

ADAPTIVE ENHANCEMENT OF AMBULATORY ELECTROCARDIOGRAMS

التقوية المتكيفة لاشارة رسم القلب الكهربائى

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الخلاصة: يعتبر تحسين جودة اشارات رسم القلب الكهربائى للاشخاص المشغولين بموضوع حيوى وهام بالنسبة لاستخدام الحاسب الالى فى التخيص ومتابعة المرضى - ولكن اختلاط هذه الاشارات بأنواع مختلفة من الضوضاء تفتى تقوية هذه الاشارات والتخلص من هذه الضوضاء. فى هذا البحث تقدم ثلاث تقنيات للمرفحات التكيفة أستخدمناها للتخلص من الضوضاء المختلفة باشارات رسم القلب وقد قيم أداء هذه التقنيات وتمت المقارنة باستخدام عدد من الاشارات المحاكية وكذلك عدة تسجيلات حقيقية لعدد من الأشخاص. وقد وجدنا أن المرشح التكيفى ذا المرحلتين بالذى تحوى المرحلة الاولى منه عن مريل ضوضاء تكيفى والمرحلة الثانية منه على مرشح تكيفى تكرارى ذو تأثير فعال فى التخلص من كافة أنواع الضوضاء مع عدم التأثير على شكل اشارة رسم القلب وسمايتها الاساسية.

ABSTRACT- Quality improvement of ambulatory electrocardiographic (ECG) signals is an important subject and crucial in computer aided diagnosis and monitoring. However, the poor quality of the signals necessitates signal enhancements. Hence, in this paper, three adaptive filter structures are presented to eliminate the diverse forms of noise. The performance of each technique is thoroughly investigated by simulated signals as well as signals obtained from human subjects. A two stage filter consisting of an adaptive noise canceller and an adaptive recurrent filter has been found to reduce efficiently the various types of noise while the characteristics of the relevant ECG signal is little affected.

INTRODUCTION

Ambulatory electrocardiogram (ECG) recording is now routinely used to detect infrequent, asymptomatic arrhythmias or to monitor effects of cardiac drugs or surgical procedures. Recently, microprocessor-based event records have been developed that carry out on-line signal processing, data reduction and arrhythmia detection [1].

Signal processing problems related to ECG include the elimination of the diverse forms of noise interfered with the ECG and the detection of the presence of R-waves to compute the heart rate. A useful method is the application of digital filtering. For example, Lynn [2] and Alste and Schilder [3] have developed integer coefficient and FIR filters, respectively, for real-time processing. Ahlstrom and Tompkins [4] described similar filters for real-time ECG signal processing. Recently, an FIR filter based on the use of a matched filter has been successfully applied to reduce the noise interfered with the ECG signal [5]. The effectiveness of this technique depends on initial

estimate of the signal waveform and on the signal-to-noise ratio. Making a good estimate may be difficult if the signal-to-noise ratio is low and spectra of the signal and noise are overlapped.

Adaptive signal processing techniques have been shown useful in many biomedical applications. Adaptive filters are self-designing filters based on an algorithm which allows the filter to "learn" the initial input statistics and to track them if they are time-varying. These filters estimate the deterministic signal and remove the noise uncorrelated with the deterministic signal. The basic idea behind adaptive filtering has been summarized by Widrow et al. [6] and used in a variety of biological signal processing applications. The closed-loop adaptive filtering technique has been applied to several biomedical signals: ECG [7,8], evoked potentials [9,10], EEG [11], and vibroarthrographic signals [12]. In particular, predictors [13] were applied to detect His-Purkinje signals and ventricular late potentials [14, 15]. Another adaptive approach which has been applied to biological signals is interference cancellation [16]. A third approach is the adaptive impulse correlated filter [17, 18] which is effective in processing signals that are time-locked to a stimulus.

The first aim of the present paper is to demonstrate adaptive filtering (AF) applications in ECG signal enhancement. We developed specialized filter combinations for cancellation of noise interfering with ECG signals and arising from diverse sources. The second aim is to compare quantitatively the performance of these adaptive filter structures in signal enhancement. Our idea is to determine the adaptive filter structure that performs the best and gives high fidelity ECG signals.

ADAPTIVE FILTER STRUCTURES

The principle, derivation and structure of predictors, canceller, and the adaptive impulse correlated filter have been documented well by Widrow et al. [6, 13] and Laguna et al. [17], respectively. Here, a brief overview is presented for the sake of convenience in the following discussion and analysis.

