ONLINE ESTIMATION OF EMG SIGNALS MODEL BASED ON A RENEWAL PROCESS

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ABSTRACT

The paper presents an online estimation of parameters of a multi-input renewal Markov process. The underlying model is derived from the physiological generation of intramuscular electromyographic (iEMG) signals, which are recorded by wire electrodes. The iEMG is the sum of several sparse spikes trains and noise. An hidden Markov model, whose parameters express the muscular activity, is developed. The time duration between spikes is modeled with a discrete Weibull distribution, helping us to reduce the complexity of the estimation done with the help of a Bayes filter.

***Index Terms*—** Markov process, bayesian method, parameter estimation, Weibull distribution

1. INTRODUCTION

Several physiological signals play a major role in the regulation and control of the body such as ElectroMyoGraphic (EMG) signals that travel through muscles and can be collected quite easily. Although these signals disclose a general view of the body control scheme, it has been shown that they could be analyzed [1] or used in quite a various range of application, such as for medical therapy [2], control of an exoskeleton [3], or control of a prosthesis [4, 5].

The decoding part of the signal has been heavily studied. Extraction and classification of features from full wave rectification signals is used to estimate users' intentions. Various approaches have been tested in previous works [6], especially based on non-invasive EMG signals. However, these studies are limited because of the extreme variability in the collected signal between users and within the user himself, and the long training of the decoding system. Moreover, these signal processing techniques only estimate a finite set of motions, without combinations of more than one movement. In addition to surface EMG signals, iEMG can also be used as source for the control of prosthetic devices. iEMG signals, if correctly decoded, can be viewed as the direct control of the brain upon muscles since the constituent sources are the output signals from the spinal cord [7].

In this paper, we present a new approach to achieve an online decomposition of an iEMG signals, based on a modeling of signals as a sum of filtered sparse binary spike trains with known impulse responses. In the single input channel case, this can be related to impulse deconvolution problems [8, 9]. It can be also related to change detection in semi-Markov models [10, 11, 12]. In a previous paper [13], we proposed a method based on a time-independence assumption of input spike trains. We propose here to model the inter-spike interval by means of a renewal process based on a discrete Weibull distribution introduced by Nakagawa et al. [14] following the study on the inter-spike intervals law of de Luca et al. [15] in the continuous case. Although the arrival of spikes is a continuous-time process, data are sampled. The approximation of discrete time location for spikes will lead to a simpler model (see previous references).

The model of the signal and the Markov representation are presented in section 2. The online estimation of parameters is presented in section 3. Results on simulated signals and experimental ones are made in section 4.

2. MARKOV REPRESENTATION

2.1. Signal modelling

As observed by Stashuk [16], the iEMG signals can be modeled as the sum of linearly filtered spike trains. The spikes before convolution are the activation signals sent by motoneurons to the muscle to excite a cluster of muscle fibres. When the cluster of fibers innervated by a motor neuron is activated, a train of motor unit action potentials (MUAP) is generated. Finally, the sum of MUAP trains coming from several motoneurons is the so-called iEMG signal.

The problem is to achieve an online decomposition of a multi-input mono-output signal, where patterns may arise naturally due to the sum of convoluted spike trains, named superposition of MUAP shapes.

The linearity in summation of electrical signals justifies the proposed model of the observed EMG signals by Farina et al. [17].

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

where u_i are signals corresponding to unknown spike trains, h_i are supposed to be known corresponding to MUAP shapes, w is the measurement noise, M is the number of motoneurons firing at discrete time n. Eq.(1) describes a model where neural control signals (the spikes trains) are filtered and summed, and where the additive noise w is assumed independent, zero-mean, Gaussian with unknown variance σ^2. The number M of firing motoneurons is assumed to be known. Moreover, the filters are assumed to be time-invariant.

2.2. Input spikes trains

Each input sequence $(u_i[n])_{n\in\mathbb{Z}}$ is a binary discrete process, independent of other sequences $(u_j[n])_{n\in\mathbb{Z}}$ for all $j \neq i$. In a previous paper [13], these sequences were assumed to be time-independent but, actually, physiological constraints make this assumption rather unrealistic. We propose to base these sequences on discrete-time and discrete-valued renewal processes [18].

