Applications of Adaptive Filtering to ECG Analysis: Noise Cancellation and Arrhythmia Detection

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***Abstract*—Several adaptive filter structures are proposed for noise cancellation and arrhythmia detection. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the noisy ECG, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with ECG in the primary input. Different filter structures are presented to eliminate the diverse forms of noise: baseline wander, 60 Hz power line interference, muscle noise, and motion artifact. An adaptive recurrent filter structure is proposed for acquiring the impulse response of the normal *QRS* complex. The primary input of the filter is the ECG signal to be analyzed, while the reference input is an impulse train coincident with the *QRS* complexes. This method is applied to several arrhythmia detection problems: detection of *P*-waves, premature ventricular complexes, and recognition of conduction block, atrial fibrillation, and paced rhythm.**

I. 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 recorders have been developed that carry out online signal processing, data reduction, and arrhythmia detection [1], [2]. Computational power of the microprocessor allows us to implement digital filters for noise cancellation and arrhythmia detection. For example, Lynn [3], [4] and Thakor and Didier [5] have developed integer coefficient and quantized coefficient digital filters, respectively, for real-time execution by microprocessors. Ahlstrom and Tompkins [6] describe similar filters for real-time ECG signal processing.

Adaptive filtering technique has been shown to be useful in many biomedical applications. The basic idea behind adaptive filtering has been summarized by Widrow *et al.* [7] and used in a variety of ECG processing applications [8], [9]. One simple but important application is in 60 Hz powerline interference cancellation. A reference signal representing powerline interference from some part of the body (other than the ECG recording area) may be used to cancel powerline interference from the ECG. Another application is in fetal ECG recording. Yelderman *et al.* [8] used the idea that the mother's own ECG recorded from one of the conventional leads can be used as a correlated noise source for adaptive cancellation. To improve the signal-to-noise ratio, multiple channels are employed for adaptive filtering. Dufault and Wilcox [10] employed multiple surface leads to discriminate *P*-waves. Another interesting application is cancellation of cardiogenic interference from an impedance plethysmographic signal. Sahakian and Kuo [11] employed ECG signal as the reference input to the adaptive filter to cancel the cardiogenic artifact from the thoracic impedance signal. A similar idea is used by Zhu and Thakor [12] to detect P-waves. However, a more comprehensive scheme is needed for noise cancellation and arrhythmia detection in ambulatory ECG.

The first aim of this paper is to demonstrate adaptive filter application in noise cancellation. We develop specialized filter structures for cancellation of noise arising from diverse sources. The second aim is to show how an adaptive recurrent filter structure detects cardiac arrhythmias. Our idea is to build an impulse response of the *QRS* complex and to detect as arrhythmias the signals whose impulse response deviates from normal.

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II. Adaptive Filter Structures

A. Basic Adaptive Filtering Structure

Fig. 1(a) shows a filter with a primary input that is an ECG signal s_1 with additive noise n_1, while the reference input is noise n_2, possibly recorded from another generator of noise n_2 that is correlated in some way with n_1. If the filter output is y and the filter error is $\epsilon = (s_1 + n_1) - y$, then

$$\begin{aligned}\epsilon^2 &= (s_1 + n_1)^2 - 2y(s_1 + n_1) + y^2 \\ &= (n_1 - y)^2 + s_1^2 + 2s_1n_1 - 2ys_1.\end{aligned} \tag{1}$$

Since signal and noise are uncorrelated, the mean-squared error (MSE) is

$$E[\epsilon^2] = E[(n_1 - y)^2] + E[s_1^2]. \tag{2}$$

Minimizing the MSE results in a filter error output that is the best least-squares estimate of the signal s_1. The adap-

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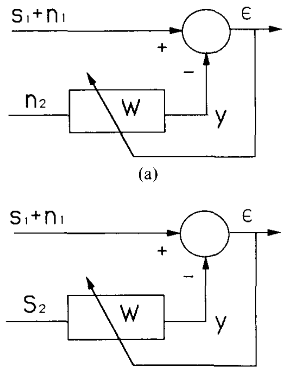

Fig. 1. Two adaptive filter structures. Type 1(a): the reference input is noise n_2 correlated with noise n_1; the desired signal appears at ϵ. Type 1(b): The reference input is signal s_2 correlated with signal s_1; the desired siganl appears at y.

tive filter extracts the signal, or eliminates noise, by iteratively minimizing the MSE between the primary and the reference inputs.

Fig. 1(b) illustrates another situation where the ECG is recorded from several electrode leads. The primary input $s_1 + n_1$ is a signal from one of the leads. A reference signal s_2 is obtained from a second lead that is noise free. The signal s_1 can be extracted by minimizing the MSE between the primary and the reference inputs. Using a procedure similar to (1) we can show that

$$E[\epsilon^2] = E[(s_1 - y)^2] + E[n_1^2]. \tag{3}$$

Minimizing the MSE results in a filter output y that is the best least-squares estimate of signal s_1.

