Prediction Error Filtering for the Extraction of Abnormal Intra-QRS Potentials in Signal-Averaged Electrocardiogram

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Abstract

The abnormal intra-QRS potentials (AIQPs) from a signal-averaged electrocardiogram (SAECG) have been proposed to indicate the risk of ventricular arrhythmias. This study developed a new method based on the prediction error filtering for the extraction of AIQPs. Two sequential SAECGs with the same noise level were used as desired and reference input signals to estimate the normal QRS and AIQPs.

The simulation results showed that the prediction error filter can effectively decorrelate the AIQPs (simulated as an autoregressive stochastic process) from the normal QRS complex under an extremely poor signal-to-noise ratio. The AIQPs of VT patients were significantly greater than those of normal subjects in leads X and Y ($p<0.05$).This work demonstrated that the AIQPs extracted by the prediction error filter were useful for the evaluation of the risk of ventricular arrhythmias.

1. Introduction

The ventricular late potentials (VLPs) recorded from signal averaged electrocardiogram (SAECG) have been associated with a reentry substrate for ventricular arrhythmias [1,2]. Although VLPs were initiated from within the normal QRS interval, they are actually characterized by the signal portion that outlasts this interval. Time-domain SAECG parameters, including fQRSD, LAS40 and RMS40, have been widely employed to quantify VLPs. However, the major limitations of time-domain analysis are an incomplete characterization of reentrant activity [3] and the poor accuracy of positive prediction [4].

The VLPs detection focuses on the evaluation of low-amplitude and high-frequency components at the terminal QRS complex. However, certain part of VLPs can be distributed over entire QRS interval. These VLPs have the same high-frequency characteristics as the large-amplitude QRS complex and its detection is relatively difficult. Moreover, an extremely poor signal-noise-ratio (SNR) (low-amplitude VLPs compared with large QRS wave) and the noise interference can limit the VLPs detection.

In addition to VLPs, Gomis et al. [5] and Lander et al. [6] have proposed the abnormal intra-QRS potentials (AIQPs) as a new index to evaluate the risk of ventricular arrhythmias. Although the formal pathophysiological bases for AIQPs have not yet been well established, numerous investigations have suggested that the activity of a reentry substrate of ventricular arrhythmias may be completely contained within the normal duration of the QRS [7]. The analysis of the AIQPs allows a potential pathophysiological signal that is completely within the normal QRS interval to be measured.

The AIQPs were assumed as the transient, unpredictable part of the QRS complex. Gomis *et al*. [5] developed an ARMA model built in the discrete cosine transform (DCT) domain to estimate the normal QRS components and analyze the AIQPs by the modeling residuals. In the DCT domain, most ECG energy is concentrated in the low-frequency band. This model can use a low order to estimate ECG signals accurately.

However the current parametric modeling is in the discrete cosine transform domain (i.e. frequency domain) to estimate the AIQPs, hence the transient and unpredictable features in time domain may not be accurately extracted. The purpose of this study is to evaluate the AIQPs directly in the time domain based on a prediction error filter.

2. Methods

2.1. High-resolution ECG recording

There were 50 normal Taiwanese (N) and 30 sustained ventricular tachycardia (VT) patients were recruited in this study. High-resolution ECGs were recorded using a commercially available Simens-Elema Megacart® machine with a bipolar, orthogonal X, Y and Z lead system. The high-resolution ECGs were recorded at rest in a supine position using a commercially available Simens-Elema Megacart® machine. A bipolar, orthogonal X, Y and Z lead system was used. A sample of 10 min raw ECG with 12-bit resolution at 2 kHz was stored on

computer hard disk for subsequent analysis. The time-domain SAECG analysis under various RMS noise levels was performed offline.

