Effects of Exercise in Diabetic Rats Using Continuous Wavelet Transform

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Abstract. This paper explores an approach to study entropy differentiations of heart's activities estimation in Low Frequency (LF) and High Frequency (HF) bands. Dataset composed of 34 ECGs, obtained from healthy and diabetic rats under normal and exercise living conditions. RR intervals extracted efficiently in order to create Heart Rate (HR) time series. Continuous Wavelet Transform (CWT) has been used, as the most appropriate approach, to evaluate the effects of exercise on healthy and diabetic HR variability (HRV). Statistical analysis performed taking into account both wavelet entropy in the low and the high frequency selected bands and the corresponding index LF/HF of the wavelet coefficients. Our results show that wavelet entropy measure based on CWT decomposition can capture significant differences between the specific frequency regions that are intrinsically related to the structure of the RR signal. According to our analysis, diabetic rats living under exercise conditions appear to have a reduced LF/HF entropy ratio compared to healthy population.

Keywords: HRV, Diabetic, Exercise, Continuous Wavelet Transform, Wavelet Entropy.

1 Introduction

Over the last three decades, signal processing in biomedical field involve the analysis of measurements to extract useful information upon which physicians can make decisions. New ways of biomedical signal processing has been discovered using a variety of mathematical functions and algorithms. One very powerful tool that has been used for the analysis of such signal is the wavelet transform [1].

In normal conditions, there is a balance between the sympathetic and parasympathetic system known as the sympathovagal balance. The RR intervals, as

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shown in Fig. 1, are the key of understanding the activity of the autonomic nervous system [2].

Changes in beat-to-beat heart rate calculated from Electrocardiograph (ECG), known as Heart Rate Variability (HRV) is under continuous research and it is being conducted with several new works. HRV allows the evaluation of the balance mentioned above and has been shown to be a predictor of the occurrence of cardiac dysfunctions [2].

Diabetes mellitus (DM) is a severe illness that has reached epidemic proportions worldwide. In particular, type II diabetes has increased significantly over the last years [3]. Patients with diabetes often develop cardiovascular diseases, like heart failure (HF) mainly caused from hypertension and coronary artery disease [4]. HRV decreases with diabetes and is associated with a high risk of cardiac arrhythmias, sudden death and an overall high mortality and morbidity rates. Exercise is an effective adjunct to pharmacological therapy of diabetes [5].

We decided to investigate this hypothesis by evaluating the entropy of HRV recordings. The estimation of entropy obtained from wavelets, providing a time-frequency representation of the signal with optimal time-frequency resolution. Wavelet entropy overcomes limitations as stationarity that fourier transform takes into account.

The application of wavelets in cardiology has been introduced with several approaches [6]. Detection of ischemia from QRS and identification of biological markers are some of the published applications [7]. All newest wavelet applications in ECG signals are reviewed lately in [8].

Especially, in time frequency analysis of HRV, different wavelet methods has been applied [9,10]. The idea of measure the wavelet entropy from CWT scales has used before in [11,12] and generally wavelets coefficients shown that could be a measure of power in frequency domain that suits to various medical applications [13].

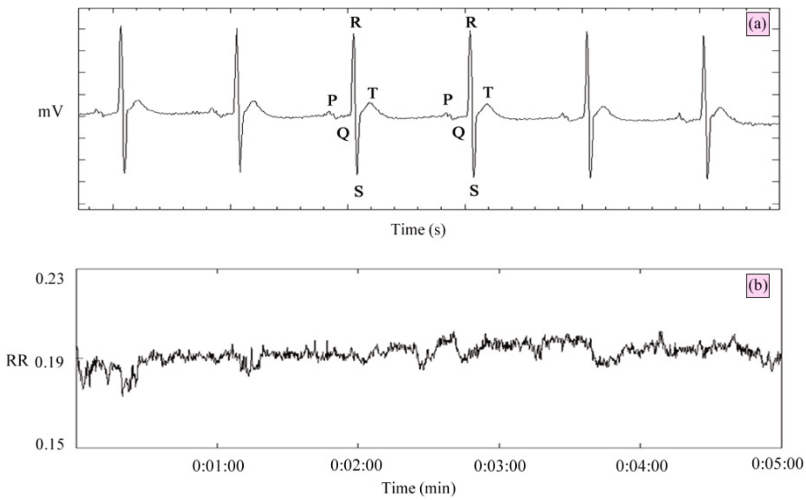

Fig. 1. This scheme demonstrates (a) An ECG graph from a healthy rat with the characteristic features and (b) RR series extracted from an ECG of a healthy rat

