MIPRO 2016, May 30 - June 3, 2016, Opatija, Croatia

HEART RATE VARIABILITY ANALYSIS USING DIFFERENT WAVELET TRANSFORMATIONS

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Abstract - Heart rhythm is modulated by the autonomic nervous system in order to adapt to changing cardiovascular loads. The resulting heart rate variability (HRV) is considered as one of the most promising non-invasive markers of the activity of the autonomic nervous system. In this work, the possibility to analyze HRV with wavelet transform was investigated. Specifically, three methods of wavelet transform (CWT, CWTFT and DWT) were compared. DWT showed to be the best one because of the simplicity of decomposition, and quality of reconstruction, high time resolution as well as the shortest computation time and lowest CPU power consumption. DWT showed to have high noise robustness, excellent temporal and good frequency resolution and small influence of the mother wavelet type. ULF, HF and LF components of HRV were assessed using DWT transform. LF/HF ratio was extracted from HRV signal during voluntary breathing apneas and compared to the respiration signal. An increase in LF/HF ratio corresponding to the times of breathing apnea could be observed, indicating that the proposed method could reveal specific changes in the HRV and that LF/HF ratio could serve as a good indicator of breathing apnea.

I. INTRODUCTION

Heart rate variability (HRV) refers to the variation of the intervals between consecutive heartbeats over time. Since the heart rhythm is modulated by the autonomic nervous system, HRV is considered as one of the most promising non-invasive markers of the activity of the autonomic nervous system. HRV power spectrum can be separated into three frequency bands with physiological importance: the ultra-low frequency (ULF) component, low frequency (LF) component and high frequency (HF) component (see Table 1).

Today's most common analysis methods of HRV are spectral analysis techniques using the Fourier transform, or fast Fourier transform (FFT), which assumes that the signal is stationary in time. The problem with such techniques is the lack of temporal resolution. The exact time instant of HRV changes remain therefore unknown. To overcome this limitation, time window frames are often used, so that small segments of the signal are analyzed, for example as in Short time Fourier transform (STFT). However, time-frequency resolution depends on the width of the window used. As a consequence, higher temporal resolution means lower frequency resolution and vice versa. From this reason Wavelet transform as a method which performs time- frequency analysis of non-periodic signal is studied, in order to asses ULF, HF, LF components of HRV.

Table 1. Frequency bands and corresponding frequencies

Ultra-low frequencies (ULF)	0.003 – 0.004 Hz
Low frequencies (LF)	0.04 – 0.15 Hz
High frequencies (HF)	0.15Hz – 0.4 Hz

II. HEART RATE VARIABLITY

Heart rate (HR) or heart pulse is a term that describes frequency of heart beats and is calculated by 1/RR (*60 to get bpm) for each two consecutive R peaks in the ECG signal. Normal HR at rest ranges from 60 to 100 bpm, but it varies according to body's physical needs and activity states (physical exercise, illness, stress, and sleeping, eating etc.).

HR is regulated by sympathetic and parasympathetic input to the sinoatrial node. Sympathetic nervous system (SNS) increases HR, e.g. by releasing hormones, and is activated during stress. On the other hand parasympathetic nervous system (PNS) controls routine functions of the body and mainly decreases heart rate. As a consequence, continuous interplay of SNS and PNS can be measured by the HRV. A static HRV indicates inhibited regulatory mechanisms and a potential pathology.

It is normal that HR changes in time, but the speed of changes (HRV) is what is very interesting to observe. It was shown that PNS is related to the power of HF band, reflecting short-term regulatory mechanisms, while on the other hand SNS activity (and partly PNS) is related to the power of LF band, indicating mid-term regulatory mechanisms. ULF band is related to very slow oscillations and indicates long-term regulatory mechanisms [1]. SNS activation presents a slow increase of HR meaning also reduction in HRV, while PNS activation causes fast decrease of HR and increase in HRV. A reduction of SNS and PNS activity on the other side will result in reverse effects. Increased activation of SNS can be caused by stress, physical activity, standing, 90˚ tilt etc. while activation of PNS can be attained by controlled respiration, cold stimulation of the face or rotational stimuli [1]. Physical exhaustion is indicated both by decrease in PNS and increase in SNS, while on the other side positive stress is indicated as increase in both PNS and SNS. SNS plays an important role in causes of arrhythmias and PNS reduces possibilities of arrhythmias thus having protective role. Altogether, PNS activity is sign of healthier people, while its reduced activity can indicate some type of dysfunction [1].

