Is the Dominant Frequency Accurate Enough for Atrial Fibrillation Signals?

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Abstract

In noninvasive studies of atrial fibrillation (AF), especially in body surface potential map (BSPM) measurements, the dominant frequency (DF) is usually defined as the highest peak in the power spectrum, after prior cancellation or removal of the ECG components related to the ventricular activity. However, the power spectrum is often hampered by phase breaks presence in atrial signals due to either signal concatenation or to chaotic behavior.

Fourier analysis (including multiple frequency components models) is used as a starting point to develop methods adapted to handle phase breaks. Fourier analysis and the average frequency derived from the phase of the analytic signal (within an AF cycle or globally) were selected as estimators of the single frequency model, and compared by means of simulations. It is found that for large phase breaks (±T/2 every half-second), and for a SNR of 5db, the 95 % confidence interval were smaller for the estimates based on the phase, within an AF cycle, of the analytic signal. For the more realistic multiple frequency model, the Fourier decomposition is extended by using a Least Mean Squares (LMS) adaptive algorithm, with or without imposing a constant magnitude. Slight differences in performances of the presented methods are exemplified on a single AF subject where the DF is computed over all the leads of the BSPM records.

1. Introduction

Atrial fibrillation (AF) dominant frequency (DF) has been shown to be a relevant feature in both determining the stage of AF, and in patient's characterization [1] [2]. However the indirect interpretation of the complexity of the AF electrogram by using surface ECG could be misleading because of amplitude and phase changes during the course of the AF, as mentioned in [3]. Assuming that AF is maintained by several sources localized in different area of the atrium and with different rates of activation, the surface ECG is thus a combination of these sources, with morphologies dependent on the location of the leads. The use of Body Surface Potential Mapping (BSPM) to establish a relationship between DF and spatial location is challenging because it may be hindered by phase jumps and other random behaviors of the activation patterns.

A Fourier based model is firstly presented with constant features such as magnitude, frequency and phase. It is shown in simulation that in the case of a single tone signal, Fourier based methods are subject to be impacted by phase breaks and that cycles based methods are more robust. In order to fit to a more realistic model, including multiple components, the Fourier based model is extended to circumvent the mismatch to phase variation observations. The performance of the proposed methods are not confronted to ground truth but simply shown through the analysis of the DF on a single AF subject.

2. Models

Although the intracardiac electrograms exhibit short duration transient shapes associated to the sequential electrical activations of local cardiac myocells, the corresponding surface signals are more cosine shapes because of the filtering of the higher harmonics. Furthermore, the global acceleration and deceleration phases of the AF electrical vector presented in [4] extends this observation to a more complex description. Considering that for complex AF several sources of depolarizations might be at the origin of the AF maintenance, the model of observation assumed in this paper for one recording lead is :

$$x(n) = \sum_{i=1}^{I} A_i \cos(2\pi f_i n/f_s + F_i(n)) \qquad (1)$$

Where n, f_s stand respectively for the sample index and the sampling frequency. The number of components I will be considered small, even equal to one. For the sake of simplicity the magnitudes A_i are considered constant although it is not strictly true. The important phase com-

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ponent $F_i(n)$ takes into account the rupture of phase during complex AF where disruptions are observed. It is important to notice that it exists an indeterminacy between the frequency component $2\pi f_i n/f_s$ and $F_i(n)$, when F_i is variable with time. Indeed, if the frequency f_i is replaced by $\tilde{f}_i$ then for the same observation we get $\tilde{F}_i(n) = F_i(n)+2\pi(f_i-\tilde{f}_i)n/f_s$ with the equality $\cos(2\pi f_i n/f_s + F_i(n)) = \cos(2\pi \tilde{f}_i n/f_s + \tilde{F}_i(n))$. This indeterminacy will explain the loss of frequency resolution that affects the methods presented thereafter. Ideally, any spectral decomposition adapted to our model should be able to find the best f_i's assuming a stepwise shape for the function $F_i(n)$ and rejecting a linear combination of n.

3. Methods

In order to limit the number of frequency components and to emphasize the components that contribute the most to the energy of the signal, Singular Spectrum Analysis (or alternatively Singular Spectrum Decomposition [5]) is firstly applied before the spectral analysis.