In this study, the CWT were utilized to extract and analyze wavelet entropy differentiations of HRV in high frequency (HF), very low frequency (VLF), ultra-low frequency (ULF) and low frequency (LF) bands. Objective of this paper was to evaluate the CWT based wavelet entropy to capture significant differences between the specific frequency regions. Another contribution of this work was to demonstrate the effects of exercise to the LF/HF energy healthy and diabetic subjects living under a daily workout program.

2 Methods

2.1 Wavelet

In the last few years, the wavelet transform has become an important tool in the field of HRV. Although the concept of the wavelets presented earlier, the first algorithm was developed in 1988 and since then many modification of wavelets has been published [14].

A wavelet is a "small wave" of small duration having an average value that is zero. Unlike fourier transform, where fourier sine and cosine functions are smooth, predictable and extend from minus to plus infinity, wavelets could be chosen from an unlimited tank of basis functions, they are usually non-symmetrical, with small duration and a finite period.

The decomposition of a signal using a wavelet transform needs a ψ function sufficiently regular and localized, called "Mother function". Wavelet transformation is a linear operation that decomposes the signal into a number of scales corresponding to frequency components and evaluates every scale with a certain resolution [15, 16].

The implementation of the WT results to a serial list of coefficients named wavelet coefficients, which represent the evolution of the correlation between the signal and the mother function at different levels of analysis (or different ranges of frequencies) all along the HRV series [17].

2.2 Continuous Wavelet Transform

Wavelet transforms categorized in essentially two distinct classes: the continuous wavelet transform CWT and the discrete wavelet transform DWT. Using a variable window width of mother function, related to the scale of observation, the CWT has the ability of isolation of the high frequency features. CWT advantage is to provide varying time-frequency resolution.

CWT that is applied to the signal $\mathrm{s(t)}$ defined as,

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} s(t)\psi\left(\frac{t-b}{a}\right) dt \tag{1}$$

Where $s(t)$ is the signal, $\psi(t)$ is the mother wavelet, a is the scaling parameter in y-axis, b is the shift parameter in x-axis and $1/\sqrt{a}$ is an energy normalization index which makes wavelets of dissimilar scale has the same amount of energy and t is the time. A wavelet family $\psi(a,b)$ is the set of elemental functions obtained from dilations and translations of a mother wavelet ψ.

There are several families of wavelet and each one has specific features. In our study, the choice of the basis function was Daubechies 6 (db6) and the selection made experimentally. The daubechies (db) wavelets have many advantages that make the db wavelets well suited for HRV analysis [18].

The RR signal was resampled at 10 Hz and the wavelet coefficients were calculated on sets of 5 minutes. If the signals included ectopic beats we removed them using a sliding window average filter. Then the sampled signals were interpolated using cubic spline interpolation and resampled in 4 Hz.

In CWT, frequency bands change with scales. We accept that the association of the center frequency F_c of the wavelet function, when the wavelet is dilated by a factor a, becomes F_c/a . Eventually, if the underlying sampling period of the signal is Δ, we also accept that the scale a is expressed as frequency from the equation 2.

$$F_a = \frac{F_c}{a\Delta} \tag{2}$$

The frequency F_a is inversely proportional to scale a. Large scale corresponds to a low frequency and small scales correspond to high frequencies providing details about the HRV signal.

Table 1. Frequency decomposition after CWT and the related scales

HRV Bands	Scales	Frequency (Hz)
ULF	36-124	0.101-0.02
VLF	14-35	0.27-0.102
LF	5-13	0.75-0.28
HF	1-4	3.65-0.90

Frequency decomposition and related scale range are listed in Table 1. After several trials we decided that using a 124 linear scales decomposition of CWT provides high resolution. The ULF band is localized in the scales 124-36, the VLF band in scales 35-14, LF band in 13-5 and the LF band in scales between 4-1.

2.3 Wavelet Entropy

The wavelet entropy (WE) has been proposed as a measurement to quantify the irregularity of a signal. In this study, we used it as a feature to study the effects of exercise conditions in healthy and diabetic rats.

To provide valuable information about these effects in the selected bands, we calculate the wavelet entropy using the wavelet coefficients $C_j(k)$ that correspond at each resolution level j.

