Atrial Electrical Activity Detection in the 12-Lead ECG using Synthetic Atrial Activity Signals

Or Perlman[1], Amos Katz[2,3], Noam Weissman[1], Yaniv Zigel[1]

[1]Department of Biomedical Engineering, Ben-Gurion University of the Negev, Beer-Sheva, Israel
[2]Faculty of Health Sciences, Ben-Gurion University of the Negev, Beer-Sheva, Israel
[3]Barzilai Medical Center, Ashkelon, Israel

Abstract

A significant key for the success of arrhythmia diagnosis using ECG is detecting the atrial electrical activity (AEA). Despite extensive research, there is a diagnostic problem in detecting AEA in some arrhythmias, especially when the AEA-wave is hidden in other waves.

Our proposed method utilizes the well-known linear combiner usually used for noise reduction, and adapted it for AEA detection. The physician/user marks one prominent AEA segment. Then, a synthetic signal is created that contains an isoelectric line in addition to a Gaussian in the delineated segment. The 6 precordial leads, lead I, and lead II, serve as reference signals, so by finding the appropriate weight coefficients, their linear combination is forced to converge to a signal that is similar to the AEA signal. At the final stage, the resulting signal is band-pass filtered and the peaks higher than a certain threshold are determined to be AEA-waves.

Sensitivity of 94.0% and precision of 90.2% were achieved in detecting AEA from the standard 12-lead ECG for various arrhythmia types.

1. Introduction

Cardiac arrhythmia is a deficiency in the heart electrical conducting system that is manifested in an irregular heart-beat or abnormal heart rhythm. It may cause chest pain, loss of consciousness, blood clots, stroke, and in some cases death. In order to identify such arrhythmias, a physician must carefully probe the ECG signal for many characteristics [1].

An important factor for the success of arrhythmia identification and classification is identifying the atrial electrical activity (AEA) waves and examining the relation between them and the other signal elements. This task is very difficult in some arrhythmias in which the AEA wave is hidden in other waves or has different morphologies; as a result, an invasive procedure using intra-cardiac electrodes is sometimes performed in order to classify (and treat) the correct arrhythmia [2].

There are several existing methods and approaches for AEA detection [3-8]. A recent method uses wavelet transformation and T-wave filtration [3]. It showed good results in some cases, but demonstrated moderate results when the AEA fell inside the QRS complex. Another familiar algorithm is QRST subtraction. This technique provides very good specificity but sometimes results in poor sensitivity [4]. Other methods use the source separation approach, usually based on principal component analysis (PCA) or independent component analysis (ICA). PCA/ICA algorithms [5,6] rely on the assumption that the atrial activity and the ventricular activity are uncorrelated or independent. Due to this assumption, those algorithms perform well on atrial fibrillation cases, but have worse performances in other cases. Another recent method suggests using an Energy Ratio Measure [7]. This showed promising results but the study cohort was small.

Our proposed method creates a linear combination of 8 surface ECG leads that represent the AEA signal. Later, the resulting signal is band-pass filtered, and the AEA-waves are detected using an amplitude relative threshold.

2. Method

The AEA detection method is based on two assumptions:

1. Each ECG lead is composed of two sources: the ventricular and the atrial activity signals.
2. An approximation of the AEA signal can be achieved by a linear combination of the surface leads.

The phases of the method can be seen in Figure 1.

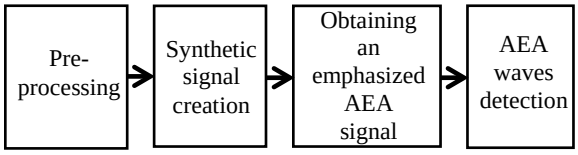

Figure 1. A block diagram of the proposed method.

2.1. Pre-processing

Band pass filtering of 0.5–49.5 Hz is digitally performed to avoid common ECG noises.

2.2. Synthetic signal creation

An initial marking of one prominent, easy to detect AEA wave is done by a physician or other user. Based on the marked (wave) segment, a synthetic signal is created that contains a Gaussian in the delineated segment and an isoelectric line in all other samples. The Gaussian's mean is the center of the delineated segment, and its standard deviation is one-quarter of the segment's length.

