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# A Ventricular Activity Cancellation Algorithm Based on Event Synchronous Adaptive Filter for Single-lead Electrocardiograms*

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*Abstract*— **Recently, it has become very important to analyze atrial activity (AA) and to detect arrhythmic AAs and, for this, complete ventricular activity (VA) cancellation is prerequisite. There have been several VA cancellation algorithms for multi-lead ECG but VA cancellation algorithm for single-lead is quite a few. In this study, we have modeled thoracic ECG and, based on this model, proposed a novel VA cancellation algorithm based on event synchronous adaptive filter (ESAF). In this ESAF, the AF ECG was treated as a primary input and event-synchronous impulse train (ESIT) as a reference. And, ESIT was generated so to be synchronized with the ventricular activity by detecting QRS complex. To evaluate the performance, it was applied to the AA estimation problem in atrial fibrillation electrocardiograms. As results, even with low computational cost, this ESAF based algorithm showed better performance than the ABS method and comparable performance to algorithm based on PCA (principal component analysis) or SVD (singular value decomposition). We also proposed an expanded version of ESAF for some AF ECGs with bimorphic VAs and this also showed reasonable performance. Ultimately, our proposed algorithm was found to estimate AA precisely even though it is possible to implement in real-time. We expect our algorithm to replace the most widely used method, that is, the ABS (averaged beat subtraction) method.**

## I. Introduction

Even an electrocardiogram (ECG) includes both atrial activity (AA) and ventricular activity (VA) related information, it has been mainly used to measure the rate and regularity of VA and to detect arrhythmic VAs. Recently, the prevalence of arrhythmic AA, especially atrial fibrillation (AF), has been increasing so to be the most common cardiac arrhythmia [1]. The atrial arrhythmia has been known that it tends to be concurrent with life-threatening ventricular arrhythmias or to be followed by them. So, it comes to be very important to analyze AA and to detect arrhythmic AAs and a complete VA cancellation is prerequisite for this. Although there have been several algorithms which can cancel VA with multi-lead ECGs, a few algorithms have been reported for single-lead ECGs. Meanwhile, once AF without ventricular arrhythmia occurs, the ECG shows normal sinus rhythm (NSR) VA as well as irregular AA with a high rate of up to more than 300 cycles per minute instead of normal P waves. Because the amplitude of this VA is generally several times higher than that of AA, the incomplete VA cancellation causes distortion of the AA within the VA cancelled period, that is, in QRS interval. And, this distortion may leads to miscalculation of the AA rate in AF ECGs, called as atrial fibrillatory rate, which has primary importance in AF maintenance and therapy evaluation [2, 3]. Because of the overlapped spectral distributions between AA and VA, linear filter based algorithms do not work properly [4]. So, the averaged beat subtraction (ABS) method [5, 6], which is applicable to single- or multi-lead AF ECGs with low computational costs, has been most widely used. In case of multi-lead AF ECG, several methods have been proposed to cancel out VA or to extract it from AF ECG with excellent results. These are blind source separation [4], spatiotemporal QRST cancelation [7], and so on. However, in case of single-lead AF ECG, a few methods were suggested; averaged beat subtraction method [5], wavelet transform based method [8], principal component analysis (PCA) based algorithm [9], singular value decomposition (SVD) based algorithm [10]. The wavelet transform based VA cancellation has showed very low temporal correlation between known AA and estimated AA and both PCA- and SVD-based algorithm have needed extremely high computational costs and manual intervention even with excellent performance. Under these circumstances, in this study, we suggested a new VA cancellation algorithm based on event synchronous adaptive filter (ESAF) for single-lead ECGs and applied it to estimate AA in single-lead AF ECGs for its performance evaluation.

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## II. Proposed Algorithm

### A. AF ECG Modeling

In this study, we have modeled a thoracic ECG as the summation of an AA related signal and a VA related signal and these are assumed as the impulse response of intracardiac atrial- and ventricular-contraction source respectively, as shown in Fig. 1 (left). As for a normal sinus rhythm (NSR), an impulse-like atrial contraction source spontaneously generated at the sinoatrial (SA) node causes atrial contraction and travels to the atrioventricular (AV) node. After a short delay, this leads to ventricular contraction. In this case, the number of ventricular contraction impulse is dependent on that of atrial contraction impulse and the ratio of them is 1:1. One the other hand, as for an AF rhythm, while irregular sources are generated from atrial ectopic sites at the same time, these sources are partially transmitted to the ventricle according to the AV node's inherent conduction properties and cause corresponding ventricular contractions.