For the calculation of energy at each time sample k we use the equation 3.

$$E(k) = \sum_{j=1}^{j} \left|C_j(k)\right|^2 \tag{3}$$

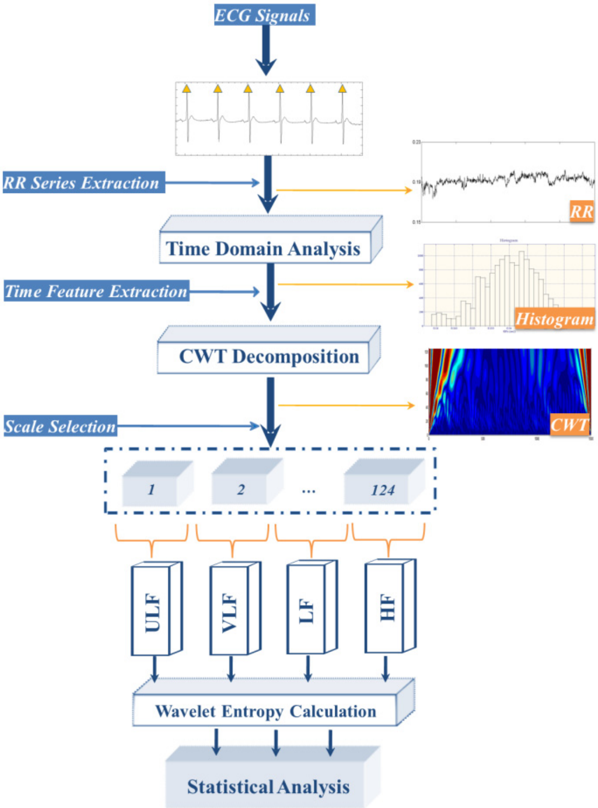

Fig. 2. The proposed method is presented for rat ECG signals. Generally, the first step involves the extraction of R peaks from the ECGs and the construction of RR series. At next step, time domain analysis provides several information for the signals such as beat-per-minute, mean values, standard deviation, etc. The CWT is then applied on the RR interpolated series and the wavelet entropy is computed at each scale. After calculation of the wavelet entropy at each corresponding frequency range the data is ready for statistical analysis.

While for the calculation of the total energy we consider the equation 4

$$E_{total} = \sum_{j=1}^{j} \sum_{k=1}^{N} \left|C_j(k)\right|^2 = \sum_j E_j \tag{4}$$

Dividing the energy at a level j by its total energy is equivalent to define a probability distribution. So the energy in scales is defined from the equation 5, where the $\sum_j p_j = 1$ and the distribution p_j considered as time-scale density.

$$p_j = \frac{E_j}{E_{total}} \tag{5}$$

At last, writing the well-known definition of wavelet entropy, wavelet entropy $H_{WT}(p)$ defined as in equation 6.

$$H_{WT}(p) = -\sum_{i=1}^{j} p_j . log_2[p_j] \quad (6)$$

2.4 Preprocessing Data

Telemetry ECGs were acquired at a rate of 1 kHz using commercially available hardware and software (Dataquest™ A.R.T. 4.0, Data Sciences International, Inc.). Baseline recordings were reviewed for the presence of arrhythmia and/or excessive movement artifacts and records containing such events were not analyzed further.

In this work, all the analysis procedure completed using custom algorithms which was developed in Matlab environment. The proposed method applied to a dataset composed of 34 ECGs, obtained by 24 hour recordings, form healthy and diabetic male Wistar rats under normal and exercise conditions. We select 5 min ECG segments from each group based on visual inspection of the most stable and rhythmic HR. After R wave peak extraction RR series generated.

As for the frequency-domain analysis of HRV, RR series were resampled by a 2nd order quadratic interpolation method at 10 Hz and NaN values removed. Power spectrum was obtained using Welch's method at 256 points with a 50% overlap and Hanning window.

3 Results

As we mentioned above, data were divided into the four groups (healthy, healthy under exercise conditions, diabetics, diabetics under exercise conditions) and CWT analysis was performed for each group. Wavelet entropy calculated for each group from the CWT scales that corresponds to each frequency domain.

