A New Methodology for Nonlinear Heart Function Analysis: Studying Just the Beat Morphology

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Abstract

Nonlinear analysis techniques have been used to study the heart rate variability series (which only contains RR interval information) and the ECG (which contains both RR interval and beat morphology information). It is still an open issue whether the RR series is chaotic or stochastic. Nonlinear properties of ECG are less controversial, despite containing heart rate information. In this work, we propose a new methodology to achieve phase space reconstruction that only uses beat morphology information; thus it avoids possible phase space contamination from stochastic components of the RR intervals. Nonlinear statistics computed with this approach are able to discriminate between healthy and congestive heart failure patients.

1. Introduction

The heart rate is largely influenced by the complex interactions of the parasympathetic and sympathetic branches of the autonomous nervous system, as well as by humoral and haemodynamic variables. Such a complex system is unlikely to be linear in nature. It has also been argued that the heartbeat morphology is determined by the nonlinear interactions of the heart tissues [1]. Hence the interest in using nonlinear techniques in the study of heart rate variability (HRV) and the ECG. It is still an open issue whether the RR series is chaotic or not [2]. Part of this controversy has its origin in the existence of stochastic phenomena that concur to the control of the myocardium. Leon Glass argued that the stochastic nature of heart rate precluded the notion of chaotic determinism in such system [2]. In this work, we have assumed Glass hypothesis which states that the heart rate is influenced by stochastic mechanisms. Therefore, the application of chaos related techniques to the RR series could not have a firm theoretical basis.

The nonlinear nature of the electrocardiogram (ECG) is less controversial. However, ECG nonlinear analysis is very resource intensive due to its large data volume. The ECG signal contains information about the beat morphology, which depends on the point of origin of the beat and on its propagation path through the myocardium; and about the RR interval, which mainly depends on the parasympathetic and sympathetic systems. In science it is often a good idea to start by studying a single aspect of a system at a time. Furthermore, stochastic components arising from the RR interval may prevent or hamper the application of nonlinear analysis techniques to the ECG. Hence the interest in developing techniques which enable nonlinear analysis of beat morphology information without possible stochastic contamination from the heart rate.

In this paper we propose a new methodology for performing nonlinear analysis of just the beat morphology, without the inclusion of heart rate information. Section 2 describes the theoretical background used in this work. Two different approaches for performing nonlinear analysis of the beat morphology are proposed. One is based on beat segmentation features, while the other is based on the representation of the beat with Hermite polynomials. Section 3 describes the results obtained with this new methodology when applied to the Congestive Heart Failure and the Normal Sinus Rhythm databases. Finally, the results of this paper are discussed and some conclusions are given.

2. Material and methods

2.1. Phase space reconstruction

Most of the nonlinear analysis techniques are based on the theory of dynamical systems and thus, the system's evolution is determined by some phase space. The phase space is a vector space such that a point in this space completely specifies the state of the system. When dealing with nonlinear time series analysis, the phase space reconstruction from the scalar observations of the time series is achieved by using the Takens' embedding theorem [3]. For

a time series $s(n)$ $n = 1, 2, ..., N$, the phase space may be reconstructed by using the vectors:

$$\{s_i = [s(i), s(i+\tau), ..., s(i + (m-1) \cdot \tau)]\}, \quad (1)$$

where $i = 1, 2, ..., N - (m-1) \cdot \tau$, τ is the time delay and m is the embedding dimension [3]. There exist a minimum number of components of the vectors s_i for achieving proper phase space reconstruction; i.e., there is a minimum number of dimensions of the phase space in order to fully define the system's state. It must be noted that using more components than those strictly necessary is not an issue because all the information required for specifying the state of the system is already known; i.e., it is possible to achieve proper phase space reconstruction with more dimensions than those strictly necessary.

Delay embeddings is the most common technique used in the literature for the reconstruction of the phase space of a time series because it preserves the topological structure of the original phase space. Thus, the geometrical and topological structure of the original phase space may be estimated by studying the reconstructed space. However, any m independent measurements taken from the system can be used for constructing a phase space in the sense of completely characterizing the state of the system. In this work, each of the m components used to reconstruct the phase space will provide information on the morphology of the beat; thus our phase space vectors are given by:

$$\left\{s_i = \left[f_1^{(i)}, f_2^{(i)}, ..., f_m^{(i)}\right]\right\}, \quad (2)$$

where $i = 1, 2, ..., L$, L is the total number of beats, s_i is the phase vector representing the ith heartbeat of the ECG and $f_j^{(i)}$ is the jth feature characterizing the ith heartbeat.

2.2.   Heartbeat characterization

We shall use two strategies to reconstruct the phase space from a set of features describing the morphology of the beats. In the first one, phase space vectors were created using features derived from heartbeat segmentation. The segmentation features were extracted using a custom implementation of the algorithm described in [4]. The available features include the height and width of the P, Q, R and S waves; the height of the P wave; the width and area of the QRS complex; the ST, PR and QT intervals; the PR and ST segments and; the ST slope and the ST elevation.