LF/HF ratio is sometimes introduced to mirror sympathetic-parasympathetic balance. During normal uncontrolled breathing, respiration seems to influence HRV for less than 10%, but controlled respiration increases this influence up to almost 50% [2]. During apnea or suspension of breathing, heart rate changes with frequencies in range from 0.01 to 0.04 Hz. This means that power of ULF band of HRV increases. Also at the same time LF/HF ratio is increased[2] as a consequence of higher sympathetic processes. Similar effect happens during sleep of patients with sleep disordered breathing, where increased LF/HF ratio reflects not only sympathetic dominance but also reduced parasympathetic control [3].

III. RELATED RESEARCH

In the past 20 years there were several papers focused on analysis of wavelet transform, its properties and possible application to HRV analysis. Their approaches were different since wavelet transform, unlike FFT, has many variations and possibilities to be analyzed and used. In [4] authors used a wavelet transform to build a simulated model of a HRV signal and to create an algorithm for HRV signal decomposition. For standard MIT database in [5] HRV data was analyzed on the basis of LF/HF ratio. Wavelet and Wigner Ville Transforms were used for data analysis. The aim of [6] was to examine a set of mother wavelet functions and its orders for implementation in HRV analysis and to highlight the benefit of this transform relating to today's methods. The power distributions in each of different levels and types of wavelets were analyzed. LF/HF ratio was studied on a subject during deep breathing test, and thus an idea of [6] was similar to the present work, but with a different approach. Whereas [6] researched a multitude of mother functions and power ratios, the present paper observes smaller number of functions but other wavelet transform properties were studied too, using various methods of analysis not only the power distribution. In conclusion of [6] more extensive evaluation was suggested, since their results have been obtained from a limited number of subjects. In [7] HRV was analyzed using wavelet and cosine packets. A comparison was made on the same database with results based on the short-term Fourier transform method.

On the other side, numerous papers focus on the application of wavelet transform in healthcare and, in particular, on HRV analysis. In [8] CWT has been used to evaluate the effect of local anesthesia on HRV parameters. The major goal of [9] was to obtain a method which allows completely noninvasive distinguishing of the patients with different levels of coronary artery disease. Evaluation of sub-frequency regions of heart rate variability in supraventricular tachyarrhythmia patients was done in [10] using wavelet packet transform. Wavelet packet transform was also used in [11] for an analysis of sympathovagal balance in patients with major depressive disorder. In order to diagnose and detect diabetes automatically in [12] DWT decomposition was performed.

This is only short overview of papers that were interested in wavelet transform itself and its application on HRV evaluation. It is clear that this is very interesting area and that this technique could further improve understanding of the interactions of the autonomic control systems with the cardiovascular system. While these papers technically analyzed wavelets and showed certain applications in medicine, the presented work compared three methods of wavelet transform by evaluating them with various techniques. At the end the best method was used on HRV analysis. By applying DWT, information not only HRs frequency components but also their timely characteristics can be obtained which are of crucial importance to explain physiological and pathophysiological events. Therefore the results of this paper might serve as starting point or component of some future research.

IV. WAVELET TRANSFORM

The most common spectral analysis technique is the Fourier transform, which assumes that the signal is stationary in time. One problem with such technique is lack of temporal resolution, limiting the precise detection of transient events. In order to overcome this drawback, short-time Fourier transform was designed which is an adapted Fourier transform in a way that only short sections of the signal are analyzed at a time. This maps the signal into two-dimensional signals where it is possible to determine the time instant of frequency changes. However, this information can be obtained only with a certain resolution which is determined by the size of time window. Consequently, once a particular size for the time window is chosen, it stays the same for all frequencies. However, many signals require a more flexible approach where we can vary the window size to determine more accurately either time or frequency.