B. The Least-Mean Squares (LMS) Algorithm

The LMS algorithm [7] is an iterative technique for minimizing the MSE between the primary and the reference inputs. Usually a transversal filter structure is employed and the filter coefficients or weights are obtained using the LMS algorithm. The LMS algorithm is written as

$$\boldsymbol{W}_{k+1} = \boldsymbol{W}_k + 2\mu\epsilon_k \boldsymbol{X}_k \tag{4}$$

where $\boldsymbol{W}_k = [w1_k\, w2_k \cdots wj_k \cdots wn_k]^T$ is a set of filter weights at time k, $\boldsymbol{X}_k = [x1_k\, x2_k \cdots xj_k \cdots xn_k]^T$ is the input vector at time k of the samples from the reference signal, d_k is the desired primary input from the ECG to be filtered, y_k is the filter output that is the best least-squares estimate of d_k

$$\epsilon_k = d_k - y_k.$$

Parameter μ is empirically selected to produce convergence at a desired rate; the larger its value, the faster the convergence. The time constant for convergence is $= 1/(4\mu\alpha)$ where α is the largest eigenvalue of the autocorrelation matrix of the reference signal [6]. This parameter may not be so large that it causes excessive misadjustment or instability. To ensure stability, $1/\alpha > \mu > 0$.

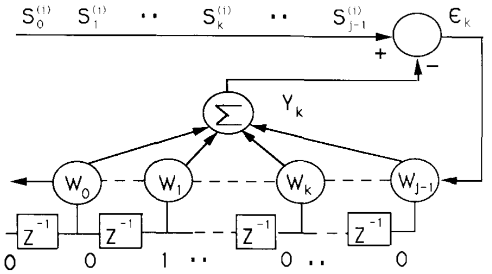

Fig. 2. Schematic of adaptive recurrent filter. Primary input $s_k(i)$ is the sample at time k for the *P-QRS-T* complex i. Reference input is an impulse sequence (indicated as 0, 0, 1 $\cdots$ 0, 0) coincident with recurrences of the *QRS* complexes. Filter output y_k is the desired impulse response. Error ϵ_k is used to adapt filter weights $\boldsymbol{W}_k$.

C. The Adaptive Recurrent Filter (ARF)

The objective of the ARF technique is to adapt filter coefficients, or weights, so that the impulse response of the desired signal is acquired. Let the *P-QRS-T* signal complex span $k = 0 \cdots (J - 1)$ samples, and therefore the transversal filter will require L weights. The reference signal is an impulse coincident in time with the first sample of the signal complex. Each recurrence $i = 1, 2, \cdots$ of the signal complex results in a new reference impulse and a new update of all the filter weights (Fig. 2). The desired impulse response is obtained by minimizing the MSE between the primary and the reference inputs.

For the adaptive recurrent filter, the reference vector is $X_k = [0, 0, 1 \cdots 0]^T$. Therefore,

$$w_{k+1} = w_k + 2\mu\epsilon_k. \tag{2}$$

At each time step only one filter weight is adapted. All the filter weights are adapted once each recurring cycle.

D. Reference Impulse Detection

To implement the ARF, we must first begin by identifying a reference impulse train coincident with the *QRS* complexes. The reference impulse is located in such a manner that the filter weights span the entire *QRS-T* complex. This may be accomplished by placing the impulse at the very beginning of the *QRS* complex. This is very conveniently done when a pacemaker is being used; the reference impulse sequence is obtained by detecting the pacemaker spike. For nonpaced rhythms, we must detect the *QRS* complex. *QRS* detection is a very common first step in all arrhythmia detection algorithms, and can be carried out in hardware [13] or in software [14], [15]. 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.

III. Noise Cancellation in Ambulatory ECG

Noise in ambulatory recordings is contributed both by biologic and environmental sources. Examples of environmental noise are 60 (or 50) Hz and its harmonics generated by power lines, radio-frequency and electrosurgi-

TABLE I
FILTER DESIGN SUMMARY

Noise Type	Filter Type	Primary Input	Reference Input	Result at	Example
Baseline wander	1(a)	ECG + noise	Constant	ϵ	Fig. 3
60 Hz	1(a)	"	Common-mode signal	ϵ	Fig. 4
EMG	1(b)	aVf	aVr–aVl	y	Fig. 5
Motion artifact	1(a)	ECG + noise	Impulse sequence	y	Fig. 6

