Analysis based on the Wavelet & Hilbert transforms applied to the full time series of interbeats for a triad of failures at the heart.

P. A. Ritto

Abstract

A tetra of sets which elements are time series of interbeats has been obtained from the databank Physionet-MIT-BIH, corresponding to the following failures at the humans’ heart: Obstructive Sleep Apnea, Congestive Heart Failure, and Atrial Fibrillation. Those times series has been analyzed statistically using an already known technique based on the Wavelet and Hilbert Transforms. That technique has been applied to the time series of interbeats for 87 patients, in order to find out the dynamics of the heart. The size of the times series varies around 7 to 24 h. while the kind of wavelet selected for this study has been any one of: Daubechies, Biortoghonal, and Gaussian. The analysis has been done for the complete set of scales ranging from: 1-128 heartbeats. Choosing the Biorthogonal wavelet: bior3.1, it is observed: (a) That the time series hasn’t to be cutted in shorter periods, with the purpose to obtain the collapsing of the data, (b) An analytical, universal behavior of the data, for the first and second diseases, but not for the third.

Keywords: Wavelet-Hilbert, failur, heart

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1. Introduction.

During many years, the study of the Electrocardiogram (ECG) has been useful at the time of prognosticating several diseases of the heart. Commonly a Physician uses to observe the ECG and according to its empirical
or scientific expertise is able to diagnose an injury at that organ. However, that visual study is not always enough to predict or prognostic a sickness of the heart because of the high complexity of the ECG. That difficulty in the study of that signal comes from the intrinsic aperiodic dynamics of the heart and perturbations of that organ due to a set of physiological parameters affecting it. Additionally, the noise coming from the electrodes due to normal changes of position of a patient could modify dramatically the diagnosis of a disease [1]. With the purpose of owning an analytical method to study the ECG, several statistical techniques have been developed many years ago [2, 3]. One of them [3] is of our interest because unveils a hidden behavior of the heart. Such a technique of analysis is useful to obtain unusual nonlinear information of the cardiac dynamics of the human being [3, 4] and another species [5]. The technique follows the steps: (i) Select a wavelet [6]: \( \Psi(m) \) (\( m \) is the \( m \)-th moment, that indicates that \( \int_{-\infty}^{+\infty} x^m \cdot \Psi(x) \, dx = 0 \)) in order to analyze the time series of interbeats: \( x_i \equiv x(t_i), i = 1, 2, ..., n \), (ii) Select a set of temporal scales: \( s \equiv 1, 2, ..., s_0 \), where \( n \in \mathbb{N} \), (iii) Apply a Continuous Wavelet Transform to the time series [6, 7]: \( W_i = \sum_j \Psi(m) \left[ s_j^{-1} (t_i - t_j) \right] \cdot x_i \), where \( W_j \) are the coefficients of the Wavelet Transform, (iv) Apply the Hilbert Transform to the time series: \( h_i \equiv W_i + iH_i \), where \( H_i \equiv H(W_i) [3, 6] \), (v) Obtain the amplitudes \( A_i \equiv \sqrt{W_i^2 + H_i^2} \) for the elements of the new time series, (vi) Normalize the area under the distribution of amplitudes, and (vii) Rescale that distribution such as \( A_i \rightarrow A_i \cdot P_{\text{max}} \) and \( P(A_i) \rightarrow P(A_i)/P_{\text{max}} \), where \( P_{\text{max}} \) is the maximum of the normalized distribution. That technique has been successfully applied to a set of time series corresponding to healthy persons, resulting after the analysis a common Gamma distribution: \( G_\nu(x) = b^{\nu+1}x^\nu e^{-bx}/\Gamma(\nu+1) \), where \( b \equiv \nu/x_o \), being \( x_o \) the value that maximizes the distribution. The wavelet used is the Gaussian: \( g_n(x) = C_n \frac{d^n}{dx^n} e^{-x^2} \). A characteristic parameter for the Gamma distribution is \( \nu = 1.8 \pm 0.1 \), during the day (6 h.), while during the night (6 h.) it is \( \nu = 1.4 \pm 0.1 \). A common Gamma distribution suggests that there is an intrinsic dynamics in the heart similar to that of a system out of equilibrium [3]. That collective behavior is characteristic also of a system that shows a phase transition [8, 9]. It has been found recently, that exists a Biorthogonal wavelet so good as the Orthogonal proposed at Ref. [3], that is useful to perform analyzes by the long term (up to the scale of \( 2^{10} \) heartbeats) [10]. If the wavelet bior3.1 is chosen a single \( \nu = 1.43 \pm 0.03 \) characterizes the heartbeat of healthy humans during the circadian pe-

