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# Adaptive filtering for ECG rejection from surface EMG recordings

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**Abstract**

Surface electromyograms (EMG) of back muscles are often corrupted by electrocardiogram (ECG) signals. This noise in the EMG signals does not allow to appreciate correctly the spectral content of the EMG signals and to follow its evolution during, for example, a fatigue process. Several methods have been proposed to reject the ECG noise from EMG recordings, but seldom taking into account the eventual changes in ECG characteristics during the experiment. In this paper we propose an adaptive filtering algorithm specifically developed for the rejection of the electrocardiogram corrupting surface electromyograms (SEMG). The first step of the study was to choose the ECG electrode position in order to record the ECG with a shape similar to that found in the noised SEMGs. Then, the efficiency of different algorithms were tested on 28 erector spinae SEMG recordings. The best algorithm belongs to the fast recursive least square family (FRLS). More precisely, the best results were obtained with the simplified formulation of a FRLS algorithm. As an application of the adaptive filtering, the paper compares the evolutions of spectral parameters of noised or denoised (after adaptive filtering) surface EMGs recorded on erector spinae muscles during a trunk extension. The fatigue test was analyzed on 16 EMG recordings. After adaptive filtering, mean initial values of energy and of mean power frequency (MPF) were significantly lower and higher respectively. The differences corresponded to the removal of the ECG components. Furthermore, classical fatigue criteria (increase in energy and decrease in MPF values over time during the fatigue test) were better observed on the denoised EMGs. The mean values of the slopes of the energy–time and MPF–time linear relationships differed significantly when established before and after adaptive filtering. These results account for the efficacy of the adaptive filtering method proposed here to denoise electrophysiological signals.
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## 1. Introduction

Several noises can corrupt electrophysiological signals such as other signals of physiological origin or interference from the electronic environment. For example, the electrocardiogram (ECG) can be contaminated by the electromyogram (EMG) [5], but it can also corrupt signals as the diaphragm EMG [7,11]. With regard to back muscles, several studies have already reported a contamination of the EMG by the ECG [2,8,10]. In these studies, the ECG was removed either by the application of a high-pass filter [10] or by the ECG subtraction performed after data acquisition [8]. In other cases, its presence leaded to the development of more complicated signal processing algorithms [2]. In the present paper, different adaptive filtering algorithms are tested and one of them proposed for the rejection of the ECG from surface electromyograms (SEMG). Adaptive filtering is able to denoise signals when signal and noise present overlapping spectra, and, to

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furthermore follow any change, either on the signal or on the noise. As evolutions of both SEMG and ECG signals are expected during a fatigue test, adaptive filtering should be really efficient for the rejection of ECG artifacts, all along the fatigue test, since it takes into account all changes occurring during the experiment, whatever the signal concerned by these changes.

## 2. SEMG and mechanical recordings

Data were obtained from 2 different populations of women. The first one (Group A) concerned the optimization of the denoising method. It contained 28 subjects, 28.6 ± 2.7 years old, 164.5 ± 5.1 cm height, 64.7 ± 9.2 kg weight and 23.8 ± 2.3 kg/m$^2$ BMI (Body Mass Index = weight(kg)/height$^2$ (m)$^2$). The second population (Group B) concerned the fatigue test. It consisted in 16 women, 27.8 ± 2.1 years old, 162.7 ± 3.9 cm height, 60.2 ± 6.8 kg weight and 22.7 ± 1.6 kg/m$^2$ BMI.

SEMGs were recorded from the right erector spinae muscle at the level of the first (L1) lumbar vertebra. Ag/AgCl electrodes (Beckman type) with an active diameter of 2 mm were filled with electrolyte cream. After the skin was abrased and cleaned with abrasive paste and alcohol, the electrodes were placed, with adhesive, parallel to the long axis of muscle fibers and with an interelectrode spacing of 15 mm. The upper electrode was approximately 3 cm external from the spinous process. The reference electrode was placed at the right wrist. The same procedure was used to record the ECG, but the electrode size was 8 mm in diameter. The electrodes for this ECG recording were located vertically and placed 15 cm apart from top to bottom of the left scapula. Preliminary recordings have demonstrated that by using this electrode position, the recorded ECG (reference noise) was similar in shape to the ECG corrupting the SEMGs. More precisely, this electrode placement allowed the recording of the ECG containing only one peak corresponding to the QRS complex as for the noising signal (see Fig. 2). We thus get free from the possible non-linearity effect of the filtering tissues that could be noticed in some cases [7]. Each signal was differentially amplified (Amplifier: Digitimer-Neurolog; NL820A. Input impedance >10 MΩ; CMRR: >60 dB; gain range 20–95 dB), filtered (bandwith: 2–500 Hz; Butterworth filter – 4th order) and digitized at a 1.024 Hz sampling frequency (A/D card type: DT9801-Data Translation; 12 bits).

