Adaptive Multiple Frequency Tracking Algorithm: Detection of Stable Atrial Fibrillation Sources from Standard 12-Lead ECG

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Abstract

In this study we investigate a means of distinguishing between stable and more complex atrial fibrillation (AF) sources by analyzing ECG signals. For this purpose, 21 episodes of AF were generated by using a 3D biophysical model of the atria. The AF episodes were classified into two groups (with or without stable sources) by visual observation of the electrical propagation on the epicardial tissue (gold standard). The simulated 12-lead ECGs of these AF episodes were computed by using a compartmental torso model. The analysis of the ECG signals was performed by applying an adaptive multiple frequency tracking algorithm. The normalized power outputs of the algorithm directly provided information concerning the stability level. The comparison of the results of our method with the gold standard yielded 85.7% of correct classifications, with a sensitivity of 100% and 75% specificity.

1. Introduction

The current diagnosis of atrial fibrillation (AF) is mainly based on visual inspection of the surface electrocardiogram (ECG), and limited to the establishment of its presence or absence [1]. During AF, multiple wavefronts propagate in either a stable or a disorganized way over the surface of the atria. The presence of sources such as focal firing sites [2], macro re-entries [3], mother-rotor [4] and/or typical atrial flutter (AFL) represent “stable” sources of sustained AF. Once AF has been diagnosed, it is usually treated by the means of elimination or isolation of its sources by curative ablation procedures [5]. The success of the latter is strongly related to the nature of the AF [6, 7]. It is therefore crucial to determine whether AF is sustained by stable or disorganized sources.

In [8], we studied the ability to identify multiple reentrant circuits on the basis of the atrial vectorcardiogram. The entire electrical activity was represented by a combination of single dipoles evolving along the surface of the atria. The conclusion was that is is possible to identify and characterize these multiple and simultaneously active reentrant circuits (stable sources) on the basis of potentials observed on the body surface.

In the present study, we investigated whether stable AF sources can be detected by using simulated ECG signals obtained comprizing realistic episodes of AF. We hypothesize that during AF episodes sustained by stable sources, ECG signals include significant components at frequencies related to the cycle length of the respective AF sources. These frequency components were jointly estimated on the 12-lead ECGs with an adaptive multiple frequency tracking algorithm. The power of these frequency components was used to estimate the number of stable stable sources.

2. Methods and materials

2.1. Simulating body surface potentials

By using a 3D biophysical model of the atria (see figure 1), an episode of AFL and 20 different episodes of AF were generated [9]. The AF episodes differ by their substrates and procedures for initiating AF. The substrate for AF consisted of patchy heterogeneities in the action potential duration, implemented through local membrane properties. AF was induced by a cross-shock protocol or by rapid pacing in either of eight different locations [10].

The stability of the 21 episodes was established by visual inspection of the propagation of the transmembrane potentials throughout the tissue. Two groups were created: group A, without any stable source, and group B, with at least one stable source. These groups served as our gold standard. Figure 1 shows two examples of stable AF episodes dynamics and one example of the AFL (group B).

The contribution of the atrial activity to the body surface potentials was computed by means of the boundary element method. It involved a compartmental torso model including blood cavities of both the atria and ventricles, the lungs and the thorax boundary (see figure 2). The body surface potentials were evaluated at 670 points distributed over the torso surface. The electrode locations of the 12-lead standard ECG formed a subset of the former.

