DETECTION OF HUMAN REFLEX RESPONSE TIME-DELAY TO A STRETCH MUSCULAR PERTURBATION

Ph. POIGNET, M. GUGLIELMI, B. VOZEL, I. RICHARD***

* Laboratoire d'Automatique de Nantes, U.R.A. C.N.R.S. 823
Ecole Centrale de Nantes / Université de Nantes
1 rue de la Noë, 44072 Nantes Cédex 03, FRANCE.
poignet@lan.ec-nantes.fr
** Service de Rééducation Fonctionnelle, Hôpital Saint-Jacques
85 rue Saint-Jacques, 44035 Nantes, Cédex, FRANCE.

ABSTRACT

The purpose of this paper is the presentation of the results of a comparative study of the respective efficiency of three parametric signal processing methods to detect abrupt spectral changes by means of the detection of abrupt model discontinuities, while they were applied to the very particular case of inspection of change in myoelectric activity of surface electromyograms (E.M.G.). The studied surface electromyograms are those of biceps brachii during a perturbed flexion-extension forearm movement in the horizontal plane. After the description of the experimental device, the problem position is then formally considered, and the different used methods are briefly recalled. Finally, the results observed on a large set of trials are showed to light the behaviour of each selected method before concluding on the opportunity to use them to characterize some neuropathies.

1. INTRODUCTION

This paper investigates how various signal processing methods may characterize changes in myoelectric activity of surface electromyograms (E.M.G.) when an external perturbation appears. The final object is to detect the different reflex activities. More particularly, the delay between the external perturbation and the E.M.G. may inform about some neuropathies [1]. The experimental device is designed to study flexion-extension forearm movements in the horizontal plane. We measure and record cinematic variables and surface E.M.G. of biceps brachii. A torque motor is mounted on the axis and allows perturbation of the ongoing motor act. The perturbation's characteristics (amplitude, duration, slope) are determined by the operator. The computer, I.B.M. PC/AT, controls the torque motor and records the signals. In the experiment described here, the subject is asked to maintain a certain position stable against an initial torque. During the experiment occurs a stepwose torque increment. The subject is instructed to resist the perturbation. The exact date of occurence and the level of the stepwise perturbation of the torque increase are unknown from the subject. This operation could be repeated several times : see figure 1 for one example of recording. Electromyograms have classically been analysed by simple signal processing methods [2]. These methods reach their limits when we consider non-stationary signals. In our case, the averaging of several trials leads to a distorsion of the signal components and tends to increase the burst width since the subject's delay response is not a deterministic one. It seems, therefore, of great interest to characterize each individual signal and to perform then statistical analysis of the parameters. In this paper, we propose three different detectors that identify model discontinuities revealing the reflex responses evoked by the perturbation. All of them used model. So we present two modeling of the E.M.G. at a low contraction level during the first part of the experiments (the signal is stationary). One model is the classical autoregressive A.R. or autoregressive with moving average A.R.M.A. model but the other modelization is an original one since it uses linear implicit state model, able to take into account abrupt changes in the parameters [3]. For the two classes, the parameter identification is performed online by means of the well-known Extended Kalman Filter [3], [4]. In the second step, after the modeling has been proved available, it is possible to achieve the three different real time detectors.

2. DETECTION BY ANALYSING SINGULAR SYSTEM

This detector is based on the tracking of parameters in a linear implicit model. The processed signal is supposed to be well described by an autoregressive linear parametric model (order p=8 [5]) in which we take into account the parameters abrupt changes. The model is then written :

$$y_k + (a_1 + s_1)y_{k-1} + ... + (a_p + s_p)y_{k-p} = v_{k-1} \qquad (1)$$

where $\{a_i\}$ are the model parameters and s_i is the possible jump on the ith parameter. The modeling, fully described in [3], leads to the following singular state model :

$$\left\{ \begin{array}{rcl} \begin{bmatrix} I_p & 0 \\ 0 & 0 \end{bmatrix} X_{k+1} & = & \begin{bmatrix} A_c & S \\ -D_s & I_p \end{bmatrix} X_k + Gv_k \\ y_k & = & [0...01\ 0...0]X_k \end{array} \right. \qquad (2)$$

where :

$$A_c = \begin{bmatrix} 0 & 1 & & \\ & \ddots & \ddots & \\ & & 0 & 1 \\ -a_p & \dots & \dots & -a_1 \end{bmatrix}, \; S = \begin{bmatrix} 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \\ -1 & \dots & -1 \end{bmatrix}$$

$$D_s = \begin{bmatrix} s_p & & 0 \\ & \ddots & \\ 0 & & s_1 \end{bmatrix}, \; G = [0 \dots 1\, 0 \dots 0]^T$$