Hermite functions can be used to represent the QRS complex. The similarity of this functions to the shape of the QRS enables its representation as a linear combination of a small number of Hermite functions [5]. The coefficients of the linear combination were used as the features that represent the QRS. In this paper, we have extracted each heartbeat's QRS by taking a 200 ms window of sampled ECG centered on the beat's position. This window is wide enough to encompass the entire QRS complex of a normal beat, but narrow enough not to include the P and T waves [5]. Since all the Hermite functions converge to zero as they tend to $\pm\infty$, 100 ms zeros were added on each side of the 200 ms window containing the QRS. The resulting 400 ms window, $x(t)$, can be represented as:

$$x(t) = \sum_{j=0}^{m-1} c_j(\sigma) \phi_j(t/\sigma) + \epsilon(t), \quad (3)$$

where m is the number of Hermite polynomials (i.e. the dimension of the phase space) used in the representation of the heartbeat, $\phi_j(t/\sigma)$ is the j Hermite function, c_j are the coefficients of the linear combination (i.e. the jth feature of the heartbeat), σ is a parameter that controls the width of the polynomial, and $\epsilon(t)$ is the error between $x(t)$ and the Hermite approximation [5]. It must be noted that the segmentation approach is able to characterize the whole heartbeat whereas the Hermite approach, as it has been used in this paper, only characterizes the QRS complex.

2.3.   Finding the embedding dimension

To find the proper embedding dimension required for phase space reconstruction in both approaches, the number of vector components was increased until the slope of the scaling regions saturated in the correlation sum. This technique has extensively been used in the literature for testing the minimum embedding dimension and the chaotic behaviour of the system being studied [6]. When using the segmentation approach we started with a set of manually selected features. Then we increased the embedding dimension by selecting the feature less correlated with those already belonging to the phase space vector. The features that we initially chose were the width of the P wave and both the width and the height of the Q, R and S waves. When using the Hermite phase space, the fact that the coefficients are orthonormal simplifies the process of increasing the embedding dimension: we just add the Hermite coefficient corresponding to the Hermite polynomial of degree $m + 1$.

2.4.   Database description

To test both phase space reconstruction methods, and the potential utility of these phase spaces, we have used the 15 recordings from the Congestive Heart Failure database (CHF) and the 18 recordings from the Normal Sinus Rhythm (NSR) database [7]. The recordings from both the CHF and the NSR databases are approximately between 20 and 24 hours long and contain two ECG leads sampled at 250 and 128 samples per second, respectively.
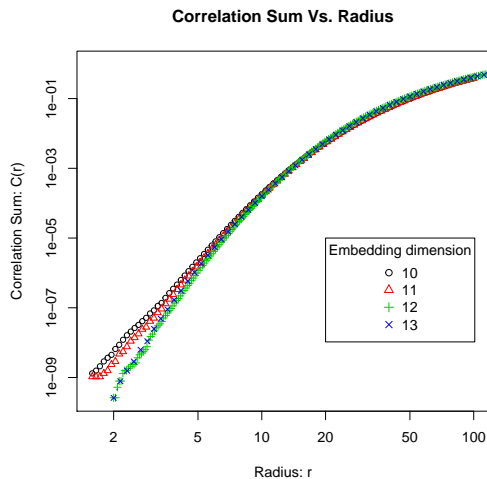
Correlation Sum Vs. Radius

Figure 1. Correlation sums in the Hermite phase space for recording *16272* of the NSR database. Note the saturation and the scaling region in the 3-10 radius zone.

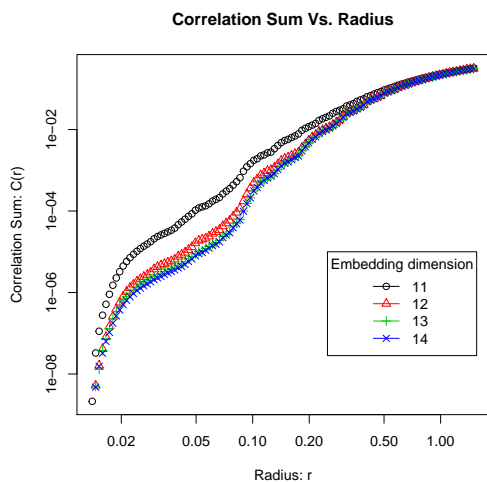**Correlation Sum Vs. Radius**

Figure 2. Correlation sums in the segmentation phase space for recording *16272* of the NSR database. Note its wavy behaviour and that there is no clear slope saturation.

3. Results

When using the Hermite phase space, scaling regions in the correlation sum saturate for an embedding dimension of 12 or more for most of the ECG recordings, as shown in Figure 1. Thus, proper phase reconstruction was achieved. On the other hand, no clear scaling regions were found in the correlation sum with the beat segmentation phase space, as seen in Figure 2, although the 18 different features available from the segmentation algorithm were used.

