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PHASE INFORMATION EXTRACTION OF ATRIAL FIBRILLATION USING REVERSE BI-ORTHOGONAL WAVELETS

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ABSTRACT

The phase information extraction of atrial fibrillation (AF) is significant in medical applications. In this method, atrial activity is decomposed into fundamental and harmonic components. Each component is divided into short blocks for which the amplitudes, frequencies, and phases are estimated. The phase delays between the fundamental and each of the harmonics, here referred to as harmonic phase relationships, are used as features of f-wave morphology. The estimated waves are clustered into typical morphologic patterns. The performance of the method is illustrated by simulated signals, ECG signals recorded from 50 patients with organized AF, and an ECG signal recorded during drug loading. The results show that the method can distinguish a wide variety of f-wave morphologies, and that typical morphologies can be established for further analysis of AF.

Keywords: *Atrial Fibrillation (AF), Electrocardiogram (ECG), Reverse Biorthogonal Wavelets, Waveform Characterization*

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I. INTRODUCTION

Atrial fibrillation (AF) is a heterogeneous disease considered to be the resulting end state of several mechanisms. Initiation of AF typically requires both a triggering event and an arrhythmia-prone anatomical substrate [1]–[3]. Suggested triggers include abnormal activity of the autonomic nervous system and rapidly firing foci located in the pulmonary veins. The arrhythmia-prone substrate may result from, e.g., impaired impulse propagation, changes in tissue structure, or alternations in atrial electrical properties induced by the arrhythmia itself. AF has mainly been viewed as an acquired disorder related to structural heart disease in patients with other cardiovascular problems, including coronary artery and mistral valve diseases and hypertension [4]; however, AF is now recognized to also have a heritable component [5]. Characterization of AF based on ECG recordings calls for separation of atrial and ventricular activity. Several approaches to such separation have been suggested based on, e.g., principal component analysis [6], [7], independent component analysis [8], and patio temporal modeling [9], [10]. The most important aspect of AF pattern analysis has, so far, been to determine the fibrillatory rate. This rate has potential value for monitoring spontaneous and autonomic maneuver-induced changes in atrial electrophysiology, monitoring and prediction of anti arrhythmic drug responses as well as for prediction of atrial defibrillation thresholds and AF recurrence following cardio version . AF with slower rates seems more likely to terminate spontaneously or to respond to anti-arrhythmic drug therapy whereas faster rates are more often found in persistent and drug- and cardio version-refractory AF . Recently, methods for characterizing temporal AF dynamics have been developed for studying mechanisms and treatment strategies. Using time-domain methods, the properties of f-waves have been investigated in terms of the plane of best fit and the spatial phase properties of different ECG

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planes . Time–frequency analysis, combined with frequency alignment of an adaptively updated spectral profile, has been used to track variations in AF frequency and f-wave morphology. Morphologic characterization was based on the harmonics pattern, expressed as the exponential decay of the harmonics' magnitude. The significance of AF harmonics has been paid little attention in the literature, one reason being that spectral analysis is almost invariably based on longer segments (> 30 s). As a Consequence, each segment contains large temporal variations in AF frequency that smears the harmonics. The aforementioned time–frequency analysis is particularly well suited to handle such variations in AF frequency as spectral alignment is performed, facilitating the detection and characterization of harmonics [23]. Several important questions related to the interpretation of AF patterns in the ECG remain unanswered, including how the patterns can be used to determine disease state and predict treatment outcome in individual patients. Other questions relate to the meaning of f-wave morphology in terms of intra-atrial activation patterns and to signal-based identification of AF subgroups. The use of AF frequency alone does not answer these questions. In this paper, we introduce a novel approach to f-wave factorization based on signal phase analysis. The method has a two-stage structure in which the atrial activity is first translated into compact sets of features, which are then clustered so that the typical waveform patterns can be discerned. The morphologic parameters of the present method offer information complementary
to the atrial rate and are not intended as a replacement to rate. The paper is outlined as follows: the method is presented in Section II, simulated and ECG signals in Section III, the results are presented in Section IV, and a discussion of the method and its performance is found in Section V.

II. METHODOLOGY

The method assumes that an atrial signal is obtained from the original ECG, produced here by spatiotemporal QRST cancellation [9]. Subsequent analysis is divided into two stages of which the first segments the atrial signal into short blocks and extracts features from each block that characterize the f-waves. Feature extraction involves signal decomposition into bandpass components that are used for estimation of AF frequency, amplitude, and phase. In the second stage, the resulting features are clustered into different waveform patterns.