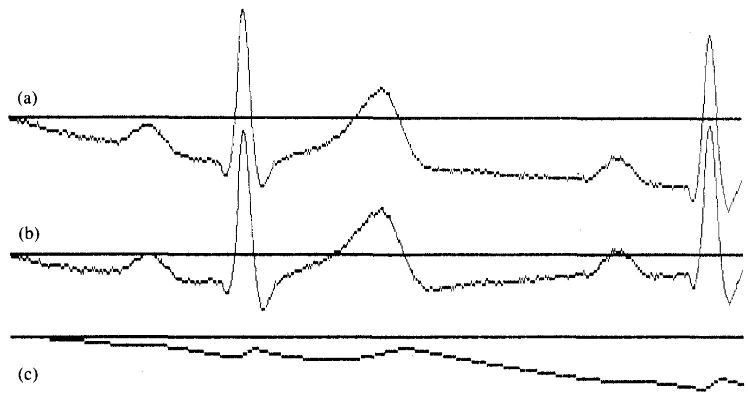

Fig. 3. Baseline wander filter: (a) original ECG with baseline wander; (b) filtered ECG; (c) baseline noise separated from ECG.

cal noise, and instrumentation noise [16]. Examples of biologic interference are: baseline drift and wander, electromyogram (EMG), and motion artifact [17]. The first aim of this paper is to present a step-by-step approach to cancellation of these diverse noise contributions to ambulatory ECG. Table I summarizes all the designs and applications considered in this paper.

A. Baseline Wander Reduction

Van Alste and Schilder [18] describe an efficient finite impulse response (FIR) notch filter that is rather effective at removing baseline wander and power line interference. The adaptive filter to remove baseline wander is a special case of notch filtering, with the notch at zero frequency (or dc). Only one weight is needed, and the reference input is a constant with a value of 1 (Table I). 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.

Frequencies in the range of 0–0.5 Hz should be removed to reduce baseline drift. If the sampling rate is 500 sample/s, the convergence parameter μ should be smaller than 0.003. Fig. 3 shows the result obtained by the adaptive baseline canceller. Parameter μ may be dynamically adjusted to obtain the desired low-frequency response. Note that this filter will produce some distortion of the ST-segment since low-frequency components of ECG are attenuated. Since the selected value of μ is small, this filter converges slowly and therefore cannot track abrupt transients produce by motion artifacts.

B. Adaptive 60 Hz Canceller

Furno and Tompkins [19] and Sahakian and Furno [20] describe filter designs that subtract a 60 Hz sinusoid from ECG. Widrow *et al.* [7] describe a filter employing two weights so that in-phase and out-of-phase components of the 60 Hz can be cancelled. In general, however, the powerline noise is not a pure 60 Hz (or 50 Hz) sinusoid, but is distorted. Therefore, we suggest the use of the true intefering signal as a reference. The common-mode signal, usually recorded at the right leg reference electrode, is truly correlated with the noise in the ECG recording. The primary input to the filter is the ECG signal to be filtered, and the reference input is the common-mode signal (Table I). Fig. 4 shows an example of 60 Hz cancellation.

C. Multilead Canceller for EMG Noise

EMG noise has a broad bandwidth which sometimes overlaps that of the ECG [22]. Simple low-pass filtering, therefore, is not adequate. Our idea is to employ more than one ECG lead. Since electrodes are usually placed at different locations, the EMG noise from various leads may be uncorrelated. We ensure uncorrelated inputs to the filter by selecting two orthonormal ECG leads. The standard ECG lead system employs three limb leads—I, II, and III—as well as three augmented leads—aVr, aVl, and aVf. From the analysis of the cardiac vector, we note that the aVr–aVl vector is orthonormal to aVf. Noise in orthonormal leads is expected to be uncorrelated. The primary

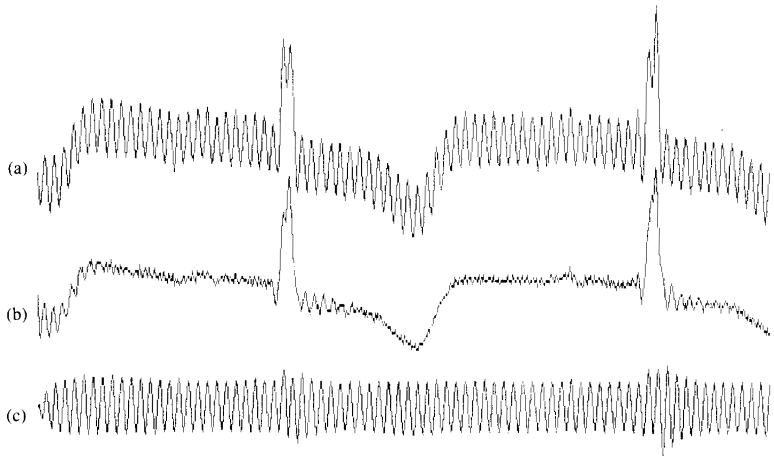

Fig. 4. 60 Hz filter: (a) original ECG with 60 Hz noise; (b) filtered ECG; (c) separated 60 Hz noise.