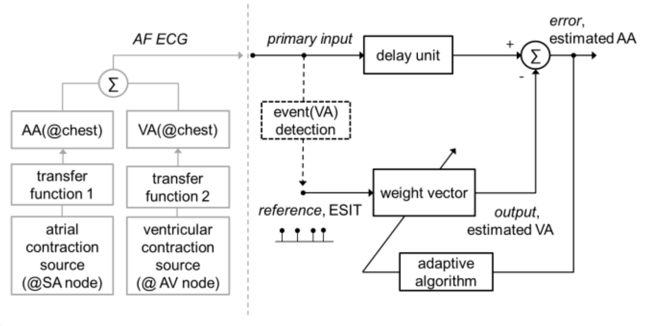


Figure 1. Block diagram of the proposed ECG modeling (left) and VA cancellation algorithm (right)

The ratio of the number of ventricular contraction impulse to that of atrial contraction impulse is unspecific and these two events become uncorrelated. When we consider an adaptive filter shown in Fig. 1 (right), whose primary input is the summation AA and VA and reference is the impulses synchronized with every VA, so-called an event synchronous impulse train (ESIT), this adaptive filter will be similar to an AA estimation problem. And, it will be solved by finding a weight vector whose impulse response is close to VA. And, this searching process of the optimal weight vector becomes equivalent to the estimation of 'transfer function 2'. Eventually, we can perform the VA cancellation by subtracting the estimated VA from the delayed primary input. Here, the atrial contraction source is excluded in our model because its priori information is hardly known and, what is more, it is not essential to solving the problem.

### B. Algorithm Implementation

Based on the proposed model, the primary input, AF ECG (*l(n)*), can be expressed as the summation of AA (*s(n)*) and VA (*a(n)*), which is assumed as a convolution of the ventricular contraction source (*c(n)*) and the 'transfer function 2'. And, we can easily detect every VA in the primary input, that is, QRS complex and can generate impulses synchronized with QRS complex, that is, ESIT. Then, we can regard this ESIT as an estimated ventricular contraction source ($\hat{c}(n)$) written in (1).

$$\hat{c}(n) = \begin{cases} 1, & r_m \le n \le r_m + W - 1 \\ 0, & otherwise \end{cases} \tag{1}$$

Here, $r_m$ represents the position of the *m*th R-wave peak and *W* is the pulse width of the impulse. The proposed adaptive filter will search the optimal weight vector whose impulse response approximates the VA closely and this estimated VA (*y(n)*) can be simply calculated by (2) thanks to the fact that output of ESIT is 0 or 1.

$$y(n) = \bigcup_{r_m \in [n-N+1, n-W]} \left( \sum_{i=n-r_m-W}^{n-r_m} h_i(n) \right) \tag{2}$$

Here, *N* represents the order of filter and ***h*** represents the weight vector. Finally, we can get a VA cancelled signal, estimated AA, as the error signal (*e(n)*) by a simple equation as like (3) where *D* means a proper delay.

$$e(n) = l(n-D) - y(n) \tag{3}$$

In this study, the detection of the R-wave peak was performed by the real-time algorithm introduced by Pan and Tomkins [11]. The LMS algorithm was used to update the weight vector in the ESAF and its learning rate was set to 0.2. The width of an impulse, *W*, was chosen as 1 so to minimize the computational cost. And, because we have dealt with AF ECGs sampled at 1000 Hz, the filter order was set to 120 based on the fact that the normal QRS duration is generally less than 120 msec. The delay of the primary input, *D*, was selected as 50 equivalent to 50msec empirically. Meanwhile, the filtering process of (2) requires K times of addition and the weight vector updating process require K times of multiply-and-accumulate (MAC) operation where K represents is the number of events, that is, VAs.

