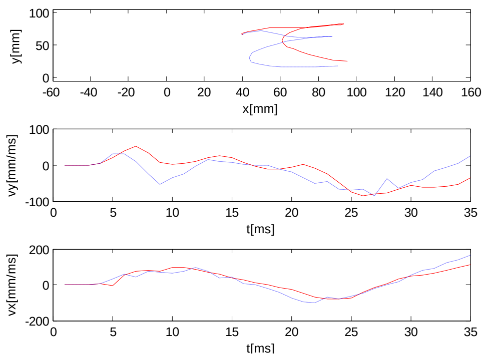


b) Data of the arabic letter "HA".

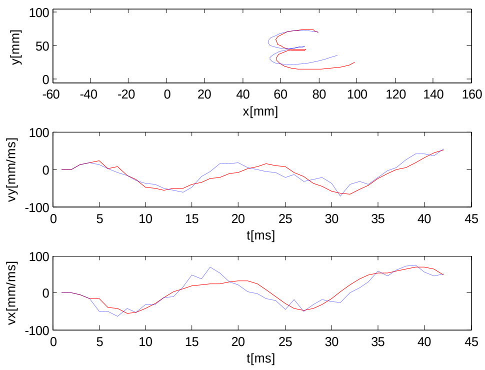


c) Data of the geometric fom "Triangle".

Figure 13. Comparison between experimental recorded data and the direct handwriting velocity model response.

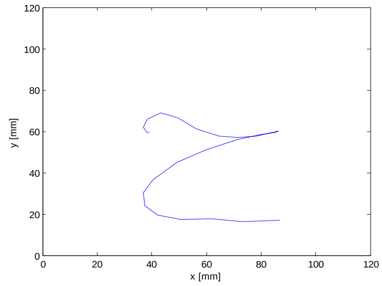


a) Data of the arabic letter "HA".

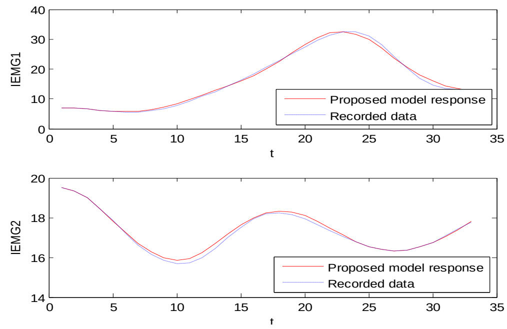


b) Data of the arabic letter "AYN".

Figure 14. Validation results of the direct handwriting model.



a) Form (Arabic letter "HA").



b) IEMG signals according to *x* and *y* directions.

Figure 15. Results of the identification of the inverse model.

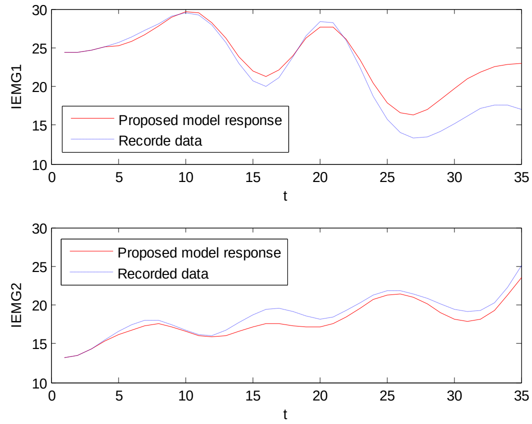
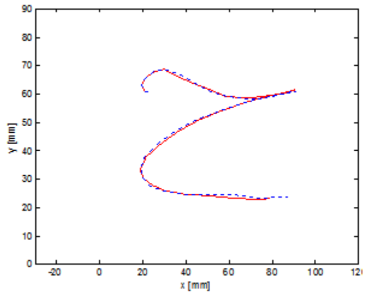


Figure 16. Validation's result of the inverse handwriting model.

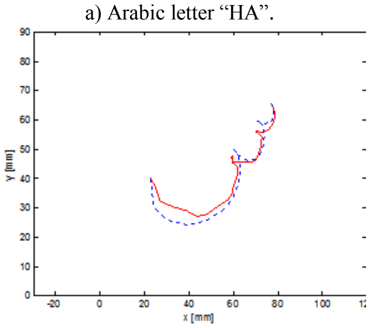
4. Results of the Handwriting IMC Structure

In order to characterize the handwriting process, the inverse handwriting velocity model acts as the controller C. The direct model represents the model M. The process P is replaced by the handwriting model based on computation of the positions of the pen-tip moving on (*x*,*y*) plane.

The results illustrated in Figure 15 confirm the ability of the proposed IMC to follow the form of the writing traces but with a very negligible error between the experimental recorded data and the answer of the proposed command structure, for some Arabic letters, Figure 17-a. For other Arabic letters, an acceptable error is shown, Figure 17-b.



a) Arabic letter “HA”.



b) Arabic letter “SIN”.

Figure 17. Responses of the IMC of handwriting process.

5. Conclusions

The study of the handwriting process and its modelling by IMC approach, constitute the main contributions of this paper. To characterize this approach, a direct and inverse handwriting models are proposed. Each one is based on the relationship between the pen-tip velocities according to (x,y) plane. RLS algorithm was used to estimate the parameters of both models.

The various developed approaches for modelling and control of the handwriting system are led with success and good results are obtained. The proposed structure can be ameliorated to obtain good results valid on (x,y,z) plane.

