ADAPTIVE FILTERING OF EVENT-RELATED BIOELECTRIC SIGNALS

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ABSTRACT

We present an adaptive filter to estimate the deterministic component of event-related bioelectric signals. This filter removes the noise uncorrelated with a signal time-locked to a stimulus. A description of the filter structure, convergence time and improvement of the signal-to-noise ratio are presented. A simulation study is carried out to evaluate its performance and compare it with signal averaging. The simulation results agree with the theoretical analysis.

1. INTRODUCTION

The study of bioelectric signals is a useful tool to obtain information of biological systems. Among the most investigated bioelectric signals are the event-related, that are time-locked to a stimulus. This stimulus is usually external (visual, auditory and somatosensory evoked potentials). In other cases the signal is related to an internal stimulus. Then a time-reference point can be defined from a wave of the same signal. The electrocardiographic signal (ECG), and specially the high-resolution ECG, can be studied under these criteria.

Bioelectric signals are often contaminated by noise of several sources: 50-Hz interference and biological noise (EMG in ECG, EEG in evoked potentials). In general, the event-related signals can be considered as a random process which can be decomposed in an invariant deterministic signal time-locked to a stimulus, and additive random noise uncorrelated with the signal. The most usual signal processing of this kind of bioelectric signals is the extraction of the deterministic signal from noise. Several techniques can be considered. Linear filtering is not possible in general, because the spectrum of signal and noise are overlapped. The signal averaging technique is a classical method to recover the signal hidden in the noise. But it needs a lot of records to obtain a good estimation of the signal, and can not show the dynamic variations of the signal shape.

A signal processing technique that improves these limitations is the adaptive filtering. These filters learn the deterministic signal and removes the noise. Therefore, they can detect shape variations in the ensemble and obtain a better signal estimation. In this work we propose an adaptive filter for event-related signals, and present a simulation study to test the performance of the method.

2. THE ADAPTIVE FILTER

The adaptive filters are an important application of adaptive systems for signal processing. In this way, *prediction* and *interference cancelling* are the better known [1]. Both types of filters have been used in biomedical signal processing.

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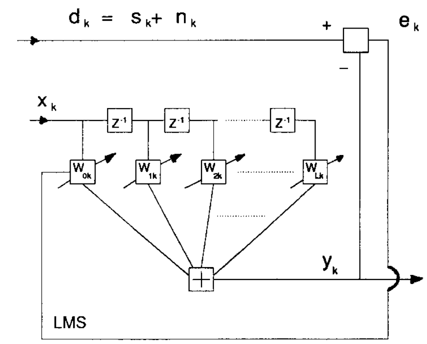
The former was selected to detect His-Purkinje signals and ventricular late potentials [2]. This filter is capable of filtering muscle noise, but not the 50-Hz interference due to its periodicity.

The latter was used to cancel 50-Hz interference and other bioelectrical signals in electrocardiography [1]. Recently, an application of this adaptive noise canceller was presented to detect P-waves in the ECG, by an adaptive QRS-T cancellation [3].

In this work we propose the next adaptive filter for event-related signals (fig. 1). The signal we want to study (d_k) is the primary signal



at time instant k. Each record of d_k, that extends $L+1$ samples, repeats with each stimulus and is composed of a deterministic component (s_k) and an additive noise (n_k), that is supposed to be no correlated with s_k:

$$d_k = s_k + n_k \quad k = 0, ..., L \tag{1}$$

The reference signal (x_k) is a unit impulse that appears at the beginning of each recurrence of s_k. This impulse is generated from an external stimulus or by means of a signal detector, if the stimulus is internal. Thus

$$x_k = \begin{cases} 1 & k = 0 \\ 0 & k = 1, ..., L \end{cases} \tag{2}$$

We will denote the reference $\mathbf{X}_k$ and the weight $\mathbf{W}_k$ vectors as

$$\mathbf{X}_k = [x_k, x_{k-1}, ..., x_{k-L}]^T \quad ; \quad \mathbf{W}_k = [w_{0k}, w_{1k}, ..., w_{Lk}]^T. \tag{3}$$

The filter output signal (y_k) and the error (e_k) are

$$y_k = \sum_{i=0}^{L} w_{ik} x_{k-i} = \mathbf{W}_k^T \mathbf{X}_k \ , \quad e_k = d_k - y_k \ . \tag{4}$$

According to the noise assumptions and since x_k is correlated with s_k but not with n_k, we can write the expected value of the squared error as

$$\xi = E[e_k^2] = E[(s_k - y_k)^2] + E[n_k^2] \ . \quad (5)$$

Minimizing ξ, the filter output y_k will aproximate s_k. According to [1] ξ can be expressed as

$$\xi = E[d_k^2] + \mathbf{W}^T\mathbf{R}\mathbf{W} - 2\mathbf{P}^T\mathbf{W} \quad (6)$$

where

$$\mathbf{R} = E[\mathbf{X}_k\mathbf{X}_k^T] \quad , \quad \mathbf{P} = E[d_k\mathbf{X}_k] \quad (7)$$

and $\mathbf{W}$ is the weight vector $\mathbf{W}_k$, taken as a variable.