This can be achieved by the Wavelet transform [13] since it offers variable size of the window. Wavelet analysis allows the use of long time intervals to observe more precise low frequency information, and shorter intervals to observe high frequency information. The name Wavelet transform origins from the fact that waveforms, instead of sinusoid function in Fourier transform, are used. The mother wavelet is a waveform of effectively limited duration that has an average value of zero. Wavelet analysis does not use a time-frequency region, but rather a time-scale region. This is because wavelet analysis works by breaking up a signal into shifted and scaled versions of the mother wavelet. Scaling a wavelet means stretching (or compressing) it, with small scale as compressed signal and large scale as stretched signal. Scale is related to the frequency of the signal in a way that smaller scale means larger frequency and vice versa. Shifting the wavelet introduces a time delay. Wavelet transform works in a way that the mother wavelet is compared sequentially to sections of the original signal. The result is a set of coefficients that are a function of scale and position. These coefficients can be represented and used in many ways. For instance, inverse transform can be performed, which can be used to reconstruct the original signal.

In following subsections three types of wavelet transform will be represented: continuous wavelet transform (CWT), continuous wavelet transform using FFT (CWTFT) and discrete wavelet transform (DWT).

A. Continuous wavelet transform - CWT

In continuous wavelet transform, the correlation of signal with mother wavelet can be calculated for any scale and shift of mother wavelet. CWT is calculated by smoothly shifting the scaled wavelet function along the signal while correlation with that signal section is measured.

B. Continuous wavelet transform using FFT - CWTFT

The problem with CWT is that it is redundant [13] and there is no unique way to define inverse. This means that it is not possible to reconstruct signals from coefficients. CWTFT uses FFT of the wavelet function in order to reconstruct signal. Not all wavelet functions can be used in CWTFT. The wavelet is required to be a real value function and that its FFT has support on only positive frequencies. Wavelets that satisfy this admissibility condition are called analytical wavelets.

C. Discrete wavelet transform -DWT

In order to speed up calculation, discrete wavelet transform was used. In DWT “dyadic” (which means based on factor two) scales are used. Even though only few scales are used to cover the whole area of frequencies, the transform is much more efficient and equally accurate. In each level of transform a signal is decomposed on “detail” and “approximation”. Details are low scale (high frequency) components of signal, while approximations are high scale (low frequency). In each consecutive level, approximation is decomposed into detail and new approximation whose scale is smaller and frequency is larger. Iteration of this process results in wavelet decomposition tree. This process could be continued indefinitely in theory, but in practice it is limited with the resolution of the signal. When individual detail consists of a single sample, the end level of decomposition is reached.

V. RESULTS ON WAVELETS

A. Comparison of methods

The basic idea was to analyze three methods of wavelet transform in order to compare their practical advantages and drawbacks and to choose the most suitable for HRV analysis. Several methods were investigated; pure coefficients comparison, reconstructed signal comparison, sum of coefficients for each of frequency band of interest (ULF, LF and HF), energy distribution and calculation time comparison. Pure coefficients were compared only for CWT and CWTFT since DWT has only few scale levels. In HF frequency range there is almost no difference between CWT and CWTFT, but as approaching to ULF frequencies differences increase (Figure 1). Unfortunately, appropriate explanation for that was not found but it is believed that it is because of some constraints of CWT for very low frequencies. Also some differences could be caused by slightly different boundary frequencies for frequency bands.

For comparison of reconstructed signals, original signal was reconstructed using coefficients for each frequency band separately. This could only be done with CWTFT and DWT method. Again, trends and shape were similar for HF and LF, only for ultra-low frequencies (UFL) differences ware more visible, but even then main trends were similar. In order to compare all three methods at the same time, sum of all coefficients for every frequency band was studied. Curve shapes are the same for all three methods with only minor differences for HF and LF band. For ULF band larger difference for CWT is noticed which agrees with previous results.

Distribution of energy through different frequencies was studied in order to compare methods with Fourier decomposition of signal. The results have shown very good correlation between frequency values of peaks of energy distribution and FFT spectrum.

