HEART RATE VARIABILITY ANALYSIS USING WAVELET TRANSFORM

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Abstract - Heart rhythm is modulated by the autonomic nervous system and from this reason HRV is considered as one of the most promising non-invasive markers of the activity of the autonomic nervous system. In this work, possibility to analyze heart rate variability (HRV) with wavelet transform was investigated. Three methods of wavelet transform were compared (CWT, CWTFT and DWT). Since, DWT showed to be the best one from several reasons: time and CPU power consumption, simplicity of decomposition and reconstruction and in the end quality, it was tested further. Quality of DWT decomposition, noise influence, mother wavelet type influence and time resolution were observed. DWT showed to have high noise robustness, excellent temporal and good frequency resolution.

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 (Table 1).

Today's most common analysis methods of HRV are spectral analysis techniques using the Fourier transform, which assumes that the signal is periodical in time. Problem with such techniques is lack of temporal resolution. 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.

II. HEART RATE VARIABLITY

Heart rate (HR) or heart pulse is a term that describes frequency of heart beats. Normal heart rate 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.).

Heart rate variability (HRV) is a measure of changes of heart periods or consecutive values of heart rate (fc.). It is indicator of many physiological processes taking place inside of the body since it is being controlled by regulatory mechanisms of autonomic nervous system which reacts immediately to any physiological state. Too static HRV is indicator that regulatory mechanisms are not working properly and that something wrong is happening with organism.

Heart rate is regulated by sympathetic and parasympathetic input to the sinoatrial node. Sympathetic nervous system (SNS) by releasing hormones increases heart rate (fc.) and thus controls some extreme situations. 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.

Heart rate plot is achieved by calculating 1/TRR for each two consecutive RR peaks on ECG signal. It is normal that HR changes in time, but the speed of changes (HRV) is what is very interesting to observe. Frequencies of HRV are separated in three bands, high, low and ultra-low as specified in Table 1.

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

It was shown that PNS is related with power of HF band and indicates short-term regulatory mechanisms, while on the other hand SNS activity (and sometimes PNS) is related with power of LF band and indicates mid-term regulatory mechanisms. ULF band is related to very slow oscillations and indicates long-term regulatory mechanisms. [1] SNS activation presents as slow increase of fc meaning also reduction in HRV, while PNS activation indicates as fast decrease of fc and increase in HRV. Increased activation of SNS can be caused by stress, physical activity, standing, 90˚ tilt ect. while activation of PNS can be attained by controlled respiration, cold stimulation of the face or rotational stimuli [6.]. 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 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.

III. WAVELET TRANSFORM

Most often used spectral analysis techniques is Fourier transform, which assumes that the signal is periodic in time. Problem with such technique is lack of temporal resolution. In order to overcome this drawback, short-time Fourier transform was designed. It is adapted Fourier transform in a way that only short section of the signal is analyzed at a time. This maps signal into two-dimensional signals where it is possible to determine when something happened and what was frequency content at that moment. However this information can be obtained only with certain resolution which is determined by the size of time window. Drawback is that once a particular size for the time window is chosen, that window is 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.

Wavelet transform is next possible method since it offers variable size of the window. Wavelet analysis allows the use of long time intervals where we want to observe more precise low frequency information, and shorter regions where we want to observe high frequency information. In Figure 1 comparison of FFT, STFT and WT is graphically represented. Wavelet transform name comes from the fact that it uses a waveform instead of sinusoid function used in Fourier transform. Mother wavelet is 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, where small scale is very compressed signal and large scale is stretched signal. Scale is related to the frequency of the signal in a way that smaller scale means larger frequency and vice versa. Shifting wavelet means delaying it in time. Wavelet transform works in a way that mother wavelet is compared sequentially to sections of the original signal. The result is set of coefficients that are a function of scale and position. These coefficients can be represented and used in many ways. In some cases, inverse transform can be done, which enables to reconstruct signal using only this coefficients.

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).

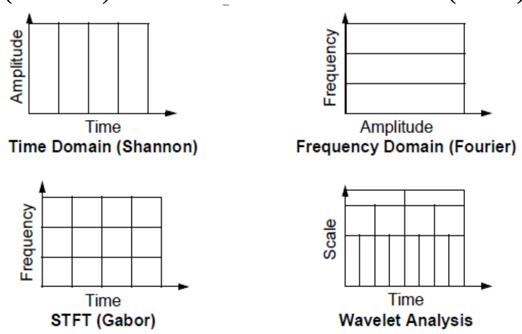


Figure 1: Comparison of temporal and frequency resolution of FFT, STFT and WT [8.]