To perform a trunk extension, the subject had to press continuously on a board (20 cm$^2$ in area) with a thick foam cover to avoid pain and discomfort. A mechanical device allowed the positioning of the board at the level of the 5th thoracic vertebra. A force transducer, linked to the board, measured the force extension of the trunk. The subject was seated, the trunk inclined down at 20° with arms crossed on the breast. The experimenter verified that these positions and angles were respected all along the extension effort. This procedure differed from those more classically described (for example subject lying prone on a couch [12]) due to the fact that the test was designed to be suitable for pregnant women. At the beginning of the experiment, the subject performed three times a maximal trunk extension lasting no more than 5 s and with a 2-min rest after each trial. The best trial, associated with the highest developed force gave the MVC (Maximal Voluntary Contraction) value. To maintain a submaximal contraction, the subject had to respect the consign value presented on the screen of a control oscilloscope where the force output signal was addressed.

For the optimization of the denoising method and the choice of the best suited algorithm, the subjects of group A had to maintain the trunk extension during about 30 s at 30% MVC. These relatively short duration and low intensity of the effort were sufficient to valid the denoising method.

After the algorithm was chosen, the method efficiency was assessed by the analysis of spectral parameters during a fatigue test performed in the following conditions by the subjects of Group B: the EMGs were recorded during an isometric trunk extension lasting about 3 min and at an intensity corresponding to 50% MVC. With such duration and intensity of the effort performed by the subjects of Group B, a fatigue process can be expected.

The spectral analysis was conducted on the noised and denoised signals using a Fast Fourier Transform (FFT) after a Hanning windowing, for the Power Spectral Density (PSD) estimation. The energy and mean power frequency (MPF) were calculated for each 0.5 s of the recorded signals. As classically, fatigue criteria were the positive slope of the energy–time relationship and the negative slope of the MPF–time relationship [6]. These relationships were established after the expression of energy and MPF values in percentage of their initial values. This normalization facilitated the interindividual comparisons and allowed the calculation of mean slope values over the population.

## 3. Adaptive filtering method and algorithm choice

### 3.1. Principle

The principle of the used adaptive filter is presented in Fig. 1. The signal of interest, $\mathrm{emg}_0(t)$, is corrupted by the noise, $\mathrm{ecg}_0(t)$. The adaptive filter requires a reference signal that is correlated with the noise, $\mathrm{ecg}(t)$, and an adaptive algorithm that controls the filter parameters, with respect to a correction criterion. The filter estimates the noise $\mathrm{ecg}_0(t)$ and, by subtracting it from the

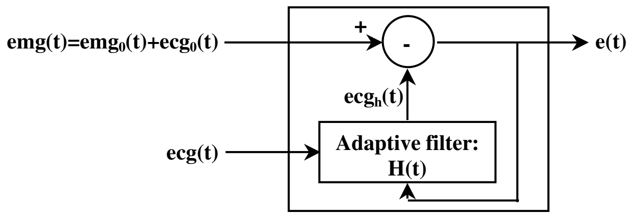


Fig. 1. Filtering principle: emg($t$), raw signal; emg$_0$($t$), signal of interest; ecg$_0$($t$), noise; ecg($t$), reference noise; ecg$_h$($t$), estimate of the noise; $H$($t$), adaptive filter; $e$($t$), filtered signal.

noised signal emg($t$), gives a denoised signal, $e$($t$), an estimate for the signal of interest emg$_0$($t$). This filter is defined in the time domain, by using a finite impulse response filter (FIR) with a length of $N$ points.

As an estimator of ecg$_0$($t$) the filter uses ecg$_h$($t$), the reference ECG filtered by $H$ (ecg$_h$($t$) = $H(t) * \mathrm{ECG}(t)$), where $H$ is the filter at the instant $t$ and ECG($t$) is the last $N$ values of ecg($t$)).

One of the main advantage of this adaptive noise canceller is that it provides a way to efficiently remove a corrupting noise from a signal of interest, even in case of overlapping spectra of the two signals. The other advantage is that, due to its adaptive basis, it is able to follow any change of the signal or of the noise characteristics during the recording.

### 3.2. Tested algorithms

The estimation of the filter parameters and their adaptation were done by the minimization, for each time value, of a performance criterion. Six different recursive algorithms were tested using two different principles: four of the gradient (least mean square, LMS) family and the other two of the fast recursive least square (FRLS) family [1,3,4].

For the LMS, assuming that the signal and the noise are uncorrelated, the filter $H$ is optimal by minimizing, for each instant $t$, the power of the mean square error:

$$E[e(t)^2] = E[(\mathrm{emg}(t) - \mathrm{ecg_h}(t))^2].$$

Four algorithms of this family were implemented: LMS, normalized LMS (NLMS), least mean absolute value (LMAV) and Sign (SIGN) [9].