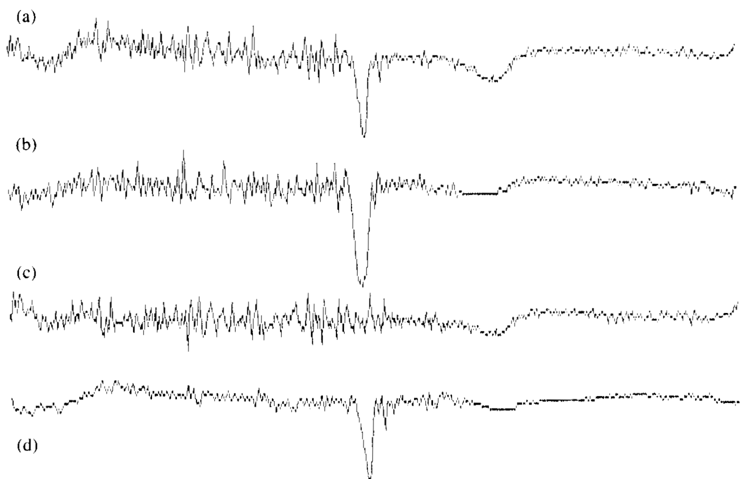

Fig. 5. EMG filter: (a) primary input, the ECG in lead aVf; (b) reference input, derived from aVr–aVl; (c) filter error ϵ, (d) filter output y.

input to the filter is the ECG signal from lead aVf, while the reference is the signal aVr–aVl (Table I). Fig. 5 shows the results of adaptive cancellation of EMG.

D. Motion Artifact Cancellation

Motion artifact is usually the most difficult form of noise to be eliminated from ambulatory ECG signals. This is because its spectrum completely overlaps that of the ECG, and its morphology often resembles that of the *P*, *QRS*, and *T* waves [17], [21]. Most linear filtering approaches fail to solve this problem. The adaptive recurrent filter [12] is useful in cancelling noise from signals that have a repetitive morphology. The primary input to this filter is the ECG signal with motion artifact, and the reference input is an impulse that is coincident with the beginning of each *P-QRS-T* complex (Table I). The adaptation takes place only for the samples spanning the signal complex, and subtraction of this complex from the ECG leaves the motion artifact as residue (Fig. 6). Note that since the filter does not adapt between *QRS* complexes, the baseline between complexes is simply interpolated. This clearly results in some signal distortion. The resulting ECG is not suitable for diagnostic quality display, but the noise-free *QRS* complexes at the filter output may be used in applications such as heart rate measurements and arrhythmia detection.

E. Two-Stage Multichannel Filter

In ambulatory ECG all forms of noise may occur simultaneously and unpredictably. Fig. 7(a) illustrates a com-

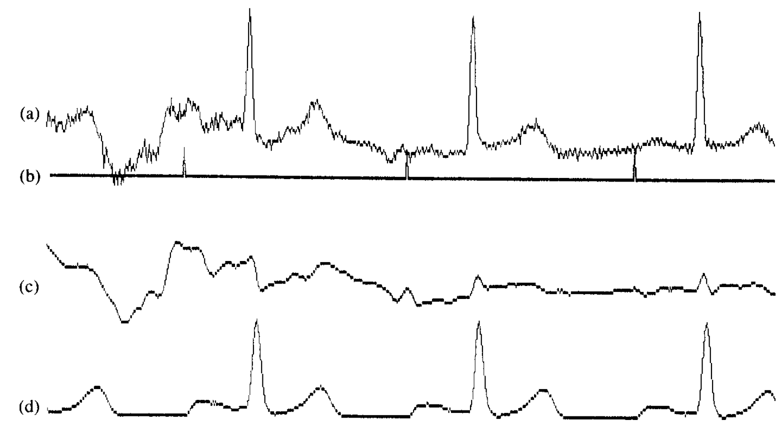

Fig. 6. Application of recurrent filter to motion artifact cancellation: (a) ECG with motion artifact; (b) impulse sequence coincident with *QRS* complexes; (c) filter error ϵ, the motion artifact, (d) filter output.

