ADAPTIVE FILTERING OF HIGH-RESOLUTION ECG SIGNALS

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Abstract

In this paper an adaptive filter for high-resolution ECG signals is presented which estimates the deterministic component of the ECG signal and removes the noise. The filter needs two inputs: the signal (primary input) and an impulse correlated with the deterministic component (reference input). It uses the LMS algorithm to adjust the weights in the adaptive process. A description of the characteristics and performance of this filter is presented.

The adaptive filter was tested by simulation using real ECG signals and its performance was compared with signal averaging technique. Several signal-to-noise ratios were considered and the effect of shape variations was also studied. An application to ventricular late potentials is presented. Results obtained using this adaptive filter and signal averaging were compared.

Introduction

The study of low-amplitude cardiac signals by means of High-Resolution Electrocardiography has been an important advance in the non-invasive cardiological diagnosis. Signal averaging has been the technique most generally used to improve the signal-to-noise ratio (SNR) of low-amplitude potentials[1]. This technique needs a large number of beats in order to estimate the deterministic component of the signal, that is supposed to keep constant for all time.

The limited acceptance in clinical use of signal averaging technique may be due to the effect of errors on the definition of a fiducial point and dynamic variations of the signal shape in real cases.

Adaptive signal processing improves the detection of the low-level potentials in High-Resolution Electrocardiography, in relation to the classical signal averaging technique. Adaptive filters permit to detect time-varying potentials and to track the dynamic variations of the signal. These types of filters learn the deterministic signal and remove the noise. Besides, they modify their behaviour according to the input signal. Therefore, they can detect shape variations in the ensemble and thus can obtain a better signal estimation.

In this work we propose an adaptive filter for signals time-locked to a stimulus. In particular, this filter can be applied to low-level potentials linked to high-level waves, in high-resolution ECG signals. Next, we present a simulation study using real ECG signals to test the performance of the method. Finally, an application to ventricular late potentials detection is presented. Results obtained using the adaptive filter and signal averaging were compared.

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The adaptive filter

Adaptive filters have been used already in bioelectric signal processing. In particular, *predictors*[2] were applied to detect His-Purkinje signals and ventricular late potentials[3]. *Predictors* consider the signal is recurrent and the noise is supposed to be random and gaussian. Thus, both inputs of the filter (the primary and the reference signals) are the same, but the former is a delayed signal of the latter. This filter removes the muscle noise, but not the 50-Hz interference due to its periodicity.

Another adaptive approach applied to bioelectric signals is the *interference cancelling*[2]. Here the reference signal must be a correlated version of the noise that is present in the primary signal. This filter was used to cancel the 50-Hz interference[2] and to detect P-waves in the ECG by QRS-T cancellation[4].

In this work we present an adaptive filter for high-resolution ECG signals that we have proposed recently[5]. This filter can be applied to event-related signals in general and, in particular, to low-amplitude potentials that are time-locked to a high-amplitude wave of reference.

High-resolution ECG can be processed with this filter. In this case, the signal we want to study (d_k) extends the interval of interest in each cardiac beat and is considered like a record of a random process defined by

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

where s_k is the deterministic component of the signal, n_k is additive noise no correlated with s_k, and $L + 1$ is the number of samples in each record.

The adaptive filter has two inputs (fig. 1). One is the primary input (d_k) that we want to filter, and the other is the reference input (x_k), that is a unit impulse time-locked with the beginning of each recurrence of s_k. This impulse can be generated by means of a signal detector or a more precise alignment method[6] from the high-amplitude waves of reference in the signal d_k. Thus

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

The output of this adaptive filter (y_k) can be expressed, accord-

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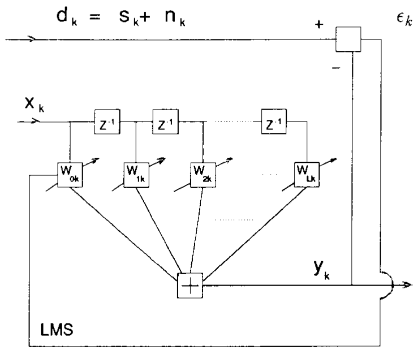

Figure 1: *Block diagram of the adaptive filter to estimate the deterministic component s_k of a signal d_k, using a nonrecursive adaptive transversal filter.*

ing to the classical notation[2], by

$$y_k = \sum_{i=0}^{L} w_{ik} x_{k-i} = \mathbf{W}_k^T \mathbf{X}_k \quad k = 0, ..., L \tag{3}$$

where $\mathbf{W}_k$ is the weight vector and $\mathbf{X}_k$ is the reference vector:

$$\mathbf{W}_k = [w_{0k}\ w_{1k}\ ...\ w_{Lk}]^T \quad , \quad \mathbf{X}_k = [x_k\ x_{k-1}\ ...\ x_{k-L}]^T \ . \tag{4}$$