The detection procedure is then composed of two parts. In the first one, we identify the a_i parameters by means of a new algorithm especially developped for the singular system [6] and based on the Extended Kalman Filtering (E.K.F.). The user's parameters of E.K.F. are choosen such as the jumps s_i keep the zero value during this time. In the second phase, we track the estimation of each s_i, $\hat{s}_i = E(s_i/measures)$. As the system is well identified with $\hat{s}_i$ values equal to zero, $\hat{s}_i$ keep the zero value up to a change occurs. Formally, observing the measurement $(y_1, \dots, y_l)$, we have to decide between two hypotheses :

$$\begin{aligned} For\ (1 \leq k \leq l)\ H_0 &\ :\ \theta = \theta_0 = (s_i) = (0) && (3) \\ H_1 &\ :\ \exists\, r_i\ (1 \leq r_i \leq l)\ / && (4) \\ For\ 1 \leq k \leq r_i - 1 &\ :\ \theta = \theta_0 && (5) \\ For\ r_i \leq k \leq l &\ :\ \theta = \theta_1,\ i.e.\ \exists s_i \neq 0 && (6) \end{aligned}$$

We design the decision function g_k^s (quadratic norm weighted by the covariance matrix) :

$$g_k^s = \theta^T \Sigma^{-1} \theta \tag{7}$$

where $\Sigma = E[\theta\theta^T]$.
If g_k^s becomes greater than a threshold λ (*a priori* fixed by the user), a change is decided.
In case of an A.R.M.A. model, assuming that only the A.R. part is subjected to changes :

$$\begin{aligned} y_k + (a_1 + s_1) y_{k-1} + \dots + (a_p + s_p) y_{k-p} &= \dots \\ v_k + c_1 v_{k-1} + \dots + c_p v_{k-p} & \end{aligned} \tag{8}$$

The modeling leads to the following singular model :

$$\begin{cases} \begin{bmatrix} I_p & 0 \\ 0 & 0 \end{bmatrix} X_{k+1} = \begin{bmatrix} A_c & -I_p \\ 0 & I_p \end{bmatrix} X_k + \dots \begin{bmatrix} M_{c,a} \\ S \end{bmatrix} y_k \\ y_k = [H\ 0] X_k + v_k \end{cases} \tag{9}$$

with :

$$A_c = \begin{bmatrix} 0 & & & & -c_p \\ 1 & \ddots & & & \vdots \\ & \ddots & \ddots & & \vdots \\ & & \ddots & 0 & \vdots \\ & & & 1 & -c_1 \end{bmatrix}, \; S = \begin{bmatrix} -s_p \\ \vdots \\ -s_1 \end{bmatrix}$$

$$M_{c,a} = \begin{bmatrix} c_p - a_p \\ \vdots \\ c_1 - a_1 \end{bmatrix}$$

The detection procedure is the same scheme as the one previously exposed in the AR case. For the real case, the order is (p, p)=(2, 2).

3. WHITENESS

The second detector tests the whiteness property of the signal innovation provided by the Kalman Filter [4].
Here again, as precise before, the processed signal is assumed to be well described in the first part of the experiment, by a classical autoregressive, order p=8, or autoregressive with moving average, order (p,q)=(2,2), linear parametric model, which both write:

$$y_k = \phi_k^T \theta + v_k \tag{10}$$

where :
y_k is the processed signal
v_k is a centered gaussian sequence of unknown variance σ_v^2
and in the A.R. case :

$$\phi_k^T = (-y_{k-1}, -y_{k-2}, \dots, -y_{k-p}) \tag{11}$$

$$\theta^T = (a_1, a_2, \dots, a_p)^T \tag{12}$$

and in the A.R.M.A. case :

$$\phi_k^T = (-y_{k-1}, -y_{k-2}, \dots, -y_{k-p}, v_{k-1}, v_{k-2}, \dots, v_{k-q}) \tag{13}$$

