Can We Find Deterministic Signatures in ECG and PCG Signals?

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Abstract: The first step in any non linear time series analysis, is to characterize signals in terms of periodicity, stationarity, linearity and predictability. In this work we aim to find if PCG (phonocardiogram) and ECG (electrocardiogram) time series are generated by a deterministic system and not from a random stochastic process. If PCG and ECG are non-linear deterministic systems and they are not very contaminated with noise, data should be confined to a finite dimensional manifold, which means there are structures hidden under the signal that could be used to increase our knowledge in forecasting future values of the time series. A non-linear process can give rise to very complex dynamic behaviours, even though the underlying process is purely deterministic and probably low-dimensional. To test this hypothesis, we have generated 99 surrogates and then we compared the fitting capability of AR (auto-regressive) models on the original and surrogate data. The results show with a 99\% of confidence level that PCG and ECG were generated by a deterministic process. We compared the fitting capability of an ECG and PCG to AR linear models, using a multi-channel approach. We make an assumption that if a signal is more linearly predictable than another one, it may adjust better to these AR linear models. The results showed that ECG is more linearly predictable (for both channels) than PCG, although a filtering step is needed for the first channel. Finally we show that the false nearest neighbour method is insufficient to identify the correct dimension of the attractor in the reconstructed state space for both PCG and ECG signals.

1 INTRODUCTION

Over the last decades, there has been an increasing interest in creating joint electrical-mechanical heart models using multi-source signals from the cardiac system. Therefore it seems crucial that we must characterize these sources. Non-linear methods have been successfully tested and used to study the dynamics of the system. One interesting idea is that aperiodicity in the data may not be due to a stochastic process but due to a non-linear deterministic system. False nearest neighbours method (FNN) (Kaplan, 1992-1993) have been widely and somewhat blindly used to estimate the minimum necessary embedding dimension. (Hegger and Kantz, 1999) identified some limitations on FNN statistic in distinguishing between low-dimensional chaotic data and their corresponding surrogate data, giving as an example a simple ECG record, although they did not make any assumptions or claim that ECG signal is a deterministic process.

In this study, we have expanded Hegger's work and incorporated PCG analysis in order to pave the way for multi-source fusion of these signals into a unified model. Possibly more importantly, we performed a null-hypothesis experiment using surrogate time series in order to distinguish and quantify the differences between PCG and ECG from a Gaussian stochastic process. This work's primary aim is to study the deterministic behaviour of a PCG and ECG signal. We aim to understand which signal is more linearly predictable and as a consequence more reliable. This will give us clues on how to combine information from the acoustic and electromagnetic system in order to create a more interesting space capable of detecting pathological diseases with higher accuracy than using a single ECG or PCG approach. If the PCG and ECG are deterministic signals then the secondary aim of this paper is to estimate their embedding dimension. An overestimation would lead to inaccurate results since all coordinates would be contaminated by noise and it also would lead to an increase in computational effort as most of the operations for prediction or classification scale exponentially with the embedding dimension. Finally, it could also lead to a

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poor performance of the general algorithm used, simply because it treats the signal to be more complicated than what it really is. A sub-estimation would result in the incapacity of the system to reconstruct the phase space.

This paper is structured as follows: ECG and PCG morphologies are presented in section 2. Surrogate time series are explained in section 3 followed by an introduction to false nearest neighbours in section 4. Materials are presented in section 5. Results and conclusions complete the paper in sections 6 and 7.

2 ECG AND PCG MORPHOLOGIES

An electrocardiogram (ECG) is an electrical signature of the heart and it can give us indicators of pathological conditions. There are 3 main deflections in an ECG (Figure 1): the P wave, QRS complex and T-wave. These waves correspond to the far field induced by specific electrical phenomena on the cardiac surface, namely, the atrial depolarization P, the ventricular depolarization, QRS complex, and the ventricular repolarization T.

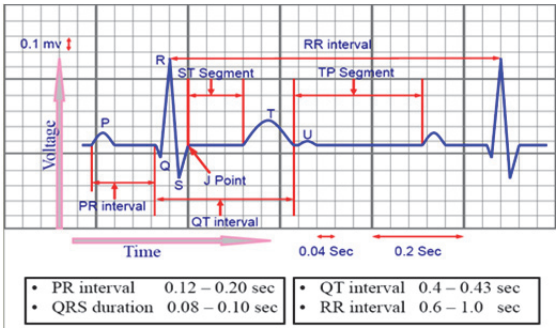


Figure 1: The main components and segments in an ECG signal (adapted from (Guyton, 2006)).