## III. Algorithm Evaluation

We have tested the proposed algorithm with two different datasets; AF ECGs containing monomorphic VAs, that is, only NSR beats and AF ECGs containing bimorphic VAs, that is, NSR beats and PVC beats. And, two index, called ventricular residue (VR) and similarity (S), were used [10, 12] for the performance evaluation. The indexes of our algorithm were compared with those of ABS method. This VR estimates the ventricular residua in the estimated AA in QRS interval and, for the *i*th QRS interval, VR is defined as

$$\mathrm{VR}_i = \frac{1}{\frac{1}{Q}\sum_{n=1}^{Q} \hat{x}_{AA}{}^2(n)} \sqrt{\frac{1}{2H+1}\sum_{k=r_i-H}^{r_i+H} \hat{x}_{AA}{}^2(k)} \cdot \max_{k=r_i-H,\dots,r_i+H}(|\hat{x}_{AA}(k)|) \tag{4}$$

where *2H+1* denotes the samples number of the QRS interval, *Q* represents the number of samples of AA, and $r_i$ represents the R peak occurrence time. For simplicity, H was fixed to 50. Consequently, the VR becomes the ratio of the maximum energy in current QRS interval to the average energy of the whole AA. Thus, the higher VR may be caused by the greater QRS residua implicating that the AA estimation performance is worse. And, the S is defined as the correlation coefficient between the original AF ECG and the estimated AA in T-Q interval [13] and this measures how much the AA estimation method preserves the atrial waveform in non-QRS interval. For the evaluation of our algorithm with monomorphic AF ECGs, 5 real AF ECGs extracted from Ann Arbor Electrogram Libraries (AAEL) Database including intra-cardiac electrogram (EGM) were used. And, for the evaluation with bimorphic AF ECGs, 5 real AF ECGs collected from the AAEL database and the MIT-BIH Atrial Fibrillation database resampled at 1000Hz. To deal with two types of VA morphologies, the proposed ESAF was expanded as shown in Fig. 2.

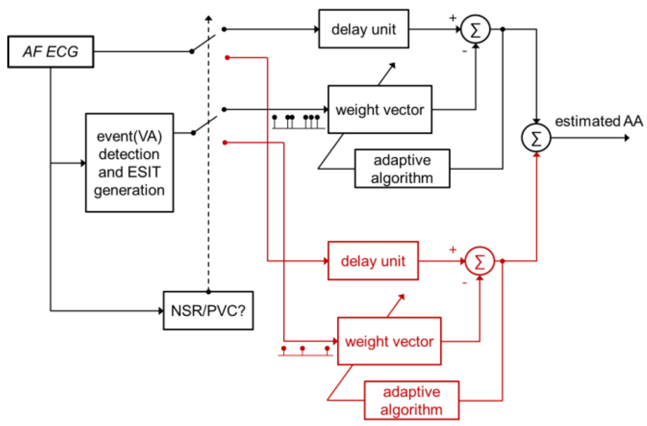


Figure 2. Block diagram of the expaned ESAF for bimorphic AF ECGs

This expanded ESAF (eESAF) consists of two ESAFs placed in parallel and the primary input, AF ECG, was designed to be fed to either of them. And, it was decided by whether the current RR interval was less than 80% of the averaged RR interval.

## IV. Results and Discussion

First, for monomorphic AF ECGs, we have examined whether the proposed algorithm can estimate AA well. An example of AA estimation resulted by the proposed algorithm is depicted in Fig. 3 including an original AF ECG, an intra-cardiac EGM, an estimated AA by the ABS method, and an estimated AA by the proposed ESAF. This figure helps us infer the performance of our algorithm and we can recognize the tendency that both the estimated AAs by the ABS and by the ESAF seem to be highly correlated with the intra-cardiac EGM.

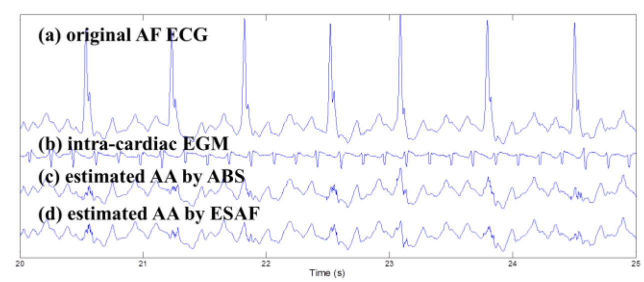


Figure 3. Comparisions of the intra-cardiac EGM and AA estimation results by the ABS and by the ESAF

However, in the QRS intervals, the maximum of estimated AA by our algorithm shows lower values than that of the estimated AA by the ABS and it can be confirmed by the numeric values of VR summarized in Table I. As shown in Table I, our algorithm remains less ventricular residua than the ABS but the similarity in T-Q interval looks quite similar each other. Even with much less computational cost, this result is quite comparable to the result of the state-of-art works [9, 10]. In spite of not presenting results, it takes 5~10 seconds for our algorithm to be adjusted so to work properly. Additionally, we have compared the rate of estimated AA (5.869±1.38Hz) with that of intra-cardiac EGM (5.83±1.38Hz) and the error was found as small as 0.12±0.17Hz.