The advantage of the FRLS family, compared to the LMS family, is that there is no more need to approximate the inverse of the autocorrelation matrix for the filter parameter adaptation. The adaptation is then based on the Fast Kalman Gain, using either a priori, or a posteriori error or both errors (FAEST, fast a posteriori error sequential technique). When the signal is stationary, a simplified formulation can be used. Two algorithms of this family were implemented: the FRLSa (using the a priori error) and the FRLSs, using the simplified formulation [3].

### 3.3. Signal pre-processing

The first step before adaptive filtering was to subtract the offset values from both signals, emg($t$) and ecg($t$). The second step was the detection of the windows of interest (WOI), defined as the time windows when a QRS complex is present. Indeed, the only part of the ECG corrupting the EMG in our recordings was the QRS complex. In other words, the only noise to be considered was the QRS complex, not the whole ECG. These WOIs were identified by computing, for each 512 point block, the energy over a 122 point sliding window, (i.e., of 120 ms, larger than the maximal QRS duration). The window associated with the maximal energy was selected as a WOI. These WOIs were first used to evaluate the initial value of the a priori error, $E_a(0)$, used in the FRLS algorithms. Indeed, $E_a(0)$ has to verify $E_a(0) \geqslant N\sigma_n^2$, where $\sigma_n$ is the noise standard deviation. $\sigma_n$ was therefore calculated only on the WOIs.

It was noticed in preliminary tests that the adaptive filtering was more efficient when the noise, ecg($t$), and the signal, emg($t$), present similar energies. The energy of the noise was taken as the energy computed on the WOIs, $\mathrm{WOI_{energy}}$. The energy of the EMG signal was computed on the related 512 point block, $\mathrm{EMG_{energy}}$. Before adaptive filtering, ecg($t$) was then multiplied by the ratio: $\overline{\mathrm{EMG}}_{\mathrm{energy}}/\overline{\mathrm{WOI}}_{\mathrm{energy}}$, in order to process signals of similar energies.

### 3.4. Parameter optimization

The WOIs therefore corresponded to the only time windows where noise was present (QRS complex). The other time windows corresponded to time periods where no noise correlated to ecg($t$) was expected on emg($t$) (ECG baseline between to cardiac beats). If the adaptive algorithm was applied to these windows, the parameters would have changed during this time to adapt themselves to the baseline ECG (which induces no noise on the SEMGs) and would have to adapt themselves again to the QRS complex, for each cardiac beat. In order to reduce the time needed for the filter parameter adaptation, the adaptation algorithms were then applied only during the WOIs. Then, the adaptation was performed only to follow the possible changes in the QRS complex characteristics.

To optimize the parameters, 3 values were computed on the 28 SEMGs recorded for this purpose. These values were:

$Y1$ = correlation between emg($t$) and ecg($t$)
$Y2$ = correlation between $e$($t$) and ecg($t$)
$Y3$ = correlation between (emg($t$) − $e$($t$)) and ecg($t$)

Maximal values of $Y1/Y2$ and $Y3$ were used as optimization criteria. The first step of this optimization procedure was to define the best parameters, for each algorithm. The second step was to choose the algorithm giving the maximal values for the optimization criteria.

Table 1 presents the results concerning the final optimization tested on the 28 SEMGs. It contains the number of cases when a given algorithm is found to be the best to reject the ECG, over the 28 tested signals. This table clearly indicates that the most efficient algorithm was FRLSs, since it was recognized as the best algorithm for 15 over the 28 tested SEMG.

Fig. 2 presents the raw SEMG (a) and ECG (d) as well as the same SEMG window after the signal was denoised thanks to the chosen algorithm (b) and the difference between the raw and the denoised EMG (c). The comparison between the recorded ECG and the difference between the raw and the denoised SEMG attests for the efficiency of this method. The denoising was considered as optimal since it minimized the presence of ECG, without modification in the characteristics of the SEMG.