$$\theta = (a_1, a_2, \dots, a_p, c_1, c_2, \dots, c_q)^T \tag{14}$$

In practical way, eq. (13) is computed with :

$$\phi_k^T = (-y_{k-1}, -y_{k-2}, \dots, -y_{k-p}, \epsilon_{k-1}, \epsilon_{k-2}, \dots, \epsilon_{k-q}) \tag{15}$$

where the signal innovation ϵ_k is defined by :

$$\epsilon_k = y_k - \phi_k^T \hat{\theta}_{k/k} \tag{16}$$

$\hat{\theta}_{k/k}$ denotes the current Kalman Filter identified model of the signal.
The whiteness of the signal innovation is finally tested by computing an ergodic estimation of the first point of its correlation function. This estimation is given by the following recursive equation :

$$\rho_k = \alpha \rho_{k-1} + (1 - \alpha) \epsilon_k \epsilon_{k-1} \tag{17}$$

where α is an constant factor ($0 \leq \alpha \leq 1$).
If the absolute value of ρ_k becomes greater than a threshold λ_ϵ (*a priori* fixed), then the presence of a change is decided.

4. DISTANCE BETWEEN TWO UNCERTAIN MODELS

The last detector uses a distance measure between two models identified within different length observation windows : a reference large one which takes into account all or almost all the past of the signal, and a test short one which only contains the L past observations (L ≈ 100). As a result, if no changes occurs, the long-term windowed observations lead to the same model than the short term ones.
Here the distance measure which is used, involves the uncertainity in the knowledge of the compared models (just estimated from finite lengh data sequences). This distance measure, which can be seen as a generalisation of the Itakura-Seito distance, is deduced from the optimal bayesian decision rule, written in a supervised classification context [7] and where the learning set is reduced to the studied signal.

Noting L_0 and L_1 the respective lengths of a long and a short window (as decribed above), $\hat{\theta}_0$ and $\hat{\theta}_1$ the estimated parameter vectors, P_0 and P_1 the estimation error variance-covariance matrices, the distance measure is defined by [7]:

$$d_k = (\hat{\theta}_1 - \hat{\theta}_0)^T((1 + \frac{L_1}{L_0})P_1)^{-1}(\hat{\theta}_1 - \hat{\theta}_0) \qquad (18)$$

If d_k becomes greater than a threshold λ_ϵ (*a priori* fixed), then the presence of a change is decided.

5. RESPONSE TIME-DELAY

To study the reflex response with large time-delay, we apply the three detectors. The E.M.G. signal (5 sec., sampled 1Khz) is composed of several phases : the first one is unusable because of the transitory, the second one is necessary for the identification (1500) before the change occurs, the third phase is the human response followed by the volontary response not studied here. The signals of which an example is given on fig. 1 are then 2000 points length. In the practical use, the detection procedure is achieved on the [1350 1650] window in the following way : we know the change time (r=1500) and the threshold varies. For the first threshold which gives a response after the change time, the time is recorded and we consider the next realisation. We achieve histogramms which represent the number of realisations with respect to the response time-delay.

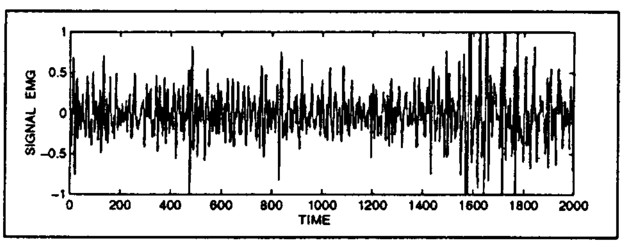

Figure 1 : Realisation of E.M.G. signal

In case of AR(8) :