The error signal (ϵ_k) is defined as

$$\epsilon_k = d_k - y_k \quad k = 0, ..., L \ . \tag{5}$$

Then, the mean-square error of a nonrecursive adaptive filter[2] can be expressed by

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

where

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

are the input correlation matrix and the correlation vector, respectively, and $\mathbf{W}$ is the weight vector $\mathbf{W}_k$, taken as a variable. Another more intuitive expression of ξ can be derived directly from (5):

$$\xi = E[\epsilon_k^2] = E[(s_k - y_k)^2] + E[n_k^2] \ . \tag{8}$$

To obtain the minimum mean-square error, the weight vector $\mathbf{W}$ must take the optimal value $\mathbf{W}^*$, known as the Wiener weight vector:

$$\mathbf{W}^* = \mathbf{R}^{-1}\mathbf{P} \ . \tag{9}$$

With the reference input considered in this application (2), we obtain a simple expression $\mathbf{R}$ and $\mathbf{P}$:

$$\mathbf{R} = \frac{1}{L+1}\mathbf{I} \quad , \quad tr[\mathbf{R}] = 1 \tag{10}$$

$$\mathbf{P} = \frac{1}{L+1}[s_0\ s_1\ ...\ s_L]^T \ . \tag{11}$$

Thus, in this case, the optimal weight vector is

$$\mathbf{W}^* = [s_0\ s_1\ ...\ s_L]^T \ . \tag{12}$$

That is, $\mathbf{W}^*$ is the deterministic component s_k of the signal d_k. In the steady state the filter output is

$$y_k = \sum_{i=0}^{L} w_i^* x_{k-i} = w_k^* = s_k \quad k = 0, ..., L \ . \tag{13}$$

Then, when the weight wector $\mathbf{W}_k = \mathbf{W}^*$ the filter output becomes the deterministic component s_k. In this case, the mean-square error is minimum and can be obtained from (1), (6), (9), (11) and (12)

$$\xi_{min} = E[d_k^2] - \mathbf{P}^T \mathbf{W}^* = E[n_k^2] \ . \tag{14}$$

The adaptive algorithm

The least-mean-square (LMS) algorithm[2] was used to adjust the weights of the adaptive filter, in order to minimize the mean-square error. This algorithm can be expressed by the following equation:

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu\epsilon_k \mathbf{X}_k. \tag{15}$$

where μ is a gain constant.

In this case (2), the weight vector converges when μ fulfils[2]

$$0 < \mu < \frac{1}{tr[\mathbf{R}]} = 1 \ . \tag{16}$$

and the time constant of weight convergence (τ_{mse}) is

$$\tau_{mse} = \frac{L+1}{4\,\mu\, tr[\mathbf{R}]} = \frac{L+1}{4\mu} \ . \tag{17}$$

where τ_{mse} is measured in sampling periods. Therefore, the gain constant controls the stability and speed of convergence. Thus, the convergence of weights can be obtained in the first record ($\tau_{mse} < L+1$) if an appropiate value of μ is selected.

The value of the gain constant is a compromise between the rate of adaptation and the *excess* mean-square error[2] due to the steady-state weight vector oscillations. The variation of the weights around the optimal value $\mathbf{W}^*$ produces a mean-square error ξ

$$\xi = \xi_{min}(1 + M) \tag{18}$$

where M is the misadjustment, that for this filter becomes

$$M = \mu tr[\mathbf{R}] = \mu \ . \tag{19}$$

Then, the mean-square error becomes

$$\xi = E[n_k^2](1 + \mu) \ . \tag{20}$$

Improvement of the signal-to-noise ratio

The interest of this adaptive filter is to estimate the deterministic component of the ECG signal and remove the noise. Therefore, the signal-to-noise ratio (SNR) must be improved.

The primary signal d_k have a signal-to-noise ratio SNR_d:

$$SNR_d = \frac{E[s_k^2]}{E[n_k^2]} = \frac{E[s_k^2]}{E[(d_k - s_k)^2]} \ . \tag{21}$$

In the steady state, the output signal y_k has a signal-to-noise ratio (SNR_y^{ss}), that can be defined as

$$SNR_y^{ss} = \frac{E[s_k^2]}{E[(y_k - s_k)^2]} \quad . \tag{22}$$

We can obtain from (8) and (20)

$$E[(y_k - s_k)^2] = \mu E[n_k^2] \quad . \tag{23}$$

Thus the improvement of the SNR in the steady state ($\triangle SNR^{ss}$)is

$$\triangle SNR^{ss} = \frac{SNR_y^{ss}}{SNR_d} = \frac{1}{\mu} \quad . \tag{24}$$

Simulation study

A simulation study was carried out to test the performance of the adaptive filter. In this way, a signal was synthesized as a sequence of records d_k. Each one is composed by the same QRS complex (s_k), selected from a real ECG signal, and additive gaussian random noise (n_k). Besides, a reference signal (x_k) was defined as an impulse at the beginnig of each record.