The last thing to consider was computation time for different methods. CWT method consumes very much time and CPU power. CWTFT takes only few (< 5min) minutes to compute even for signals with almost million samples in comparison to CWT which takes few hours (<3h) for the same task. On the other hand DWT is even faster than CWTFT and it takes under one minute to do the decomposition.

In conclusion, DWT is the most suitable method for the wavelet decomposition for several reasons: time and CPU power consumption, simplicity of decomposition and reconstruction and the quality of decomposition and reconstruction itself.

B. DWT method analysis

1) Quality of decomposition

Quality of decomposition was tested using artificial sinusoidal signals of known frequencies. Frequencies within different frequency bands were used. Energy distribution globally and how well the peak of maximal energy corresponds to the frequency of sinusoid was studied. Reconstruction signals using separately HF, LF and ULF frequency bands ware observed (their amplitude and period) too.

Classification to the correct frequency band from reconstructions could only be performed precisely for frequencies which are in the middle of the frequency band. As the frequency gets closer to the boundaries, other bands too detect these frequencies, but with lower amplitude and wrong period.

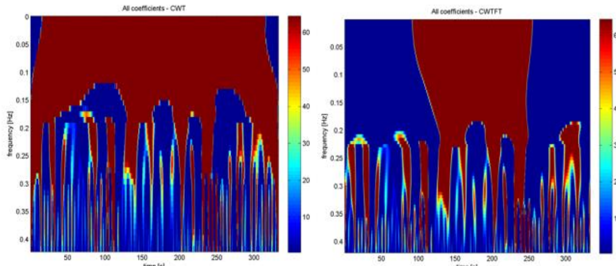


Figure 1. Coefficients comparison for CWT (left) and CWTFT (right).

In addition, the quality of detection based on energy distribution depends whether the frequency is closer or further from one of the frequencies corresponding to the scales that were used in decomposition (since DWT uses dyadic scales). Frequency detection was very precise for ULF and LF band, but less precise for HF band, since here, the frequency resolution is smaller and the error is larger.

2) *Noise influence*

Signal which consists of sinusoid waves of three different frequencies (each within one frequency band) was used. To this signal two different levels of Gaussian noise were added. Reconstruction and energy distribution for signal with and without noise were studied (Figure 2).

Results showed that noise didn't influence decomposition and reconstruction even when amplitude of noise was in range of signal amplitude (SNR 1:1). This is another very positive property of DWT transform.

3) *Influence of chosen wavelet function*

Finally, the influence of chosen mother wavelet function on energy distribution and reconstruction was studied. Four wavelets from Daubechie's family were used: "db3", "db5", "db8" and "db10" as shown in Figure 3. Result of comparison is that the difference is very small for LF and HF band, but for ULF there are noticeable differences. For LF and HF, reconstruction signals look very similar especially for "larger" Daubechie wavelet functions This can be explained by the fact that larger orders of Daubechie functions are more complex, but also more similar to each other than the ones of small order (for example Db1 is actually step function and Db3 is shown in Figure 3). For this reason it is suggested to use enough large Db wavelet functions (≥Db8) for precise calculations. It should be noted, that reconstructed signals in each band are not sinusoid functions as one may expect. This is due to the fact that borders of frequency bands in DWT are not very precise.

4) *Temporal resolution*

For this analysis, a signal with frequency variations was used. First part of the signal is sinusoid with frequency of 0.3Hz which is in HF band, then sinusoid of 0.1Hz (LF band) follows and at the end sinusoid of 0.01Hz (ULF band). It can be seen from reconstruction signals for different frequency bands that time detection of each sinusoid within input signal is very precise (Figure 4). Also energy distribution clearly shows peaks on frequencies values of original signal. This confirms DWT ability to analyze signal in frequency and time domain.

