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Decomposing Atrial Activity Signal by Combining ICA and WABS

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Abstract— **In this paper we proposed a novel technique for Atrial Activity (AA) decomposition in Electrocardiogram (ECG) of Atrial Fibrillation (AF). The main purpose of our proposed technique is to decompose AA signal by combining two statistical methods, Independent Component Analysis (ICA)-existing and Weighted Average Beat Subtraction (WABS)-new, for AF with multiple stable sources, respectively. We found the limits of BSS algorithms which are mostly used to extract AA signal, while beauty of our proposed algorithm is that it decomposes multi-lead AA signals from surface ECG with AF. Our proposed technique is verified with clinical data and the results demonstrate that our proposed method is feasible.**

I. Introduction

Atrial fibrillation (AF) is the most common super-ventricular arrhythmia, with a rate of 0.4% to 1% in common population. AF may lead to atria's structural change, and it is related with stroke, heart failure, and all-cause mortality [1]. With the rapid increase of population and miserable untoward effects on human's health, AF has attracted more attention in academia and industry research recently.

Body surface ECG comprises P waves and QRST complexes which represent atrial activity (AA) and ventricular activity (VA), respectively. When AF occurs, P wave in surface ECG is replaced by continual, irregular fibrillatory (f) wave, which has important information related to AF, and some of the features of f wave such as: central frequency [2], phase [3] and entropy [4] have been used in several applications, for example, AF mechanism study, AF pattern classification, monitoring effect of pharmacy on daily life of patients with AF [5]. However, in order to utilize these features, f wave must first be extracted from surface ECG. In the past decade, many f wave extraction algorithms presented. Among these, blind source separation (BSS) based algorithms outperform than others. BSS-based algorithms further classified into two groups: ICA-based algorithm [6][7][8] and two-stage-BSS-based algorithm [9].

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BSS theory can be applied to f wave extraction when three conditions approximately satisfied: 1) f wave and VA signals are mutually statistically independent, and at most one of them is Gaussian distributed. 2) They are mixed on human body surface according to the linear instantaneous model. 3) The mixture matrix has full column rank. Actually, in real applications, the above conditions are not fully satisfied, for example; the mutual independence between VA signals is not mentioned before. Hence, there are still some problems that need more attention to analyze further. In this paper, the discordance between real applications and ideal model is discussed, and a novel AA decomposition method by combining ICA and WABS for AF with multiple stable sources is proposed. The remainder of the paper is organized as follows. Section II describes the limits of the existing BSS-based algorithms. A novel AA signal decomposition algorithm combining ICA and WABS (weighed average beat subtraction) is presented in Section III. Experiments and discussion are discussed in Section IV. Section V concludes paper with future research directions.

II. Limits of BSS-based Algorithms

BSS-based algorithms assume that the mixing of AA and VA signal on body surface satisfies the linear instantaneous model. The mutual independence and non-Gaussian distribution of AA and VA signals are described in [6]. But there are two aspects, have never been addressed before: 1) the meaning of source signals except AA signal, namely, f wave obtained by BSS. 2) The number of source signals that represent f wave, namely, whether f wave can further be decomposed. With the help of ICA-based algorithm we will discuss them in detail.

A. The meaning of every source signal obtained by BSS

Generally, after ICA decomposition, several source signals are obtained, and only one source signal is recognized as f wave, some are identified as noise, and the rest of the source signals are VA signals. Here is the question, can mutual independence between f wave and VA signals be guaranteed? From our point of view it is hard to say something about mutual independence between VA signals using BSS. No one has presented a proof or evidence that there are some electrophysiological independent regions within ventricular. Due to that main reason ICA fails to satisfy basic conditions and BSS-based algorithms are unstable to achieve appropriate results at all the times.

B. Whether f wave can further be decomposed

All the existing BSS-based algorithms assume that AA signal corresponds to single source. If this assumption is valid, then AA signal in different lead ECG recordings must be strictly proportional. Actually, the morphologies of f waves in

different lead ECG recordings vary a lot. Fig.1 shows several AA signals, extracted by QRST cancellation algorithm, of different lead recordings from the same person. It can be seen that AA signals of different lead recordings are far from being proportional.