2.2. Signal averaging

Offline signal averaging procedure in our program followed the standards of 1991 ESC, AHA and ACC Task Force [2]. Each incoming heartbeat was aligned with the template waveform. An alignment was accepted when the correlation coefficient is larger than 0.98. The template was then updated every eight beats averaged to prevent any possible corruption from proliferation. Each averaged ECG of lead X, Y and Z was filtered with a four-pole 40-250 Hz high-pass Butterworth filter working with the bi-directional mode. The filtered signal-averaged vector magnitude (VM), which is defined as the filtered QRS complex, was calculated as the square root of $(X^2 + Y^2 + Z^2)$.

A 40 ms section where the root-mean-square voltage was minimum in the ST segment of the VM was selected as the noise sample for the evaluation of the noise level. The onset and offset of SAECG were defined as the midpoint of the 5-ms segment in which the mean voltage exceeded the mean noise level plus three times the standard deviation of the noise sample.

The final noise level of SAECG was set at 0.7 μV. Two successive SAECGs with the same noise level were performed for the follow-up prediction error filtering.

2.3. Prediction error filtering

Figure 1 shows the block diagram of the prediction error filtering for the evaluation of the AIQPs. The delay time T represents the time of one cardiac cycle. The design of a finite-impulse-response Wiener filter, $W(z)$, is to produce the minimum mean-square estimate of the desired input $d(n)$ by filtering a set of observations of a statistically related reference input $x(n)$.

This study introduced two successive SAECGs to be desired and reference input signals respectively. Each SAECG was assumed to contain two main parts – (1) the normal QRS, $S_i(n)$, and (2) the AIQPs, $v_i(n)$, $i = 1,2$. The normal QRS are assumed to be uncorrelated with the AIQPs. Two successive AIQPs are also assumed to be uncorrelated with each other. Because two successive normal QRS are highly correlated, we can try to use the wiener filter with a low order to separate the normal QRS and the AIQPs in the desired input SAECG.

The normal QRS can be estimated by the output of the pth-order filter. That is,

$$y(n) = x(n) \otimes w(n) = \sum_{i=1}^{p} w(l)x(n-l) \tag{1}$$

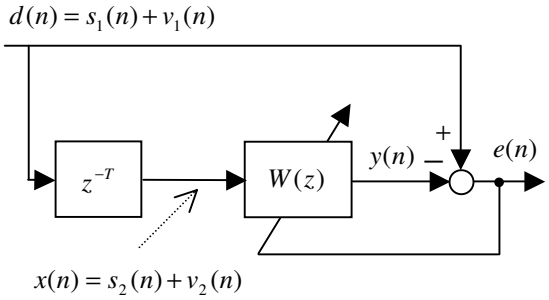

Figure 1. Block diagram of the prediction error filtering for the evaluation of the abnormal intra-QRS potentials.

where $\otimes$ is the symbol of the convolution sum, and $w(l)$ is the l th filter coefficient. The Wiener filter design problem requires that we find the filter coefficients, $w(l)$, that minimize the mean-square error

$$\xi = E\{|e(n)|^2\} = E\{|d(n) - y(n)|^2\} \tag{2}$$

The optimal filter coefficients can be derived from the Wiener-Hopf equations [8] as follows.

$$\mathbf{w}_o = \mathbf{R}_x^{-1}\mathbf{r}_{dx} \tag{3}$$

where $\mathbf{R}_x$ is the autocorrelation matrix of the reference input $x(n)$, $\mathbf{w}_o$ is the vector of the optimal filter coefficients, and $\mathbf{r}_{dx}$ is the vector of cross-correlations between the desired input $d(n)$ and the reference input $x(n)$.

When the prediction error filter is optimized in the minimum mean-square error sense, the filtering output can be evaluated as

$$y(n) = s_2(n) \otimes w_o(n) + v_2(n) \otimes w_o(n), \tag{4}$$

where $s_2(n) \otimes w_o(n)$ is the optimal estimation of $s_1(n)$, and $v_2(n) \otimes w_o(n)$ is the interference of the estimation. The filtering error can also be derived as

$$\begin{aligned} e(n) &= d(n) - y(n) \\ &= [s_1(n) - s_2(n) \otimes w_o(n)] + v_1(n) \\ &\quad - v_2(n) \otimes w_o(n), \end{aligned} \tag{5}$$

where $s_1(n) - s_2(n) \otimes w_o(n)$ and $-v_2(n) \otimes w_o(n)$ both are the interferences for the estimation of the AIQPs ($v_1(n)$).