VI. RESULTS ON HRV

A five minute HR signal, sampled with 1000 sample/s, is used to present input and output data of HRV analysis using DWT method. In Figure 5a) original signal and DWT coefficients (absolute value) separately for ULF; LF and HF frequency band are presented. As previously mentioned, PNS is the major contributor to HF component. Slight disagreement exists in respect to the LF component. Some studies suggest that LF is a quantitative marker of SNS activity, while other studies view LF as reflecting both sympathetic and parasympathetic activity. Consequently, the LF/HF ratio is sometimes introduced to mirror sympathetic-parasympathetic balance and also to reflect the sympathetic modulations.

LF/HF ratio is obtained by dividing values of LF coefficients with HF coefficients. Absolute value is used because we are interested in "power" of the LF and HF band in time. After division, LF/HF ratio was averaged in time using median filter with a window size of 1000 samples which corresponds to one second. This way resolution of LF/HF ration is one second which is reasonable considering physiological modulations.

Respiration and HR signals were measured at the same time. Deep breathing or apnea was performed during recording. Such tests are usually used in clinical testing or calibrations. In the signal on Figure 5b) it can be noticed that LF/HF ratio is increased in times that precisely correspond to the times of breathing apnea from respiration signal which indicates that DWT can serve as LF and HF signal extraction from HRV and that such calculated LF/HF ratio can serve as a good indicator of breathing apnea. Moreover, voluntary apnea recordings from 18 subjects, it was shown that the proposed method could reveal specific changes in the HRV.

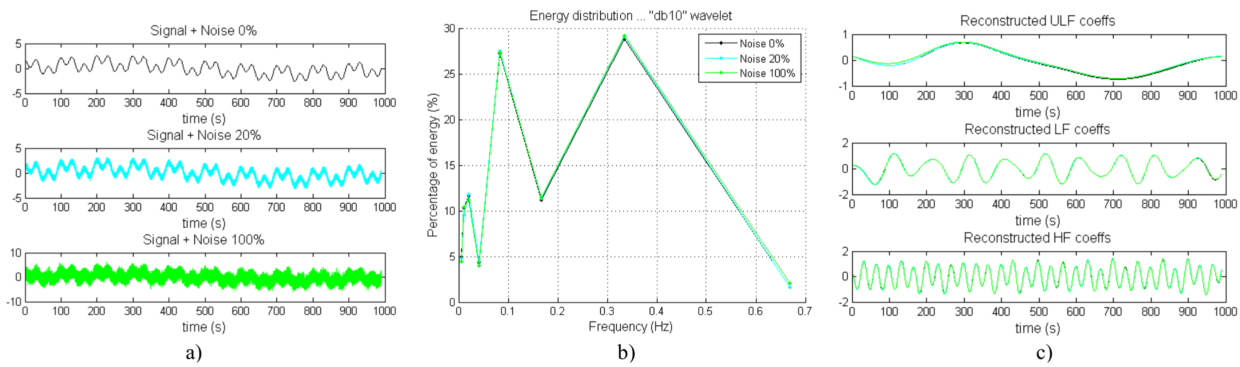


Figure 2. Original sine signal with different levels of noise (a), energy distribution (b) and reconstruction (c).

