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***Abstract*—EMG signals are an image of the control from the central nervous system transmitted to muscles. Intramuscular EMG signals are collected directly in muscles. The collected data contain information on the neural control of the muscle. This information can be used for controlling external devices (myoelectric control), however realtime processing of intramuscular EMG signals is complex.**

The aim of this paper is to present a sequential method to estimate parameters which can lead to an active drive of an upper limb prosthesis. A system model will be presented and then an algorithm detailed. Results of the proposed algorithm applied to simulated and experimental data will be discussed.

I. Introduction

A. EMG signals

Advanced techniques of functional rehabilitation include the use of physiological signals to drive and control limb prostheses. Various physiological signals can be used for this purpose, such as from the brain (ElectroEncephaloGram, EEG), peripheral nerves or muscles (ElectroMyoGram, EMG). Currently, the technological limitations and risks associated to invasive brain or nerve interfacing impede the use of these approaches in large-scale clinical applications, [1]. Conversely, EMG signals are already used in commercial devices for controlling artificial hands and upper limb prostheses.

EMG signals are collected with electrodes placed at the surface of the skin or in the muscle. These signals are constituted by the superimposition of the activity of several motor units, triggered by motoneuron activity. Each motor unit activity is characterized by a basic wavelet, called Motor Unit Action Potential (MUAP) [2], and a firing pattern of activation [3] [4]. Each muscle is controlled by several motoneurons. Thus, the superimposition in picked up signals can be explained by the multiplicity of firing motoneurons controlling a muscle and the control of more than one muscle at the same time. The effect of passive body filters makes the interpretation of these signals difficult.

Our main objective is to drive an upper limb prosthesis using signals that express motoneuron activity. Therefore, the command signals of servo-valves will be optimized from identified firing rates of motoneurons and pre-stored references [5]. A criterion for the validation of the process may be a correct imitation of motions by a virtual prosthesis equiped with musculotendons [6] [7], taking into account the phenomenon of co-activation [8].

B. Signal processing

Prosthesis control is usually performed with surface EMG signals. The analysis of surface EMG signals with descriptors extracted from Fourier transform, auto-regressive models, time-frequency or time-domain analysis along with a classification [9], is indeed sufficient for many applications. In this case, the results are an on-off move of the prosthesis (pattern recognition). Proportional control can be achieved by identifying the activity of individual motor units. Methods for the analysis of motor unit behavior are often based on intramuscular EMG signals (e.g., [10]). However, the decomposition of intramuscular EMG is usually time consuming, and current methods are therefore implemented only off-line

Our contribution is to introduce a sequential technique for on-line estimation of firing rates of active motoneurons from intramuscular EMG. In the future, these estimations will feed the control of a multi-degree of freedom prosthesis.

II. Method and model

A. Data Acquisition

The experimental intramuscular EMG signals were recorded from the biceps brachii muscle of five healthy men (age, mean $\pm$ SD = 21.3 $\pm$ 3.2yr) with a pair of wire electrodes made of Teflon coated stainless steel (A-M Systems, Carlsborg, WA, USA; diameter 50m) inserted into the muscle belly with a 25 G needle. The intramuscular EMG signals were amplified bipolarly (Counterpoint EMG, DANTEC Medical Skovlunde, Denmark), band-pass filtered (500 Hz-5 kHz), and sampled at 10 kHz. The signals were recorded while the subjects performed isometric contractions at 5% or 10% of the maximal voluntary contraction (MVC) force.

B. System model

A classic model of the observed intramuscular EMG signals, see Farina et al. [11], is a linear sum of filtered spikes trains.

$$y[n] = \sum_{i=1}^{M} (h_i * u_i)[n] + w[n] \quad (1)$$

where u_i are signals corresponding to unknown spike trains, h_i are human body filters (corresponding to MUAP shape), w is the measurement noise, M is the number of motoneurons firing around discrete time n. (1) describes a model where neural controls are filtered and summed, and where the noise w is additive.

Moreover, general assumptions are made (see [11] for more detailed assumptions):

- each u_i is an independant Bernoulli-Gaussian process with firing rate $q_i \in [0, 1]$ (*i.e.* the probability to have a spike at each discrete time);
- each h_i is a finite impulse response system;
- w is a zero-mean independant gaussian noise with variance r.

In this paper, we assume that the noise variance r, the number of firing motoneuron M and the associated filters h_i are known. Moreover, the filters are time-invariant.

C. Estimation algorithm

The main objective is to estimate the firing rates q_i, since they can be considered as the main input of prosthesis control. The problem is that the inputs u_i are unknown. At each time n, there are $2^{M\,n}$ possible paths $U[n]$ filled with 0 and 1:

$$U[n] = (u_i[k])_{\substack{1 \le i \le M \\ 1 \le k \le n}}$$

For instance, if $M = 2$, each path can be completed at $n + 1$ with 4 possible forks, since:

$$\begin{pmatrix} u_1[n] \\ u_2[n] \end{pmatrix} \in \left\{ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\}$$

If the paths u_i are known, the estimation of the q_i is straightforward, since this is the mean value of each path component. The proposed algorithm consists in the evaluation of the posterior probability of each possible path. Then, the estimated q_i are the weighted mean of the solutions obtained from each path (the weights being the posterior probability). To avoid an exponentially increasing computational load, at each time, the K most probable paths are kept, where K is a parameter of the method.