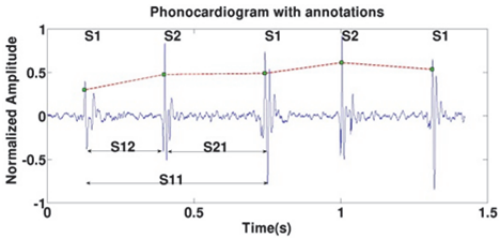


Figure 2: A typical heart sound and its four main components: S1, S2, Systole and Diastole.

In Figure 2 we can observe the various components of a heart cycle, including S1 (first heart sound) and S2 (second heart sound). These establish the boundaries of the other two fundamental components of a heart cycle: the systole (period between S1 and S2), and the diastole (period between S2 and S1). S1 and S2 are generated by the opening and closing of the various heart valves and in some auscultations we have the presence of additional sounds such as S3, S4 or murmurs (Guyton, 2006).

3 SURROGATE TIME SERIES

The ECG and PCG signals gives us a time series. In order to find a phase space we need to convert the observations $\{s(n)\}$ into state vectors. A delay reconstruction is formed by delay vectors given by :

$$x^i(n) = [s(n), s(n+\tau), \cdots, s(n+(m-1)\tau)] \quad (1)$$

Where n is the sample time, m is the embedding dimension and τ is the delay time; the choice of the two embedding parameters m and$\tau$are crucial to probe deterministic behaviour with minimal computational effort. Taken's theorem (Kantz, 2004) states that for ideal noise-free data, there exists a dimension m such that the delay vectors $x^i(n)$ are equivalent to phase space vectors. If m is enough for this purpose every $m' > m$ will work as well, but this redundancy when considering chaotic data leads to a lower performance of many algorithms. In particular, the noise that is always present contaminates all the components of our delay vector and the computational cost is higher, which compromises any attempt for prediction or control. Also in this way the minimum embedding dimension gives us a lower bound on the dimensionality of the system. The delay time τ measures the temporal correlation between the states of $x^i(n)$. If τ is small compared to the time scales successive elements of the delay vectors are strongly correlated. On the other hand, for large τ successive elements are almost independent. In the limit of infinite data and infinite precision any time delay would work but in reality we have a range of acceptable values for τ. This motivates the search for optimal embedding parameters (m, τ) for our problem.

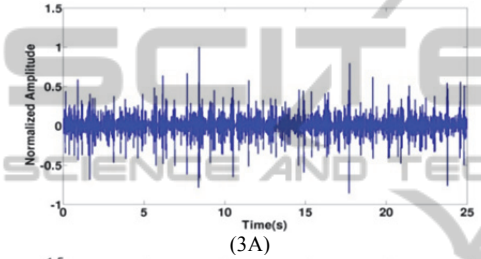
3.1 Algorithm to Generate the Surrogates

In this paper the process to generate the surrogates of the original data is the Iterated Amplitude Adjusted Fourier Transform (IAAFT) surrogates, since it already takes into account the bias towards a

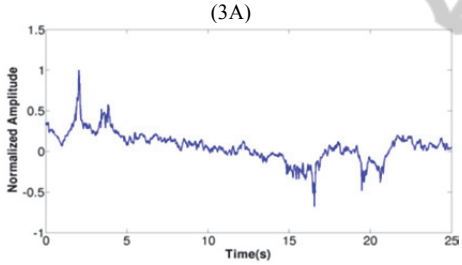
too flat spectrum, when the length of the time series is not large enough, like it happens in Amplitude Adjusted Fourier Transform (AAFT) (Schreiber, 2000).

$$S_k^2 = \left|\sum_{n=1}^{N} s(n) e^{\frac{i2\pi kn}{N}}\right|^2 \quad (2)$$

These components are multiplied by a random phase $e^{i\phi_k}$ where ϕ_k are uniformly distributed in $[0,2\pi]$ and $\phi_{N-k} = -\phi_k$. Different phases yield new surrogates. As a first step we apply a random shuffle to $\{s(n)\}$ that returns $\{s(n)^0\}$. The i-th shuffle $\{s(n)^{i-1}\}$ must have the desired power spectrum. This is accomplished taking the Fourier transform of $\{s(n)^{i-1}\}$ and replacing the squared amplitudes $S_k^{2,i-1}$ by S_k^2 and then transforming back.