In order to extract further information about from the data, classical time domain analysis and frequency analysis performed using custom algorithms as described in details previously [19]. We also calculate the RMS (Root Mean Square), the signal power contained in ultra-low, very low, low and high frequencies using the Welch method [19]. Using the RSM power, we calculate the index of LH/HF, which represents the sympathovagal balance of the heart.

Statistical analyses were performed to evaluate the ability of the wavelet energy to discriminate the effect of exercise in healthy and diabetic population of rats.

All data values normalized and the Analysis of Variance (ANOVA) was used to test the null hypothesis that there is no difference of the mean values of the index of LF/HF of the WE between the groups "healthy – healthy exercise" and "diabetes – diabetes exercise" by analyzing or comparing the sample variance of groups. Statistical significance was established at the $p<0.05$ level.

ANOVA test pointed out that between the groups healthy – healthy exercise and diabetes – diabetes exercise, low and high frequency components and the index HF/LF quantified by WE have significant differences. We also used ANOVA to test the hypothesis for the mean values of index LF/HF calculated from the RMS but the results show significant differences between the healthy and healthy exercise group but no significant differences between diabetic and diabetic exercise group.

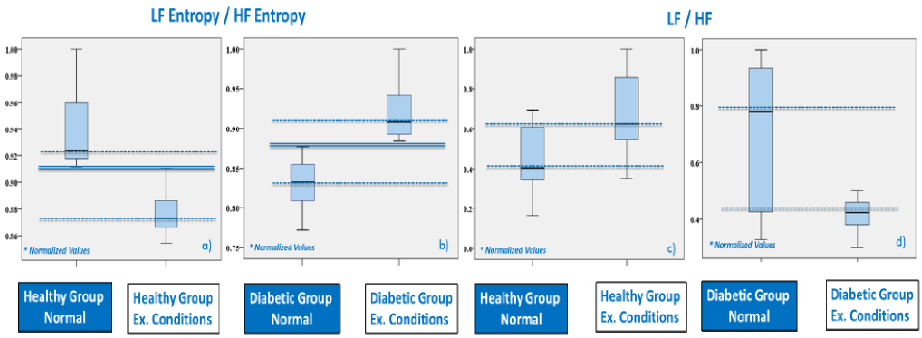

Fig. 3. Box-and-whisker plot of wavelet entropy (normalized) based on CW transform, computed for Healthy, Healthy under exercise, Diabetic and Diabetic under exercise conditions heartbeat intervals. The median for each group presented with the mark (−) in the box, the edges of the boxes are the 25th and 75th percentiles.

We present box-and-whisker plots of the index of LF/HF, calculated from the wavelet entropy from the CWT scales (Fig. 3(a), 3(b)) and from RMS (Fig. 3(c), 3(d)). In Fig. 3, box-and-whisker graphs show the distribution of the LF/HF using the lowest value, highest value, median value and the size of the first and third quartile. It is more clearly shown from the box-and-whisker plots in Fig. 3(a), 3(b) that exercise has notable effects the wavelet coefficients energy of the divided frequencies something that we didn't notice in power spectral indexes (LF and HF powers).

The results of this study showed that the index of LH/HF energy from wavelet coefficients significantly increased in normal subjects under exercise conditions compared with normal subjects. We also find out something very interesting. The index of LF/HF energy from CWT scales noticeable decreased in healthy rats under exercise conditions compared with healthy rats (Fig. 3(a), 3(b)). We couldn't get clearly the same results when we compare the LF/HF from RMS of the HRVs of the same groups as it can be shown in Fig. 3(c), 3(d).

The ANOVA method was also used to statistically test whether exercise conditions produced significant effects on the VLF and ULF bands derived from wavelet scales. Results demonstrated that there wasn't any significant difference in both pair of groups.

4 Conclusion

This study presents an approach based on CWT to estimate the impact of exercise in the wavelet entropy calculated from the wavelet coefficients in four frequency bands. ECGs collected from healthy and diabetic rats under normal and exercise conditions.

To discriminate the effect of exercise in healthy and diabetic population of rats statistical analyses were performed and the results presented with box-and-whisker plots.

We demonstrated that wavelet entropy produced discrimination in LF/HF energy ratio between both pairs of group. Especially, the increment of LF/HF energy index in healthy exercise group compared to healthy group and the decrement of LF/HF energy index in diabetic exercise group compared to diabetic group are very important.

These results suggest considerable potential in using wavelet entropy to estimate the effects of exercise in healthy and diabetic during HRV analysis.

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