With the reference input considered in (2) we obtain

$$\mathbf{R} = \frac{1}{L+1}\mathbf{I}, \quad tr[\mathbf{R}] = 1 \quad and \quad \mathbf{P} = \frac{1}{L+1}[s_0, s_1, ..., s_L]^T \ . \quad (8)$$

The weight vector that minimizes ξ is denoted by $\mathbf{W}^*$. From [1] and taking $\mathbf{R}$ and $\mathbf{P}$ from (8)

$$\mathbf{W}^* = \mathbf{R}^{-1}\mathbf{P} \quad , \quad \mathbf{W}^* = [s_0, s_1, ..., s_L]^T \quad (9)$$

If we minimize (6), in the steady-state $\mathbf{W}^*$ is the deterministic signal s_k and (4) becomes

$$y_k = \sum_{i=0}^{L} w_i^* x_{k-i} = w_k^* = s_k. \quad (10)$$

Thus, the filter output y_k is the deterministic component s_k when ξ is minimized ($\xi = \xi_{min}$), and from (1), (6), (8) and (9)

$$\xi_{min} = E[d_k^2] - \mathbf{P}^T\mathbf{W}^* = E[n_k^2] \quad (11)$$

This ideal situation, when the minimum is reached, can be approximate using the LMS algorithm in the adaptation [1]:

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu e_k \mathbf{X}_k. \quad (12)$$

The LMS converges when the gain constant μ satisfies

$$0 < \mu < \frac{1}{tr[\mathbf{R}]} = 1 \quad (13)$$

In this case, (8), the convergence time (τ_{mse}) of ξ is

$$\tau_{mse} = \frac{L+1}{4\,\mu\, tr[\mathbf{R}]} = \frac{L+1}{4\mu} \ , \quad (14)$$

where τ_{mse} is measured in sampling periods. Regarding (13) and (14), and selecting the appropriate μ, τ_{mse} can take a value around $L+1$. This implies a convergence in the first occurrences of s_k.

The misadjustment (M) of the LMS after convergence [1], produces an oscillation of $\mathbf{W_k}$ around $\mathbf{W}^*$, in the steady-state, that increases ξ:

$$\xi = \xi_{min}(1 + M) \quad where \quad M = \mu tr[\mathbf{R}] = \mu \ . \quad (15)$$

From (5), (11) and (15) we have

$$E[(s_k - y_k)^2] = \mu E[n_k^2] \ . \quad (16)$$

If the primary signal d_k have a signal-to-noise ratio SNR_d:

$$SNR_d = \frac{E[s_k^2]}{E[n_k^2]} = \frac{E[s_k^2]}{E[(d_k - s_k)^2]} \ , \quad (17)$$

in the steady-state the filter output y_k will have a signal-to-noise ratio (SNR_y), that will be, from (16),

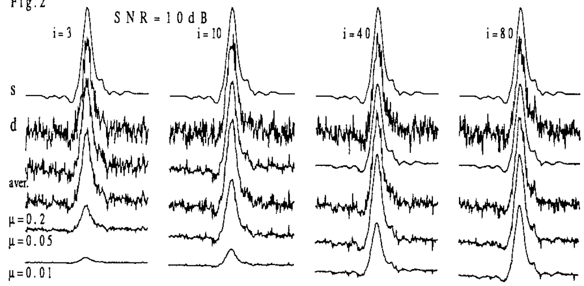
$$SNR_y = \frac{E[s_k^2]}{E[(y_k - s_k)^2]} = \frac{SNR_d}{\mu}. \quad (18)$$

Then, with this adaptive filter we improve the SNR by $1/\mu$. Small μ would be desirable, but then τ_{mse} would become high. A compromise must be taken that depends of the SNR_d and of the convergence time required. If s_k is estacionary, no dynamic changes occur. Thus, a good performance in the steady-state is more important (μ low, SNR_y high) than a fast convergence time (τ_{mse} high). If s_k is no estacionary, dynamic readaptations can recommend lower τ_{mse}. This is opposite to a high improvement of SNR, and then a compromise must be taken.

SIMULATION

The adaptive filter described before was tested by means of simulated signals. Thus, a QRS complex from a real ECG signal was taken as a deterministic component (s_k) of an ensemble of records contaminated by additive gaussian random noise (n_k). Then, the filter was applied to this sequence of records taking an impulse (x_k) at the beginning of each record. A comparison of performance was

Fig.2



carried out for different values of μ. The results were compared with the signal estimated by signal averaging. Fig. 2 shows at the top the deterministic component present in each record of the ensemble. The second row shows different records with a SNR_d=10 dB. Next, the signal estimated by signal averaging is displayed after averaging i records (i = 3, 10, 40 and 80). Finally, the output of the adaptive filter, after filtering the same i records, is displayed for different values of μ (0.2, 0.05 and 0.01).

Calculated values of the SNR improvement (18), by means of this filter, agree with the experimental values obtained in the simulation study. A low value of μ (μ=0.01) causes a large improvement of SNR (SNR_y/SNR_d=100), but a convergence time of 25 records. On the other hand a value of μ=0.2 improves the SNR in a factor of 5, with a convergence time of practically one record. In fact, we can see in fig. 2 the effect of the selected values of μ in the filtering process.

CONCLUSIONS

An adaptive filter for event-related bioelectric signals has been proposed. This method allows us to filter the uncorrelated noise with a stimulus time-locked to the signal.

The analysis of the filter performance has been presented. Specially the convergence and the improvement of the SNR has been evaluated. The simulation results agree with the theoretical analysis.

Therefore, the proposed filter has shown to be a good method to filter event-related signals. In comparison with the signal averaging technique, this filter has the advantage that permits to learn the deterministic component of the signal, although the signal shape could present dynamic variations.

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