A. *Continuous wavelet transform - CWT*

In continuous wavelet transform correlation of signal with mother wavelet can be calculated for any scale and shift of mother wavelet. CWT is calculated in a way that scaled wavelet function is shifted smoothly along the signal and correlation with that signal section is measured.

B. *Continuous wavelet transform using FFT - CWTFT*

Problem with CWT is that it is redundant and there is no unique way to define inverse. This means that it is not possible to reconstruct signal from coefficients. CWTFT uses FFT of the wavelet function in order to reconstruct signal. Not all wavelet functions can be used in CWTFT. Condition is that it is 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 even more, 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, transform is much more efficient and equally accurate. In each level of transform 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. Example of one decomposition tree is shown in

Figure 2 [7.]. 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.

IV. 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 [10] authors used a wavelet transform to build a simulated model of an HRV signal and to create an algorithm for HRV signal decomposition. For standard MIT database in [11] HRV data was analyzed on the basis of LF/HF ratio. Wavelet and Wigner Ville Transforms were used for data analysis. The aim of [12] 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 [12] was similar to idea of this paper, but not completely the same approaches were used. Whereas [12] researched a multitude of mother functions and power ratios, this 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 [12] more extensive evaluation was suggested, since their results have been obtained from a limited number of subjects. In [13] HRV was analyzed using wavelet and cosine packets. A comparison was made on the same data base with results based on the short-term Fourier transform method. But again focus and the methods used were not the same as in this paper.

On the other side number of papers were focused more on application of wavelet transform on detection of various health problems using HRV analysis. In [14] Continuous Wavelet Transform (CWT) has been used to evaluate the effect of local anesthesia on HRV parameters. The major goal of [15] 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 [16] using wavelet packet transform. Wavelet packet transform was also used in [17] for an analysis of sympathovagal balance in patients with major depressive disorder. In order to diagnose and detect diabetes automatically in [18] 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. Therefore the results of this paper might serve as starting point or component of some future research.

V. METHODS ANALYSIS

A. *Comparison of methods*

Idea was to analyze mentioned three methods of wavelet transform in order to compare them, detect what advantages and drawbacks of each are and to choose the best one on which HRV analysis will be further studied. Several methods were tried; 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 3). 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 was only possible to do with CWTFT and DWT method. Again, difference was very small for HF and LF, only for ultra-low frequencies (UFL) difference was more visible, but even then main trends were the same. In order to compare all three methods at the same time, sum of all coefficients for every frequency band was studied. Results are very similar 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 minute to do the decomposition.

Conclusion is that DWT is the best 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.

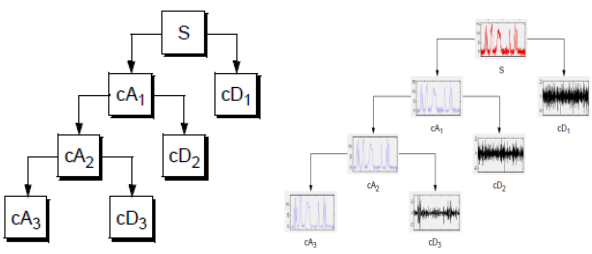


Figure 2: Wavelet decomposition tree [4.]

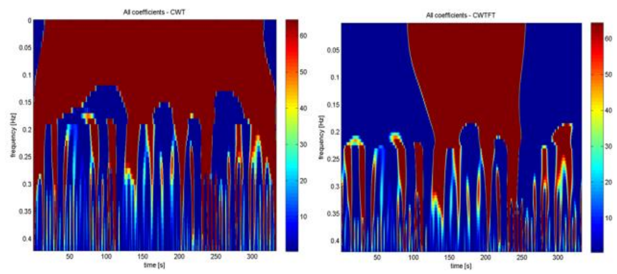


Figure 3. Coefficients comparison for CWT and CWTFT

Detection to which band some frequency belongs, based on reconstruction is precisely detected only for frequencies which are in the middle of the frequency band and further from the boundaries. As getting closer to the boundaries other bands detect these frequencies too, but with lower amplitude and wrong period (Figure 4) Also 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 for them frequencies 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 was studied (Figure 6).

