SOME STRUCTURAL POINTS OF NON-LINEAR HRV ANALYSIS
REVISITED

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Abstract: In this paper we analyze the heart rate signal and compute the correlation dimension that is required so that we may describe it as a result of a non linear and complex process. We present our results which, although coherent with other methods, are unique in their application as well as in their acquisition. The basic analysis tool used here is the Method of Delays (MOD), for which we show that the use of the Euclidean norm, as opposed to the commonly used infinity norm, produces better results. We also use the False Nearest Neighbors and the Approximate Entropy methods. Finally, we address certain aspects of data acquisition that may not be receiving the attention we believe they deserve. The above methods are applied with the process we propose to a group of long-term ECG recordings demonstrating coronary pathology and another group where the ECGs appear normal, showing no sign of coronary artery disease. All of the above applications, when used carefully and as illustrated in our work, produce clear and clinically significant results.

Introduction

Electrocardiogram (ECG) analysis with chaotic timeseries methods has become quite popular among researchers in the last decade. Since the time of Goldberger [1] and Babloyantz [2], who in 1987 and in 1988 respectively pioneered this effort, a large number of researchers have worked on this subject. Chaotic timeseries analysis methods in ECG analysis have both been warmly accepted [3-6] as well as criticized [7] as vulnerable and sensitive, casting doubt on their efficacy in clinical applications. Therefore, much work is still being done to establish where the scientific community stands on the issue.

Beyond their value in ECG analysis, these methods are indeed sensitive and depend on many parameters which, if not evaluated properly, may alter the results. Regarding the process of choosing the proper parameters for the application of these methods, few steps have been taken, since all bibliographical propositions remain open and none has been chosen as the standard.

The contribution of this study will be focused on three basic points, each one of which is discussed in the next three paragraphs.

The heart rate signal is analyzed using MOD [8] and the required dimension is computed when represented as a non-linear system. The conclusion reached is that the heart is a high-dimensional system with high complexity. We used the false nearest neighbors (FNN)[9] method (i) in order to find the required embedding dimensions rate and (ii) in order verify the MOD results. We also compute the approximate entropy (ApEn) [10] of the signal and check for coherence. These methods comprise independent approaches to the problem and the coherence of the results is important. Finally, the surrogate data method [11] is also applied, since it has become a standard practice that any result implying the existence of a correlation dimension is accompanied by this inspection.

The above analysis leads to results which call for greater inspection of the ways in which the MOD may be applied. The way in which the MOD is applied here is indicated by the nature of the heart rate signal, which is different from any other application (such as meteorological research, etc). We differentiate our method from other similar ones and select the Euclidean norm as opposed to the infinity norm. The former is by its nature more capable of utilizing all the information as opposed to the latter, which provides a quick and simple computational approach. It is found that the infinity norm does not produce clear plateaus in the slope correlation integral graphs, a fact that sets the credibility of the method under question.

Finally, we raise the issue of data acquisition since this factor can greatly affect the final output and may even lead to erroneous data.

In the rest of this paper, we will address the above points independently and in more detail, presenting our contribution to the field.

Heart Rate Signal Complexity

With the term complexity of a signal we mean the degree of non-linearity of the underlying dynamics from which it is generated. Heart rate variability characterizes the cardiac dynamical system, which is still greatly abstract. The evaluation of an unfamiliar dynamical system is done through non-linear timeseries analysis, which contains certain temporally ordered measurements of some order of the dynamical system. Non-linear analysis includes the correlation dimension estimation with the method of delays, the false nearest
neighbors and the approximate entropy estimation method. As is required with this type of research, the validity of the results is tested with the surrogate data method.

In MOD analysis, the first step is the phase space reconstruction from the timeseries, assuming an embedding dimension, \( m \) and time lag, \( \tau \). We then compute the correlation dimension integral, \( C(m,r) \) and plot \( \log(C(m,r)) \) vs. \( \log(r) \), where \( r \) represents distances between points in the reconstructed phase space. The same procedure is repeated for different embedding dimensions. From the resulting figure, we chose a scaling region and compute the slope. If, when increasing the embedding dimension, we see that the slopes of this region tend to a particular value, then this is the correlation dimension. Furthermore, plotting the differences of \( \log(C(m,r)) \) vs. \( \log(r) \) leads to the appearance of plateaus that also tend to a value. If the linear regions, parameters, or the entire method has not been properly implemented then the plateaus do not appear in the figure.

