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Characterizing Complexity of Atrial Arrhythmias through Effective Dynamics from Electric Potential Measures

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Abstract

The cardiac electrical activity follows a complex dynamics whose accurate description is crucial to characterize arrhythmias and classify their complexity. Rhythm reflects the connection topology of pacemaker cells at their source. Hence, characterizing the attractors as nonlinear, effective dynamics can capture the key parameters without imposing any particular model on the empirical signals. A dynamic phase-space reconstruction from appropriate embedding can be made robust and numerically stable with the presented method.

1. Introduction

The traditional approach to cardiodynamics consists of qualitatively characterizing the peculiar shapes of potential signals. Some signatures of such shapes are specific of arrhythmias and so mark the success of this approach, particularly from electrocardiograms. Alternatively, but in a quite similar way, the statistical approach tries to signal specificities that are not present in the electrical signals themselves but in the distribution function of the signal or of some measure derived from it. Statistical methods for processing cardiac signals have had a notable success in several areas, e.g., providing measures of complexity of a certain arrhythmia. Additionally, they output quantitative measures, they provide confidence intervals, and sometimes we know how to apply them robustly. Limitations of this approach consist of restrictive hypotheses on the processes behind the processed signals, or parameters that do not have any direct physical interpretation, e.g., entropy of a continuous variable diverges [1].

Statistical methods do not always respect the signal invariances. This fact motivates looking for fractal [2–4] or multifractal [5–7] approaches to heart rate variability, which capture the multiscale properties of the process. More interestingly, multifractal analysis reconnects the statistical features of the signal with a geometrical interpretation linked to the effective macroscopic transfer of information in the signal [8–13]. Taking a different path, embedding methods can also reconstruct the effective attractor of the system that produced the signal. This effect reinforces the possibilities for cross-validating the obtained parameters as well as obtaining their physical interpretation [14].

The paper has the following structure: section 2 introduces the basic methods used for processing the cardiac electrical signals; we show our results in the identification of dynamical regimes. Finally, in section 3 we discuss the results and present the conclusions of our study.

2. Statistical methods based on nonlinear dynamics

The electrical activity of the heart is often described as a complex system. Complexity can have multiple interpretations varying in both nature and extent. Nevertheless, the effect in all cases is that the behaviour of the system as a whole is an emergent behaviour, which could not be derived from separately considering the microscopic mechanisms (be them at cell level or even at molecular level). This non-separability of the different scales involved is a consequence of nonlinear interactions or, in other words, expressing the effect at a given level requires more than just the sum of effects at lower levels. This is what makes global synchronization possible, also can amplify microscopic fluctuations to perturb the whole regime [6, 7].

Emergence of chaos becomes even more important in complex arrhythmic regimes, where linearized descriptors fail to provide meaningful parameterizations except only possibly for very short time windows, or microscopic space or parametric scales. In this context, any appropriate processing methodology must be nonlinear in nature. Singularity analysis provides a robust framework that identifies dynamical transition fronts and information content

[8, 10, 15] which is useful for cardiac electric potential signals [12, 13, 16].

2.1. Singularity analysis

The degree of singularity or regularity of a given point in a signal tells how rare is the signal at this point and therefore how much information it contains. A local expansion of the signal around this point has a leading order that dominates at the local neighbourhood (short distances, or small perturbations of the position). This leading order is the scale parameter raised to an exponent, which is not necessarily integer. A signal $s(\mathbf{x})$ has a (fractional) singularity exponent $h(\mathbf{x})$ at point $\mathbf{x}$ if

$$\mathcal{T}_\Psi \mu(\mathbf{x}, r) \;=\; \alpha_\Psi(\mathbf{x})\, r^{h(\mathbf{x})} \;+\; o\left(r^{h(\mathbf{x})}\right) \qquad (r \to 0). \tag{1}$$

with $\mathcal{T}_\Psi \mu(\mathbf{x}, r) = \int_{\mathbb{R}} \mathrm{d}\mu(\mathbf{x}')\, \Psi\left((\mathbf{x} - \mathbf{x}')/r\right)$ as the wavelet-projected measure μ at scale r and Ψ as a certain wavelet kernel. The measure is differentially defined: $\mathrm{d}\mu(\mathbf{x}) = \|\nabla s\|(\mathbf{x})\, \mathrm{d}\mathbf{x}$.