The average power of the filtering error to lie in

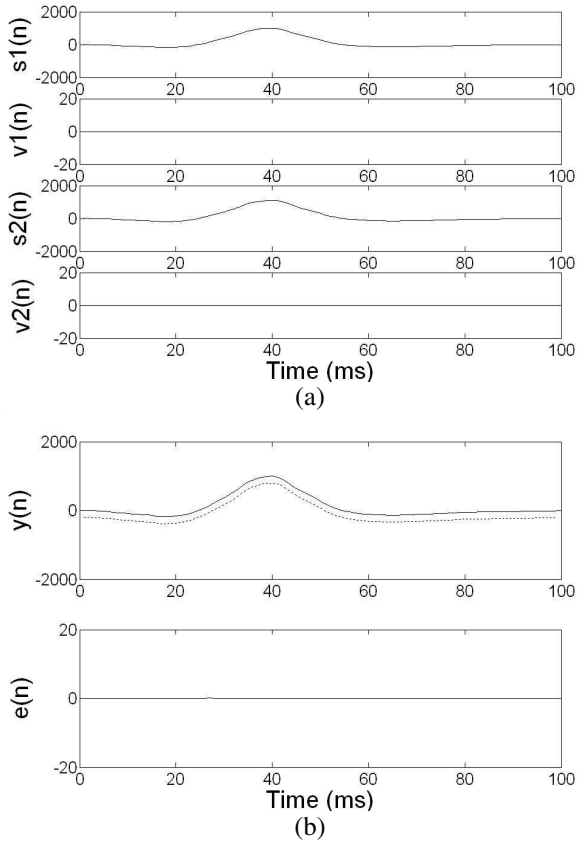

Figure 2. Simulation results without AIQPs, (a) the desired and reference inputs, and (b) filtering output and error. The dotted line is the original normal QRS ($s_1(n)$) in the plot of $y(n)$.

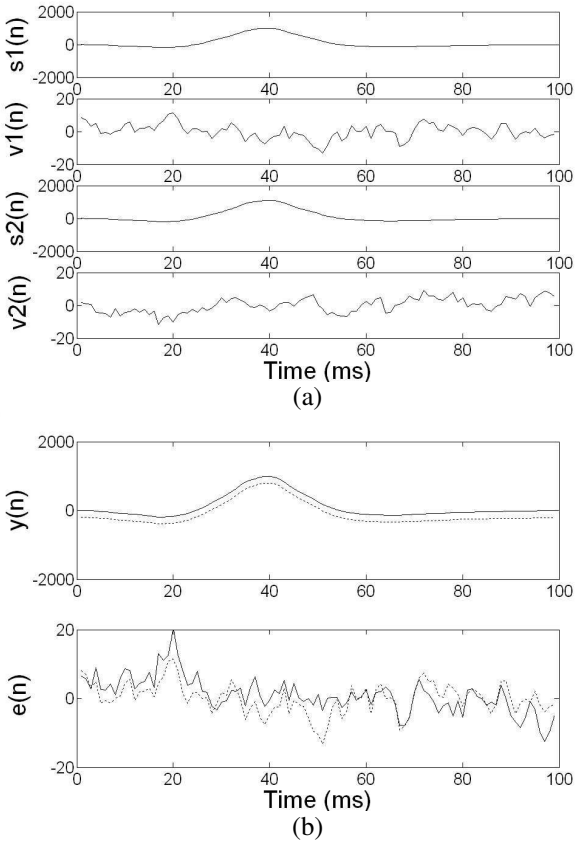

Figure 3. Simulation results with AIQPs, (a) the desired and reference inputs, and (b) the filtering output and error. The dotted lines are the original normal QRS ($s_1(n)$) in the plot of $y(n)$, and the original AIQPs ($v_1(n)$) in the plot of $e(n)$ separately.

between onset and offset of QRS complex is used to quantify the AIQPs in leads X, Y and Z (AIQP_*l* represents AIQPs in lead *l*, *l*=X, Y or Z).