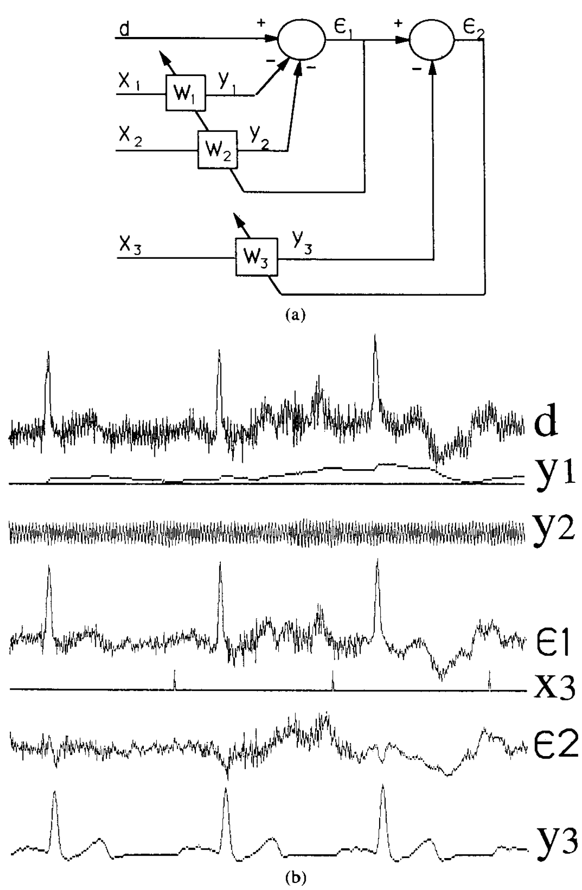

Fig. 7. (a) Two-stage multiinput adaptive filter: *W*1: filter for baseline removal; *W*2 filter for 60 Hz cancellation; *W*3: filter for EMG and motion artifact cancellation. (b) Cancellation of baseline wander, 60 Hz, EMG, and motion artifact from ambulatory ECG: d: ECG signal to be filtered; *y*1: filter estimate of baseline wander; *y*2: filter estimate of the common-mode 60 Hz noise; ϵ1: ECG without 60 Hz and baseline wander; *x*3: impulse coincident with *QRS* complex; ϵ2: EMG and motion artifact; *y*3: filtered ECG.

bination filter structure. The primary input is the ECG signal recorded from a subject who is jogging. The noise includes 60 Hz, baseline wander, EMG noise, and motion artifact. The first stage of the filter separates baseline wander $y1$ and 60 Hz noise $y2$ [Fig. 7(b)]. The second stage is a recurrent filter (Section II-C) to remove EMG noise and motion artifact. A two-stage filter is necessary: if we did not remove the baseline and 60 Hz noise first, there might be false *QRS* detections, and these would cause the impulse sequence to the recurrent filter to be incorrect. The output of the second stage $y3$ is the desired signal free of noise.

IV. Arrhythmia Detection

Adaptive filtering can be applied to arrhythmia analysis. This application is facilitated by two facts: 1) the ECG signal is usually characterized by a well-defined *P-QRS-T* complex, and 2) the signal compexes are recurrent with each heart beat. Under normal situations, the morphology remains stable from beat to beat (although there may be some minor variations). Any significant departure in morphology indicates presence of an arrhythmia. Under normal circumstances the *P-QRS-T* complex remains well synchronized. If this normal sequence is disrupted, as in the case of many arrhythmias, the adaptive filter picks out uncorrelated components in the sequence.

A. Adaptive Cancellation of the QRS-T Complex

Let us first examine the ability of the ARF to acquire the impulse response of the *QRS-T* complex. Fig. 8 illustrates the waveform of a normal ECG, coincident impulses obtained after *QRS* detection, and a gradual adaptation of the transversal filter. The result is an excellent cancellation of the *QRS-T* complex, leaving behind the *P*-wave sequence as the filter error. If a large enough convergence parameter μ is selected, the ARF should adjust to small beat-to-beat variations in the *QRS* morphology. *P*-waves can subsequently be used by algorithms to detect atrial arrhythmias.

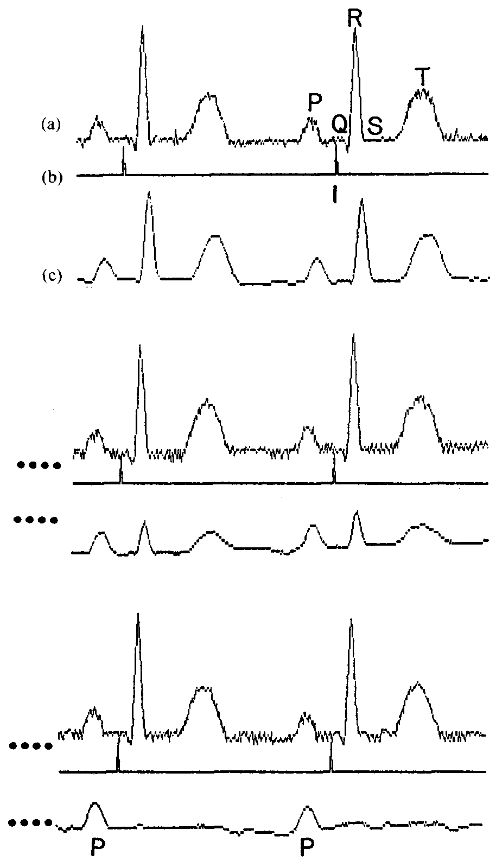

Fig. 8. (a) A normal ECG signal with well defined *P-QRS-T* sequence. (b) Each reference impulse *I* coincides with the begining of each *QRS-T* complex. (c) The filter error output. The ARF learns the impulse response of the *QRS-T* complex, and cancels the learned complex from the ECG at each successive beat. After several beats the adaptation is complete, so that the *QRS-T* complex is completely cancelled, leaving *P*-waves as residue (or the filter error output).