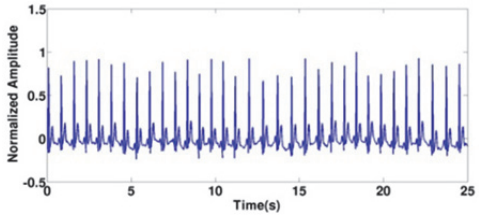


(3A)

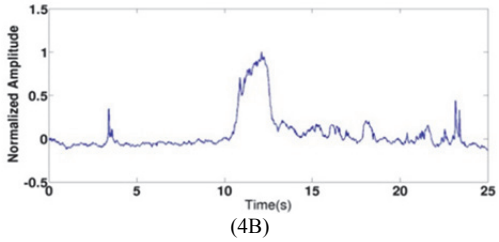


(3B)

Figure 3: PCG signal (A) and it is corresponding surrogate (B).



(4A)



(4B)

Figure 4: ECG signal (A) and it is corresponding surrogate (B).

Although we achieve the correct spectrum, the distribution is modified. A second-step is required to rank-order the resulting series to strictly assume the values taken by $\{s(n)\}$. This modifies the resulting spectrum $\{s(n)^i\}$ so the 2 steps have to be repeated several times until the algorithm converges. The TISEAN implementation was used to this end (Kantz, 2004).

3.2 The Null Hypothesis

The null hypothesis is defined for a time series in terms of a class of processes that is assumed to contain the specific process that generated the data (Schreiber, 2000). In this section we are interested in understanding the underlying dynamics of the signal, mainly if deterministic signatures are present. In other words, we want to test if the data was not generated by a random stochastic process but by a deterministic system. If that assumption is true, we should observe temporal correlation in our data points which is something that could not happen in a surrogate time series, since any linear temporal correlation between successive data points have been completely destroyed by the process. We choose the AR (autoregressive) linear model with nonzero coefficients and two consecutive lag samples.

$$y[n] = c_1 y[n-1] + c_2 y[n-2] \quad (3)$$

Where c_1 and c_2 are the model coefficients. These are calculated during the training phase using the first half of the signal. After this optimization step, the algorithm is going to predict the newest values using the second half of the signal (equation (3)). Finally the mean square error ($\bar{e}^2$) is computed from the observed and the predicted values, as it described in equation (4).

$$\bar{e}^2 = \frac{\sum_{i=1}^{N}\{(y_i^{pre} - y_i^{obs})\}^2}{N} \quad (4)$$

We argue that if a signal is deterministic it may be more predictable than a non-deterministic one, unless in cases of very noisy systems. A pre-processing step is thus recommended in order to attenuate the noise. First we select a residual probability α of a false rejection, corresponding to a level of significance $(1-\alpha)*100\%$, then for the one-sided test we generate $M = \frac{K}{\alpha} - 1$ surrogate sequences, where K is a positive integer corresponding to a total of $\frac{K}{\alpha}$ sets. Therefore the probability of the data has one of the K smallest prediction errors is exactly α. In our case, K is set

equal to 1 in order to minimize the computational effort, since mostly of the computational time is generating the surrogates.

4 FALSE NEAREST NEIGHBOURS METHOD (FNN)

The False Nearest Neighbours (FNN) method was developed (Kennel, 2002) to estimate the minimum embedding dimension necessary to correctly represent the dynamics of a system. It is based on the uniqueness property of the phase space trajectory for deterministic systems in which points that are close in the phase space remain close under forward interaction. The nearest neighbour of a point is considered to be a false neighbour if they are close purely by a projection effect. Therefore, the optimized value for the embedding dimension is the minimum value which correctly represents the attractor (only for correlation dimension) (Kennel, 1992). For the implementation we take a given $x^i(n)$ in m dimensions and find the nearest neighbour $\tilde{x}^i(n)$. The Euclidean distance in m-dimensions is:

$$R_m^2(n) = \sum_{k=1}^{m} ([s(n+k\tau) - \tilde{s}(n+k\tau)])^2 \quad (5)$$

The same is done for $m+1$ dimensions, where this is simply the previous vectors with an extra component $s(n+m\tau)$. So:

$$R_{m+1}^2(n) = R_m^2(n) + ([s(n+m\tau) - \tilde{s}(n+m\tau)])^2 \quad (6)$$

The specific test for false neighbours is given as:

$$\rho_r = \frac{s(n+m\tau) - \tilde{s}(n+m\tau)}{R_m(n)} \quad (7)$$

If the increase in distance is larger than a given threshold ρ_r (usually $10 < \rho_r < 20$) we name these points as false nearest neighbours. When this quantity drops to zero we have unfolded the attractor into a m-dimensional Euclidean space.