Now, the sole requirements of being deterministic, linear, isotropic and translational invariant permit to define a local reconstruction kernel [11, 17]. Actually, this minimal-assumption reconstruction identifies a *reduced* signal which is reconstructed only from the orientation of the signal on its most singular points [13]. The actual signal and its reduced counterpart are related through a complex but slow-changing modulation called *source field*, SF:

$$SF(\vec{x}, t) = \frac{\mathrm{d}\mu_{\mathrm{s}}}{\mathrm{d}\mu_{\mathrm{r}}}(\vec{x}, t). \tag{2}$$

2.2. Phase-space reconstruction

Time series evolution is mapped to an object embedded in a phase space in abstract coordinates. m independent observations construct an mD phase space, as per the embedding theorem [18, 19]. The dimension m is the least one that embeds the dynamics (which is twice plus one the Minkowski dimension of its attractor set) and the time lag τ is the shortest for which the m coordinates do not mutually interfere.

With appropriate filtering, the method is robust and adapted to empirical signals. The result is a compact dynamical description that characterizes complexity degree and information distribution [20–22].

Both singularity analysis and phase-space reconstruction give a geometric perspective to the dynamics of the system, which is only partially observed as variables resulting in the electrograms. In both cases, all the structural complexity of the system is abstractly represented as means of effective dynamics. In practical terms, singularity analysis follows an approach that is radically different

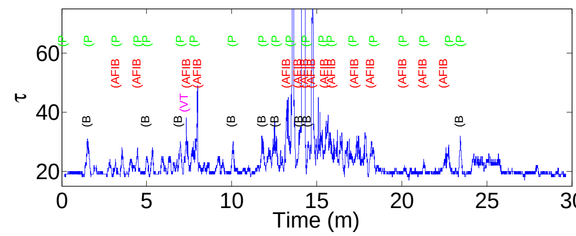

Figure 1. Time lag τ (expressed in samples, at 360 Hz) of local phase-space reconstruction for MIT-BIH Arrhythmia Database [23, 24] case #217: a fragmented electrogram with many intermittent episodes of atrial flutter and fibrillation, which appear well segmented by the lags.

from the one of a local phase-space reconstruction. Time lag fluctuations of reconstruction correlate with atrial fibrillation episodes, as we can observe in Figure 1. Correspondingly, the dynamical changes implied from singularity analysis also highlight atrial fibrillation in a local way, as described in [13] and presented as well in [12, 16].

3. Discussion and conclusions

Nonlinear analysis provides appropriate tools to characterize cardiac dynamics. Singularity analysis and phase-space reconstruction are physically meaningful complexity measures with minimal assumptions on the underlying models. These methods are based on effective descriptions derived from first principles, and as a consequence, parameters are robustly estimated. We have validated this approach on ECG, endocavitary catheter measures and electrocardiographic maps [16].

Key parameters vary infrequently and exhibit sharp transitions, which show where information concentrates and correspond to actual dynamical regime changes. Singularity exponents sift a simple fast dynamics from its slow modulation [12, 13]. In space domain, extreme values highlight arrhythmogenic areas. We observe a correspondence of time lag fluctuations of phase-space reconstructions with atrial fibrillation episodes in the same way as with the dynamical changes coming from singularity exponents. This characterization of information transitions could be used in the regularization of inverse-problem mapping of electrocardiographic epicardial maps. Furthermore, this opens the way for improved model-independent complexity descriptors to be used in non-invasive, automatic diagnosis support and ablation guide for electrical insulation therapy, in cases of arrhythmias such as atrial flutter and fibrillation [13, 14].

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