Once a proper phase space reconstruction was achieved

by using the Hermite representation, several nonlinear statistics were computed for the 33 recordings from the CHF and the NSR databases. The statistics were computed for several embedding dimensions ranging from 12 to 14. In this way we have ensured that the statistics saturated when increasing the embedding dimension (which is required since the statistics must be invariant). It should be noted that these statistics do not characterize the vectors obtained with the Hermite decomposition, but its dynamic evolution in phase space.

The correlation dimension (CDIM) was computed by using the correlation sums obtained when calculating the embedding dimension. Although clear scaling regions were obtained for most of the recordings, the correlation dimension was not able to discriminate between both groups, as shown in Table 1. The most important parameters from the Recurrence Quantification Analysis (RQA) [8] were also computed: Recurrence (REC), Determinism (DET), Laminarity (LAM), Ratio (RT), Averaged diagonal line length (LEN), Trapping time (TT), Longest diagonal line (L_{max}), Longest vertical line (V_{max}), Divergence (DIV) and the Entropy of the diagonal lines (ENTR). As shown in Table 1, some RQA parameters presented statistically significant differences for both databases. Thus, the Hermite approach allowed to discriminate between the different groups. Just by establishing a threshold on the length of the maximum vertical line ($V_{max} = 12.5$) of the recurrence plot, sensitivity 86.7% and specificity 94.4% were achieved when classifying the recordings of the CHF and of the NSR databases.

	NSR	CHF	p-value
CDIM	8.6 ± 0.8	8.5 ± 1.4	0.967
REC	0.04 ± 0.05	0.03 ± 0.02	0.580
RT	6 ± 2	11 ± 8	0.009
DET	0.15 ± 0.10	0.25 ± 0.12	0.004
DIV	0.13 ± 0.04	0.08 ± 0.04	< 0.001
L_{max}	8 ± 3	19 ± 14	< 0.001
LEN	2.11 ± 0.10	2.3 ± 0.2	0.001
ENTR	0.36 ± 0.18	0.6 ± 0.3	0.001
LAM	0.996 ± 0.003	0.996 ± 0.004	0.531
V_{max}	10 ± 4	30 ± 24	< 0.001
TT	1.15 ± 0.12	1.3 ± 0.2	0.018

Table 1. Statistics obtained from the Hermite representation. P-values were obtained using a Wilcoxon test.

4. Discussion

No scaling regions were found in the correlation sum in the beat segmentation phase space for any embedding dimension (see Figure 2). Moreover, the correlation sums showed a wavy behaviour in all the embedding dimen-

sions. This is consistent with these phase space vectors being too noisy for proper attractor reconstruction due to inaccuracies in beat segmentation. It is well known that beat segmentation algorithms are not very stable, especially when identifying the start and end of the waves. Nonlinear analysis techniques are very sensitive to the presence of noise in the data, hence the results we have obtained.

Proper phase reconstruction was achieved when using the Hermite representation. In this context, proper phase reconstruction means that the correlation sums behaviour is consistent with nonlinear phenomena. Twelve Hermite polynomials are able to reconstruct a beat with high accuracy [5]. This increases our confidence that we are correctly capturing the characteristics of the heartbeat using this phase space. It should be noted that the representation of the beat through Hermite polynomials is quite robust in the presence of noise in the ECG; this is an advantage when applying nonlinear analysis.

The nonlinear statistics obtained in the Hermite phase space cannot be compared with those obtained using the delay embeddings over the ECG since we got rid of all the heart rate information. Furthermore, the phase space achieved with the Hermite approach will probably differ from the Takens' phase space since we have introduced a nonlinear measure (the Hermite decomposition) to obtain the reconstruction. Further study is needed in order to determine the relative importance of the nonlinearities due to the Hermite decomposition and due to the heartbeat morphology. The introduction of this nonlinear measure in the Hermite decomposition is related to the fact that this method does not preserve the topological structure of the original phase space, in contrast with the delay embeddings method. The differences between the correlation dimension obtained using the Hermite approach and the ECG [1], [9] support that the phase spaces are different.

The results in the previous section also show that the Hermite representation may be useful for identifying pathologies such as congestive hearth failure. It must be noted that our technique only analyzes heartbeat morphology information. Thus, this technique is likely to have limited applicability in the study of diseases that are manifested primarily in RR intervals.

5. Conclusions

This paper presents a new methodology for performing non linear analysis of the heartbeat morphology that ignores possible stochastic contribution of the heart rate. Two approaches for achieving phase space reconstruction were tested: the coefficients of the Hermite and beat segmentation features. The Hermite representation succeeded reconstructing phase space, whereas that the segmentation approach did not, probably because this phase space is too noisy. The Hermite phase space allowed us to calculate

nonlinear statistics that can discriminate between patients with congestive heart failure and control patients. In the future we will study the possible pathophysiological interpretation of this new methodology as well as its applicability to study other pathologies.

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