4.1 FNN statistics

The previous criterion alone does not provide a safe standard to determine a proper embedding dimension. It is known that stochastic processes (characterized by high dimensional attractors) yield a vanishing or at least a small fraction of false nearest neighbours. The fact is that even if $\tilde{x}^i(n)$ is the closest neighbour to $x^i(n)$ when $R_m(n)$ is comparable with the size of the attractor R_A the criterion does not count this as a false neighbour. So, a second test gives $(\tilde{x}(n))^i$ as a false neighbour if :

$$\rho_A = \frac{s(n+m\tau) - \tilde{s}(n+m\tau)}{R_A} \quad (8)$$

ρ_A has typical values between 1 and 2. R_A is usually chosen as :

$$R_A = \left(\frac{1}{N} \sum_{n=1}^{N} [s(n) - \bar{s}]^2 \right)^{1/2} \quad (9)$$

where $\bar{s}$ is the average value of the observed data.

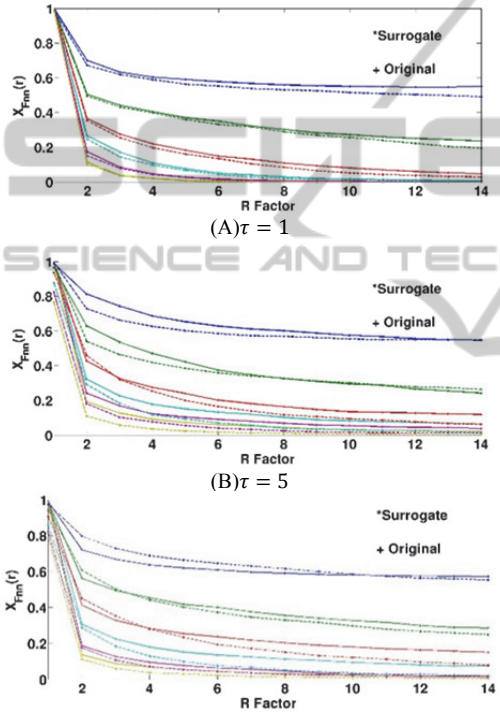
5 MATERIALS

The used dataset was collected in the Center for Cardiothoracic Surgery (CCT-CHUC) and the Cardiology Department (DCCHC-CHUC) of the Centro Hospitalar e Universitário de Coimbra under the scope of the HeartSafe project. The dataset is composed by 33 healthy patients: 31 males and 2 females. The Body Mass Index average is 24 (BMI) and their age average are 30 are summarized in Table 1. Two ECG channels and one PCG were recorded simultaneously and annotated by an expert physician.

6 RESULTS

We test the null-hypothesis for both ECG and PCG signals with and without filtering. The ECG signal is filtered using a low-pass filter followed by high-pass filter in order to form a bandpass filter in the 5-15Hz frequency range and normalized at last. In Figure 3.A it is represented a typical phonocardiogram signal (PCG), which was used to generate the surrogate data plotted in Figure 3.B. Different time lags were chosen in order to demystify its importance in the false nearest neighbours (FNN) statistic. The results in Figure 5 showed a lack to sensitivity of the false nearest neighbour method to distinguish the original PCG from the surrogate. In other words, both curves show the same trend regardless of the dimensionality m. These results can be extrapolated easily to the ECG as it is shown in Figure 6 (Govindan, 1998). The false nearest neighbour method revealed itself as not capable to distinguish deterministic from a stochastic process in both PCG and ECG signals. All graphics plotted in Figures 5-6 show that the percentage of FNN tends to zero more quickly for a higher embedding dimension m, independently of the time delay τ. This can be explained

by the fact of adding an extra $(m+1)^{th}$ component $s(i+m\tau)$ in a vector $y(i)$ of dimension$m$. As an alternative explanation, this can be due to a specific geometric characteristic of the attractor. This topic will be explored in future works. Regarding the embedding dimension tested, the decay velocity is faster in ECG than in PCG, which possibly means that an ECG signal is more folded than a PCG one in the reconstructed phase space. In some cases, it is observable an increase in FNN statistics. This might be happening because of noise, since a high dimension system is by nature more susceptible to it than a lower one.



(A)$\tau = 1$

(B)$\tau = 5$

(C)$\tau = 10$

Figure 5: Percentage of FNN for PCG data and their surrogate for $m = 1 \rightarrow 6$ (from top to bottom) using different τ, R factor is the maximum distance between pairwise points to be considered a true neighbours.

