Characterizing complex variability in ECG signals using DFA

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Abstract: *The cardiac time series represented by the electrocardiogram (ECG) has different patterns of complexity inherent to the health conditions and to physical environment of the patient involved. In this work we use the Detrended Fluctuation Analysis (DFA) to characterize the complexity of real and synthetic ECG signals and compare the fine variability of the signals in normal conditions with the signals in the microgravity simulated conditions. With this approach, we can detect the presence of scaling for both simulated and pathologic ECG signals. We validate the MCTS model as a normal ECG simulator and try simulate the pathologic conditions. We can also study the effects of the microgravity in the ECG signals and its changes in complexity.*

1 Introduction

The electrical activity of the heart shows complex behavior in various scales of time and frequency, usually characterized by patterns of variability seen in the electrocardiogram (ECG). A great challenge in the area of biomedical engineering is the automatic and robust characterization of the typical and pathological patterns. The analysis from the electrocardiogram (ECG) provides a qualitative description of the heart electrical activity and is used in the hospital routine in the detection of heart diseases.

A single cycle of ECG represents the successive atrial depolarization/ repolarization and ventricular depolarization/repolarization occurring every beat. This can be roughly associated with the peaks and through the forms of wave known as P, Q, R, S, T, as shown in Figure 1.

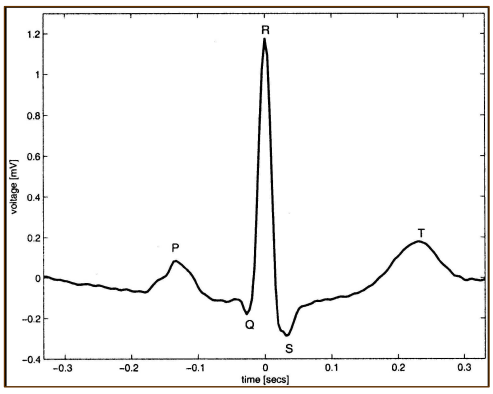


Figure 1: ECG morphology of a normal patient.

MCTS model

The model proposed by McSharry *et al*, known here as MCTS model [1], is a new approach to modeling the cardiac activity. It is a model based on three coupled ordinary differential equations, capable of generating ECG signals synthetic realistic. This model simulates the spread of the electrical impulse throughout the heart, making a sum of all the waves of heart electrical activity (P, Q, R, S and T) (Figure 2) and not only the electrical activity of the ventricles as the best-known models, which, in general, only simulate the ventricular action potential.

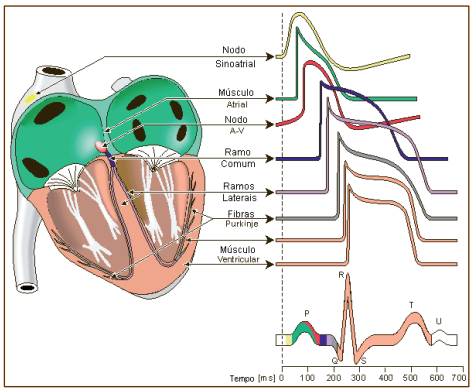


Figure 2: Diagram of the different action potential of various heart cells

The MCTS model generates a trajectory in 3D phase space with the coordinates (x, y,z), as shown in Figure 3. The equations of the dynamic model are described by the equation 1:

$$\begin{aligned} x' &= \alpha x - \omega y \\ y' &= \alpha y + \omega x \\ z' &= -\sum_{i \in P,Q,R,S,T} a_i \Delta\theta_i \exp\left(\frac{-\Delta\theta_i^2}{2b_i^2}\right) - (z - z_0) \end{aligned} \tag{1}$$

where $\alpha = 1 - \sqrt{x^2 + y^2}$, $\Delta\theta_i = (\theta - \theta_i) \bmod 2\pi$ $\theta = a\tan 2(y,x)$, ω is the angular velocity of trajectory as it moves around the limit cycle, $z_0(t) = A\sin(2\pi f_2 t)$, f_2 is the respiratory rate, a_i is the position of the waves in z and b_i is the gaussian width of the waves. This model uses visual analysis of an ECG to assimilate real parameters and variables such as angles, time, a_i and b_i.

The values of parameters used for the implementation of the model, as proposed by McSharry [4] are shown in Table 1.