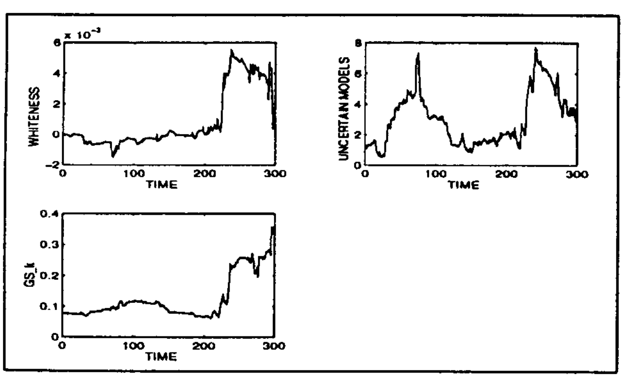

Figure 2 : Realisations of each detector

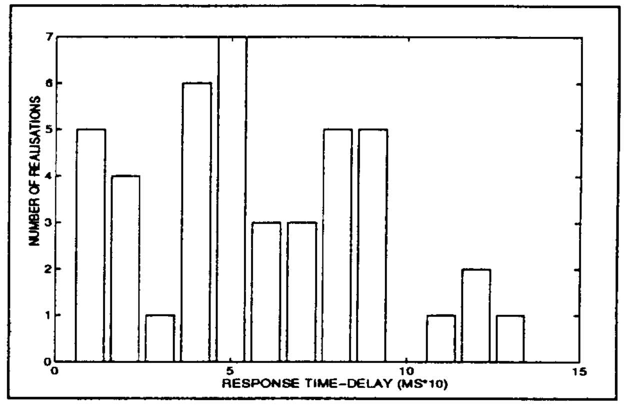

Figure 3 : Histogram for g_k^s

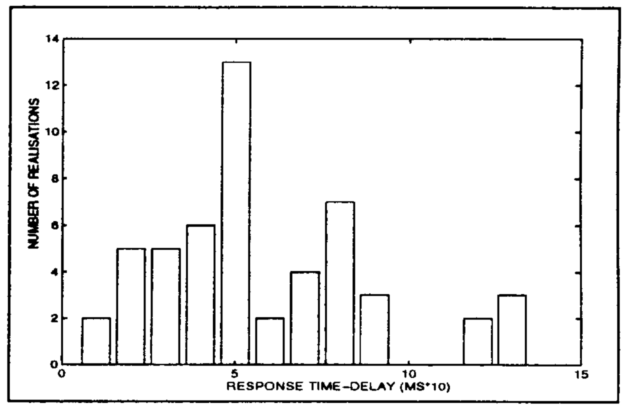

Figure 4 : Histogram for whiteness

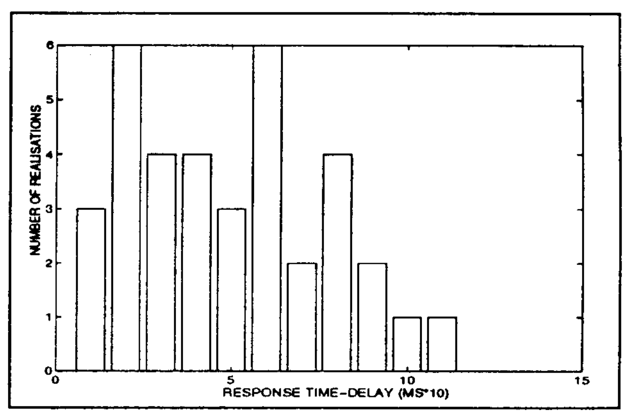

Figure 5 : Histogram for uncertain models

In case of ARMA(2,2) :