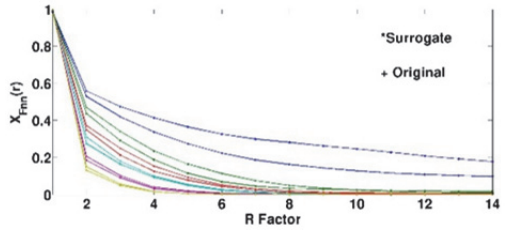


Figure 6: Percentage of FNN for ECG data and their surrogate for $m = 1 \rightarrow 6$ (from top to bottom) using $\tau = 1$, R factor is the maximum distance between pairwise points to be considered a true neighbours.

The null-hypothesis was designed to test if the ECG and PCG data represents a deterministic process. In order to create a 99% statistic significance test, we have generated M = 99 surrogates using the IAAFT algorithm. For the evaluation of the AR performance in the surrogate data, we have followed the same procedure discussed on the previous sections.

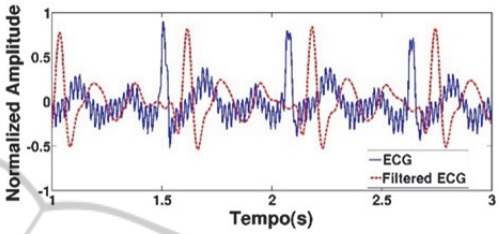


Figure 7: The ECG (blue) and its filtered (red) in channel 1. The bandpass filter used is adding a constant phase to the original ECG signal.

We have tested the null-hypothesis using two ECG and one PCG signal. The ECG signals were recorded at 600Hz and 44100Hz sampling frequency from two different channels (Figure 7). The PCG was recorded at 44100Hz sampling frequency.

Table 2: Mean square error ($\bar{e}^2$) from the Original ECG and PCG series and their corresponding surrogates.

	Original	**Surrogate$_{Min}$**
$ECG^{channel1}$	2.02E-3	1.70E-3
$ECG^{channel2}$	1.18E-7	7.65E-5
$ECG^{channel1}_{Filtered}$	2.00E-7	8.43E-4
PCG	5.51E-6	1.47E-4

The HeartSafe dataset is composed by 960 seconds of record in average, although we used records of only 9.6 seconds to speed up the process. Results are presented in Table 2.

With the exception of the non-filtered ECG in channel 1, both PCG and ECG have smaller mean square error ($\bar{e}^2$) than their corresponding minimum surrogate series. Therefore we can conclude with a 99% of confidence level that ECG and PCG were not generated by a random stochastic system but instead by a non-linear deterministic system. For the non-filtered ECG in channel 1, the noise level was unusually high (Figure 7), therefore the noisy stochastic components are predominant under the sources of information. This result lead to an impossibility of rejecting the null-hypothesis for such noisy levels.

Table 3: HeartSafe dataset results.

	ECG Ch1	ECG Ch2	PCG	ECG Ch1 Filt
$\bar{e}^2$	3.29E-4	1.67E-7	1.87E-6	2.48E-7

We also compare the fitting capability of ECG and PCG to AR linear models (Table 3). We make an assumption that if a signal is more linearly predictable than another one, it may adjust better to these AR linear models. The HeartSafe dataset results showed that filtered ECG is a more linearly predictable signal than filtered PCG. The first ECG channel exhibits higher noise levels when compared to the second one, as a consequence $\bar{e}^2$ is greater in the first channel making it a more unreliable channel.

7 CONCLUSIONS

Using a null hypothesis test, we concluded with 99% of confidence that the PCG and ECG data came from a deterministic system, although potentially contaminated with a broad type of noises.

The FNN statistic revealed itself to be insufficient to extract an embedding dimension from both PCG and ECG signals, simply because it was never observed a zero fraction of false neighbours. Therefore any attempt to build a phase space turns to be insufficient to completely describe the dynamical system so the embedding dimension does not insure a deterministic mapping. This can be caused by the measurement noise (error which is independent of the system, where all observations are contaminated by some amount) or dynamical noise (feedback process where in the system is perturbed by some amount in each time step (Schreiber, 1996)). Dynamical noise may sometimes be a higher dimensional part of the dynamics with small amplitude. At least one type of the dynamical noise in a PCG is not static but it is periodic or quasi-periodic and it depends on the breathing cycle, making the analysis of PCG a more difficult task. Finally, in the HeartSafe dataset, ECG revealed to be a more linearly predictable signal when compared to the PCG, although a filtering step is needed in channel 1. Therefore, in order to improve the predictability of a multi-signal acquisition system , we suggest to have more PCG than ECG channels, since they are more linearly unpredictable signals.

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