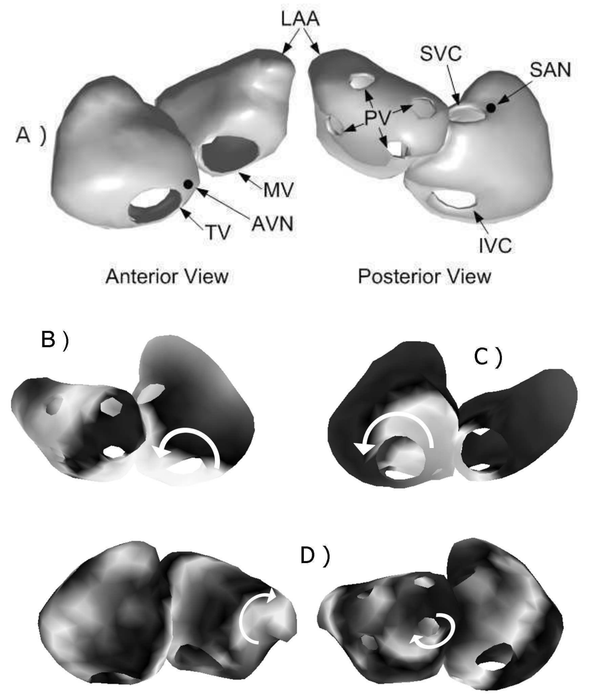

Figure 1. Panel A: Geometry of the model representing the atria from the left anterior 45° view and from the right posterior 45° view. The major anatomical details are indicated: the tricuspid valve (TV), the mitral valve (MV), the inferior vena cave (IVC), the superior vena cave (SVC), the four pulmonary veins (PV), the sinoatrial node (SAN), and the left atrium appendage (LAA). Panels B, C, D: Illustration of three stable atrial activity dynamics over the 21 episodes of simulated AF. White arrows represent the sources. B) mother-rotor around the TV, C) counterclockwise flutter, D) mother-rotor in the LAA + mother-rotor around the lower right PV.

2.2. Adaptive filtering of ECG signals

The estimation of each frequency component (related to one source) was performed using a multi-signal extension of a single frequency tracker (SFT). A basic SFT [11] is composed of a single pole bandpass filter with an adaptive transfer function and a feedback mechanism that adapts the central frequency of the filter based on its output signal. In the multi-signal case, the update of the center frequency is obtained as a weighted average of the updates computed separately for each lead. A problem with this scheme is the possible cross-talk between the various SFTs, due to the fact that the corresponding filters are not perfect bandpass ones. A solution to this problem is to use all-zero filters (AZF) in a cross-coupled fashion to suppress interference from other frequency components in each SFT [12]. Finally the adaptive multiple frequency tracking algorithm can be assimilated to an adaptive filter bank with K channels. Each channel is composed of an adaptive bandpass filter and an AZF. We hypothesize that AF cannot be sustained by more than three different stable sources. Subsequently, each episode was processed by an adaptive filter bank with three channels. Three different sets of filtered ECG signals (outputs) were obtained by applying this filter bank to the 12-lead ECGs. The average of the center frequencies of the bandpass filters (f_{a}) provides frequency estimates (cycle length) of the sources.

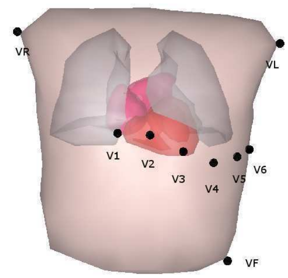

Figure 2. Geometry of the model representing the torso from left anterior 20° and the position of the nine standard 12-lead ECG electrodes.

2.3. Discrimination feature

The ratio r between the sum of the filtered 12-lead ECG signal powers (outputs) and the sum of the 12-lead ECG signal powers (inputs) was used as the discrimination feature to estimate the number of sources. Dividing by the sum of the input signal powers made the scheme scale independent. For each of the 21 episodes of AF, we obtained three different values of r. If the AF episode did not contain a stable source, none of the estimated frequency components had significant power, and three ratio values r were low. On the contrary, if one (or two, or three) source was stable, one (or two, or three) r value(s) r was large.

3. Results

In the database composed of 21 AF simulated episodes, nine were characterized by complex dynamics (group A). Group B comprised 11 simulated AF episodes having a single stable source and one having two stable sources. The r values (averaged over the three frequency components) observed were $r = 0.05 \pm 0.04$ (mean $\pm$ SD) in the group A and $r = 0.28 \pm 0.17$ in the group B. With a discrimination threshold set at 0.14, no stable AF source was detected in group A. Eight single AF sources were detected among the 11.