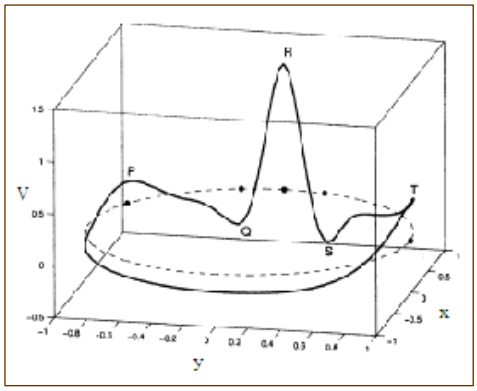


Figure 3: Typical trajectory generated by the dynamic model in 3D space given by (x, y, z).

Table 1: MCTS Model Parameters

Indice (i)	P	Q	R	S	T
tempo (s)	-0.2	-0.05	0	0.05	0.3
θ_i (rad)	$-\pi/3$	$-\pi/12$	0	$\pi/12$	$\pi/2$
a_i	1.2	-5.0	30.0	-7.5	0.75
b_i	0.25	0.1	0.1	0.1	0.4

Microgravity

Due to the limited number of studies that may be conducted in microgravity in space, various simulations have been carried out of microgravity on Earth. Moreover, there is great difficulty in obtaining data from astronauts and also simulated data through parabolic flights by Space Agencies. Thus, the simulation of microgravity has been proposed with different methods and different approaches. The test of inclination (Tilt test) has been used frequently to study the changes in autonomic control in response to the slopes upside down or up [2].

The data used in microgravity in this work were collected by the Laboratory of Microgravity at PUC-RS, using the protocol of the Head Tilt-down test with 0°, 60°, -35° inclination. The effect of microgravity is found in -35 º.

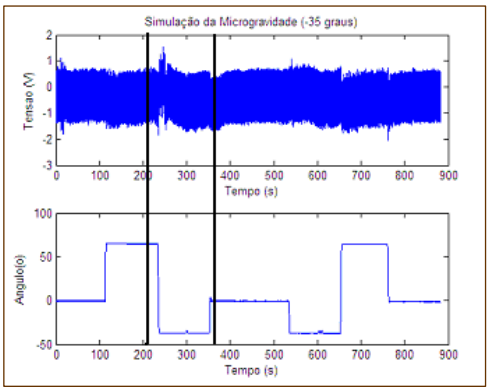


Figure 4: Time evolution of ECG and the angle of inclination.

Detrended Fluctuation Analysis

The Detrended Fluctuation Analysis (DFA), has become widely used in determining the properties of fractals or multifractals scales and the detection of long-range correlations in noise and non-stationary time series. The DFA is the method most used to study the properties of scale in biological signals. Its implementation is direct, robust and has no problems with overlapping linear trends [3].

In this technique the signal originating is first integrated:

$$y(k) = \sum_{i=1}^{k} \{x(i) - E[x]\}$$

In that, E[x] is the average of the signal.

Subsequently, the integrated time series is divided into "boxes" of the same size n. In each "box" the trend place $y_{i,n}$ (k) is calculated by polynomial fitting (least squares) and then, and y(k) is "detrended" subtracting $y_{i,n}$(k). Finally, the square root of the average fluctuation is calculated by:

$$F(n) = \sqrt{E\left[(y(k) - y_{i,n}(k))^2\right]}$$

This calculation is repeated on all scales of time (sizes of "boxes"), generating a relationship between the average fluctuations F (n) and size of the "box" n. If this relationship is linear in a log-log chart, this indicates the presence of power law in scale, according to:

$$F(n) \approx n^A \Rightarrow \log F(n) \approx A \log n$$

In which A or α is the scale exponent, which can be calculated by linear regression in a log-log chart [4].

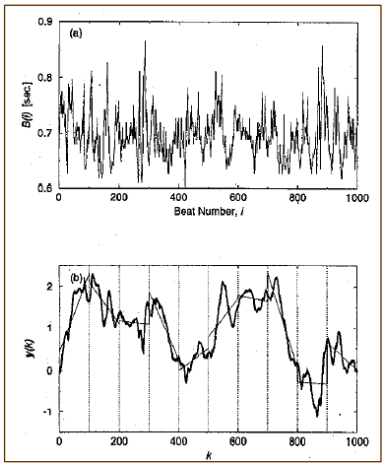


Figure 5: Procedure for calculating the DFA

Results

We could separate the different groups of ECG studied (Figure 7). The ECG in microgravity conditions showed intermediary behavior between the normality and the pathology, showing an increase in the complexity as we can see in Figure 8.

In the Figure 9, the results indicate that the model can be validated. The synthetic normal data has values of α closer to the normal ECG's and the synthetic pathological data has values of α closer to the real pathological ECG's.