B. Detection of Ectopic Beats

Ectopic beats are usually characterized by a morphology that is distinct from that of normally conducted *QRS* complexes. Fig. 9 shows an ECG signal with infrequent ectopic beats that are abnormally conducted and, therefore, have different morphologies. The ARF first adapts to the impulse response of the normally conducted *QRS* complexes, resulting in a minimal filter error. A subsequent ectopic beat results in a significant misadjustment. The filter error, or residue, clearly delineates the ectopic beat. The ARF quickly reacquires the impulse response of the normal complexes, and as a result adaptation error for subsequent beats is minimal.

C. P-Wave Detection in Conduction Blocks

P-waves, in view of their small amplitudes, are very difficult to detect. In conduction disorders, the P-waves are dissociated from the *QRS* complexes, making the detection problem even more difficult [10], [12]. In fact, *P*-waves may occasionally and randomly overlap the *QRS* complexes in the case of second or third degree blocks. Fig. 10 shows that the ARF first achieves complete cancellation of the *QRS-T* complex as described earlier. The adaptation error now prominently displays the *P*-wave sequence. Since the *P*-wave sequence is uncorrelated with the *QRS-T* complex, the adaptive filter considers it as noise and does not adapt to it (even when there is a perfect overlap of a *P*-wave and a *QRS* complex). The present results are by no means perfect. Further signal processing may be required, especially when EMG or motion artifact is present.

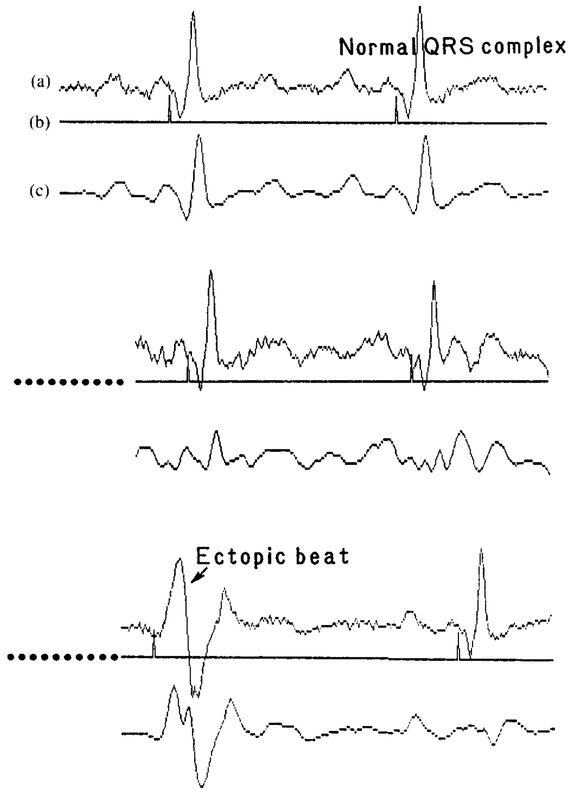

Fig. 9. Detection of ectopic beats by the ARF. (a) ECG signal. (b) Impulses coincident with *QRS* complexes. (c) Filter error output. The filter first acquires the impulse response of the normal *QRS* complex, so that the *QRS* complex is gradually cancelled (top set of traces). When the filter input contains ectopic beats (middle and lower set or traces), the filter produces a very large adaptation error. As a result, the filter error output clearly delineates the ectopic beats.

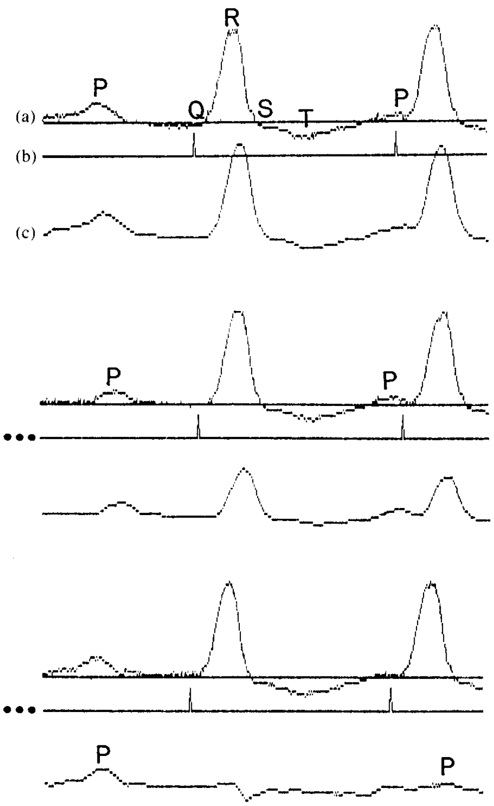

Fig. 10. Detection of conduction block. (a) ECG signal with *P*-waves marked. As a result of the conduction block, the *P*-waves and the *QRS* complexes are dissociated. (b) A series of impulses that are coincident with the *QRS* complexes. This serves as the reference input to the filter. (c) The filter error output. The ARF adapts only the impulse response of the *QRS* complexes, and cancels these from the ECG signals. This results in *P*-waves as filter error. Even when *P*-waves and *QRS* complexes overlap (partially or fully) they are delineated.