Examples of filtered ECGs are shown on the figure 3. In each panel, the dotted line represents the signal obtained on lead V1 (input), and the solid lines of panels 1), 2) and

3) are the filtered V1 signals (outputs) jointly estimated on the 12-lead ECGs with the algorithm described in section 2.2.

The panel (a) corresponds to an episode which was classified in group A. The signal obtained from lead V1 (dotted line) clearly shows that the dynamics of this AF episode is complex. Indeed, no dominant frequency was tracked by the algorithm. None of the three output signals fit with the input signal. They are characterized by power ratio values lower than the threshold.

Episodes (b) and (c) and (d) were classified in the group B. Episode (b) was characterized as a counter-clockwise flutter. The pattern of regular F waves indicative of atrial flutter can be observed on the input signal (lead V1, dotted line). The periodicity of the F waves pattern was well estimated by the second adaptive bandpass filter. The output of the third filter could be associated to an harmonic of the second estimated component with an r value lower than the feature threshold.

The AF of episode (c) is essentially sustained by a mother-rotor around the TV. The stability of this rotor can be observed on the second panel. The output signal fits most of the time with the input ($r = 0.33$). On the panel 1) and 3), as the output signals do not fit well with the signal V1, their r value are low.

The dynamics of episode (d) is more complex. The AF is sustained by two sources: a mother-rotor in the LAA and a mother-rotor around the lower right PV. The second and third filter outputs are characterized by r values of 0.25 and 0.15 for average frequencies 5.56 Hz and 7.25 Hz, respectively. Obviously these two components are not harmonically related. The two stable sources of this episode were correctly detected.

Finally, on the database of 21 AF simulated episodes our method yields 85.7% of correct classification, 100% of sensitivity and 75% of specificity.

4. Discussion and conclusions

The results reported in the section 3, show that the proposed approach was able to detect the presence of stable sources on the basis of potentials observed from the 12-lead system. By observing the value of the discrimination feature r and the value of the average frequency f_a, we are able to distinguish between several stable sources and a stable source with harmonics.

The distinction between AFL and AF was performed successfully by the observed r value. Large values of r seem to be associated with AFL.

With this procedure, no false detection took place (sensitivity: 100%). Detection error occur for episodes having stable dynamics around lower and upper right PV. But it is known that the standard 12-lead system is not optimized to observe dynamics evolving on the back of the atria. A lead system dedicated to the analysis of atrial signals [13] with an electrode on the back could increase the performance of the detection. In group B, the average stability duration was 7.35s, and the average stability duration of the wrongly classified episodes were around 4s. We thus conclude that the proposed method needs at least around 5s of stability to detect the sources.

It appears that a focal dynamics is not easy to detect. Even if the focal activity is periodic, the activation is concentrated in a small region of the atria with no circuit to generate periodic F waves which leads to small r values.

The proposed approach provides information about the presence of stable AF sources. This information may lead to a more accurate identification of patients suitable for specific AF ablation procedures.