The recursion at time n writes:

- Observation of data at time n, that is $y[n]$.
- For each path $U[n]$ with prior probability $\bar{p}_{U[n]}$:
  - the noise-free observation $\hat{y}_{U[n]}[n]$ is simulated
  - the unnormalized posterior probability $\tilde{p}_{U[n]}$ is computed:

    $$\tilde{p}_{U[n]} \propto \bar{p}_{U[n]} \cdot g(y[n] - \hat{y}_{U[n]}[n], r)$$

    where $g(., r)$ is the probability density function or the zero-mean Gaussian law with variance r; the posterior probability consists of the product of the prior probability and the local likelihood of the current data.
- Selection of the K paths with the highest probabilities.
- Posterior probabilities are normalized:

  $$p_{U[n]} = \frac{\tilde{p}_{U[n]}}{\sum_t \tilde{p}_t}$$

- For each selected path $U[n]$, computation of the estimated firing rates:

  $$\hat{q}_{i,U[n]} = \frac{\sum_{k=1}^{n} u_i[k]}{n} \quad (2)$$

- Computation the final estimate of the firing rates, as a weighted mean of all paths solutions:

  $$\hat{q}_i = \sum_{U[n]} \hat{q}_{i,U[n]} \, p_{U[n]} \quad (3)$$

- For each selected path $U[n]$ and each possible fork u^+ of the value taken by $u[n + 1]$:
  - building of the extended paths:

    $$U[n + 1] = \begin{bmatrix} U[n] & u^+ \end{bmatrix}$$

  - computation of their prior probabilities:

    $$\bar{p}_{U[n+1]} = p_{U[n]} \prod_{i=1}^{M} (1 - \hat{q}_{i,U[n]})^{1-u_i^+} \, \hat{q}_{i,U[n]}^{u_i^+}$$

This sequential method of estimation of firing rates tallies with a rigorous bayesian filtering approach.

D. Modified algorithm for tracking

Note that the storage of the paths is useful only for deconvolution purposes. In practical implementations, the paths do not need to be stored to just estimate the firing rates. Furthermore, most of the formula above are presented as an offline computation for sake of simplicity, but they can be recursively computed.

For example, the estimation (2) of the firing rate of each path $U[n]$ can be obtained from parent path $U[n-1]$ through the formula:

$$\hat{q}_{i,U[n]} = \hat{q}_{i,U[n-1]} + \frac{1}{n} \left(u_i[n] - \hat{q}_{i,U[n-1]} \right) \quad (4)$$

In another hand, the firing rates are obviously time-varying in real cases. Thus, inspired by forgetting factors proposed in [12], we can obtain a tracking algorithm by replacing formula (4) by:

$$\begin{cases} \ell[n] & = 1 + \left(1 - \frac{1}{\ell_\infty}\right) \ell[n-1] \\ \hat{q}_{i,U[n]} & = \hat{q}_{i,U[n-1]} + \frac{1}{\ell[n]} \left(u_i[n] - \hat{q}_{i,U[n-1]} \right) \end{cases} \quad (5)$$

With $\ell[0] = 1$, $\ell[n]$ is the length of a growing window, whose final length is ℓ_∞. ℓ_∞ has to be set according to desired adaptivity. There is no tracking when $\ell_\infty = +\infty$.

III. Tests and discussion

A. Simulated Data

Simulated signals are created upon the model presented in (1). Spike trains result from draws following time-discrete Bernoulli processes at a sample frequency of 10 kHz, and are convolved with time-invariant finite impulse filters. The probability successes of the Bernoulli processes range from $1.5 \cdot 10^{-3}$ to $3.5 \cdot 10^{-3}$, meaning an average of fifteen to thirty-five spikes per second. A noise is added. The method was tested on signals made up of one to six trains and SNR varying from 15 dB to 30 dB. At each run, the noise variance, the number of train and the filters were known. A forgetting factor corresponding to a window length at infinity ℓ_∞ of 2 seconds is applied to present smooth results. A shorter window length allows a better tracking, but a higher variability of the value of the parameters.

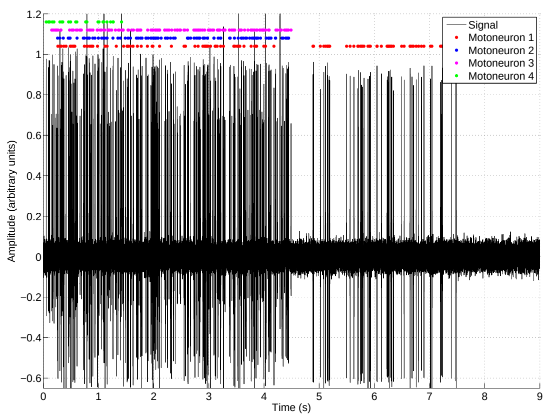

Fig. 1. Simulated signal with four Bernoulli processes sampled at 10 kHz and a SNR of 17 dB

