Emerged Signals Derived from Decorrelated Interbeat Intervals Resemble Fourier-Like Filters for Low Frequency Bands

Fausto Lucena (P), Allan Kardec Barros, and Noboru Ohnishi
[1)]Nagoya University, Graduate School of Information Science, Aichi, Nagoya, Japan
[2)]Federal University of Maranhão, Department of Electrical Engineering, MA, Sao Luis, Brazil

lucena@ohnishi.m.is.nagoya-u.ac.jp

Abstract — Interbeat power spectrum density illustrates the autonomic system controlling the heart. Alternatively using coding theory, we suggest that cardiac electrical activity can be seen as frequency band division. Normal cardiac rhythm resembles Fourier-like filters between 0.0 – 0.15 Hz. Moreover, those filters lose the maximally localization in time character for mild to serious non-sinus rhythm.

***Keywords* — Coding theory, Electrocardiogram, Principal Component Analysis, Interbeat intervals, Time and frequency analysis**

1 Introduction

Generative models are thought to be able to give insights of the causes underlying a specific ensemble of the data. The causes can be seen as the genesis of the observed information throughout a specific ensemble of data, such as auditory, visual, and the olfactory systems. On the other hand, interbeat intervals are biological signals derived from the electrocardiogram (ECG) used to access the autonomic control of the heart. Those signals are able to reflect the homeostatic balance of the body expressed by the cardiac rhythm based on the activity of the autonomous nervous system: sympathetic (SNS) and parasympathetic nervous system (PNS) [1]. The density probability function of the interbeat signals were stressed elsewhere [2], but the basis features composing those temporal structures remain uncovered. What are the principles underlying the stimuli into the heart? Is it possible to infer about the frequency bands division of the heart beat signals?

On the basis of the cardiac neural regulation, one can see that physical signals are received by the sensory neurons and are transmitted to the medulla and the spinal cord. This signal is then transmitted by the motor neurons on behalf of the autonomic control functions to regulate the normal rhythm of the heart. Adapting the efficient-coding theory [3] for autonomic cardiac information implies that if the cardiac cells are receiving several stimuli of biological sensors, those ones are ``somehow" efficiently tuned to respond to the pattern of the neural code used to control the heart rhythm. In fact, the neural discharge occurs in the sinoatrial node by antagonistic stimuli controlling the heart rate. If one discharge stimuli from higher brain area acting into the sinoatrial node (SNS) might be balanced by the other to counter the previous stimuli (PNS), and then the normal sinus rhythm is maintained. We can assume that the simplest framework to uncover the cardiac stimuli regulation is decorrelating the outputs of the cardiac system using principal component analysis.

2 Modeling the Causes of the Cardiac Control

By taking n information segments, we can see the observed signal $x(t)$ as a linear combination of sparse ``causes" s, i.e. being modeled by an infinite number of basis functions A as

$$x_n(t) = As. \tag{1}$$

The problem is to find the filters $W = A^{-1}$. Thus Eq. (1) becomes, $s = Wx$.

Given that W and s are unknown, we need to infer about the statistical structure of $x(t)$ to find the structure that is more approximate for the pattern of the signal analyzed. Since there are several solutions for this problem, we assume that sources s are uncorrelated, i.e. $ss^T = I$. Then we obtain

$$W^T W = C^{-1}, \tag{2}$$

where C is the covariance matrix of the observed signal $x(t)$, or similarly it can be solved by $AA^T = C$. Assuming that W is mutually orthogonal, the solution becomes principal component analysis (PCA). It means that vectors of PCA represent the maximum variance of the $x(t)$, where the coefficients are $E\left[a_i a_j\right] = E\left[a_i\right] E\left[a_j\right] = 0$.