For each input channel, inter-spikes intervals $\Delta_i[N]$ - discrete time length between spikes numbered N and $N+1$ - are supposed to be independent and identically distributed, with a parameterized probability mass function (PMF) defined by $\mathrm{P}(\Delta_i[N] = t|\Theta_i)$, for all integer $t \geq 1$, where Θ_i is the parameter.

Let's introduce the ongoing sojourn times $(T_i[n])_{i\in[1:M]}$; for each channel, $T_i[n]$ is the discrete duration since the last spike (then, with the Kronecker delta function: $u_i[n] = \delta\left(T_i[n]\right)$).

Using the so-called failure rate (well known in reliability theory [14]):

$$r_{\Theta_i}(t) = \frac{\mathrm{P}(\Delta_i[N] = t|\Theta_i)}{\mathrm{P}(\Delta_i[N] \geq t|\Theta_i)} \tag{2}$$

The transition distribution of $T_i[n]$ writes:

$$\begin{aligned} &\mathrm{P}(T_i[n+1] = t|T_i[n], \Theta_i) \\ &= \begin{cases} r_{\Theta_i}(T_i[n]+1) & \text{if } t = 0 \\ 1 - r_{\Theta_i}(T_i[n]+1) & \text{if } t = T_i[n]+1 \\ 0 & \text{elsewhere} \end{cases} \end{aligned} \tag{3}$$

We have chosen the discrete Weibull distribution [14] with three parameters $\Theta = (t_0, \beta, T_r)$. t_0 represent an approximated median of the distribution, β is a concentration parameter and T_r is a shift in the acceptable time values - which here correspond to the refractory period when muscle fibers loosen up, which is well-known in EMG signals [7]. For all $t \geq T_r + 1$:

$$\mathrm{P}(T = t|\Theta) = \mathrm{e}^{-\left(\frac{t-T_r-1}{t_0-T_r}\right)^\beta} - \mathrm{e}^{-\left(\frac{t-T_r}{t_0-T_r}\right)^\beta}$$

This renewal distribution is chosen because it corresponds to a closed-form failure rate r_Θ; for all $t \geq T_r + 1$:

$$r_\Theta(t) = 1 - \mathrm{e}^{\left(\frac{t-T_r-1}{t_0-T_r}\right)^\beta - \left(\frac{t-T_r}{t_0-T_r}\right)^\beta}$$

The special case $T_r = 0$ and $\beta = 1$ which gives a constant failure rate, a geometric interspike interval, and independent input spikes trains, corresponds to the paper [13]. Here, the value $(t_0 - T_r)\Gamma(1+1/\beta) + T_r$ can be considered as a measure of activation rate of the muscles in the case where t_0 is large [15], which can be used in prosthesis control for example.

2.3. Markov representation

Assuming impulse responses are known and of finite length L, smaller than the refractory period T_r, one obtains a Markov representation, where the state vector is composed of: $T[n] = [T_i[n]]_{i\in[1..M]}$ the M sojourn times and Θ, the concatenation of the M vectors of parameters related to input dynamics.

The Markov representation is then

$$\begin{cases} \Theta \text{ constant} \\ \mathrm{P}(T[n+1]|T[n], \Theta) \quad \text{from Eq.(3)} \\ y[n] = [\varphi(T_1[n]) \ldots \varphi(T_M[n])]\, H + w[n] \end{cases} \tag{4}$$

where y is the noisy output of the system, and φ is a vector of size L full of zero, except an one in position $T_i[n]+1$ in the case where $0 \leq T_i[n] < L$. The observation model is equivalent to the representation (1).

3. ONLINE PARAMETER ESTIMATION

3.1. Principle

We have to recursively estimate the Weibull parameters of every input channels by means of the growing data sequence $Y^n = [Y[1] \ldots Y[n]]$.