Fourier analysis, using the Fourier transform, is a powerful tool for analyzing the components of a stationary signal (a stationary signal is a signal that repeats). For example, the Fourier transform is a powerful tool for processing signals that are composed of some combination of sine and cosine signals.

a) Acquisition system

A total of 56 chest and back leads were acquired simultaneously for each subject in addition to the standard limb leads. The predefined site walls are shown in Figure 2.Chest leads (N=40) were arranged as a grid around V1 with an inter-electrode distance of 2.2 cm. (See Figure 2) while back leads (N=16) were arranged in a similar fashion around V1post (placed on the back at the same level than V1). We designed a new belt for specifically attaching the electrodes in the correct position on the chest and back of the patient. Perforations are applied to the belt according to the electrode grid designed. Elastic bands cover the perforations providing fixation of the electrodes and applying the needed pressure. The front and back parts of the belt are joined with stripes of adjustable length, adapting to the shape of the patient. This attachment system allows repeatability in the measurements and provides a good contact of the electrodes with the skin of patient, reducing movement artefacts.Signals were acquired at a sampling rate of 2048 Hz, with a resolution of 1 microvolt and a bandwidth of 500 Hz. Before acquisition, signal quality of all leads was visually inspected and an ECG recording of 10 minutes was stored for off-line processing.

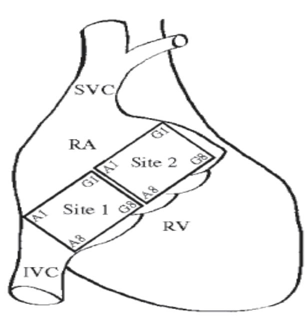

Fig.1 Predefined sites at the right atrial-free wall

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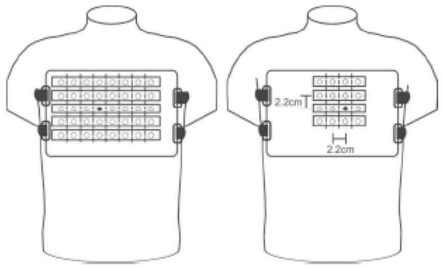

Fig.2 Arrangement of the electrodes and belt used for their attachment to the patient.

b) ECG Signal Processing

ECG signals were processed using Mat lab 7.0.1 (The Math works Inc, The Netherlands). Baseline wandering was reduced by subtracting the baseline to the recording, calculated by using a 3rd order low-pass Chebyshev filter. Signals were low-pass filtered in order to avoid my electric interference by using a low-pass Butterworth filter (fc=40 Hz) and down sampled to 512 Hz in order to speed up the calculations. Only long segments free from ventricular content were included in the study. For that purpose, the peaks of QRS complexes were detected in V1. RR intervals longer than 950 ms were first selected and a TQ segment was defined as starting 400 ms after the QRS peak and ending 150 ms before the next QRS peak. All TQ segments were visually inspected in order to avoid wrong detections or inclusion of T segments. After this step, only segments free from ventricular activity and longer than 400 ms were considered. Typically, one to three leads presented noticeable baseline wandering which was comparable or greater than the amplitude of the AF signal. In order to avoid this baseline wandering, AF segments were filtered again. First, the mean value in each lead was subtracted and the baseline was again calculated and subtracted. For the estimation of the baseline, segments were down sampled (fs=128 Hz) and low-pass filtered (fc=3.3 Hz). Then, the baseline was up sampled to 512 Hz and subtracted to the segment. After baseline wandering correction, AF segments were low-pass filtered (fc=20Hz). All leads in all segments were visually inspected. Leads presenting noticeable noise contributions (typically, a transient loss of contact in one electrode) were discarded and interpolated from its neighboring electrodes by cubic spline interpolation. No segment presented more than three discarded leads, and we considered that the loss of signal content of less than 4 electrodes out of the 56 available was acceptable. Once AF segments had been isolated and processed, maps for each time instant belonging to the each segment were constructed. For that purpose, potentials at a given time instant were arranged in two matrices: one for the front (5x8) and one for the back (4x4). In such matrices, signals recorded from neighboring electrodes are placed together. In order to obtain a smooth representation of the maps, finer matrices for the front (50x80) and the back (40x40) were created. Potentials for unknown positions were interpolated by cubic spline interpolation. Two display modes were implemented: the is potential mode and the waterfront propagation mode. In the is potential mode, voltages at a given time instant were represented according to a color scale. Videos of each AF segment were generated. In the wave front propagation mode, only lines connecting points on the surface with a voltage equals to zero were represented. This display mode allows the visualization of both the polarization and re polarization wave fronts depending on the time interval selected. The succession of wave fronts is represented using a color scale according to the time instant in which each wave front appears. We used a method as previously reported [16]. After removal of a 50-Hz disturbance component emanating from power supplies, and after subtraction of the mean signal level of all recordings, data reduction by means of low-pass filtering, and resembling at rate of 100 Hz, experimental data from the 78 electrode array were arranged in impulse response matrices of dimensions the number being the number of data points in each recording between two consecutive heart beats. Subsequent impulse response analysis and simulation of the resulting state-space realization were applied as described in next section.