2.3. Obtaining an emphasized AEA signal

Linear combiner is a well-known method for noise and artifact removal [9] (e.g., removal of undesired eye-movement noises from the electroencephalogram signal). The main concept of this method is subtracting an appropriate linear combination of reference signals (that represent noise signals) from the observed signal, in order to remove the noise.

Our proposed AEA detection method uses an adaptation of that technique. We will refer to the synthetic signal created in section 2.2 as an observation signal, and denote it as $x[n]$. We will denote the desired AEA signal as $v_0[n]$, which contains a few AEA-waves. $x[n]$ can be referred to as a summation of $v_0[n]$ and a noise signal, denoted as $s[n]$.

$$x[n] = s[n] + v_0[n] \tag{1}$$

Our goal is to detect the AEA signal $v_0[n]$. We try to get an estimation of that signal, denoted by $\hat{v}_0[n]$, by creating a linear combination of eight ECG surface leads (the 6 precordial leads, lead I, and lead II):

$$\mathbf{v}[n] = \left[v_1[n] v_2[n] \cdots v_8[n]\right]^T \tag{2}$$

Using the weights vector:

$$\mathbf{w} = \left[w_1\ w_2\ w_3\ w_4\ w_5\ w_6\ w_7\ w_8\right]^T \tag{3}$$

so that the resulting combination:

$$\hat{v}_0[n] = \mathbf{w}^T \mathbf{v}[n] \tag{4}$$

will be as close as possible to the synthetic signal $x[n]$ in the minimum mean square error (MSE) sense:

$$MSE = E\left[(x[n] - \mathbf{w}^T \mathbf{v}[n])^2\right]. \tag{5}$$

Since the dominant component in $x[n]$ is the "AEA-wave" synthetic Gaussian, satisfying the MSE condition is equivalent to forcing $\hat{v}_0[n]$ to be assimilated to $v_0[n]$ in an optimal manner. The solution of equation (4), i.e., the optimal weights vector $\mathbf{w}^*$, can be obtained by finding the correlation matrix $\mathbf{R}$ of the reference signals:

$$\mathbf{R}_v[n] = E\left[\mathbf{v}[n]\mathbf{v}[n]^T\right] = \begin{bmatrix} r_{v_1v_1} & \cdots & r_{v_1v_8} \\ \vdots & \ddots & \vdots \\ r_{v_8v_1} & \cdots & r_{v_8v_8} \end{bmatrix} \tag{6}$$

and the cross-correlation vector $\mathbf{r}$ between the synthetic signal $x[n]$ and the surface leads $\mathbf{v}[n]$:

$$\mathbf{r}_{xv} = E\left[x[n]\mathbf{v}[n]\right] = \left[r_{xv_1} \ldots r_{xv_8}\right]^T \tag{7}$$

r_{xy} can be calculated as follows:

$$r_{xy} = \frac{1}{N}\sum_{n=0}^{N-1} x[n]y[n] \tag{8}$$

where N is the signal's length. The optimal weights vector $\mathbf{w}^*$ can now be calculated:

$$\mathbf{w}^* = \mathbf{R}_v^{-1}\mathbf{r}_{xv} \tag{9}$$

By multiplying the optimal weights vector $\mathbf{w}^*$ by the reference signal $\mathbf{v}[n]$, we now have an emphasized AEA signal $\hat{v}_0[n]$. A diagram of the described process can be seen in Figure 2.

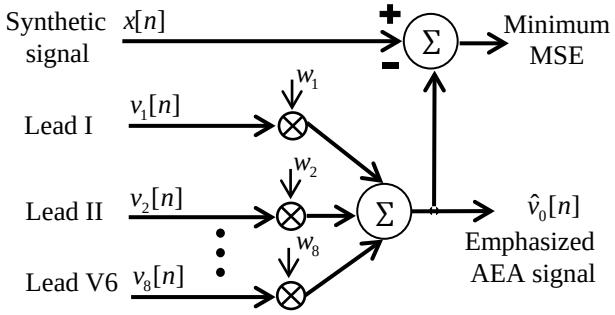

Figure 2. Obtaining an emphasized AEA signal using a synthetic signal and a linear combination of 8 ECG leads.