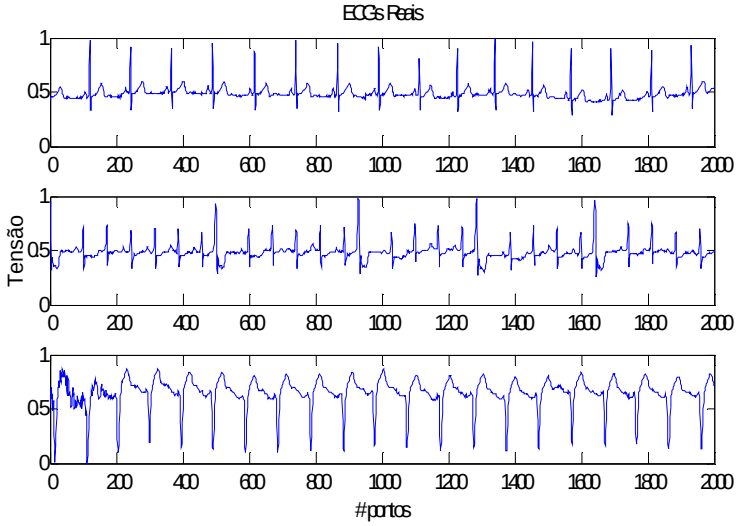


Figure 6: Example of the reals ECG's: normal, with fibrillation and with the sudden death.

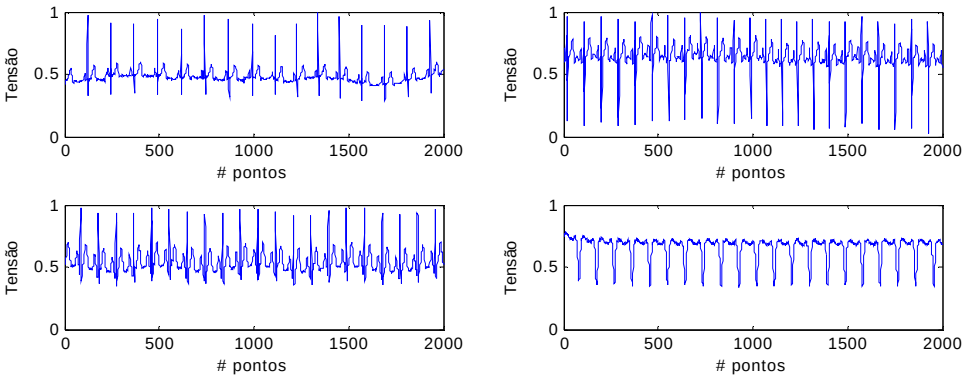
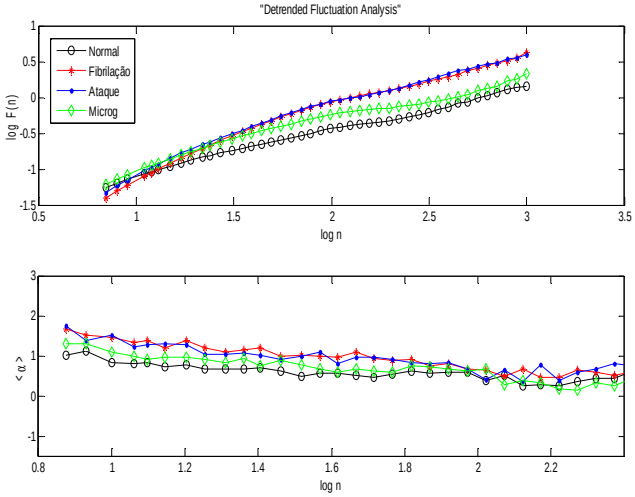


Figure 7: Example of ECG's: Real Normal and in Microgravity conditions and Synthetic (normal and pathological).