III. RESULTS AND DISCUSSION

Maps were generated for all the segments considered in the study and visually inspected. Single or multiple simultaneous wave fronts, wave breakages and disorganized electrical activity could be observed. Figure 2 shows some selected wave front propagation maps representative patterns observed. In panel 1a, a succession of wave fronts from patient 3 is observed. A single wave front can be observed in both panels 1a and 1b. In panel 1a wave fronts

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are mostly parallel to each other. Panel 1b shows the next succession of wave fronts, which differ from panel 1a.Panels 2a and 2b show two consecutive depolarization waves from patient 3 which present a similar pattern. Surface wave fronts rotate along a similar axis in both panels. The same pattern was observed in the consecutive wave fronts appearing in the same segment (total=5).Panel 3 shows two consecutive depolarization waves from patient 5.

Depolarization wave shown in panel a is first shown in the leftmost part on bottom of the grid and spreads towards the center and top until it gets blocked. A second depolarization wave starts in the uppermost part on the right of the grid and propagates towards the bottom and the left until it gets blocked in roughly the same position where the previous wave arrived. It can be observed that one wave front is blocked by the previous propagation contributing to a chaotic propagation. Panels 4a and 4b show depolarization waves in patient 6. Multiple waves arise at the same time, propagate and then disappear in an uncoordinated fashion.

By analyzing the 10-minute recording of each patient, we observed that the wave front propagation patterns were, to some extent, repeatable. Patient 3 showed clear wave fronts with similar patterns in most segments analyzed. Patients 1, 5 and 6 showed a completely unstable pattern with multiple simultaneous activation wave fronts that changed widely even in short time intervals. Patients 2 and 4 presented an intermediate degree of repeatability, with one or two simultaneous propagation wave fronts that could both differ greatly or slightly from one activation to another. By application of the state-space realization algorithm to every heart beat with a period of approximately 1 s and 175 ms during atrial fibrillation, it was possible to reproduce the electro gram impulse response which, in turn, makes possible a quantitative comparison as to the variation and complexity of a set of consecutive heart beats. The wavelet decomposition of scddvbrk signal is shown in Figure 3.

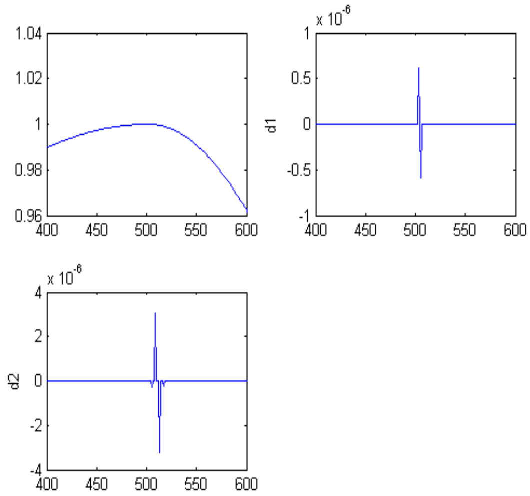

Fig.3 wavelet decomposition of scddvbrk signal

Relative prediction error versus model order and the singular value sequences indicate a model order to be relevant for the SR and the atrial pacing, whereas a model order is relevant for atrial fibrillation. As for the temporal and channel-dependent autocovariances and cross covariance of data and residuals, it is apparent that atrial fibrillation data exhibit other temporal covariance than data of SR and of artificial atrial pacing data. The phase curve extraction of standard signals like scddvbrk, freqdbrk and cuspamax provides useful information in the atrial fibrillation. The phase curve extraction of scddvbrk signal using “bior1.3” is shown in Figure4.