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riod. The robustness of the technique set up by H. E. Stanley et al. together the diversity of cardiac data at the public databank Physionet \[11\], suggests to test both with the goal of learning about the dynamics of the heart in patients owners of a failure at that organ. In this work it is studied a triad of different sets of patients, suffering of an abnormality at the heart \[12\]: Obstructive Sleep Apnea (OSA), Congestive Heart Failure (CHF) or Atrial Fibrillation (AF), during periods of the order of a day. With the purpose to quantify the change in the distribution of normalized amplitudes due to the wavelet chosen, that one is selected from any of the three quite different families \[6\]: Orthogonal (Daubechies), Biorthogonal, and Non Orthogonal: The Gaussian function, which is used by the authors of the wavelet technique of statistical analysis.

2. Obstructive Sleep Apnea.

This disease consists of the recurrent interruption of the breathing and is associated with diverse physiological injuries: drowsiness, high blood pressure, heart failures, and in general increased mortality. In spite of all these symptoms, OSA is quite difficult to detect and usually it is necessary an expensive research inside a specialized hospital room. Fortunately there are statistical techniques that from the time series of the heartbeat and the breath also, are able to find patterns that could avoid those traditionally prolonged studies \[14, 15\].

3. Congestive Heart Failure.

This is a dysfunction of the heart that avoids that the flux of blood circulates adequately through the organs of the body \[12\]. Characteristic symptoms are: enlarged legs or ankles or difficulty on breathing. Some of those symptoms are produced by \(e.g\). narrowed arteries, past heart attack, high blood pressure, or heart defects present at birth. There is not reference at the literature of a study of CHF using the statistical technique applied here. Interested by answering the same question: Is there a Gamma distribution that represents the CHF sickness? we did exactly the same procedure indicated in previous section but now focused to CHF.
4. Atrial Fibrillation.

This is a disorder of the heart that consists in the quivering of the two atria, instead of its normal synchronized beating. The blood isn’t pumped properly so that the clotes stop its proper fluxing producing a stroke. AF is understood also as a stationary electric wave at the ventricles. It is one of the first malfunctions of the heart in the world. The intrinsic dynamics of the heart in patients suffering of AF is also of our interest.

5. Analysis of the data.

The analysis is done for the following databases at Physionet-MIT-BIH Databank [11]: Polysomnographic (slp), BIDMC Congestive Heart Failure (chfdb), Congestive Heart Failure RR Interval (chf2db), and Atrial Fibrillation (afdb). The full set of recordings have been acquired at Boston’s Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). The data is analyzed after choosing the next wavelets\footnote{The notation for wavelets is used according to Ref. [6]. For Orthogonal and Non Orthogonal wavelets it is used: wavabrN, where small letters indicate the abbreviation for the wavelet “wavabr” and N corresponds to the N − 1-th moment. For the Biorthogonal wavelet the notation is: biorNrNd, where NrNd corresponds to the moments Nr of reconstruction and Nd of decomposition.}: Daubechies: db1, db2, db3, Biorthogonal: bior3.1, bior3.3, bior3.5, and Gaussian: gaus1, gaus2, gaus3, following the steps suggested at the Section 1. The range of selected scales for the study is 1-128 heartbeats.

5.1. Obstructive Sleep Apnea.

A set of 20 OSA patients (slp): men and women between 27 and 60 years of age, with weights ranging 53-153 Kg. is selected with the purpose of studying the statistical behavior of the heartbeat of those sick\footnote{The notation for wavelets is used according to Ref. [6]. For Orthogonal and Non Orthogonal wavelets it is used: wavabrN, where small letters indicate the abbreviation for the wavelet “wavabr” and N corresponds to the N − 1-th moment. For the Biorthogonal wavelet the notation is: biorNrNd, where NrNd corresponds to the moments Nr of reconstruction and Nd of decomposition.}. The length of the recordings varies in length from 7-10 h., sampled at 100 data per second. The RR interbeats where obtained directly from Physionet and then applied to them the wavelet analysis.