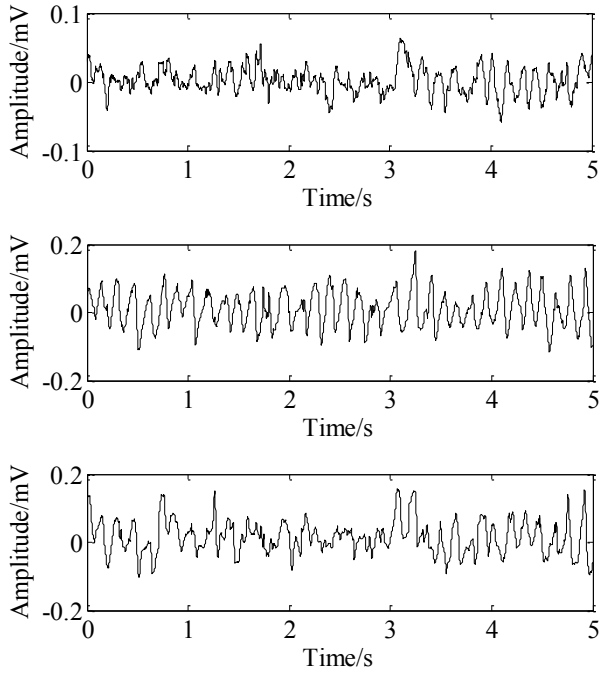


Fig.1 AA signals extracted from different lead ECG recordings

Actually，it is possible that there exist multiple stable independent micro reentrant circuits within atria when AF occurs [10]. Lazar, et.al, presented that the central frequencies of atrial activity in different regions within atria are different [11]. Thus, if there are multiple stable independent micro reentrant circuits, then f wave must possess multiple central frequencies or different morphologies. Oosterom, et.al [11], performed an experiment on 94 subjects with AF, and found 16 of them have f wave with two central frequencies.

In whole, 1) there is no independence between VA signals thus extracting f wave from body surface ECG directly using BSS algorithms makes no sense. 2) It is possible to further decompose AA signal when there exist multiple stable independent micro reentrant circuits within atria. Due to above two reasons, we proposed a novel method to decompose AA signal by combining ICA and WABS.

III. OUR PROPOSED ALGORITHM

The principle diagram of our proposed method is presented in Fig.2. Considering that there is no mutual independence between VA signals, ICA applied to multi-lead pure AA signals, namely, ECG recordings within TQ segments. Meanwhile, to get the whole AA signal, WABS method is applied to every channel of ECG recordings. Then the decomposed AA signals are obtained by multiplying whole AA signal with the decomposition matrix.

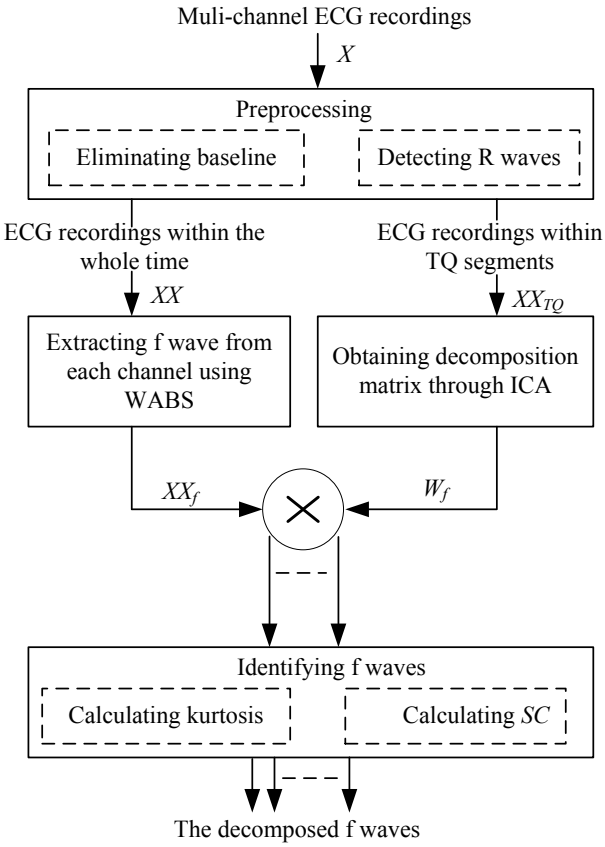


Fig.2 The principle diagram of proposed method

A. Preprocessing

In order to eliminate the baseline wander, a high pass filter with a cutoff frequency of 0.8Hz is used. In order to avoid misleading due to incorrect R wave detection, R waves are manually determined. Finally, the timing points of Q wave onset and T wave offset are estimated by (1):

$$t_Q(i) = t_R(i) - 43.75\text{ms}, \quad t_T(i) = t_R(i) + 350\text{ms} \tag{1}$$

Where, $t_Q(i)$, $t_R(i)$ and $t_T(i)$ are the timing points of Q wave onset, R wave peak and T wave offset, respectively.