TABLE I. Summarized Perromance Indexes of ESAF and ABS

| recording | VR | | S | |
|---|---|---|---|---|
| | ***ESAF*** | ***ABS*** | ***ESAF*** | ***ABS*** |
| A181345 | 2.143 | 2.977 | 0.969 | 0.976 |
| A221734 | 0.578 | 1.038 | 0.977 | 0.965 |
| A224135 | 1.749 | 2.150 | 0.953 | 0.954 |
| A286063 | 1.100 | 1.824 | 0.998 | 0.998 |
| A377b91 | 0.930 | 1.149 | 1.000 | 0.999 |
| mean(std.) | 1.300(0.635) | 1.828(0.792) | 0.979(0.020) | 0.978(0.020) |

If an AF ECG has bimorphic VAs, the arrhythmic VA causes the larger ventricular residua than the NSR VA regardless of methods. To overcome this limitation, we also proposed the eESAF containing two different ESAFs (Fig. 2). For bimorphic VAs, this eESAF tends to remain much less ventricular residua than the ESAF as well as than the ABS and an example of eESAF result is shown in Fig. 4. In this figure, we have also inserted VR values for each three different methods; the ABS, the ESAF, the eESAF. Observing the signals and the numeric values of VR within dash-lined areas, the AA estimation by the eESAF looks to have superiority over the others. This superiority can be reconfirmed by Table II presenting summarized VRs of all three methods. In all recordings, the VR of ABS method shows the largest mean and standard deviation and this may be caused by the fact that, for the NSR VAs, the ABS returns similar level of VR to the other method but, for the arrhythmic VAs, results in much bigger level of VR than the other methods. For the arrhythmic VAs, the eESAF shows 121% less VR than the ABS and 70% less than the ESAF on average. Finally, we can conclude that the eESAF works effectively in case of the AF ECGs with bimorphic VA.

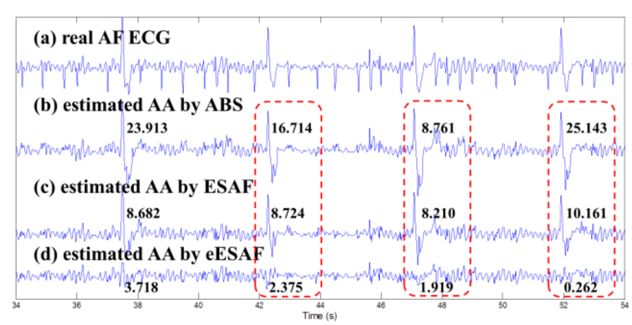


Figure 4. An example of VR comparason among the ABS, the ESAF and the eESAF for bimorphic VAs

## V. Conclusion

In this study, we developed a model of ECG and proposed a VA cancellation algorithm based on with this model background ESAF for single-lead ECGs. Comparing our proposed algorithms with the most widely used method - the ABS method, it showed quite good performance for AF

ECGs. And, its performance was even comparable to that of the state-of-art works [9, 10]. In the aspect of computation cost, it needs such a small computation cost as the ABS does so that it can be implemented in real-time. In case of AF ECG with bimorphic VA, we could cancel out both type of VA successfully with simple modification while the ABS could not. We expect our algorithm to replace the ABS method.

TABLE II. SUMMARIZED VRS OF ABS, ESAF AND EESAF

| recordings | VR | | |
|---|---|---|---|
| | ***ABS*** | ***ESAF*** | ***eESAF*** |
| MIT203* | 3.419(5.700) | 2.259(3.068) | 1.790(1.204) |
| MIT210* | 2.083(5.190) | 1.521(3.076) | 1.168(0.899) |
| A182430** | 4.232(5.054) | 3.609(4.886) | 1.105(1.193) |
| A224135** | 2.510(6.234) | 2.068(3.011) | 1.700(0.962) |
| A239140** | 1.818(7.541) | 1.392(4.232) | 0.608(0.489) |

* recordings from MIT-BIH Atrial Fibrillation database

** recordings from Ann Arbor Electrogram Libraries (AAEL) Database


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