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

3) *Influence of chosen wavelet function*

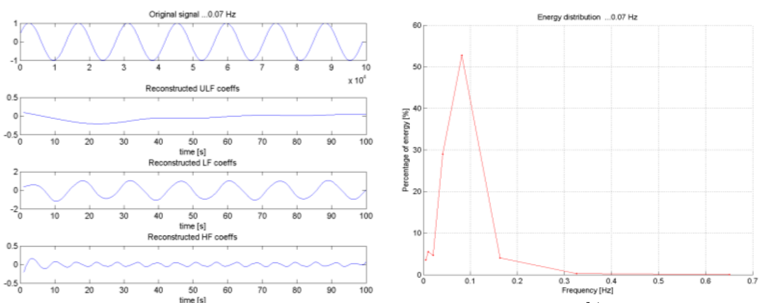
Finally, the influence of chosen mother wavelet function on energy distribution and reconstruction was studied. Four wavelets from Daubechie's family were used: "db3", "db5", "db8" and "db10" as shown in Figure 5. Result of comparison is that difference is very small for LF and HF band, but for ULF there are noticeable differences. For LF and HF, reconstruction signals look very similar especially for "larger" Daubechie wavelet functions (Figure 7). It is because larger orders of Daubechie functions are more complex ones, 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 5). For this reason for precise calculation it is suggested to use enough large Db wavelet function (>Db8). Last thing to notice is 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*

Signal whose frequency content changes in time 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 8). 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. HRV ANALYSIS

Five minute signal of heart rate sampled with 500 sample/s is used to present input and output data of HRV analysis using DWT method. In Figure 9a) original signal (top one graph) and DWT coefficients separately for ULF; LF and HF frequency band are presented.



a) b)

Figure 4. Reconstruction of sine signal (a)) (0.7Hz) and its energy distribution (b))

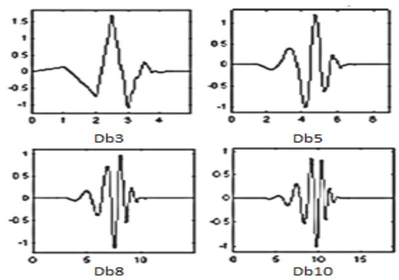
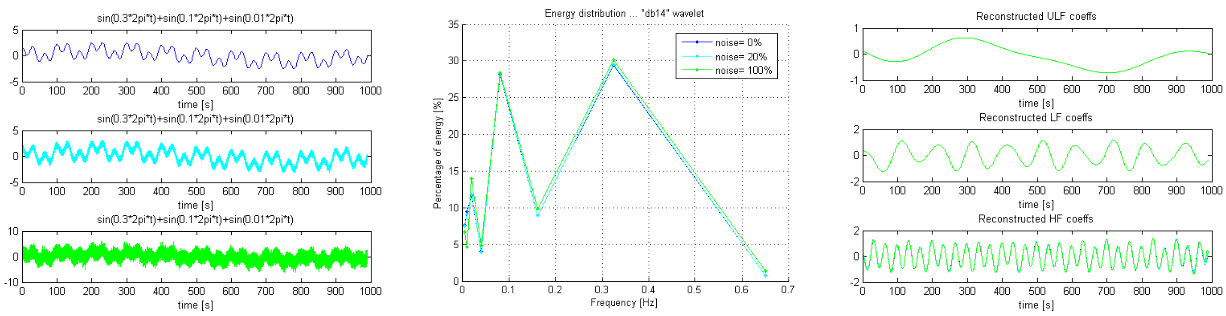


Figure 5. Different types of Daubechies wavelet function



a) b) c)

Figure 6. Original sine signal with different levels of noise (a)), energy distribution (b)) and reconstruction (c))

As previously mentioned, parasympathetic nervous system (PNS) is major contributor to HF component. Slight disagreement exists in respect to the LF component. Some studies suggest that LF is a quantitative marker of sympathetic (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 500 samples which corresponds to one second. This way resolution of LF/HF ration is one second which is reasonable. In order to visually better see connection between LF, HF coefficients and LF/HF ratio in Figure 9b), absolute values of coefficients are plotted.

In this signal HRV during respiration is observed. Such, deep breathing or apnea, tests are usually used in clinical testing or calibrations. During normal uncontrolled breathing respiration seems to influence HRV for less than 10%, but controlled respiration increases this influence up to almost 50% [5.]. 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 [4.] 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 [4.]. In the signal on Figure 9b) it can be noticed that LF/HF ratio is increased in time between approximately 130th and 230th second. In the same time interval ULF coefficients values are relatively large in comparison to the rest of the time. These two things indicate that at this time interval patient might have suppressed breathing. This could be confirmed if breathing was also recorded at the same time.