In practice, of course, these plateaus are not always clear, but rather it is more common to see smaller plateaus in certain regions of the \( r \)-values. This is the reason the method is often deemed sensitive and vulnerable to the application procedure.

Figure 1 shows the correlation integral for a healthy subject and Figure 2 shows the slope of the correlation integral. It is from this signal, assuming that there exists a convergence as well as plateaus, that we find a correlation dimension value for the subject. This is repeated for all the timeseries and a correlation dimension value is obtained for all subjects. Figure 3 illustrates the slopes of the healthy (solid line) and unhealthy subjects (dashed line). It is apparent that there is a clear distinction between the two groups of subjects. Computing the correlation dimension for the healthy subjects led to a mean value of \( D_2=9.6 \) with a standard deviation of \( \text{std}=1.008 \). The correlation dimension for the unhealthy subjects led to a mean value of \( D_2=5.003 \) with a standard deviation of \( \text{std}=0.43613 \). These results are statistically acceptable for a good discrimination.

![Log(c) vs Log(r) correlation integral plot for a healthy subject.](image)

**Fig 1:** Log(c) vs Log(r) correlation integral plot for a healthy subject.

![Differential Logarithm of Correlation integral, vs Logarithm of r. The plateaus are identified between log(r)=1 and log(r)=1.3](image)

**Fig 2:** Differential Logarithm of Correlation integral, vs Logarithm of \( r \). The plateaus are identified between \( \log(r)=1 \) and \( \log(r)=1.3 \)

![Correlation Dimension Estimation](image)

**Fig 3:** The resulting correlation integrals for the two groups of subjects. The dashed lines represent the data of the unhealthy subjects while the solid lines represent those of healthy subjects.

Table 1 shows the correlation dimension values from similar studies as this one. There is an obvious divergence in the values of each study, indicating the fact that there is still much work that needs to be done in the field so that more coherent results can be obtained.

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Length</th>
<th>Correl. Dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Costa et al</td>
<td>5 5</td>
<td>30 min</td>
</tr>
<tr>
<td>Babloyantz et al</td>
<td>4 4</td>
<td>4 min</td>
</tr>
<tr>
<td>Nashomi et al</td>
<td>10 7</td>
<td>20 min</td>
</tr>
<tr>
<td>Gazzetti et al</td>
<td>7 24 h</td>
<td>3.29-5.16</td>
</tr>
<tr>
<td>Otsuka et al</td>
<td>116 4</td>
<td>4 h</td>
</tr>
<tr>
<td>Podd and Holcik</td>
<td>7 4</td>
<td>3.29-5.16</td>
</tr>
<tr>
<td>Ganz et al</td>
<td>79 15 min</td>
<td>7</td>
</tr>
<tr>
<td>Proposed here</td>
<td>6 6</td>
<td>2 h</td>
</tr>
</tbody>
</table>

* Holter

**Table 1:** Different values of Correlation Dimension estimation according to various studies. Group A represents healthy subjects, group B represents subjects with cardiac pathology.

According to the authors of [7], it is not possible to accurately compute the dimensions and they support that the RR-HRV timeseries have the feel of a random process. Apart from that study, the first researchers that dealt with this issue produced relatively low values for the correlation dimension and had used timeseries of few points or from Holter recordings. More recent work
has shown that the correlation dimension values tend to be relatively high for both subject groups, while the data used were ECG long recordings.

In our work and based on our findings, we cannot state with certainty that there is no appearance of chaos for the healthy subject data. We can, however, clearly state that there is no low-dimensional chaos. On the contrary, there is a lot of complexity as well as determinism present. In the case of the unhealthy subject data, there does exist relatively low-dimensional dynamics, with a correlation dimension of 4 to 5.