The Widrow-Hoff LMS Algorithm

Fig. 1 shows a schematic of an adaptive filtering system with the basic components i.e. the tapped delay. In the figure z^{-1} represents a one-sample delay and j stands for the time instant. The output signal y_j is formed as the weighted sum of a set of input signal samples $x_j, x_{j-1}, \dots, x_{j-N+1}$. Mathematically, the output y_j is expressed as:

$$y_j = \sum_{k=1}^N w_{kj} x_{j-k} = X_j^T W_j \quad (1)$$

During the adaptation process, the weights are adjusted according the LMS algorithm [13]. Let x_j stands for primary input which contains the signal s_{j0} plus additive noise n_{j0} . They are assumed to be

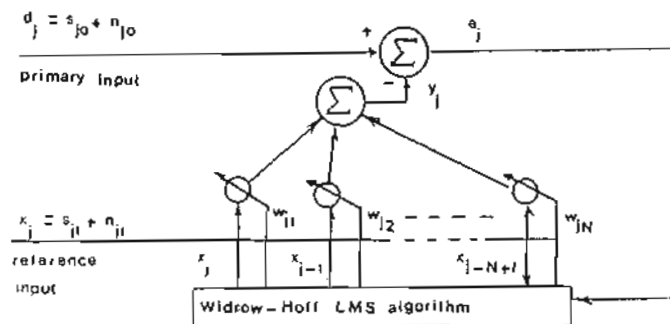


Fig.1 An adaptive filtering system with the tapped delay line

uncorrelated with each other. The reference input x_j contains noise n_{j1} and signal s_{j1} . A general expression for the error as a function of the weight vector can be obtained as follows:

$$e_j = d_j - y_j = d_j - X_j^T W_j \quad (2)$$

Using the steepest-descent method and approximating the gradient mean squared error (MSE) by gradient squared error, the well-known Widrow-Hoff LMS algorithm is derived [13]:

$$W_{j+1} = W_j + 2 \mu e_j X_j \quad (3)$$

with

$$W_j = [w_{j1}, w_{j2}, \dots, w_{jN}]^T \quad (4)$$

$$X_j = [x_j, x_{j-1}, \dots, x_{j-N+1}]^T \quad (5)$$

where x_j is the reference signal at time instant j , w_{kj} ($k = 1, 2, \dots, N$) are the k th coefficients of the adaptive filter at time j , and N is the length of the adaptive filter and μ is the step size which controls the convergence rate and the stability of the system. The larger the value of μ , the larger is the gradient noise that is introduced, but the faster the algorithm converges, and vice versa.

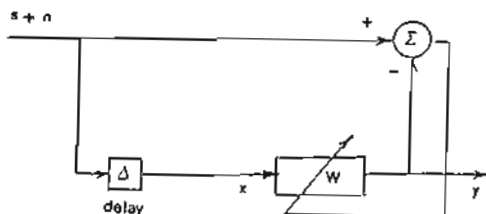


Fig.2 The adaptive predictor

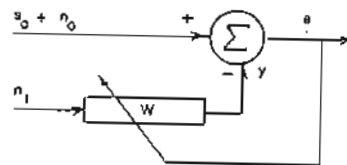


Fig.3 The adaptive noise canceller

The Adaptive Predictor

The adaptive predictor or the adaptive line enhancer is shown in Fig.2. The primary input d_j contains a desired signal s_j and noise n_j . The reference input x_j is derived from the primary input d_j by only inserting a delay Δ . Assume the primary input consists of a correlated signal s_j , such as periodic signal, and uncorrelated noise n_j . The only difference between the primary and the reference inputs is the delay Δ . If the delay is chosen such that the noise $n_{j-\Delta}$ in the reference input becomes uncorrelated with n_j in the primary input then the output of the adaptive filter contains the signal s_j alone after convergence of the adaptive algorithm, i.e. the mean squared value of the error signal e_j is minimal and the output of the adaptive filter, y_j is the best estimate of the signal s_j in the primary input in the sense of the mean square [6]. More generally, the adaptive filter generates a replica of the part of the primary input which is correlated with the reference input (or input to the adaptive filter).

The Adaptive Noise Canceller

The Widrow-Hoff LMS algorithm creates an LMS estimate of the noise in the primary input by filtering the reference noise. The filtered reference noise is subtracted from the primary input to yield the system output, which in turn is an LMS estimate of the primary signal. A critical requirement for the successful operation of this scheme is that the primary and the reference noise sources must be uncorrelated with the primary signal component, but correlated with each other. This can be seen through the following demonstration (for convenience the subscript j is omitted).