B. Independent Component Analysis (ICA)

The linear instantaneous model can be expressed as:

$$X(t) = A \cdot S(t) \tag{2}$$

Where, $X(t)$ and $S(t)$ are observed signals with M variables, and source signals with N variables, respectively. $A_{M\times N}$ is called mixture matrix. The function of ICA is to get $S(t)$ with A unknown. It has been proved that $S(t)$ can be accurately obtained if $S(t)$ and A satisfy three basic conditions [6]. There are many ICA solutions, among these; FASTICA [12] is the most popular one and we used here.

The main function of our proposed method is to avoid influence of VA signals. ECG recordings within TQ segments are used to calculate the decomposition matrix. Since ICA only uses statistical information about the time structure of

variables which is totally reasonable while using discontinuous recordings.

C. Weighted Average Beat Subtraction (WABS)

WABS is an optimum algorithm to minimize least square error. Suppose that N continual QRS complexes are used to construct QRS template, then the ith QRS template is [14]:

$$XX_{TP}(m) = \sum_{k=1}^{N} p_{k,m} XX_k(m), \quad m = 1,\cdots \tag{3}$$

$$p_{k,m} = \begin{cases} \dfrac{\mathrm{D}\left(XX^{AA}\right)/N}{\mathrm{D}\left(XX^{AA}\right)+\mathrm{D}\left(XX^{VA}(m)\right)}, & k \neq i \\ \dfrac{\mathrm{D}\left(XX^{VA}(m)\right)+\mathrm{D}\left(XX^{AA}\right)/N}{\mathrm{D}\left(XX^{AA}\right)+\mathrm{D}\left(XX^{VA}(m)\right)}, & k = i \end{cases} \tag{4}$$

Where, XX_{TP}, XX^{AA} and XX^{VA} are the QRS template, AA signal and VA signal, respectively; M is the length of QRS complex and $\mathrm{D}(\cdot)$ is variance operator.

The f wave extracted by WABS has less VA residual, since QRS template is constructed for each beat. By using WABS algorithm, multi-lead AA signals are obtained.

D. Identifying decomposed f waves

Generally, f wave is sub-Gaussian distributed and with minus kurtosis. In addition, spectral concentration (*SC*) is often used to evaluate f wave's quality, higher *SC* less distorted f wave will be. Here, we used kurtosis and *SC* to identify whether the decomposed signal is the true AA signal or just noise. Kurtosis of variable z has zero mean and unit variance is defined as:

$$kurt = \mathrm{E}\left(z^4\right) - 3 \tag{5}$$

SC is defined as:

$$SC = \frac{\sum_{f_i=1.17 f_0}^{f_i=0.82 f_0} P_{AA}(f_i)}{\sum_{f_i=0}^{f_i=f_S/2} P_{AA}(f_i)} \tag{6}$$

Where, f_0 is the central frequency of f wave, and $P_{AA}(\cdot)$ is power spectrum of f wave, which is computed using periodogram. If the decomposed signal has *SC* greater than 15%, a kurtosis less than -0.3 and the central frequency within 3Hz~10Hz, then it is identified as a decomposed AA signal.

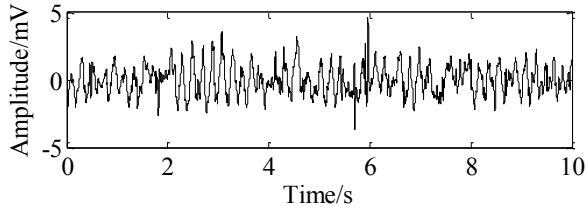
IV. Experiments and Discussion

Clinical ECG recordings with AF are taken from PTB database [15]. Each recording includes 15-lead ECG, standard 12-leads and X-Y-Z leads. There are 15 subjects with atrial fibrillation or atrial flutter, and two of them; 153 and 201 have evident f waves in body surface ECG recordings. We used these two ECG recordings to verify our proposed method.

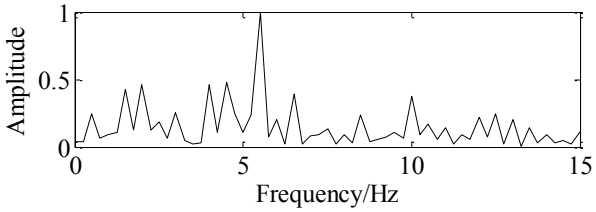
The kurtosis, central frequency and SC of the decomposed signals of the two subjects are shown in Table I. Fig. 3 and Fig. 4 show the identified f waves and their normalized spectra for two subjects, respectively. Note that the extracted f waves in Fig. 3 (a), Fig. 4 (a) and Fig. 4 (c) have unit variance.