The main idea of the global estimation process is to estimate Weibull parameters for all possible path t_i^n of the sawtooth sequences T_i^n ($[T_i^n]_{i\in[1..M]}$ is denoted T^n). The final estimation of these parameters is then the mean value over all possible sawtooth sequences weighted by their posterior probabilities.

$$\hat{\Theta}(Y^n) = \sum_{t^n} E\{\Theta|T^n\}\mathrm{P}(T^n{=}t^n|Y^n) \tag{5}$$

By means of Bayes filter, the probability can be expressed recursively as:

$$\mathrm{P}(T^n = t^n|Y^n) \propto g(y[n] - \hat{y}(t^n), \sigma^2) \times \\ \mathrm{P}(T[n]{=}t[n]|T^{n-1}{=}t^{n-1})\mathrm{P}(T^{n-1}{=}t^{n-1}|Y^{n-1}) \quad (6)$$

where $\hat{y}(t^n)$ is the simulated ouput at time n for input sequence t^n computed with the respresentation (4) and $g(., \sigma^2)$ stands for the probability density function of the zero-mean Gaussian law with variance σ^2.

Then, using the law of total probability, the independence of all inputs, and Eq.(3), the middle term writes:

$$\mathrm{P}(T[n]{=}t[n]|T^{n-1}) = \prod_{i=1}^{M} \cdots \quad (7)$$

$$\begin{cases} E\{r_{\Theta_i}(T_i[n-1]+1)|T^{n-1}\} & \text{if } t_i[n]{=}0 \\ 1 - E\{r_{\Theta_i}(T_i[n-1]+1)|T^{n-1}\} & \text{if } t_i[n]{=}T_i[n-1]+1 \\ 0 & \text{elsewhere} \end{cases}$$

3.2. Dynamic parameters

The expected value of the failure rate does not have a closed-form solution, so we first choose to linearize the failure rate around the expected value of the parameter $E\{r_{\Theta_i}(t)|T_i^n\} = r_{E\{\Theta_i|T_i^n\}}(t)$. We propose to replace the computation of $E\{\Theta_i|T_i^n\}$ by a simple estimation $\hat{\theta}_i(T_i^n)$ with maximum likehood (ML) based estimator which leads to a practical online implementation. Let us note $T_{i*}^n = (T_i[2], \ldots, T_i[n])$, the sequence T_i^n in which the first term has been dropped. Although the actual ML estimation for a given observation t_i^n of the sawtooth sequence is $\arg\max_\theta \mathrm{P}(T_i^n = t_i^n|\Theta_i = \theta)$, we will use in this paper

$$\begin{aligned} \hat{\theta}(t_i^n) &= \arg\max_\theta \mathrm{P}(T_{i*}^n{=}t_{i*}^n|\Theta_i{=}\theta, T[1]{=}t[1]) \\ &= \arg\min_\theta \underbrace{-\frac{1}{n}\ln \mathrm{P}(T_{i*}^n{=}t_{i*}^n|\Theta_i{=}\theta, T[1]{=}t[1])}_{J_{t_i^n}(\theta)} \end{aligned}$$

This is a standard way to handle end-effect when starting a recursion (for example in the so-called *autocovariance method* for estimating parameters of autoregressive models [19]). Using Markov property of sawtooth sequences the objective function J_{t^n} recursively writes, for all $n \geq 2$, by means of transition probability:

$$\begin{aligned} J_{t^n}(\theta) = &-\frac{1}{n}\underbrace{\ln \mathrm{P}(T[n]{=}t[n]|\Theta{=}\theta, T[n-1]{=}t[n-1])}_{-Q_{t^n}(\theta)} \\ &+ (1-\frac{1}{n})J_{t^{n-1}}(\theta) \end{aligned}$$

Note that, if $\hat{\theta}(t^{n-1})$ attains the minimum of $J_{t^n}(\theta)$, the first derivative of the objective function gives [20]

$$\frac{dJ_{t^n}(\hat{\theta}(t^{n-1}))}{d\theta} = \frac{1}{n}\frac{dQ_{t^n}(\hat{\theta}(t^{n-1}))}{d\theta}$$