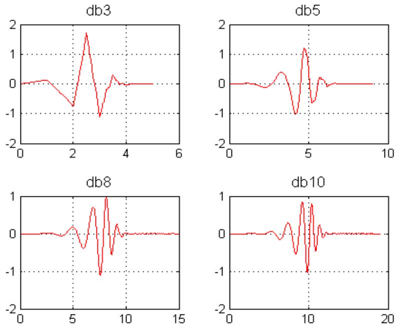


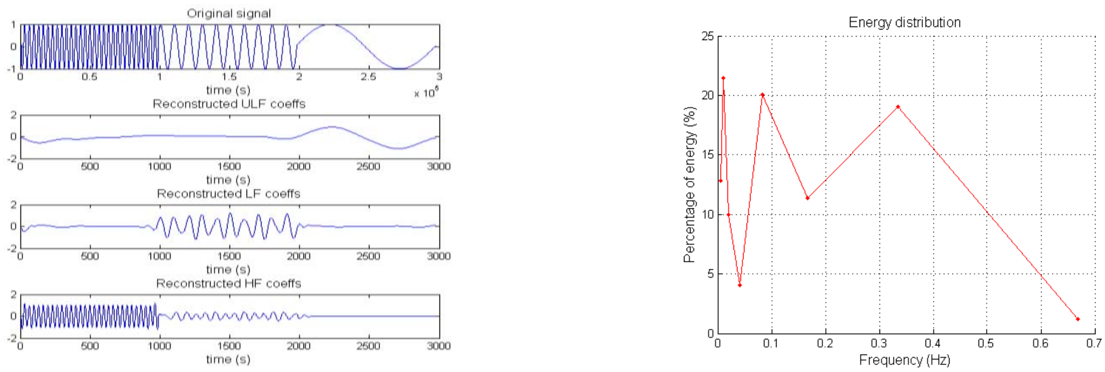
Figure 3. Different types of Daubechies wavelet function

VII. CONCLUSION

In this work, performance and possibilities of different wavelet transform for HRV analysis were investigated. Three methods of wavelet transform were compared using reconstruction for different frequency bands, sum of coefficients for every frequency band, energy distribution per frequencies and computational time needed to conduct decomposition. DWT showed to be the most suitable technique in terms of computational time, CPU power consumption, simplicity of decomposition and reconstruction and analysis quality.

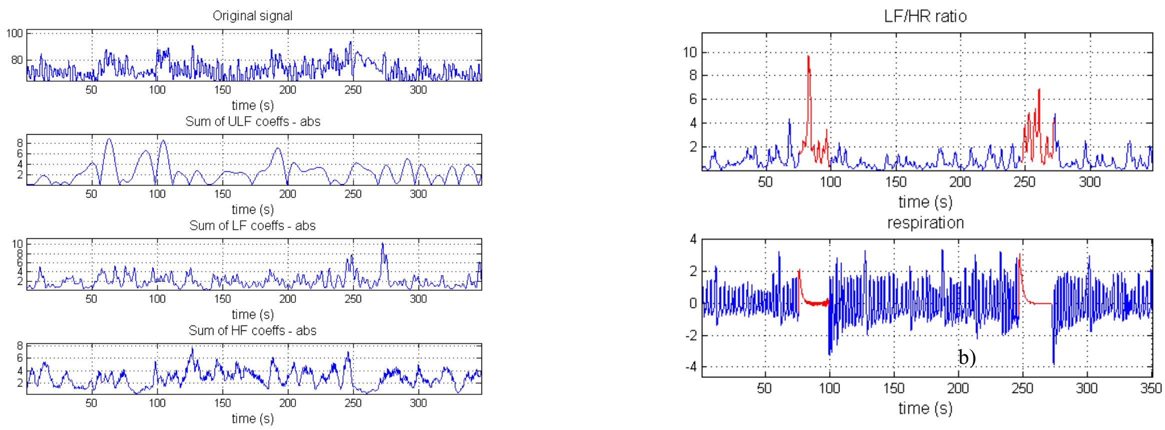
Quality of DWT method was further evaluated, observing noise influence, mother wavelet type influence and time resolution. Quality of detection based on energy distribution depends whether the frequency is closer or further from one of the frequencies corresponding to the scales that were used in decomposition. Even though the mapping to exact frequency bands is not perfect, reconstruction using coefficients from decomposed signal is very accurate. Noise didn't influence decomposition and reconstruction even when SNR was 1:1. In order to achieve precise decomposition and reconstruction some "large" (≥Db8) mother wavelet function from Daubechies family should be used. Temporal resolution was shown to be very precise, which confirms DWTs' ability to analyze signals in frequency and time domain.

Discrete wavelet transform showed to be a suitable candidate for fast and precise HRV analysis with potential application for scientific and clinical purposes.



a) b)

Figure 4.Test of temporal resolution a) Reconstructed signal b) Energy distribution



a) b)

Figure 5. DWT applied to HR signal a) Absolute value of sum of coefficients
b) LF/HF ratio and corresponding respiration signal

ACKNOWLEDGEMENT

This work was done during Erasmus+ exchange on Technical University of Vienna. I would like to thank to the University of Zagreb and Erasmus+ program that gave me opportunity and financial support to be one of the exchange students.

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