TABLE I. KURTOSIS, CENTRAL FREQUENCY AND SC OF THE DECOMPOSED AA SIGNALS

Num		S_1	S_2	S_3	S_4	S_5	S_6
153	f_0 (Hz)	1.75	4.75	5.75	3.75	5.75	1.25
	SC (%)	7.3	12.7	15.1	5.2	11.5	4.8
	kurt	-0.95	-0.77	-0.57	0.33	-0.17	0.06
201	f_0 (Hz)	1.25	7.25	2.75	7.25	1.75	6.75
	SC	3.8	24.2	7.2	16.6	3.6	15.1
	kurt	2.30	-0.70	-0.90	-0.55	0.21	-0.17

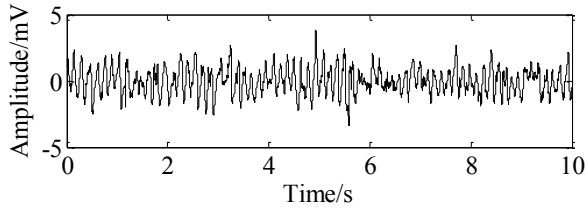


(a) The identified f wave (S_3)

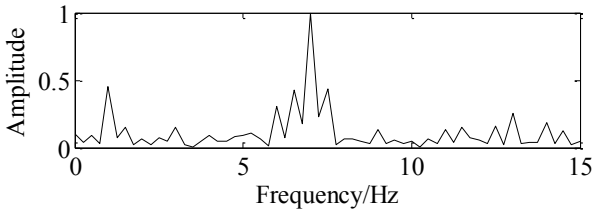


(b) The normalized spectrum of S_3

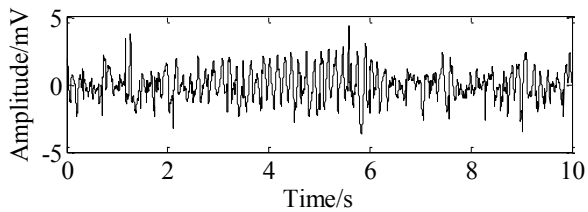
Fig.3 The identified f wave and its normalized spectrum for 153



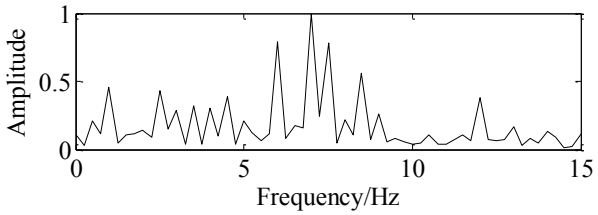
(a) The identified f wave (S_2)



(b) The normalized spectrum of S_2



(c) The identified f wave (S_4)



(d) The normalized spectrum of S_4

Fig.4 The identified f wave and its normalized spectrum for 201

From Table I, it is cleared that, only one signal, S3, is identified as f wave for subject 153, and two signals, S2 and S4 are identified as f waves for subject 201. Subject 153 is annotated with atrial flutter in the PTB database, so it is reasonable that to consider only one f wave. Two f waves extracted from recordings of subject 201 both have the assumed features. Though their central frequencies are same but temporal morphologies and spectra are totally different. Clearly there are multiple peaks (central frequencies) in the spectrum of S4. Their mixture vectors, A2 and A4, for 12-lead ECG recordings (ordered by I, II, III, aVR, aVL, aVF, V1, V2, V3, V4, V5 and V6) are as follows.

$$A_2 = 10^{-3} \cdot [-2.2 \quad -3.9 \quad -1.7 \quad 3.1 \quad -0.3 \quad -2.8 \quad 47.8 \quad 25.0 \quad 24.3 \quad 16.3 \quad 6.7 \quad 0.6]^T$$

$$A_4 = 10^{-3} \cdot [13.2 \quad 14.4 \quad 1.3 \quad -13.8 \quad 5.9 \quad 7.9 \quad -9.3 \quad 34.9 \quad 35.2 \quad 29.4 \quad 16.2 \quad 8.0]^T$$

Take subject 201 as an example, there exist two main fibrillation regions within its atria. One is close to V_1 lead but far from limb leads and other is close to limb leads. Obviously, recordings on chest leads, like V_1, V_2, V_3 and V_4, show strong S_2, while limb leads does not. The recordings of all leads have strong S_4 except III.

V. Conclusion

We presented a novel idea of decomposing multi-lead AA signals from the ECG of AF with multiple stable sources by combining two statistical methods, ICA which is already used to get source signals with unknown mixture matrix and WABS which is an optimum because it minimizes least square error. We addressed the weak points of BSS algorithms which are used by most of the researchers for extracting AA signal from the body surface ECG with AF. Our proposed technique is of great potential to be used to estimate the origins of fibrillation by using the corresponding mixture vectors and atria's anatomical structure.

The experimental results indicate that our method is very promising and feasible. In near future we will collect more clinical ECG recordings to perform more experiments.

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