The first method (named *WA_cycle*) presented here uses a simplified version of (1) where a single component ($I = 1$) is considered. If this assumption is valid then that the wrapped phase of the analytic signal has a sawtooth wave shape in the range $[-\pi;\pi]$. The derivative of this phase provides a stepwise function delimited by negative spikes separated by the period of the cosine. Each value of the sequential steps, i.e. the mean value of the derivative between two spikes, are theoretically equal to $2\pi f_i/f_s$. Values of these steps that are not in the expected range of AF frequencies, e.g. $[5-8]Hz$, can be rejected for the next processing. The simplest way to compute the final estimation of the single frequency is to average all the step values obtained over the entire signal. A more efficient estimation consists in additionally calculating the standard deviation of the derivative between two consecutive spikes and to use it in a weighted averaging where the weights are the normalized inverse of the standard deviation. The second method (named *Median_ssa*) also assumes the same model but the frequency is not estimated based on each cycle but globally by computing the median value of the derivative of the unwrapped phase of the analytic signal. From (1), it is easy to show that in the absence of phase jumps the computed value of the derivative is a constant function equal to $2\pi f_i/f_s$. The use of the median operator aims to reduce the effect of the phase jumps, if present.

One could argue that in real cases and especially with complex AF, a single frequency component is not sufficient to describe the sum of multiple atrial contributions characterized by different activation rates. In that case the previous presented methods provide us an average frequency value, lacking frequency resolution. The simultaneous presence of multiple tones is usually addressed by using the well know Fourier decomposition which can be derived as a mean square estimation. In that case $F_i(n)$ is assumed to be constant and for a given value of f_i a linear model can be derived such that:

$$\begin{aligned} A_i\cos(2\pi f_i n/f_s + F_i) &= A_i\cos(F_i)\cos(2\pi f_i n/f_s) \\ - A_i\sin(F_i)\sin(2\pi f_i n/f_s) &= a\cos(2\pi f_i n/f_s) \\ &+ b\sin(2\pi f_i n/f_s) \quad (2) \end{aligned}$$

Then a model matrix is built such that $\mathbf{M}_f = [\mathbf{cos}_f \ \mathbf{sin}_f]$ where $\mathbf{cos}_f$ stands for the cosine vector (and respectively for $\mathbf{sin}_f$) computed for a given value of f and all values of $n = 1, \ldots, 15000$, corresponding to almost 1 minute of signal sampled at 256 Hertz. Note that in addition the two vectors are energy normalized. Finally, for a given value of f in the range $[5-8]Hz$ and with step of 0.02Hz the mean square error estimator is used to compute the reconstructed version of the observation $\mathbf{x}$ (the vector formed by all the recorded samples) at frequency f:

$$\hat{\mathbf{x}}_f = \mathbf{M}_f(\mathbf{M}_f^T\mathbf{M}_f)^{-1}\mathbf{M}_f^T\mathbf{x} = \mathbf{M}_f[a \ b]^T \quad (3)$$

, with $[a \ b]$ the estimated parameters of the model, and the normalized 2-norm error used for the spectral analysis:

$$Four(f) = \|\mathbf{x} - \hat{\mathbf{x}}_f\|_2 / \|\mathbf{x}\|_2 \quad (4)$$

This fourier model imposes the constant magnitude, frequency and phase features. It means that this model does not address the presence of phase jumps. Although used in almost all dominant frequency studies, this model is not really adapted to our observations and is affected by departures from constant features as shown thereafter. One easy and convenient way to adapt the model to time-varying features is to use a Least Mean Squares (LMS) adaptive approach [6]. In that case the values of the two scalar parameters $[a \ b]$ in (3) are updated for every new recorded sample and the convergence speed is fixed by the value of the forgetting factor μ. Note that recursive least squares could also be used to update parameters. In both cases, the two time-varying scalars are then varying with time, catching simultaneously the variation of phase and magnitude. As already mentioned, it is expected a loss of frequency resolution because the phase variation could also adapt to a frequency mismatch. Then a slow convergence (corresponding to a low forgetting factor in LMS filtering) will imply a higher frequency resolution but a lower ability to track fast changes of phase, i.e. the phase jumps, and conversely for a fast convergence. This pure LMS adaptation will be named *Four_lms(f)*.