The reason for initially using only 8 ECG leads instead of 12 is that the other 4 leads – lead III, aVR, aVL, and aVF – have a built-in linear dependency on lead I and lead II. Therefore, adding them to the described combiner

will not add information and might only complicate the calculations. This decision is supported by the fact that some modern ECGs do not record the 4 leads mentioned, and calculate them separately by their linear dependence of the other leads.

2.4. AEA-wave detection

In order to remove QRS remnants and low frequency noise, the emphasized AEA signal is 2–16 Hz band-pass filtered, using a Butterworth filter of order 8. Then, the peaks in the resulting filtered signal higher than a certain threshold are determined as AEA-waves. The threshold is taken as a relative amplitude value. E.g. for a peak to be determined as an AEA-wave when the threshold is 10%, it should be in the highest 10% of the filtered emphasized AEA signal amplitudes. A demonstration of the entire AEA detection process can be seen in Figure 3.

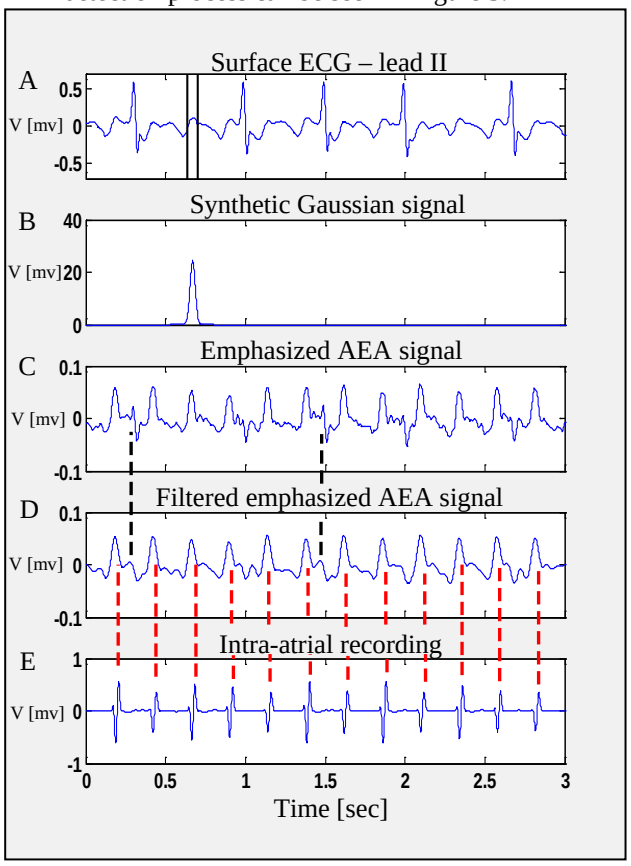

Figure 3. A. Atrial flutter (lead II), the two vertical lines mark the delineated AEA segment. B. The synthetic signal. C. Resulting emphasized AEA signal. D. Filtered emphasized AEA signal. The black broken lines connect the QRS remnants in the emphasized AEA signal (C) and their smoothed version in the filtered emphasized AEA signal (D). E. Intra-atrial electrode signal. The red broken lines indicate that the actual AEA-wave locations match the locations of the AEA-waves found in the filtered emphasized AEA signal.

3. Experiment setup

In order to evaluate the performance of the proposed method we used signals from the GE Cardiolab IT, which records standard 12-lead ECG and intra-cardiac recordings of the AEA from the high right atrium with sampling frequency of 977 Hz. The intra-atrial signal is considered a gold standard reference, and was used for performance evaluation. The signals were taken from Soroka and Barzilai Medical Centers, Israel, during EP study. The study cohort involved 38 patients who presented atrial flutter, atrioventricular reentry tachycardia (AVRT), atrioventricular nodal reentry tachycardia (AVNRT), atrial tachycardia, sinus tachycardia, atrial fibrillation, premature ventricular contraction (PVC), premature atrial contraction (PAC), and sinus rhythm. A total of 495 10-second long signals, containing 14,738 AEA-waves, were evaluated. All algorithms were implemented using Mathworks Matlab software.