5.2. Congestive Heart Failure.

A set of 15 CHF-1 patients (chfdb, NYHA: III-IV \footnote{The notation for wavelets is used according to Ref. [6]. For Orthogonal and Non Orthogonal wavelets it is used: wavabrN, where small letters indicate the abbreviation for the wavelet “wavabr” and N corresponds to the N − 1-th moment. For the Biorthogonal wavelet the notation is: biorNrNd, where NrNd corresponds to the moments Nr of reconstruction and Nd of decomposition.}): 8 females and 7 males between 22-71 years old is studied. Each one of the recordings is around 20 h. in length, sampled at 250 data per second. Another set of 29
CHF-2 patients (chf2db, NYHA: I-III): 2 females, 8 males, and 21 undefined persons between 34-79 years age is analyzed too. That database consists of RR time series sampled at 128 Hz.

5.3. Atrial Fibrillation.

Here, a set of 23 AF patients has been studied. Individual recordings are around 10 h. in duration, sampled at 250 data per second.

In this study the moments of the wavelets chosen are not considered to be higher than 3 because the patients at the hospital are supposed to be almost in rest during the day, and that they don’t use to follow activities that modify their physiological states in a specific way: at least that has not been indicated at the databank Physionet [13]. However, during this work, in some cases, it is necessary to use moments up to 9 because of the complexity of the signals. Analyzes using wavelets in this way have been done previously [17].

The long term study of the heartbeat of sick people starts applying a filter to the time series of RR intervals, according to the algorithm at Ref. [18], in order to avoid the spurious data. After that step it is followed the procedure of wavelet analysis for each of the wavelets and scales already selected. The complete analysis of the cardiac time series is done using a software for the analysis of ECGs that has been previously described at Ref. [19].

6. Results.

Results of the analysis for OSA are shown in Figs. 1-4. Good data collapse holds for: (a) OSA: Scales: 1-128, Wavelet: bior3.1; (b) CHF-1: Scales: 8-128, Wavelet: All of them; (c) CHF-2: Scales: 16-128, Wavelet: Any one with moment higher than 3; (d) AF: Scales: 1-128, Wavelet: None.

The result in (a) shows a quite stable Gamma function through the scales of analysis. If it is chosen the wavelet bior3.1 $\nu = 1.23 \pm 0.05$. This value is quite close to the proposed at Ref. [3] in the case of healthy humans monitored by night. The intrinsic, universal dynamics of the heartbeat of the patients suffering of OSA is now unveiled using the wavelet bior3.1 in the analysis. That does not happen selecting any other wavelets already considered in this work.

The result in (b) suggests that the breathing does affect the dynamics of the heart at the low scales 1-8, that are in the range of the normal breathing. Scales higher than 8 does show data collapse of the times series of CHF-1, for
the full set of wavelets applied. As a consequence, due to CHF-1 the intrinsic dynamics of the heart is hidden, if it is focused at the scale of breathing. The parameter $\nu = 1.56 \pm 0.07$ for representative Gamma distributions, using the wavelet bior3.1. On the other hand, result in (c) shows good data collapse considering scales of the order of 16 and higher but momenta of the order of 3, indicating that the high non stationarity of the ECG corresponding to CHF-2 is not easily characterized -perhaps- because a hugger perturbation of the breathing on the heartbeat. In this case $\nu = 1.35 \pm 0.08$.

The result in (d) indicates that data collapse is not possible applying any of the wavelets previously selected. In order to look for the hidden dynamics of the heart, higher moments up to 9 in Daubechies and Gaussian wavelets are chosen, obtaining a similar answer. Additional Biorthogonal wavelets bior2.2, bior3.7, and bior3.9 are unuseful also at the time of looking for that universal behavior of the data. That suggests that the dynamics of AF patients is so perturbed, that it seems there is not a function representing the time series of heartbeatings.