2.4. Statistical analysis

Data were presented as mean ± standard deviation (SD). All statistical analyses were done with Statistical Package for the Social Sciences® (SPSS). Normal distribution tests were performed on all quantitative variables [9]. Statistical significance was defined as p values less than 0.05. Comparisons between pairwise groups were performed using a Student t test for normally distributed continuous variables. Levene's test was used to check the homogeneity of variance between variables. The Mann Whitney U and Wilcoxon Rank Sum tests were used for those non-normally distributed [10].

3. Results

3.1. Simulation results

A simulation experiment was performed to determine whether the prediction error filtering could extract the transient and unpredictable AIQPs. Figure 1(a) shows two successive SAECG without AIQPs. Their normal QRS parts with a peak-to-peak range about 1200 μV are highly correlated ($s_1(n) = s_2(n) - 0.1 \times s_2(n-1)$). The optimal filtering output and error are shown in Figure 1(b). This study selected a 20th-order filter for analyzing the AIQPs of all SAECGs. Because of the absence of the AIQPs, the normal QRS $s_1(n)$ can be exactly estimated and no AIQPs presented in the filtering error.

Figure 2(a) shows two successive SAECG with AIQPs. Their normal QRS parts are same as those in Figure 1(a). An autoregressive stochastic process was used to simuate the AIQPs as follow.

$$v_1(n) - 0.8 \times v_1(n-1) = u(n)$$

$$v_2(n) = v_1(n-T) \qquad (6)$$

where $u(n)$ is drawn from a white-noise process of mean zero and variance one, and T represents the time of one cardiac cycle. The SNR is only about -37 dB.

Figure 2(b) shows that the normal QRS $s_1(n)$ can also be exactly estimated by the filtering output $y(n)$, and the filtering error can estimate the AIQPs but including certain interferences.

3.2. Results of AIQPs analyses

Table 1 shows the results of AIQPs analyses of SAECG. The mean AIQPs from leads X and Y of the VT group significantly exceeded that of the normal group ($p < 0.05$). Although the mean AIQPs from lead Z of the VT group was larger than that of the normal group, the difference was not statistically significant.

Table 1: Summary of the AIQPs analyses

	AIQP parameters (μV)		
Subjects	AIQP_X	AIQP_Y	AIQP_Z
VT	39 ± 36	45 ± 44	51 ± 50
Normal	18 ± 9 *	23 ± 18 *	36 ± 32 NS

The equivalent non-parametric Mann Whitney U and Wilcoxon Ranked Sum tests were performed to compare the means between VT and VPC or Normal groups. Abbreviations: NS, not significant ($p>0.05$); *, $p < 0.05$; AIQP_*l*, abnormal intra-QRS potentials from lead *l*, where *l* = X, Y or Z).

4. Discussion and conclusions

This study proposed a new method based on the prediction error filtering to evaluate the AIQPs. Two successive SAECGs were adopted as the inputs of the prediction error filters. Because two successive normal QRS were highly correlated, the normal QRS can be estimated from the filtering output and then the filtering error can used to estimate the AIQPs. The simulation results also showed the performance of the proposed prediction error filter with and without the presence of the AIQPs.

This work demonstrated the AIQPs extracted from the prediction error filtering are useful for the evaluation of the risk of ventricular arrhythmias. However, the extracted AIQPs from the filtering error still included certain interferences. This may affect the clinically diagnostic performance.

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