D. Detection of Atrial Fibrillation

Atrial fibrillation exhibits no apparent *P*-waves, and instead a fluctuating wave pattern is seen throughout the baseline. The *QRS* complexes may not recur at regular intervals. Using the ARF, we acquire the impulse response of the *QRS* complex and adaptively cancel the *QRS* complexes from the ECG. The residue comprises the atrial signal. Slocum *et al.* [23] suggest calculating the autocorrelation function to extract the rhythm of the atrial waveform. Fig. 11 shows the autocorrelation of the ECG signal, the ventricular signal, and the adaptation error comprises principally of the atrial signal. Atrial fibrillation is thus identified from the differing autocorrelation functions of the atrial and the ventricular rhythms.

E. Paced Rhythms

When a patient has a pacemaker implanted, the surface ECG carries a pacemaker spike artifact. The pacemaker spike is only a few milliseconds wide and hence is readily detected. The ARF is triggered by the pacemaker spike, and the impulse response of the paced rhythm is acquired by adapting the filter weights (Fig. 12). Occasionally the pacemaker fails to initiate paced rhythm (owing to lead failure or the altered pacing threshold of the heart). In that case the paced and the nonpaced signal complexes exhibit different morphologies. The ARF, triggered by a nonpaced beat, registers a large adaptation error. This technique can be used to monitor pacemaker performance and failure.

V. Discussion

There are several advantages to the adaptive filtering approaches just described. The most significant feature of these filters is that they allow estimation of the underlying signal in the absence of *a priori* knowledge of the statis-

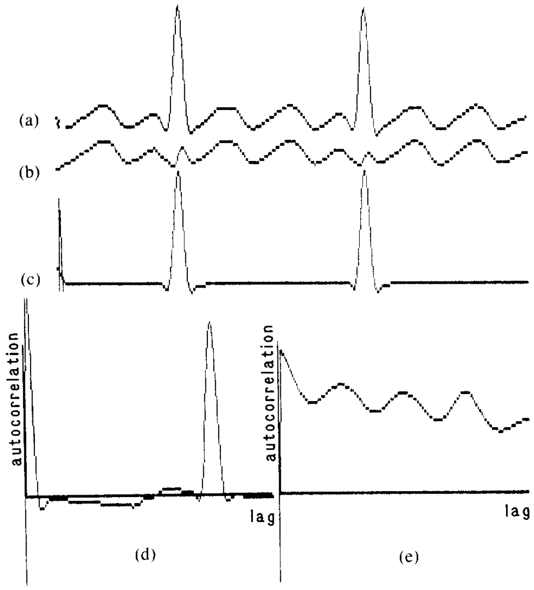

Fig. 11. Detection of atrial fibrillation. (a) Composite atrial fibrillation signal. (b) Filter error (mainly atrial rhythm). (c) Filter output (mainly ventricular rhythm). Adaptive cancellation of the *QRS* complex leaves behind the baseline signal consisting mainly of atrial fibrillation waves. Different rhythms of ventricular and atrial signals can be distinguished from the autocorrelation functions. (d) Autocorrelation function of the ventricular rhythm. (e) Autocorrelation function of the atrial rhythm.

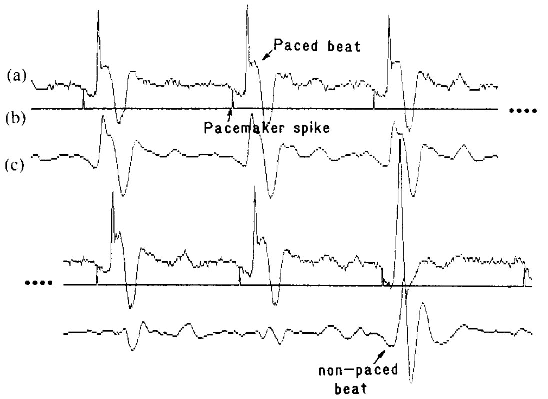

Fig. 12. Analysis of paced rhythm. (a) Composite ECG signal with paced and nonpaced beats. (b) Impulses derived from pacemaker spikes and *QRS* pulses. (c) The filter error output. The ARF is triggered by the pacemaker spikes and may be used to detect failure of the pacemaker to initiate a beat. The ARF adapts to the impulse response of the paced beats and cancels these from the ECG signal. The resulting filter error output highlights the nonpaced beats.

tical or spectral properties of the signal and noise. These filters are easy to implement on modern microprocessors with numeric capabilities. An ideal application of these filters is in ambulatory arrhythmia monitoring [1], [2].