Since a constant magnitude is assumed with the Fourier decomposition, we propose to combine constant magnitude and time-varying phase by modifying the LMS algorithm. It should be reminded that the magnitude A_i in (2) is directly computed from (3) by $A_i = \sqrt{a^2 + b^2}$. Then, after the updating step of the parameters a and b in the LMS algorithm (see [6]) it is added the following substitution:

$$[a \;\; b] \leftarrow [a \;\; b] D / \sqrt{a^2 + b^2} \qquad (5)$$

where D is an imposed magnitude. This substitution does not change the estimated phase but only the magnitude. The best selection of the imposed magnitude D is achieved by using a nonlinear programming solver such the simplex search method with an initial value fixed by the magnitude computed with $[a \;\; b]$ from (3). This last modified LMS adaptation will be named *Four_lms_mod(f)*

In summary, methods described and used in this part are: *WA_cycle*, *Median_ssa* well adapted to single frequency Fourier model and *Four(f)*, *Four_lms(f)*, *Four_lms_mod(f)* adapted multiple components Fourier model. Simulations and application of these methods to a real case will be presented below.

4. Simulations

The simulation consists in generating a constant magnitude 6 Hertz single tone signal with random phase breaks, or jumps, every fixed 150 samples. The sample frequency is 256 Hertz and the total length is 15000 samples. The range of the phase breaks is variable, from 0 to ± T/2, T being the period of the single tone. The *WA_cycle*, *Median_ssa* methods, together with FFT applied to raw data (*FFT_raw*) and after the SSA preprocessing (*FFT_ssa*), were compared using a Monte Carlo approach with a noise level equal to 5dB. For each of the 500 trials a new sequence of noise and random phase breaks are generated.

In Fig. (1) is given the estimate of the dominant frequency at 95% confidence interval for different range of phase breaks and for the four methods. It is clear that for large phase jumps the adapted methods *WA_cycle* and *Median_ssa* performed better with a light improvement for the one using a weighted averaging. However it is worth noticing that FFT based methods are not especially designed for single tone signals but as foreseen they are clearly affected by the presence of phase jumps.

5. Application to BSPM data

For this illustration, BSPM were recorded in one patient with persistent AF using a custom configuration of 184 leads with 120 anterior and 64 posterior leads (ActiveTwo BSM Panels Carbon Electrodes, Biosemi B.V., The Netherlands). ECGs were sampled at 256Hz. A one-minute segment was selected, low-quality leads were excluded (low signal-to-noise ratio, poor electrode contact, motion artefacts), and Wilsons Central Terminal was subtracted in line with conventional ECG analysis. After

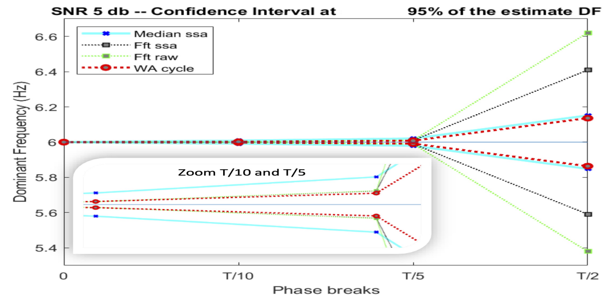

Figure 1. Methods performances for single component model with phase breaks.

band-pass filtering the signals between 1 and 100Hz (3rd order Chebyshev), QRST cancellation was performed using an adaptive singular value decomposition method. The extracted atrial signals were post-filtered with a zerophase notch filter at 50Hz to suppress power line noise, and with a 3Hz zero-phase highpass filter (3rd order Chebyshev) to remove low-frequency residuals not related to (persistent) AF.

In this example, the methods developed for multi components analysis based on (3) are applied to all the leads of the BSPM record. To understand the different results on the whole BSPM, it is shown in Fig. (2) the normalized 2-norm error (4) for the different methods applied to the lead where the DF is the highest. The lowest value of the criteria gives the frequency that better fits the observation vector, namely the DF. It can be observed a lower frequency resolution for the LMS based methods compared to *Four* and that for an identical μ value the *Four_lms_mod* method exhibits a higher frequency resolution than *Four_lms*. It should be also observed that the DF, i.e. the frequency corresponding to the minimum value, depends on the method and cannot be explained only by a lower frequency resolution. In addition, when μ increases the error decreases because the trackings of the phase changes (for both *Four_lms_mod* and *Four_lms*) and the magnitude changes (for *Four_lms* only) are more efficient but at a cost of a lower frequency resolution. In addition, the *WA_cycle* method provides by design a single value that is equal to 6.4Hz in that case.