From Fig. 3, the system output is the error given by

$$e = s + n - y \quad (6)$$

Then, the MSE can be obtained as

$$E(e^2) = E(s_0^2) + E(n_0 - y)^2 \quad (7)$$

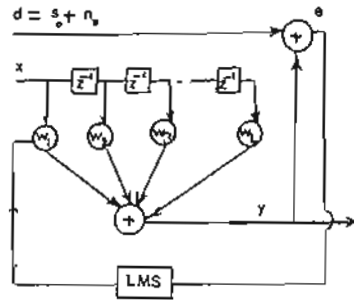


Fig.4 Schematic of adaptive recurrent filter

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s_0 . The adaptive filter extracts the signal, or eliminates noise, by iteratively minimizing the MSE between the primary and the reference inputs.

The Adaptive Recurrent Filter

The adaptive recurrent filter (ARF) is an extension of the LMS adaptive filter. It is applicable to the estimation of that subset of nonstationary signals having recurring (but not necessarily periodic) statistical character [17]. Its objective is to adapt the filter weights so that the impulse response of the desired signal is acquired.

The primary input d that is the signal s_0 of recurring nature with additive noise n_0 . The reference input is a unit impulse sequence synchronized in time with the beginning of each recurrence of s_0 . Each recurrence $i = 1, 2, \dots$ of the signal results in a new reference impulse and a new update of all the filter weights (Fig.4). Thus, the reference input is $X_j = [0, 0, 1, \dots, 0]^T$. This impulse sequence X_j can be generated in different ways, depending on the signal d_j . A signal detector can define the impulse from high-amplitude waves as in the case of ECG signals. For a signal of span L , the transversal filter will require L weights. At each time step only one filter weight is adapted. All the filter weights are adapted once each recurring cycle.

In case of the ECG signal, in order to implement the ARF, the QRS complexes must be detected first using any QRS detection algorithm [19]. The reference impulse is now coincident with each occurrence of the QRS complex. The actual filter weights are once again selected so as to span the entire QRS complex.

SIMULATION STUDY

A simulation study has been carried out to test the performance of the three different structures of adaptive filtering. A signal was synthesized as a sequence of records d_i . Each one consisted of the uncorrupted ECG beats s_i taken from a real ECG record, and additive simulated noise n generated from different sources.

The Uncorrupted ECG Signal

The uncorrupted signal was obtained by recording the Lead II ECG of a human volunteer on a Philips analog ECG recorder. This recording was digitized using a sampling rate of 250 (samples/s). The digitized signal cycle of the ECG was copied and appended to itself repetitively in order to form an ensemble of 37 beats of the ECG for a total of 32 s of data. The digitized ECG was plotted on a graphics terminal and subsequently edited until it appeared consistent with the analog recording. The heart rate is a constant 69 beats per min, the QRS width is 88 ms (22 samples), and the R-wave amplitude is 1.08 mV. Fig. 5 shows the simulated noise-free ECG signal (the deterministic component s in each primary input).

The Simulated Noise

Six different representative noise sources were selected and simulated in this study: (a) Power line interference, (b) Baseline drift due to respiration, (c) Abrupt shifts in the baseline due to its large first derivative, (d) Electromyographic interference (EMG), (e) Motion artifacts noise, and (f) A composite of all of the previous.

We simulated the above types of noise using the models proposed by Freisen et al., [19]. A detailed description for computer generation of these noises is given in [20]. Fig. 5 shows the ECG signal, corrupted with the six different types of simulated noise. Several signal-to-noise ratios (SNR) were studied.

The Adaptive Enhancement Scheme

Due to its simplicity and ease of implementation, the principles of adaptive signal enhancement discussed above have been successfully applied in processing various biomedical signals [7-18]. Depending on the practical problem and on how the principle is used, the structure of the adaptive filtering system, the interpretation of the signal vectors, and the parameters of the filter, may all vary from application to application. In this subsection, we present a practical adaptive signal for the enhancement of ambulatory ECG signals.

A- Removal of Motion Artifacts and Abrupt Changes in Baseline

The adaptive filter used to remove baseline wander and motion artifacts is a special case of the noise canceller (a notch filter), with the notch at 0.04 Hz (or almost dc). Only one weight is needed and the reference input is a simulated unit step. This filter has a "zero" at dc and consequently creates a notch with a bandwidth of $(\mu/\pi) * f_s$, where f_s is the sampling rate [16].