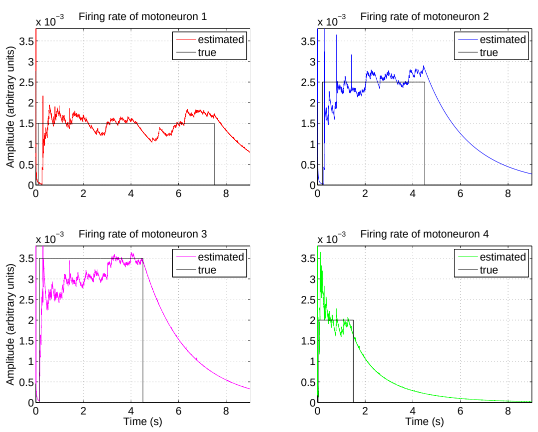

Fig. 2. Estimation of probability successes with a forgetting factor corresponding to $\ell = 2$ seconds and 16 stored paths (processing time $\approx$ 340 sec)

Fig. 2 presents representative results obtained after an implementation of the method. At the start, the quick variations of the estimated parameters are due to the short length of the window ℓ. After few seconds, the estimated parameters (colored-solid line) catch up with the true values (boxcar function, black-solid line). The peaks, between origin and two seconds, occur when a path with false positives is kept due to its high probability. It influences greatly estimated values, see (3). Finally it is discarded with regard to a path without false positives. Also some false negatives may occur at the beginning of the signal, extending the period for the catching up.

B. Experimental Data

The validation on experimental data was performed by comparing the results of the proposed method with those provided as reference results by manual decomposition of an expert operator using the EMGLAB tool [13]. The proposed method was applied in a fully automatic way, without any intervention by the operator.

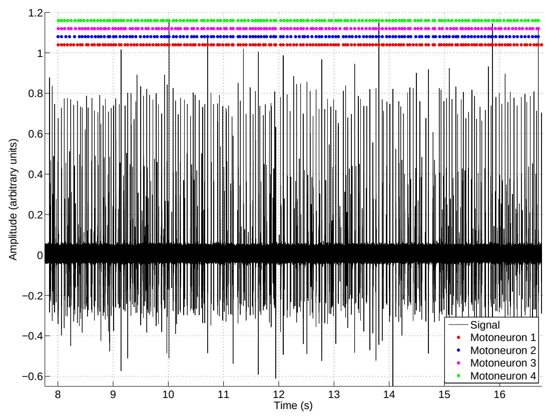

Fig. 3. Intramuscular EMG signal recorded from the biceps brachii muscle during an isometric contractions at 10% of the MVC force

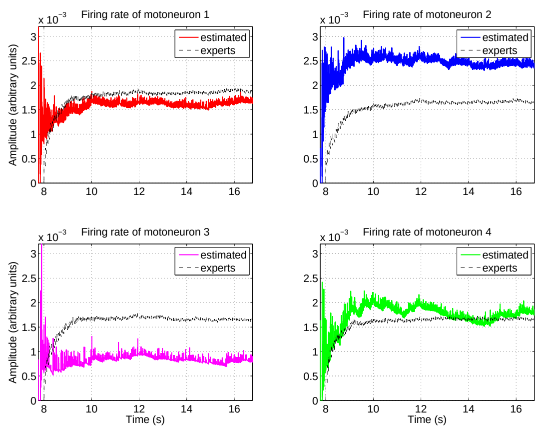

Fig. 4. Estimation of firing rates q_i of four firing motoneurons with a forgetting factor corresponding to $\ell = 2$ seconds and 16 selected paths (processing time $\approx$ 340 sec)

As for the simulated data, the number of firing motoneurons was known, the noise variance was estimated and the MUAP shape of each motor unit was extracted manually.

Representative experimental data can be seen in Fig. 3. The dots denotes the identification of a spike coming from one of the firing motoneurons. The experts identified 4 firing motoneurons. The noise variance is estimated at the start of the recording, but appears not to be a white noise. The MUAP shapes are varying through time because of physiologigal changes in the muscles and a sampling problem (short impulse responses are badly sampled).

The phenomenon of peaks is observed as previously, but are now observed during the whole process. For both the first and the last motor unit, the parameters follow experimental parameters, whereas for the second and third motor unit, there are respectively an overestimation and a underestimation compared to the experimental values. This may be associated to the MUAP shapes for these two sources. Two proposed explanations are that the MUAP shape of motoneuron 3 varies greatly over time and constructive/destructive interferences between MUAP shapes render the identification difficult.

IV. Conclusion and future work

A model and an algorithm have been presented and applied to both simulated and experimental data. Though estimations are very good on simulated data, estimations on experimental data show some flaws due to the simple model assumed in the paper. Future improvements will be online estimation of the MUAP shapes and the number of firing motoneurons. The algorithm has to estimate these parameters automatically for an application of prosthesis control in patients. Moreover the activities of motor units are correlated, and a refractory period is present between two impulses of a motor unit. Further statistical studies will focus on these aspects to improve the model.

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