VII. CONCLUSION

In this work, possibility to analyze heart rate variability (HRV) with wavelet transform was 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. Since, in the end DWT showed to be the best one from several reasons: time and CPU power consumption, simplicity of decomposition and reconstruction and in the end quality, it was tested further. Quality of DWT decomposition, noise influence, mother wavelet type influence and time resolution were observed. 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 detection to which frequency band some frequency belongs is not perfect, reconstruction using coefficients from decomposed signal is very good. Noise didn’t influence decomposition and reconstruction even when amplitude of noise was in range of signal amplitude. In order to achieve precise decomposition and reconstruction some “large” (≥8) mother wavelet function from Daubechies family should be used. Temporal resolution was shown to be very precise, which confirms DWTs’ ability to analyze signal in frequency and time domain.

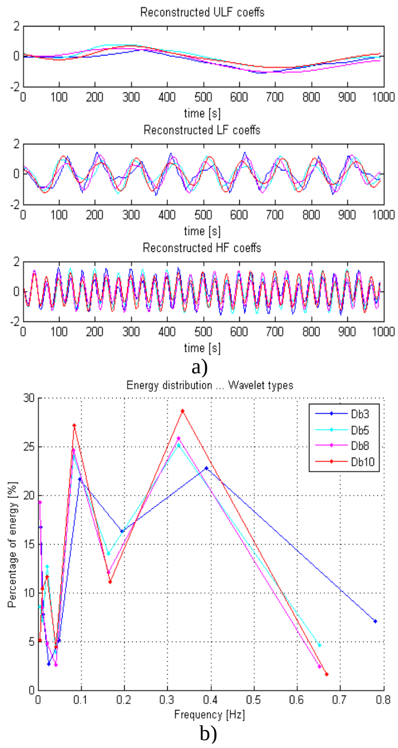


Figure 7.Test of wavelet type influence
a) Reconstructed signal
b) Energy distribution

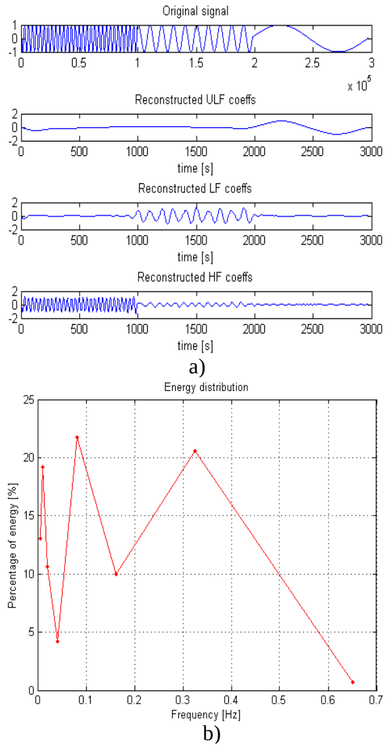


Figure 8.Test of temporal resolution
a) Reconstructed signal
b) Energy distribution

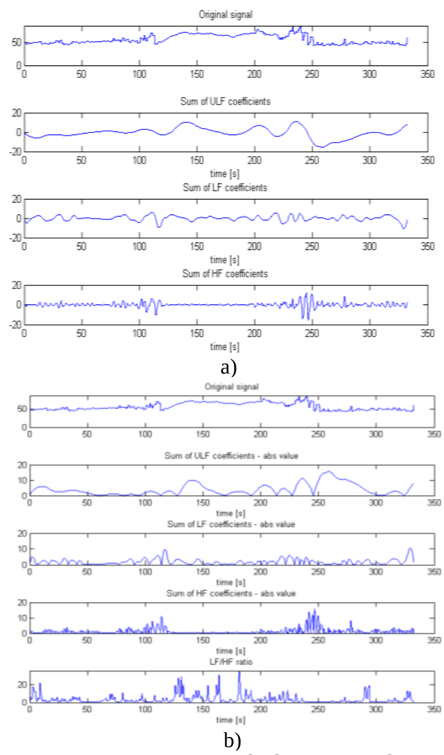


Figure 9. DWT applied to HR signal
a) Sum of coefficients b) Absolute value of sum of coefficients and LF/HF ratio

As product of all analyses conducted, discrete wavelet transform showed to be very good candidate for more precise analyses and someday even usage for other scientific and clinical purposes.

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