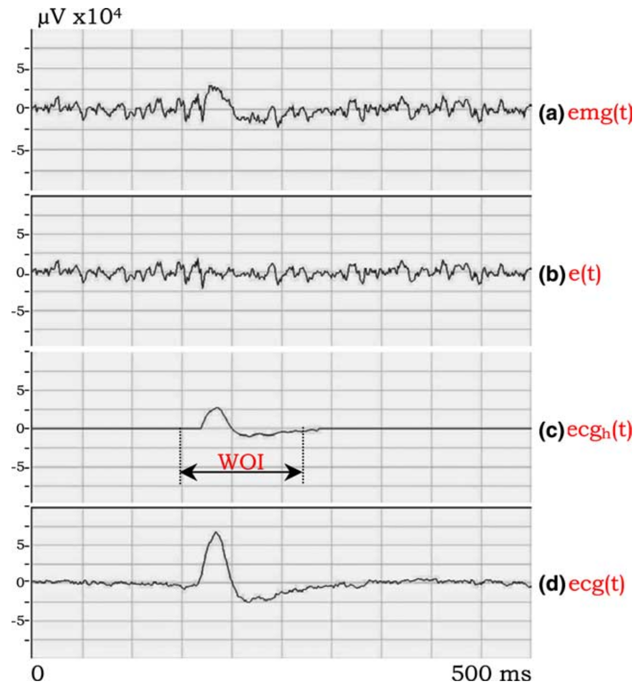


Fig. 2. Example of SEMG denoising from ECG signal. (a) emg($t$): raw SEMG of the Erector Spinae muscle, (b) $e(t)$: denoised SEMG, (c) $ecg_h(t)$: difference between the raw and the denoised SEMGs, (d) ecg($t$): recorded ECG.

## 4. Results about the fatigue study to test the algorithm efficiency

To test the applicability of the adaptative filtering, spectral criteria of muscle fatigue, namely a decrease in the Mean Power Frequency (MPF) values and an increase in the energy values (see notably [6]) were compared for noised and denoised EMGs, knowing that these fatigue criteria also concern the erector spinae (see notably [12]). Table 2 compares the initial values of spectral energy and MPF as well as the slopes of the Energy–time and MPF–time linear relationships, with the FFT computed before and after the application of the adaptive filtering. The mean value of initial energy of the signal after filtering was lower than that of the non-filtered signal, since the energy corresponding to the ECG signals was removed. In the same way, the mean value of MPF was higher for filtered EMGs, due to the low frequency content of the ECG (mean MPF value of the ECG signals: 24.1 ± 11.2 Hz) which was removed from these signals. Mean values of the slope of the energy–time and MPF–time relationships significantly differed for filtered and non-filtered EMGs (with a 95% confidence level), proving thus that the fatigue criteria were better attested for filtered signals, i.e., after the removing of the ECG spectral component. Indeed, the increase in energy and the decrease in MPF over the time are steeper after denoising (see Table 2).

## 5. Discussion and conclusions

This denoising method provides an efficient tool for the rejection of the ECG corrupting trunk Erector Spinae SEMG. Compared to the methods used in other works for ECG rejection [10,8], the advantage of this method is to reject specifically all the components correlated to the QRS complex. This is not the case when classical linear filtering is used, due to the overlapping spectra of ECG and SEMG. Obviously, in the case of abnormally high T wave, some modifications of the WOI duration should be made to remove also this noising T wave. Another advantage is that the adaptive filter is also able to follow any change, either on the signal or on the noise. As an evolution of both SEMG and ECG signals is expected during a fatigue test, adaptive filtering is really efficient throughout the test, whatever the signal concerned

Table 1
Results of the optimization

| Algorithm | LMS | NMLS | LMAV | SIGN | FRLSa | FRLSs |
|---|---|---|---|---|---|---|
| Rate/28 | 0 | 2 | 1 | 2 | 8 | 15 |

Rate/28 represents the number of times (over 28 tested SEMGs) when the algorithm gives the best result in terms of maximum of $Y1/Y2$ and maximum of $Y3$.

Table 2
Initial values (means ± SD, $n = 16$) of energy and MPF, and slopes of the energy–time and MPF–time relationships computed from the spectral analysis of surface EMG without (raw SEMG) or with adaptive filtering (denoised SEMG) during a fatigue test involving the erector spinae

| | Raw SEMG | Denoised SEMG | |
|---|---|---|---|
| Energy initial values ($\mu V^2$) | 864.76 ± 800.93 | 803.76 ± 800.12 | $p < 0.001$ |
| MPF initial values (Hz) | 74.78 ± 22.47 | 87.40 ± 38.32 | $p = 0.042$ |
| Energy slope (%/s) | 0.454 ± 0.509 | 0.524 ± 0.535 | $p = 0.016$ |
| MPF slope (%/s) | −0.052 ± 0.081 | −0.082 ± 0.069 | $p = 0.030$ |

by the changes and whatever the type of changes. Due to the proper ECG electrode positioning, and due to the same physical origin of the noise and of the signal (electrophysiological signals), we have not been faced with problems of tissue nonlinearities encountered in some works [7]. In these conditions, the simple algorithm derived from the FRLS family has been efficient enough to properly reject the ECG from back SEMG.

Furthermore, its application is not prejudicial to the analysis of non- or slightly corrupted SEMGs. The last advantage could be that adaptive filtering could simplify any further signal processing (segmentation, parameter calculation etc.) [2]. It permits us to obtain correct parameter evolutions when tracking trunk muscle fatigability, despite an important corruption of some SEMGs by the ECG. These algorithms will be used as a pre-processing method before calculating the spectral parameters in a following work, concerning back muscle fatigability of pregnant women.

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