In Fig. (3), (4), (5), (6) the DF computed with some of the presented methods are given for each lead and displayed on the subject torso. Clearly, the *WA_cycle* suffers from a lack of frequency resolution visible through the smoothed distribution of DF. The differences between all other methods are not very large. It can be noticed that the highest DF are localized in the vicinity of V1 (red circle) for *Four* although it is distributed on a larger area for *Four_lms_mod* and on a different parts of the torso. However, because intracardiac electrical activity is not recorded it is impossible to compare results to the ground truth.

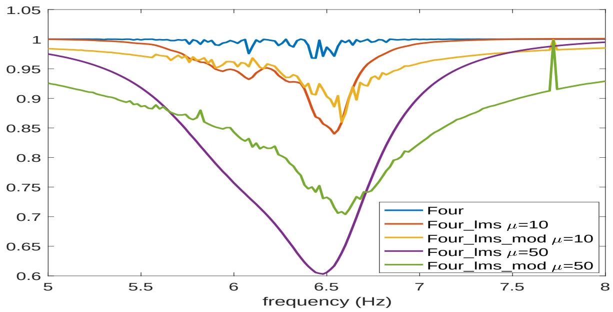

Figure 2. Comparison of spectral decompositions for multiple components model for the highest DF among the BSPM leads.

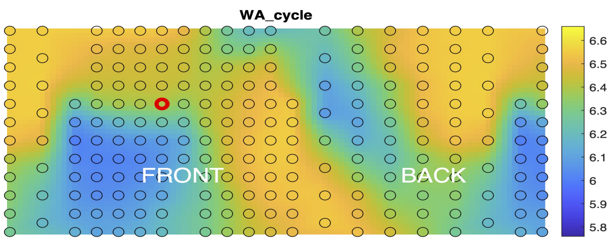

Figure 3. DF distribution over the BSPM leads for the *WA_cycle* method. Red circle stands for V1 location. Values on the color bar are expressed in Hertz.

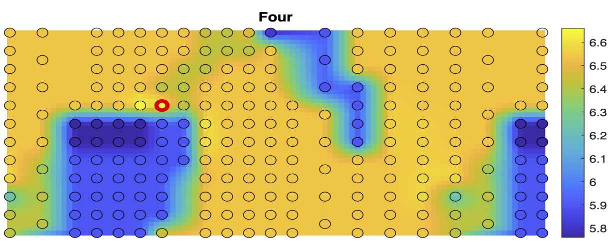

Figure 4. DF distribution over the BSPM leads for the *Four* method.

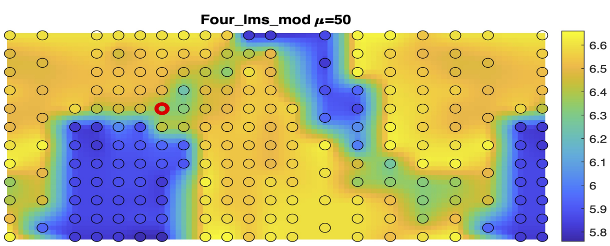

Figure 5. DF distribution over the BSPM leads for the *Four_lms_mod* method with μ=50.

6. Conclusions

This study aimed to question the relevance of the DF computed with Fourier based methods. It is shown in simulation that the assumption behind the use of the classical Fourier analysis is not well adapted to phase jumps likely present during AF episodes. We derived several methods to get rid of the impact of these changes but at the

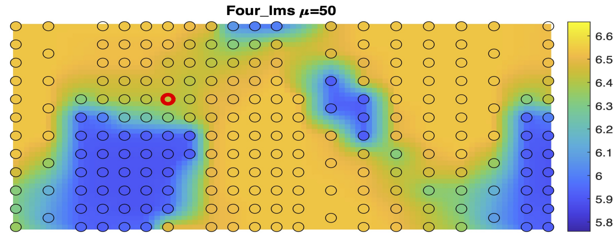

Figure 6. DF distribution over the BSPM leads for the *Four_lms* method with μ=50.

cost of a lower frequency resolution. The use of a LMS based method imposing a constant magnitude seems to be promising but it should be confirmed by the analysis of intracardiac signals.

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