The adaptive filter was applied to these signals d_k and x_k. Several signal-to-noise ratios of the signal d_k were studied, and different values of gain constant μ were applied. A comparison of the results obtained with adaptive filtering and with signal averaging technique was carried out.

Fig. 2 shows the results for a SNR=10dB, after different number of adaptations (ada). At the top, we can see the deterministic component s_k, that is present in each beat. The second row shows differents records with the same SNR_d. The third row displays the signal estimated by signal averaging after processing ada beats. Next, the estimation of the deterministic signal by means of the adaptive filter (weights of the filter) is shown for different values of gain constant μ and after ada records.

Calculated values of $\triangle SNR^{ss}$ (24) agree with the results obtained in the simulation study. Thus, for example, a value μ = 0.01 causes a $\triangle SNR^{ss}$ = 100, a convergence time of 25 records. In this case, adaptive filtering and signal averaging obtained comparable results, and thus we can validate that the filter converges to deterministic component in ideal conditions.

Another and more interesting situation is when the deterministic component s_k doesn't keep constant during all records. Fig. 3 shows a case where the first 80 records have a deterministic component s_k, and the next 80 records have another s'_k. Here the adaptive filter achieves better performance than signal averaging, because it can learn more quickly the new s'_k. Thus, for example, we can observe it comparing the results after 120 beats with signal averaging and adaptive filtering (figure 3).

Application to ventricular late potentials

The adaptive filter described before was applied to high resolution ECG signals in order to detect ventricular late potentials (LP). Several μ values were applied and a comparison with signal averaging was also carried out.

The ECG signals were measured by low-noise high-gain isolated amplifiers and recorded with a PC-based digital acquisition system. The signals were sampled at 5 KHz, with a resolution of 16 bits. The uncorrected orthogonal leads (X, Y, Z) were used in this study. These three bipolar leads were independently processed by the adaptive filter and signal averaging. In both cases, a matched filter[6] was used as alignment method to define the x_k signal and synchronize the beats, respectively.

Figure 4 shows, in the first row, a sequence of records that include the QRS complex and ST segment from an ensemble of 100 cardiac beats. These signals correspond to an X lead from a patient who had ventricular tachycardia and is a candidate to show LP. Next, the results after averaging and adaptive filtering are displayed in the same way as the simulation results.

Figure 5 shows the corresponding signals to fig. 4, after high-pass filtering. The applied digital filter was a FIR filter with a bandwidth of 50-250 Hz. In this filtered signal, we can see remarkable late potentials estimated by signal averaging and adaptive filtering. In this signal, the deterministic component appears practically constant. Thus, signal averaging achieves a signal estimation that keeps constant from the 25 first beats. The adaptive filter obtains also good estimations, but is more sensitive to dynamic variations.

Conclusions

An adaptive filter for high-resolution ECG signals has been presented. This filter estimates the deterministic component of the signal, removing the noise uncorrelated with an impulse generated from a signal detector or an alignment method applied to the signal.

The theoretical performance of the filter have been presented. In particular, the convergence and the improvement of the SNR. The simulation results agree with this study. The adaptive filter have shown a better performance than signal averaging when the signal present dynamic variations. By other hand, if the signal keeps constant both techniques obtain comparables results.

Finally, the presented filter has shown to be a good method to detect LP, and it permits to track the dynamic variations of the signal. Then, a compromise between the convergence time and the improvement of the SNR must be taken.

References

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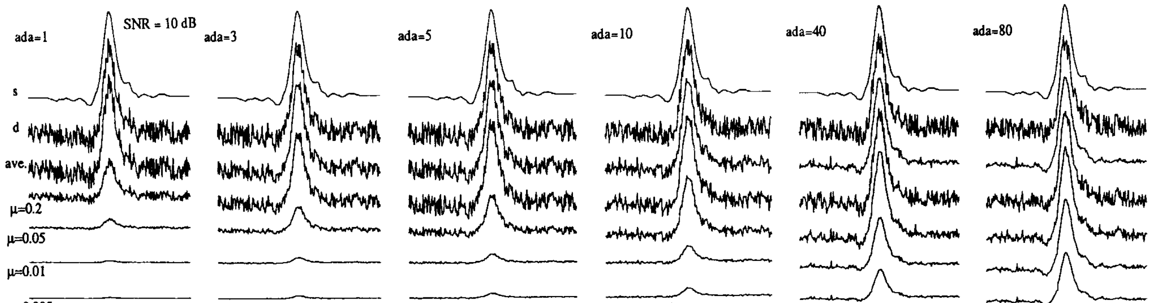