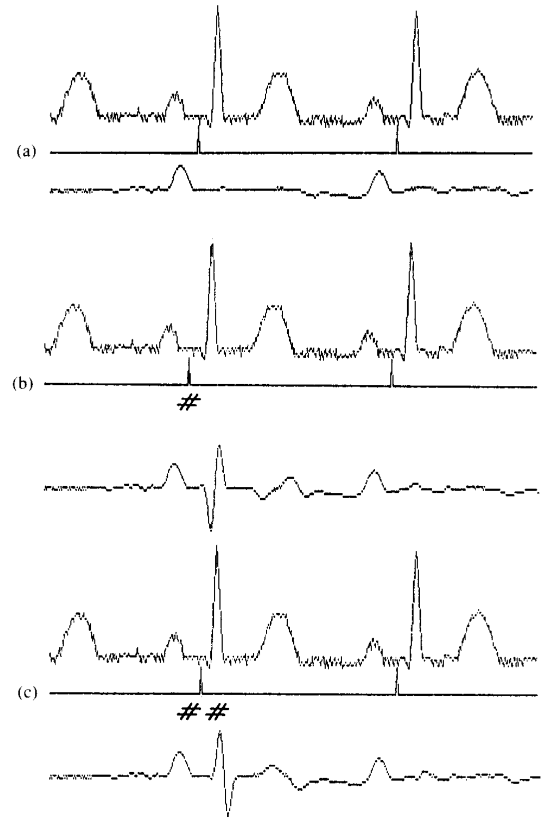

Fig. 13. Distortion arising from inaccurate placement of the reference impulse. (a) Correct cancellation of the *QRS* complexes with *P* wave as the residue. (b) Leftward movement (marked #) of the impulse results in inaccurate cancellation of the impulse response of the *QRS* complex. (c) Distortion resulting from a rightward movement (marked ##) of the impulse.

The ARF acquires the impulse response of the normal *QRS* complex. This filter structure is superior to the conventional adaptive filter that continuously adapts since filter weights degrade between signal complexes. Previously, Ferrera and Widrow [9] proposed a time-sequenced filter in which a large number of separate transversal filters are constructed for each sample within the signal complex. The principal limitation of the time-sequenced filter is that it requires a great deal of memory.

Two limitations of the ARF technique are apparent. The first problem is that the reference impulse must be exactly coincident with the signal complex. When this is done independently by detecting *QRS* complexes, there is the possibility of uncertainty and error. *QRS* detection, especially in the presence of noise and artifact, can be inaccurate. Fig. 13 shows the filter error and resulting distortion in the impulse response of the *QRS* complex, due to inaccurate placement of the reference impulse. The second problem arises from unusual beat-by-beat variation that may prevent complete adaptation from taking place. On the one hand, abrupt variation (as in Fig. 9) can be detected from a large filter error, and even can be used to detect ectopic beats. On the other hand, gradual variations in *QRS* morphology (due, for example, to sinus arrhythmia) may lead to incomplete adaptation and insufficient filter error for detection purposes. The convergence parameter μ must be carefully selected to track rapid or slow changes as desired.

Noise cancellation requires different strategies for different sources. An adaptive filter with constant or unity reference input is used to cancel baseline wander. Implementation of the baseline wander filter is considerably simpler than in previous designs [18]. Still, the lower corner frequency may be high for some applications. This filter is inappropriate when the ST-segment shape must not be distorted at all. Powerline noise (60 Hz) can be cancelled by a variety of methods, including simple analog and digital notch filters. The adaptive filter does not offer a significant advantage, except that the notch bandwidth can be easily controlled by a single convergence parameter. Our new idea here is to use a common-mode signal as the reference, so that the reference is highly correlated with noise in the ECG. EMG noise is usually reduced by conventional low-pass filtering. The adaptive filter helps remove EMG components whose spectrum may overlap that of the ECG. Our idea is to take advantage of the lack of correlation in the noise from orthonormal ECG leads. The multichannel filter, of course, does not work effectively when only a single lead is available or when EMG noise originates at all the electrodes. Motion artifact is the most difficult problem, and the recurrent filter only partially solves it. Because of the relatively slow convergence time of the filter, large nonstationary motion artifacts that overlap with the *QRS* complex cannot be cancelled. The recurrent filter also distorts the signal somewhat since adaptation takes place only over the *QRS* complex samples spanning the filter. Consequently, this filter is more suited to applications such as rhythm analysis in ambulatory monitoring and less suited to diagnostic ECG analysis.

The adaptive recurrent filter is employed in various forms for ectopic beat and arrhythmia detection: *P*-wave detection, ectopic beat detection, atrial arrhythmia analysis, and pacemaker evaluation. Arrhythmia detection is a complex problem, often involving diverse morphologies and rhythms that vary among different subjects as well as over time for the same subject. A data adaptive algorithm, therefore, is desirable. The proposed adaptive filters only form one step in a complex strategy to detect arrhythmias. In view of their minimal computational burden, these filters should find application in microcomputer-based arrhythmia monitors [2]. Additional pattern recognition algorithms [23] may be required to detect a vast range of arrhythmias normally encountered in diagnostic ECG analysis [1].

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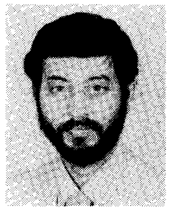

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