Figure 4 presents the results of the FNN, which computes the percentage of false nearest neighbors after sequential embeddings in increasing dimensions. A false nearest neighbor is one that disappears in the larger dimensions. The FNN gives an estimation of the embedding space dimension necessary for the proper description of the underlying dynamics. Since this value is close to the correlation dimension, the FNN is used mainly to ensure the coherence of the methods.

Figure 5 shows the results of the application of the ApEn, which gives the approximated entropy of the signal and serves as a strong tool for the evaluation of the complexity contained in a signal. Healthy subjects exhibited increased entropy as opposed to the unhealthy ones.

All of the above methods have also been tested with the surrogate data method. More specifically, the above methods were applied to surrogate time series that were acquired with the randomization of the phase (Unwindowed Fourier Transform Algorithm), the Windowed Fourier Transform and the Amplitude Adjusted Fourier Transform [11]. All three approaches showed an increase in the discrimination statistics (i.e. the correlation dimension), clearly indicating the presence of determinism.

**Assessment of Norms**

In order to compute the correlation integral, it is necessary first to select a norm. For computational reasons, the most common norm that is applied is the infinity norm, rather than the Euclidean. Although in theory the two norms are equivalent, in practice it has been shown that the Euclidean norm is more robust than the infinity norm. This is not an important fact in certain applications, e.g. meteorological studies, but in our case, where the way in which the method is applied is crucial, using the infinity norm may lead to erroneous results.

The most common distortion is that the plateaus are altered, preventing an accurate computation of the correlation dimension and introducing a random aspect to the final outcome. This is indeed shown in Figure 6, which presents the infinity norm plateaus analogous to those of Figure 2. The alteration of the data is clear.

![Fig 4. False Nearest Neighbors method. Unhealthy subjects exhibit many false nearest neighbors for lower embedding dimension values. Healthy subjects do not.](image)

![Fig 5. Approximate Entropy. Circles represent the healthy subjects, diamonds the unhealthy. The discrimination is clear.](image)

![Fig 6. Differential Logarithm of Correlation Integral calculated with the Euclidean norm](image)

**Data Acquisition**

To ensure that valid and precise data was acquired, a cardiologist was present to guarantee that all preparation and procedure details during cardiogram acquisition were followed properly. All recordings were performed in a quiet room, between the hours of 15.00-17.00, in the supine position, with a steady respiratory rate (12/min at about) under continuous monitoring by the cardiologist who confirmed the absence of any cardiac rhythm disturbances throughout the recording. Neither the healthy nor the unhealthy subjects were taking any medication that affects the heart rate. For the recordings
a 12-lead digital electrocardiograph (“Cardioperfect”) with 8 channels and 12-bits quantization (satisfactory accuracy) was used. Data were acquired with a sampling rate of 300 Hz. An R-R timeseries was generated by extracting the R-values from the ECG using a typical QRS detection algorithm [12]. Long ECG recordings were preferred for more accurate analysis and since large amounts of data ensure higher precision of the results; especially in non-linear methods, the amount of data is a crucial issue. An alternative solution would have been to concatenate short recordings, but this would forcibly result in inaccurate results.

Conclusions

The MOD is indeed a sensitive method. With the same data, one could argue that the saturation of the correlation dimension estimation is not so clear. However, if the method is applied using the above guidelines and if the data is properly acquired, it produces larger correlation dimension values for the healthy subjects compared to those of the unhealthy group. This suggests larger complexity and nonlinearity. This postulation is further verified by the results obtained using the approximate entropy and as illustrated in Figure 5. Despite all these arguments, it is evident that plots of healthy subjects exhibit unambiguously increased nonlinearity compared to the others. Therefore, despite their sensitivities, these nonlinear methods still produce an obvious and incontrovertible discrimination between the two subject categories. This is further verified by demonstrating coherence among all methods by applying them all to the data. In addition, experimental results have been verified with other recordings freely available in the internet. The MOD appears to be useful for clinical discrimination between healthy subjects and those with coronary pathologies, even in some cases where the physician make an inaccurate diagnosis.

References