This derivative is straightforward to compute when using the transition probability produced by a discrete Weibull law. The objective function is recursively minimized by a stochastic gradient update

$$\hat{\theta}(t^n) = \hat{\theta}(t^{n-1}) - \frac{1}{n}G_{t^n}^{-1}\frac{dQ_{t^n}(\hat{\theta}(t^{n-1}))}{d\theta} \quad (8)$$

$$G_{t^n} = \frac{1}{n}\frac{dQ_{t^n}(\hat{\theta}(t^{n-1}))}{d\theta}\frac{dQ_{t^n}(\hat{\theta}(t^{n-1}))}{d\theta}^\top + (1-\frac{1}{n})G_{t^{n-1}}$$

where the Riemannian metric tensor is updated for all $n \geq 2$ and can be interpreted as a quasi-Newton online optimization [21, 22].

3.3. Algorithm

In practice, it is impossible to explore all the possible paths of sawtooth signals. Thus, at each time index n, all paths are completed with all possible forks, the posterior probability is computed thanks to formulae (6), and only K paths with maximum posterior probability are kept, where K is a parameter of the method. Then, the estimated Weibull parameters are computed with Eq.(8) as a mean over different paths weighted by their posterior probability.

4. SIMULATIONS AND EXPERIMENTS

Simulated signals are created upon the model in Eq.(1). Multi-input spike trains are drawn from the failure rate of Eq.(2) following independently, on each channel, a time-discrete Weibull process at a sample frequency of 10 kHz, and convolved with time-invariant finite impulse filters. Those filters are taken on true iEMG signals. The parameters $t_{0,i}$ range from 30 ms to 50 ms, β_i range from 2 to 7, and T_r is set at 30 ms. The experimental iEMG signals were recorded from the extensor digitorum muscle of a healthy subject (age 21 years), with a pair of wire electrodes made of Teon coated stainless steel (A-M Systems, Carlsborg, WA, USA; diameter 50μm) inserted into the muscle belly with a 25 G needle. The iEMG signals were amplied bipolarly (Counterpoint EMG, DANTEC Medical Skovlunde, Denmark), band-pass ltered (500 Hz-5 kHz), and sampled at 10 kHz. The subjects performed isometric contractions at 5% of the maximal voluntary contraction force (MVC) to gather iEMG signals over a period length of approximately one minute.

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 [23]. The proposed method was applied in a fully automatic way. The number of selected paths K is set to 64.

On both Fig.1 and Fig.2, the upper graphs show a detail view of the input signal (dashed line) and the reconstructed signal (solid line), and for each source, true or expert's spikes

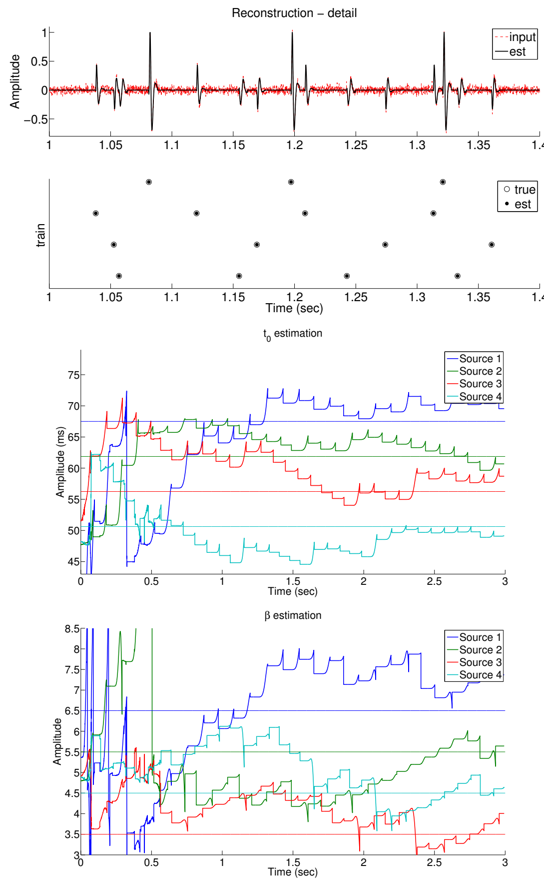

Fig. 1: Reconstruction of the simulated signal and estimation of parameters t_0 and β for four simulated sources