To extend this process to heartbeat intervals, we need to understand that SNS and PNS are structurally different from natural images or speech. For the neural regulation of the heart rate, the higher brain areas do not

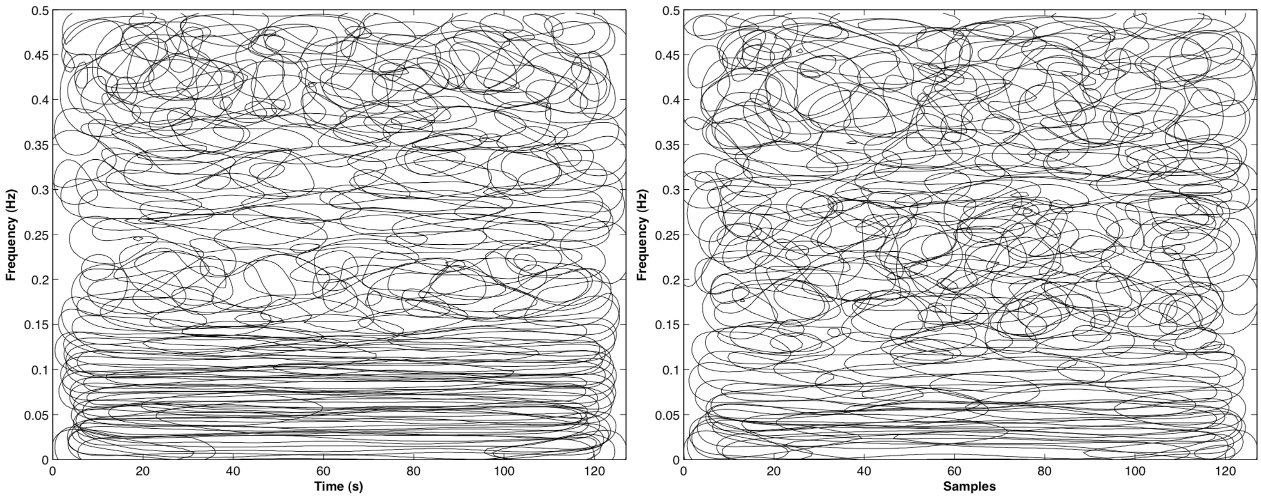

Fig. 1: Contour plot highlighting the core of the energy for 128 emerged basis functions represented in time and frequency space. (Left) Normal sinus rhythm. (Right) Cardiac heart failure.

need to have edge detectors (images) or cochlear cells tuned to speech. Although, we might assume the existence of neurons responding to different frequencies as the latter, but much less specialized, because it is mainly limited to frequency bands connected to two neural discharges: PNS (0.15 – 0.5 Hz) and PNS+SNS (0.03 – 0.15 Hz, where the SNS is more active in this frequency band than the PNS) acting as the motor information.

In this context, the relationships between the input signal and the ensemble that emerges based on PCA analysis are connected by the statistical structure of the interbeat intervals. Hence, we simplify the space of characteristics by selecting interbeat intervals with cardiac rhythms that have representative statistical proprieties among others, such as normal sinus rhythm (NSR), and cardiac heart failure (CHF). The main point is to observe the differences between normal and extreme cases in cardiac rhythms.

3 Results

Figure 1 shows that the emerged basis functions using PCA are mostly meaningless. Although the PCA with representative basis seems to carry enough information to reinforce the idea that the heart rhythm became less complex when accompanied by some physiological process altering the normal heart rate (Fig. 1, left).

As expected for analyzing the maximum variance of the normal and cardiac heart failure dataset, our results show that mutually orthogonal basis functions are represented by partially globalized Fourier transforms. It is remarkable that the emerged filters are tuned until 0.15 Hz of the frequency band intervals, as expected for the spectral response in a controlled healthy subject (Fig. 1 Left) [1]. It might give a partial statistical cause for the defined frequency bands division. Furthermore, the cardiac heart failure (Fig. 1, right) shows the expressive lose of this pattern that can be used as a clinical triage.

4 Discussion and Conclusion

The goal of this work is to use PCA coding scheme to understand what are the causes underlying cardiac neural discharges. Generally, it is quantified by the spectral responses of heartbeat intervals exploited in two defined frequency bands without statistical explanation for this behavior. Herein, we give the first step towards using statistical methods to justify the frequency band division of the autonomic tones.

Our results suggest that heartbeat signals yield a partial PCA code, that is, the emerged signals in low frequency bands (0.0 – 0.15 Hz) show a maximally localized time position (for a healthy heart) that correspond to the Fourier transform definition, whereas the high frequency bands (0.15 – 0.5 Hz) are not maximally localized in time. On the other hand, those principles are not applied to cardiac heart failure. Moreover, Fig. 1 reinforces the standard frequency band division defined [1] for the power spectrum of the interbeat intervals.

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