Table 1. The study cohort.

Arrhythmia	Number of Patients
Atrial flutter	10
AVRT	7
AVNRT	8
Atrial tachycardia	6
Sinus tachycardia	1
Atrial fibrillation	5
PVC	4
PAC	5
Sinus rhythm	19
Total*	38

*Some patients presented more than one arrhythmia.

4. Results

Evaluation of the AEA-detection is based on [10], but instead of 85-millisecond proximity as a maximum bound for good detection, we chose 60 milliseconds. True positive (TP) is calculated as the number of AEA-waves that we have detected in at most 60 milliseconds from the true AEA-waves (as appear in the intra-atrial electrode recordings). False positive (FP) is calculated as the number of false AEA-waves detected by our algorithm (detected waves that have no true AEA-wave in 60 milliseconds). False negative (FN) is the number of true AEA-waves that the algorithm missed (in 60 milliseconds). Then, we calculated sensitivity (*Se*) and precision (*Pr*, also referred to as positive predictive value).

$$Se = \frac{TP}{TP + FN} \qquad (10)$$

$$Pr = \frac{TP}{TP + FP} \quad (11)$$

The resulting sensitivity and precision values are presented in Table 2. As seen in this table, a different threshold for the final phase of the algorithm can be set in order to get the desired trade-off between the performance evaluation values.

Table 2. Performance evaluation of the proposed AEA-waves detection method.

Threshold [%]	Se [%]	Pr [%]
6.5	80.6	97.0
7.5	84.9	95.8
9.5	91.0	93.3
11.5	94.0	90.2
14.5	95.9	85.1
17.0	96.8	80.7

In our case, the common ROC curve that uses sensitivity and specificity is not possible since the true negative (TN) measure is undefined. We will show a similar curve that uses precision (actually 1-precision) instead of specificity (see Figure 4).

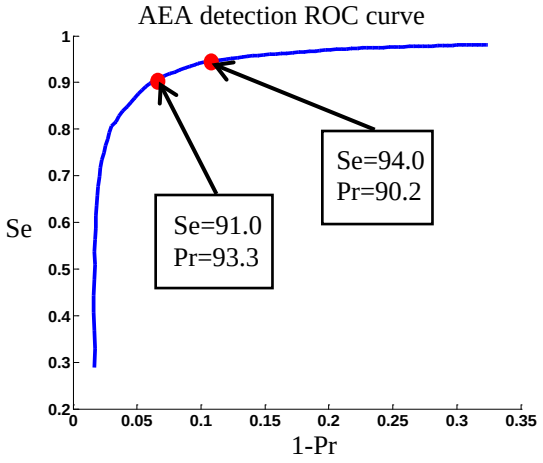

Figure 4. AEA detection ROC curve.

5. Discussion and conclusions

The proposed method resulted in sensitivity (Se) of 94.0% and Precision (Pr) of 90.2%, which shows that it can be used for AEA-wave detection. Moreover, the last phase of the algorithm provides user and application flexibility, so by a simple change of the threshold, the detector may result in a higher sensitivity or precision (as shown in Table 2). The detector advantages are very short running time, relatively low complexity, and the ability to detect hidden AEA-waves, which is the most significant weakness in other known algorithms. As opposed to other methods, the proposed algorithm is arrhythmia-type independent. The detector disadvantage is the need to perform initial manual segmentation of one AEA-wave. Nevertheless, this can be overcome by performing an automatic detection of one AEA-wave using another AEA detection method and sending it as an input to our algorithm. Since in many arrhythmias at least some AEA waves are unhidden, the described combination could result in a fully automated robust method.

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Address for correspondence.

Or Perlman.
Granit 1, Mizpe Gilon, D.N Misgav, Israel.
perlmano@post.bgu.ac.il