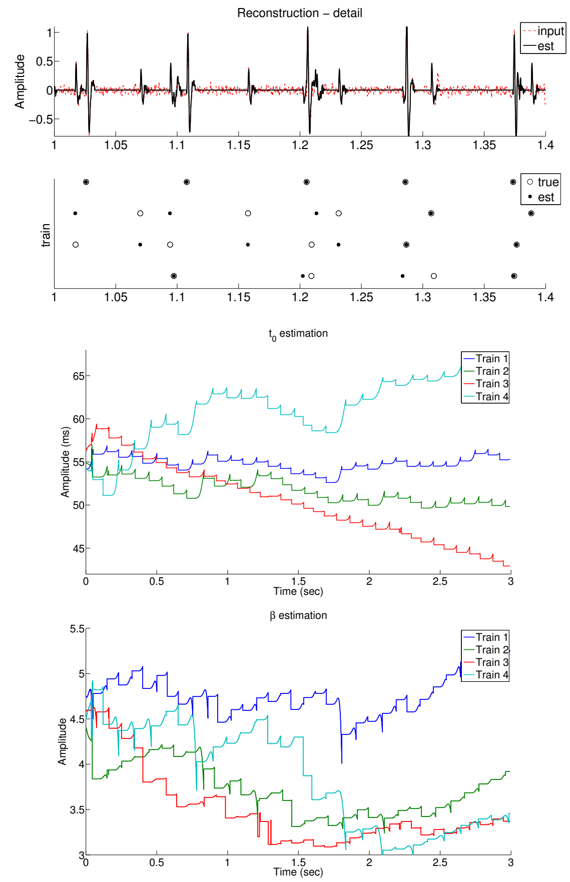

Fig. 2: Reconstruction of the iEMG signal and estimation of parameters t_0 and β for four firing motoneurons

train (circle) and reconstructed spikes train (dot inside circle). The middle and lower graphs present the estimations of the discrete Weibull law parameters.

For the simulation results, the true and estimated spike trains are very close. The $t_{0,i}$ parameters converged on their true values (straight lines) after one second, while for β_i parameters, two seconds were necessary. Note the characteristic saw aspects of the estimation graphs. For the experimental results, the reconstruction appear to be close to the true iEMG signal. The decomposition of the sum of spikes trains wass well achieved. However, there are differences between the expert's decomposition and the proposed method. Around 1.0 second, there is a switch between the second and third sources: visually the reconstructed signal from our method is better than the one guessed by the expert. This may be due to a close shape and amplitude of the two MUAP shapes. Around 1.4 seconds, a spike is missed by both the expert and the decomposition algorithm: the shape is unknown, and thus can not be recognized. The estimations of discrete Weibull law parameters look stable.

The difference between the actual signal and the reconstructed output is expressed by a root mean square error: 0.0549 for the proposed method and 0.0509 for the expert (to be compared to the standard deviation of the signal, 0.0387). Although both methods produced different decompositions, they explained correctly the actual iEMG signal.

5. CONCLUSION

This paper proposes a Markov model of a multiple-input channel, single-output channel system. The explicit expression of the hazard rate allow to compute an online estimation of system parameters by the mean of a quasi-Newton like method. The results obtained in simulation and on experimental data are really conclusive, even though some drawbacks have to be studied. The estimated parameters caught up very quickly the true parameters. Improvements of the method are coming from the introduction of non Bernoulli distribution for spike arriving, but a discrete-time Weibull distribution.

Some hypotheses have to be addressed to make the method usable: online estimation of response filters, number of input channels, estimation of the noise variance.

6. REFERENCES

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