Figure 2: *Results for 80 beats (d_k) with the same deterministic component (s_k).*

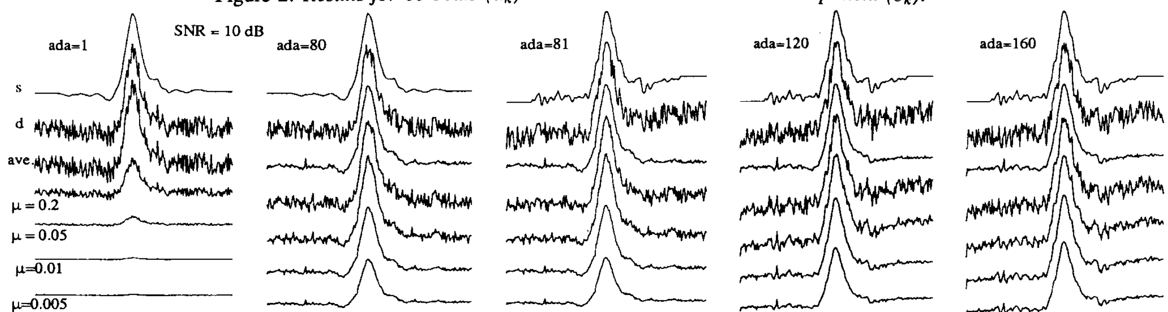

Figure 3: *Results for 160 beats (d_k) with a change of morphology of s_k at the beat 81.*

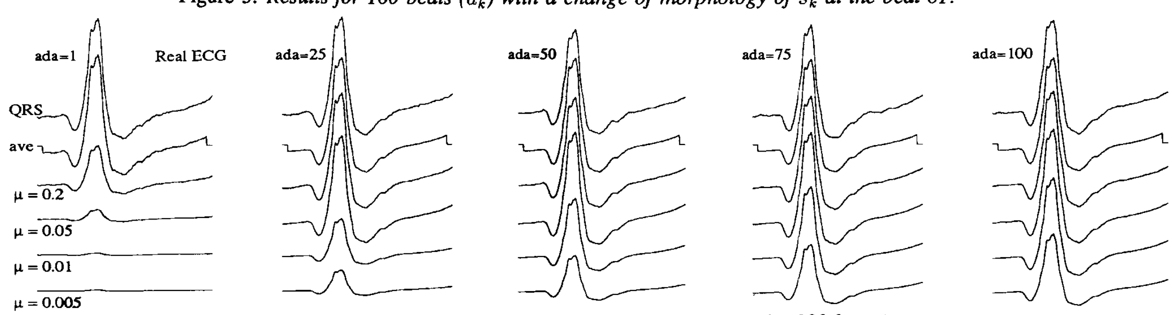

Figure 4: *Application to real high-resolution ECG signals (100 beats).*

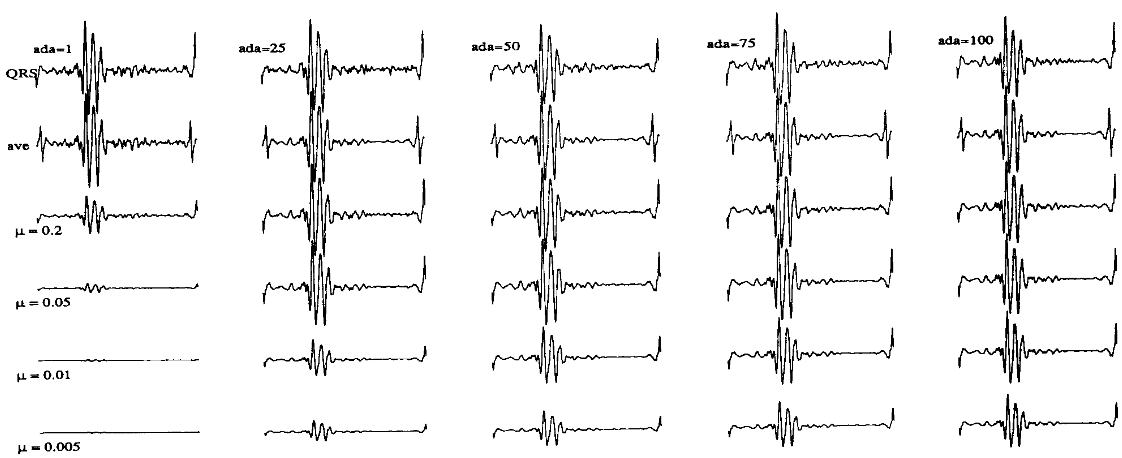

Figure 5: *Filtered versions of the signals displayed in fig 4.*