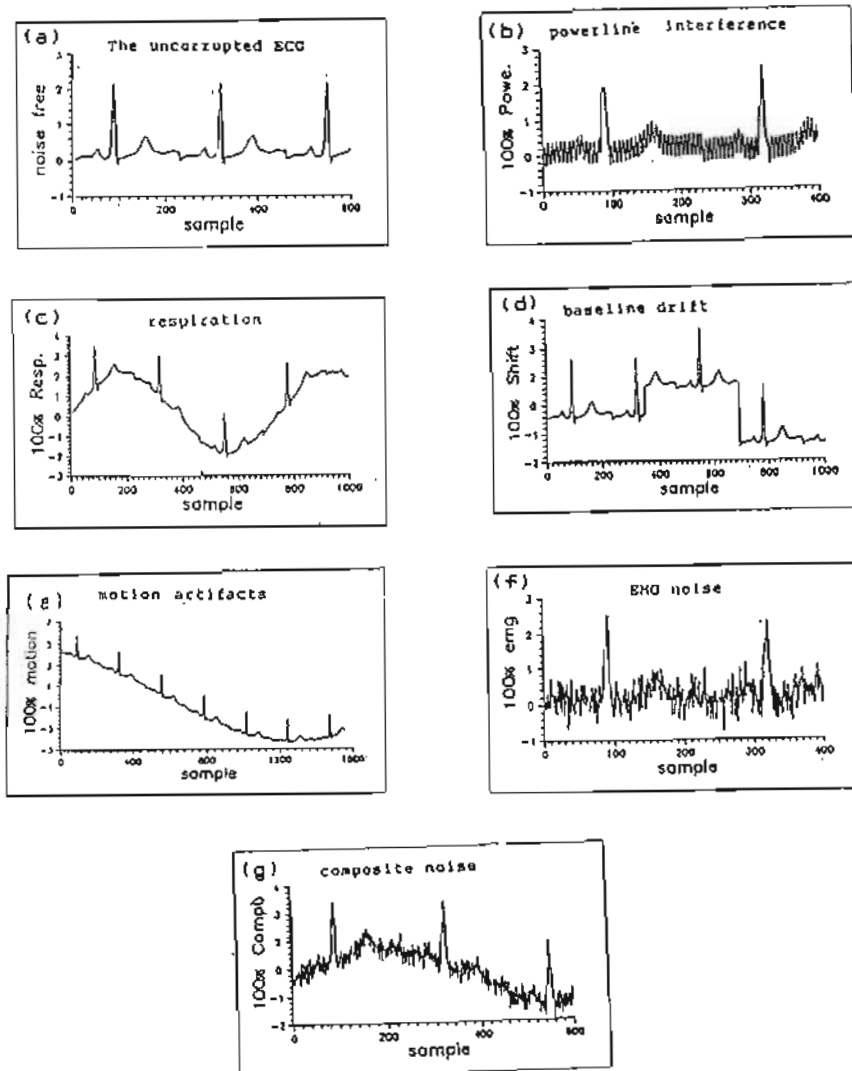


Fig. 5 The simulated signals (a) the uncorrupted ECG, (b) the ECG corrupted with the 50 Hz noise, (c) with respiratory artifacts, (d) with abrupt change, (e) with motion artifacts, (f) with EMG noise, and (g) with composite noise.

B- Removal of Baseline Drift Due to Respiration

The adaptive filter used for removing the respiration effect is a notch filter, with the notch at 0.33 Hz. There is only one weight and the reference input is a simulated sinusoid with frequency of 0.33 Hz.

C- The 50 Hz Powerline Interference Cancellation

The adaptive filter used here employs two weights so that in-phase and out-of-phase components of the 50 Hz powerline noise can be canceled. The primary input to the filter is the ECG signal corrupted with 50 Hz powerline interference and the reference input is a simulated sine wave having a frequency of 50 Hz.

D- Cancellation of Electromyographic Noise

Two types of adaptive filters were alternatively utilized to cancel the effect of EMG noise. The first is the adaptive predictor (line enhancer) which needs no external reference input to be available. The reference input is a version of the primary input delayed with 1 sample. The second filter is the adaptive recurrent filter (ARF). The reference input consists of impulses coincident in time with the beginning of each P-RS-T complex. The primary input is the ECG signal to be filtered. As the QRS in the simulated signal has 22 samples length, therefore, the filter requires 22 weights. Each recurrent beat of the signal complex results in a new reference impulse and a new update of all filter weights.