7. Conclusions.

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References

[1] H. Riekkinen and P. Rautaharju, Circulation 53 (1) (1976) 40; C. U. Vogel et al, Eur. J. Pharmacol. 60 (2004) 461.

[2] T. Mäkilä, Oulu, University library, Oulu, Finland (1998); S. M. Pikkujäämsä et al, Circulation 100 (1999) 393; M. C. Teich et al, Heart rate variability: Measures and Models, Nonlinear Biomedical Signal Processing, Vol. II, Dynamics Analysis and Modeling, Ch. 6, pp. 159-213, edited by M. Akay. IEEE Press, New York (2001).

[3] P. Ch. Ivanov et al, Nature 38 (3) (1996) 323.

[4] Y. Kimura et al, Am. J. Physiol. Heart Circ. Physiol. 275 (1998) 1993.

[5] P. A. Ritto et al, Physica A 349 (2005) 292.
[6] The MathWorks, Inc., The MathWorks-Wavelet Toolbox-Analyze and synthetize signals and images using wavelet techniques 1994-2006 [http://www.mathworks.com/products/wavelet].

[7] J. S. Murguía y E. Campos-Cantón, Rev. Mex. Fís. 52 (2) (2006) 155.

[8] B. J. West, V. Bhargava y A. L. Goldberger, J. Appl. Physiol. 60 (3) (1986) 1089.

[9] J. F. Valdés, Bol. Soc. Mex. Fís. 16 (2) (2002) 85.

[10] P. A. Ritto, Preprint arXiv:0705.3817 (2007).

[11] A. L. Goldberger et al, Circulation 101 (23) (2000) e215 [Circulation [electronic pages: http://circ.ahajournals.org/cgi/content/full/101/23/e215].

[12] American Heart Association, Circulation 93 (5) (1996) 1043 [Circulation [electronic pages: http://circ.ahajournals.org/cgi/content/full/93/5/e1043].

[13] New York Heart Association (NYHA) Classification. Class I: Patients with no limitation of activities; they suffer no symptoms from ordinary activities. Class II: Patients with slight, mild limitation of activity; they are comfortable with rest or with mild exertion. Class III: Patients with marked limitation of activity; they are comfortable only at rest. Class IV: Patients who should be at complete rest, confined to bed or chair; any physical activity brings on discomfort and symptoms occur at rest.

[14] T. Penzel, J. McNames, P. Chazal, B. Raymond, A. Murray, and G. Moody, Med. Biol. Eng. Comput. 40 (2002) 402-407.

[15] J. E. Mietus, C. K. Peng, P. Ch. Ivanov, A. L. Goldberger, Computers in Cardiology 27 (2000) 753-756.

[16] A. A. Aghili et al., Phys. Rev. Lett. 74 (1995) 1254.

[17] S. Havlin et al, Physica A 273 (1999) 46; L. Menglong et al, Chemistry Online 65 (2002) 02071 [http://htxb.icas.ac.cn/2002/c02071.htm]; A. Kourzi, 13th European Signal Processing Conference,
Antalya, Turkey (2005) [http://www.ee.bilkent.edu.tr/signal/defevent/html/abstract/a1469.htm]; S. Rein et al, IEEE International Conference on Acoustics, Speech, and Signal Processing, Montreal, Canada, IV (2004) 341; Ma et al, J. of Zhejiang University SCIENCE A 7 (3) (2006) 361.

[18] K. Ho et al, Circulation 96 (1997) 842.

[19] P. A. Ritto, Acalán: Revista de la Universidad Autónoma del Carmen 40 (2006) 17.
Figure 1: Distribution of the analyzed data corresponding to OSA, after CVAA (shown in small black squares here and at the next figures). The parameters of the fit are $\nu = 1.29 \pm 0.04$ and $\chi^2 = 0.29$. 
Figure 2: Distribution of the analyzed data corresponding to CHF-1, after CVAA. The parameters of the fit are $\nu = 1.53 \pm 0.06$ and $\chi^2 = 0.27$. 
Figure 3: Distribution of the analyzed data corresponding to CHF-2, after CVAA. The parameters of the fit are $\nu = 1.29 \pm 0.06$ and $\chi^2 = 0.85$. 
Figure 4: Distribution of the analyzed data corresponding to AF, after CVAA. Data collapse does not happen.