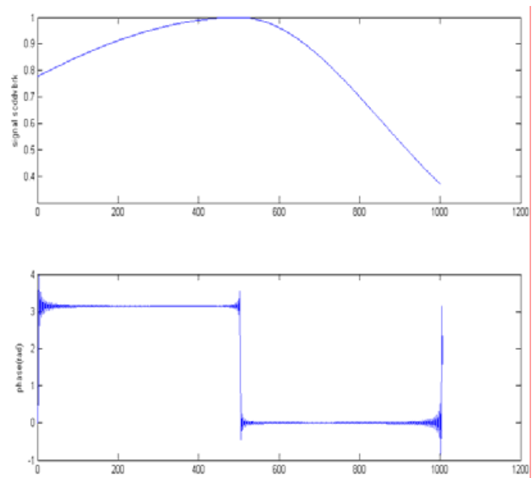
Fig.4 Phase curve extraction using bior1.3

The phase curve extraction of cuspamax signal using bior1.5 is shown in Figure 4.

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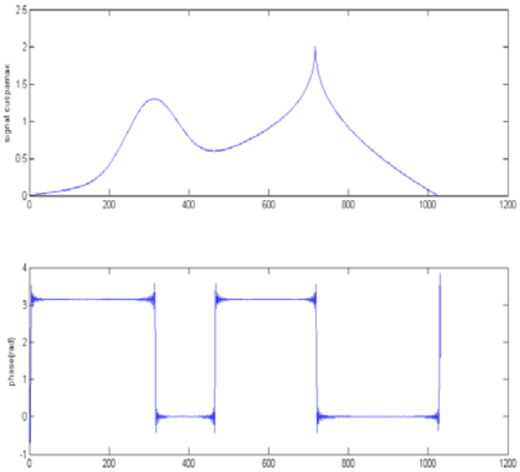

Fig.5 Phase curve extraction of cuspamax Signal using bior1.5

Modeling: Generally, the purposes of theoretical models are to pinpoint deficiencies in our knowledge about a system and to predict properties of the system which otherwise should not have emerged. In our case we have studied heart surface properties of impulse propagation as the impulse response to natural and artificial pacing. Thus, the nonlinear modeling needed to reproduce the impulse generation and refractory tissue properties is not included. As for all behaviorist models, the models obtained here provide no final or definite answer as to the underlying physiological mechanisms. Although the linear properties of the underlying physiological processes might be challenged, the system identification provides linear approximate models of finite and low complexity and good prediction accuracy. As for methodological extensions, the realization theory applied here lends itself to modeling by linear partial differential equations by using the spatial information available in the electro gram data.

The linear models obtained for electro grams of SR, atrial pacing, and atrial fibrillation have been validated by means of approximation notions and (preliminary) extensions of statistical validation properties including cross validation on data sets not used for system parameter estimation. The phase curve extraction used above are applicable to the ECG signal. The raw ECG data is denoised and applied to phase curve extraction using reverse bi-orthogonal wavelet is shown below.

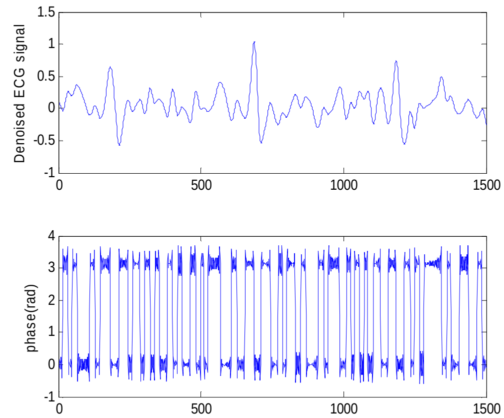

Fig.6 Phase curve extraction of ECG signal using reverse bi-orthogonal wavelet

Thus, the models obtained actually provide a means for prediction of behavior and for classification purposes—e.g., for distinction among various beat-to-beat behaviors. In contrast to the hypotheses of Hoekstra et al. [14], no evidence of chaotic nonlinear dynamics was found. By application of the state-space realization algorithm to every heart beat with a period of approximately 1 s and 175 ms, respectively, it was possible to reproduce the electro gram impulse response which, in turn, makes possible a quantitative comparison as to the variation and complexity of a set of consecutive heart beats (Figs. 2–4). The residual autocovariance and cross covariance between residuals and data provide good or excellent model agreement for atrial fibrillation, artificial pacing rhythm, and SR.

IV. CONCLUSION

The phase information extraction in atrial fibrillation has been presented. Since phase extraction provides more information about the signal, we applied it to the various signals and ECG signal. Different patterns of electrical activation and degrees of stability of the activation patterns have been observed. The comparison of this new method for the quantification of the degree of organization of the atrial electrical activity with other methods such as spectral analysis and validation by comparison with invasive mapping data will be of great interest in future studies. Although observations from the present study have not been compared to the effectiveness of any specific treatment, there is a great potential in

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further analyzing the activation patterns of the electrical wave fronts occurring in the atria as observable in body surface maps.

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