E- Cancellation of Composite Noise

Composite noise is a more realistic model of the noise problem which would be expected in a clinical setting. Therefore, the ECG corrupted with composite noise is processed using the adaptive enhancement system shown in Fig.6. It consists of two stages, the first stage consists of stage W1 and stage W2 in parallel functions as processing unit for reducing the nonwhite noise. The primary input is the ECG signal to be filtered. Stage W1 separates the baseline wander, motion artifacts and the respiratory effects. The second stage W2 is a noise canceller to remove the 50 Hz noise. The last stage W3 consists of either a recurrent filter or a predictor to remove EMG noise. The output of the third stage is the desired signal free of noise.

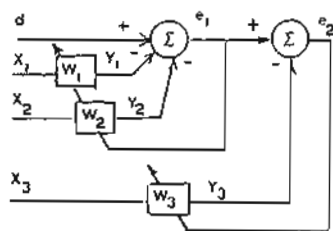


Fig.6 Two-stage adaptive filter: W1: filter for 50 Hz cancellation; W2: filter for baseline removal; W3: filter for EMG removal

Performance Analysis

The three structures of adaptive filters: the adaptive noise canceller (ANC), the adaptive predictor (AP) and the adaptive recurrent filter (ARF) were applied to the corrupted ECG signal d_i to remove the different noise interferences. The reference input signals used in the noise canceller are also simulated signals.

Fig.7 shows the results obtained for $SNR_i = 2$ dB. At the top, we can see the corrupted signal d_i . The second row shows the estimation of the deterministic signal by means of adaptive filtering.

The performance of the different combinations of adaptive filters has been evaluated quantitatively using three measures: the normalized root mean squared error (RMSE), the correlation coefficient (R), and a well known SNR estimate (SNR_o). By comparing the values of the three parameters before and after the filtering procedure, we can determine which structure performs the best. The normalized root mean square error (RMSE) is calculated from

$$RMSE = \frac{\sqrt{\sum_{i=1}^L |s_o(i) - y(i)|^2}}{\sqrt{\sum_{i=0}^L s_o^2(i)}} \quad (8)$$

where $y(i)$ denotes the output signal and $s_o(i)$ is the uncorrupted ECG signal.

The correlation coefficient (R) between two signals x_1 and x_2 is calculated from

$$R = \frac{S_{x_1 x_2}}{S_{x_1} S_{x_2}} \quad (9)$$

where $S_{x_1 x_2}$ is the covariance of the signals x_1 and x_2 and S_{x_1} and S_{x_2} are the standard deviations of signals x_1 and x_2 , respectively.

A third parameter was used for comparing the performance from the point of view of SNR improvement. A well known SNR estimator was utilized. This estimator computes an estimate of the SNR of a pair of noise corrupted signals x_1 and x_2 , that have been sampled n times [20]. It is based on the sample correlation coefficient between two signals x_1 and x_2 :

The most significant features of these filters are that they allow estimation of the underlying signal in the absence of a priori knowledge of the statistical or spectral properties of the signal and noise. Other advantages are their adaptive capability, their low output noise, and their low signal distortion. The adaptive capability allows the processing of inputs whose properties are unknown and in some case stationary. It leads to a stable system that automatically turns itself off when no improvement in SNR can be achieved. Output noise and signal distortion are generally lower than can be achieved with conventional filter configurations.

Signal enhancement requires different strategies for different noise sources. The adaptive noise canceller has been found to be effective for the removal of the baseline wander, respiratory artifacts, and the 50 Hz interference. The adaptive predictor affects random noise (EMG, electrode contact, sampler, quantizer, ...etc.) to a reasonable extent, however, the adaptive recurrent filter is more effective in this aspect as indicated by the obtained values of the root-mean squared error, the correlation coefficient and the SNR improvement.

The performance of each adaptive filtering technique has been thoroughly investigated. It has been shown that a two stage adaptive filter that consists of an adaptive noise canceller as the first stage and an adaptive recurrent filter in the second stage can substantially eliminate the effect of the different types of noise that may interfere with ambulatory ECG. The ECG signal itself has been little affected and consequently, the signal-to-noise ratio has been significantly improved.

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