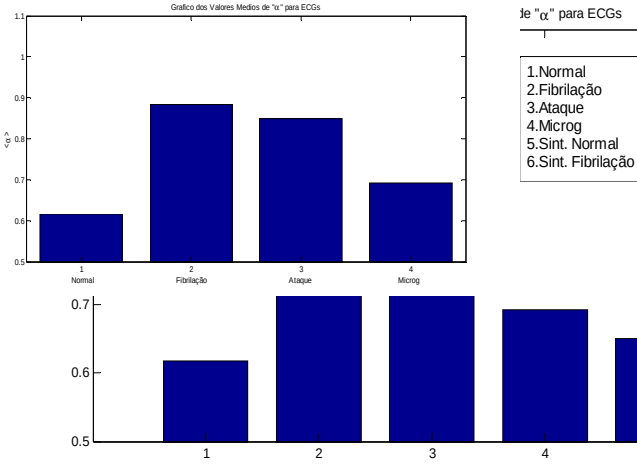
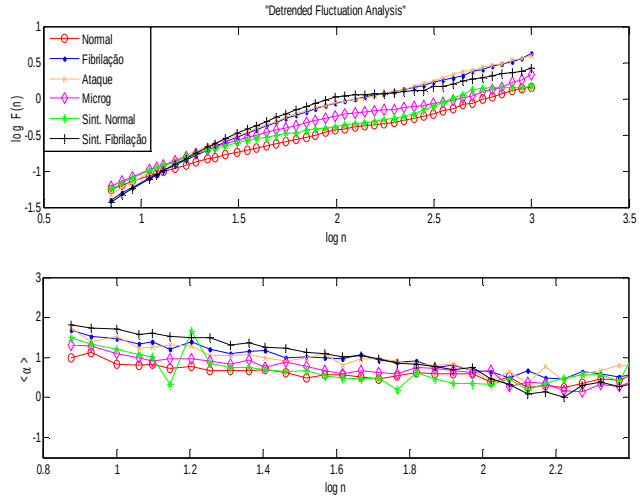
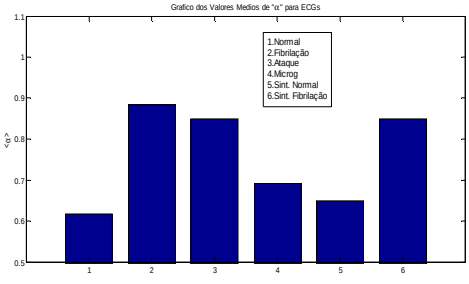


Figure 8: Result of DFA and Histogram of the average of a pathological) and condition of simulated microgravity.





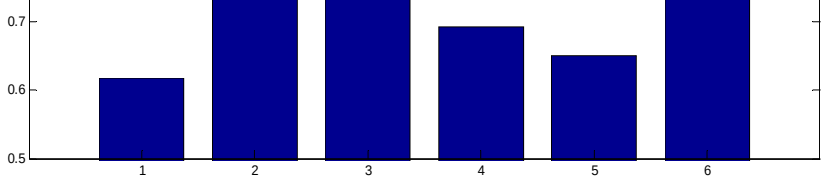


Figure 9: Result of DFA and Histogram of the average of alpha applied to ECG's real and synthetic.

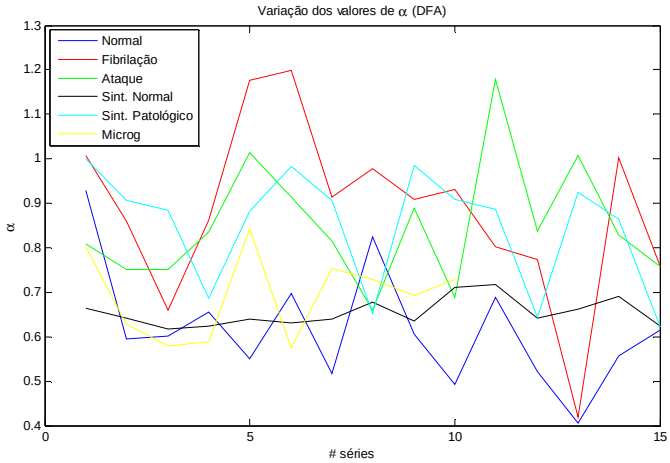


Figure 10: Variations in the values of α for each different group of ECG

Discussion

The technique DFA succeeded in characterize the different groups of ECG's. In the figures above we can see the separation of the groups of normal and pathological ECG's, even for synthetic data. Thus, the model was validated for both the situations of normality and pathology.

The ECG's in microgravity conditions showed intermediary behavior between the normality and pathology, it can indicate the changes that occur in the ECG when the gravity is reduced or zero, making it more complex and similar to the pathologic ECG's.

References

[1] P.E. McSharry, G.D. Clifford, L. Tarassenko, L.A. Smith, IEEE Transactions on Biomedical Engineering, v.50, n.3, pp. 289-294 (2003).

[2] T. Trappe, S. Trappe, G. Lee, J. Widrick, R. Fitts, D. Costill, J Appl Physiol, v. 100, 951-957 (2006).

[3] J.W. Kantelhardt, E. Koscielny-Bunde, H.H.A. Rego, S. Havlin, A. Bunde, Physica A 295, pp. 441-454 (2001).

[4] C.K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Phys Rev, v.49,1685-1689 (1994).