References

[1] Alimi M., “Contribution au Développement D’une Théorie de Génération de Mouvements Simples et Rapides Application au Manuscrit,” PhD Theses, Université de Montréal, 1995.

[2] Benrejeb M., Abed-Abdelkrim A., and Naoui S., “Handwriting Process Controlled by Neuronal and Neuro-Fuzzy IMC Approaches,” *in Proceeding of International Symposium on Computational Intelligence and Intelligent Informatics*, Nabeul, pp.16-20, 2003.

[3] Chaabouni A., Boubaker H., Kherallah M., El-Abed H., and Alimi A., “Static and Dynamic Features for Writer Identification based on Multi-Fractals,” *The International Arabic Journal on Information Technologies*, vol. 11, no. 4, pp. 416-424, 2013.

[4] Chihi I., Abdelkrim A., and Benrejeb M., “Analysis of Handwriting Velocity to Identify Handwriting Processs from ElectroMyoGraphic Signals,” *American Journal of Applied Sciences*, vol. 9, no. 10, pp. 1742-1756, 2012.

[5] Chihi I., Abdelkrim A., and Benrejeb M, “Inverse Handwriting Velocity Model To Reconstruct Electromyography Signals,” *Journal of Communication and Computer*, vol. 10, no. 2, pp.149-155, 2013.

[6] Ding F., Shi Y., and Chen T., “Auxiliary Model Based Least Squares Identification Methods for Hammerstein Output Error Systems,” *Systems and Control Letters*, vol. 56, no. 5, pp. 373-380, 2007.

[7] Ding F., “System Identification. Part F: Multi-Innovation Identification Theory and Methods,” *Journal of Nanjing University of Information Science and Technology: Natural Science Edition*, vol. 4, no. 1, pp. 1-28, 2012.

[8] Gayadeen S. and Heath S., “An Internal Model Control Approach to Mid-Ranging Control,” *7th IFAC International Symposium on Advanced Control of Chemical Processes*, vol. 42, no. 11, pp. 542-547, 2009.

[9] Kaneko O., Wadagaki Y., and Yamamoto S., “Fictitious Reference Iterative Tuning for Internal Model Controller,” *IFAC International Workshop on the Adaptation and Learning in Control and Signal Processing*, vol. 43, no. 10, pp. 133- 138, 2010.

[10] Kherallah M., Haddad L., Alimi A., and Mitiche A., “Online Handwritten Digit Recognition based on Trajectory and Velocity Modeling,” *Pattern Recognition Letters*, vol. 29 , no. 5, pp. 580-594, 2008.

[11] Liu D., *System Identification Methods and Applications*, National Defense Industry Press, 2010.

[12] MacDonald J., “Experimental Studies of Handwriting Signals,” *MIT Research Laboratory of Electronics PhD Dissertation*, 1964.

[13] Meulenbroek R. and Thomassen A., “Stroke-Direction Preferences in Drawing and Handwriting,” *Human Movement Science*, vol. 10, no. 2-3, pp. 247-270, 1991.

[14] Plamondon R., Alimi A., Yergeau P., and Leclerc F., “Modelling Velocity Profiles of Rapid Movements: a Comparative Study,” *Biological Cybernetics*, vol. 69, no. 2, pp. 119-128, 1993.

[15] Ren X., Rad A., Lo W., and Chan P., “Adaptive Internal Model Control with Reference Input Predictor for Time-Delay Systems,” *IFAC World Congress*, vol. 38, no. 1, pp. 265-270, 2005.

[16] Tutunji T., Molhim M., and Turki E., “Mechatronic Systems Identification, using an Impulse Response Recursive Algorithm,” *Science Direct Simulation Modeling Practice and Theory*, vol. 15, no. 8, pp 970-988, 2007.

[17] Van Der Gon D., Thuring J., and Strackee J., “A Handwriting Simulator,” *Physics in Medical Biology*, vol. 6, no. 3, pp 407-414, 1962.

[18] Yasuhara M., "Experimental Studies of Handwriting Process," *Japanese Journal of Medical Electronics and Biological Engineering*, vol. 12, no. 2, pp. 233-254, 1975.

Ines Chihi was born in Tunisia in 1984. She obtained the Master degree of Automatic Control in 2009 and the Ph. D degree in Electrical Ingineering from the National School of Engineers of Tunis. From to 2009 to 2013, she was a Research Assistant. She is currently an Assistant Professor at the High Institut of Sciences and Technologie. Her current research interests are modeling, identification and control of complex systems and the characterization of handwriting process.

Afef Abdelkrim was born in Tunisia in 1976. She obtained a Diploma of Engineer in 2000 and the PhD in Electrical Engineering at the National School of Engineers of Tunis in 2005; she is now a Professor at the High School of Technology and Computer Science. Her research interests are in handwriting process modelling and synthesis and in the artificial neuronal network domains.

Mohamed Benrejeb was born in Tunisia in 1950. He obtained the Diploma of Ingineer IDN (French Grande Ecole) in 1973, The Master degree of Automatic Control in 1974, the PhD in Automatic Control of the University of Lille in 1976 and the DSc of the same University in 1980. Full Professor at the National School of Engineers of Tunis since 1985 and at the Central school of Lille since 2002, his research interests are in the area of analysis and synthesis of complex systems based on classical and non conventional approaches and recently in the SED domain.