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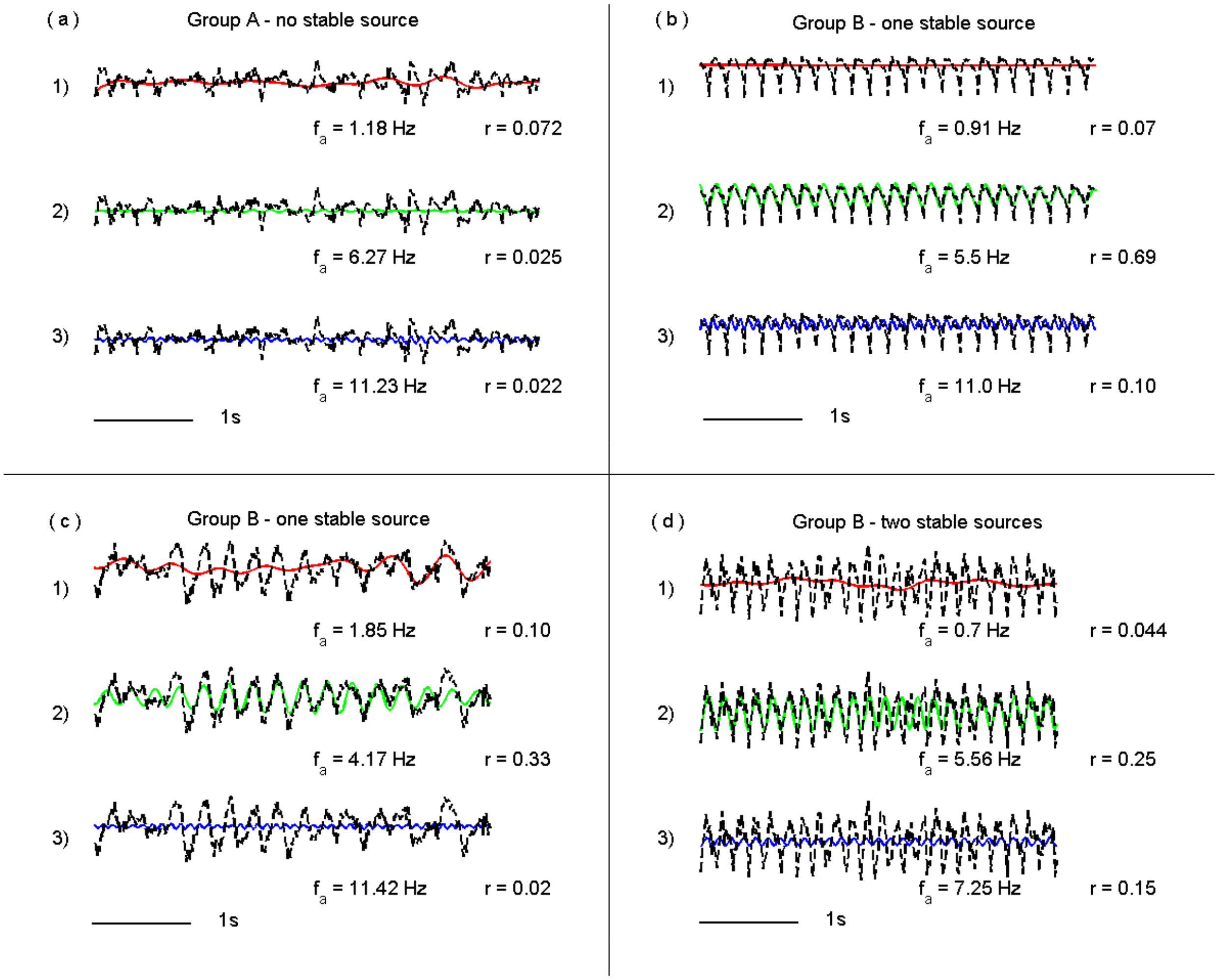

Figure 3. Example of original and the 3 filtered ECG signals (lead V1) obtained with 4 AF episodes. The episode (a) was classified in the group A with no stable source and presents a complex dynamics. The episodes (b) and (c) and (d) were classified in the group B. There dynamics were: a counter-clockwise flutter (b), a mother-rotor around the TV (c), a mother-rotor in the LAA + a mother-rotor around the lower right PV (d). On each panel, the dotted line is the signal obtained on lead V1. The continuous lines in panels 1), 2) and 3) are the filtered V1 signals jointly estimated on the 12-lead ECGs with the algorithm described 2.2. The average frequency of the center frequencies of the banbpass bandpass filters f_{a} and the power ratio r are indicated in each case.

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