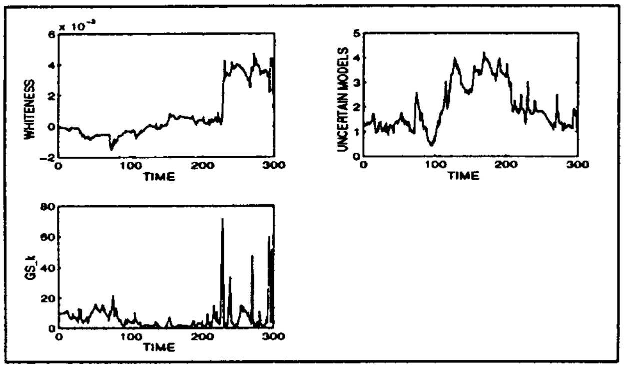

Figure 6 : Realisations of each detector

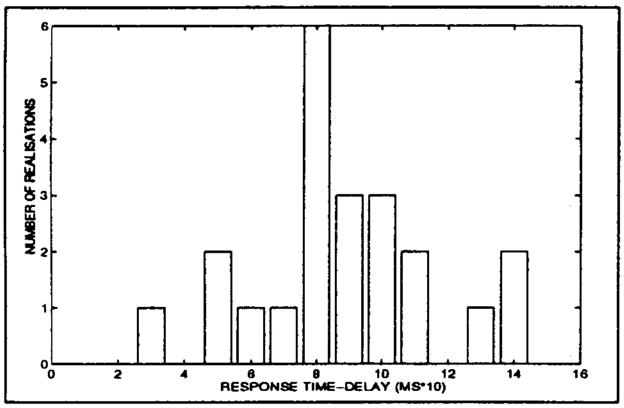

Figure 7 : Histogram for g_k^s

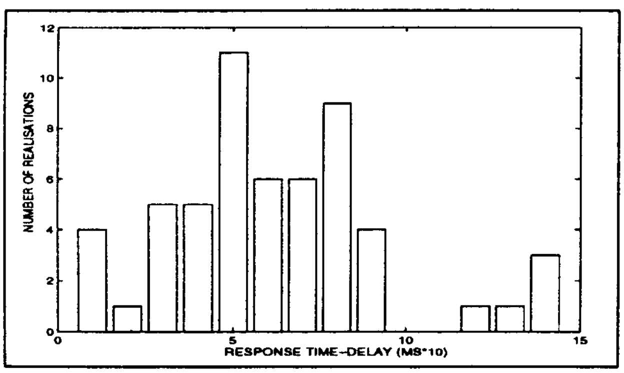

Figure 8 : Histogram for whiteness

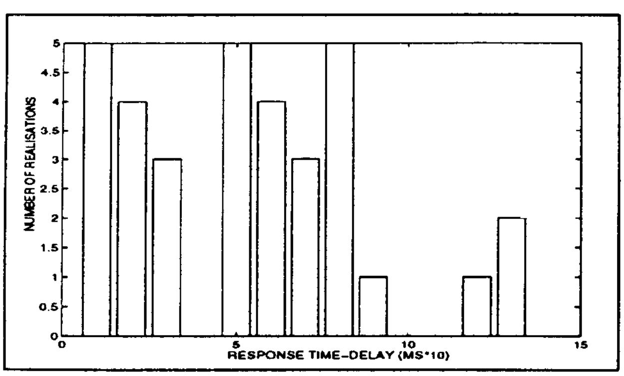

Figure 9 : Histogram for uncertain models

6. CONCLUSION

The impossibility to define a model after the abrupt changes and consequently the difficulty to use different length of windows justify the contribution of the singular model. The comparison between the three detectors is achieved by means of a statistical study.
The non-repetitivity of the response time-delay due to human factors oblige us to treat individually each signal. Therefore the statistical are presented with the histogram. The results show that something happens at about 60 ms but it's difficult to say precisely how long is the response time-delay because it is composed of the detector and human response time-delay. Therefore we plan to design a new protocol to reduce the detection time-delay.
This study provides an over-view of which methods are avalaible in the very particular case of the E.M.G. signal abrupt changes detection. For example the distance considering two uncertain models seems less efficient than the two other one. At last, we should say that there the solution is not unique and the expert may have an opinion with different points of view.

7. REFERENCES

[1] **Bizzi E. and Abend W. :** *"Posture control and trajectory formation in single or multi-joint am movement. Motor control mechanisms and deseases", Ed. J.E. Desmedt, Raven Press, pp 31-47, New-York 1983.*

[2] **Bouisset S. :** *"Fundamental motor patterns in simple volontary movements", Biomechanics VIII B Mathsui et Kobayashi, Ed. Human kinetics publisher Champeign III, 1983.*

[3] **Poignet Ph. and Guglielmi M. :** *"Abrupt changes detection via singular system analysis", EUSIPCO-94, Edinburgh, Sept. 1994.*

[4] **Ljung L. and Soderstrom T. :** *"Theory and pratice of recursive identification", MIT Press 1983.*

[5] **M. Guglielmi, M.F. Lucas, C. Doncarli, I. Richard, and J.F. Mathe :** *"Burst detection in surface emg during a perturbed forearm movement", Conférence invitée : 12th Annual International Conference I.E.E.E./E.M.B.S., Philadelphie, USA, November 1990.*

[6] **Poignet Ph. and Guglielmi M. :** *"Identification of time-invariant descriptor systems by means of extended kalman filtering", I.E.E.E.-E.R.K., Portoroz, Sept. 1993.*

[7] **Vozel B. :** *"Etude comparative d'algorithmes récursifs de détection de ruptures spectrales", Thèse de doctorat, Nantes, Feb. 1994.*