HEART RATE VARIABILITY ANALYSIS USING WAVELET TRANSFORM

Project: Biomedical sensors and signals (351.029)

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CONTENTS

1 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. LF component is thought to be of both sympathetic and parasympathetic nature and HF component is mostly connected with parasympathetic nervous system.

Today's most common analysis methods of HRV are spectral analysis techniques using the Fourier transform, which assumes that the heart rate series is stationary. 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-stationary signal is studied.

Three methods of wavelet transform will be analyzed on HR signal. The best one will be chosen and further studied in order to detect what are advantages and drawbacks in HRV analysis. Frequency and time resolution influence of noise and type of wavelet and energy distribution will be taken into account. In the end interpretation of such decomposition will be given.

2 Heart rate variability – HRV

Heart rate (HR) or heart pulse is a term that describes how often heath contracts per unit of time and usually is expressed in number of beats per minute (bpm). Normal heart rate at rest ranges from 60 to 100 bpm, but it varies according to body's physical needs. It also depends on our different activities and states: physical exercise, illness, stress, sleeping, eating ect. Tachycardia is a fast heart rate, defined as above 100 bpm at rest, while bradycardia is a slow heart rate, defined as below 60 bpm at rest. When the heart is not beating in a regular pattern, this is referred to as an arrhythmia.

Since heart rate is closely related with other body signals and physiological processes in the body, its measurement is of high importance for diagnostics and therapy. There are various methods to record heart activity but most common is electrocardiogram. Electric signals from heart muscle excitation are measured and signal consisting of waves and peaks is recorded. One period of a heart beat can be divided into five visible waveforms: P, Q, R, S and T waveform. Each one of them is a reflection of a certain change in heart. P wave indicates atrial depolarization, Q septal depolarization, R and S early and late ventricular depolarization and T repolarization of ventricles. Examples of ECG signal with description and scheme of changes inside heart is shown in Figure 1 Heart rate is usually expressed as f_c while heart period ($1/ f_c$) is usually referred to as RR period, the time between two consecutive R peaks.

Major factors that increase HR are: decreased level of O_2, decreased blood pressure, increased Ca^{2+}, decreased K^+ and Na^+, increased body temperature, increased body exercise ect. Major factors that decrease HR are opposite factors from the ones increasing HR.

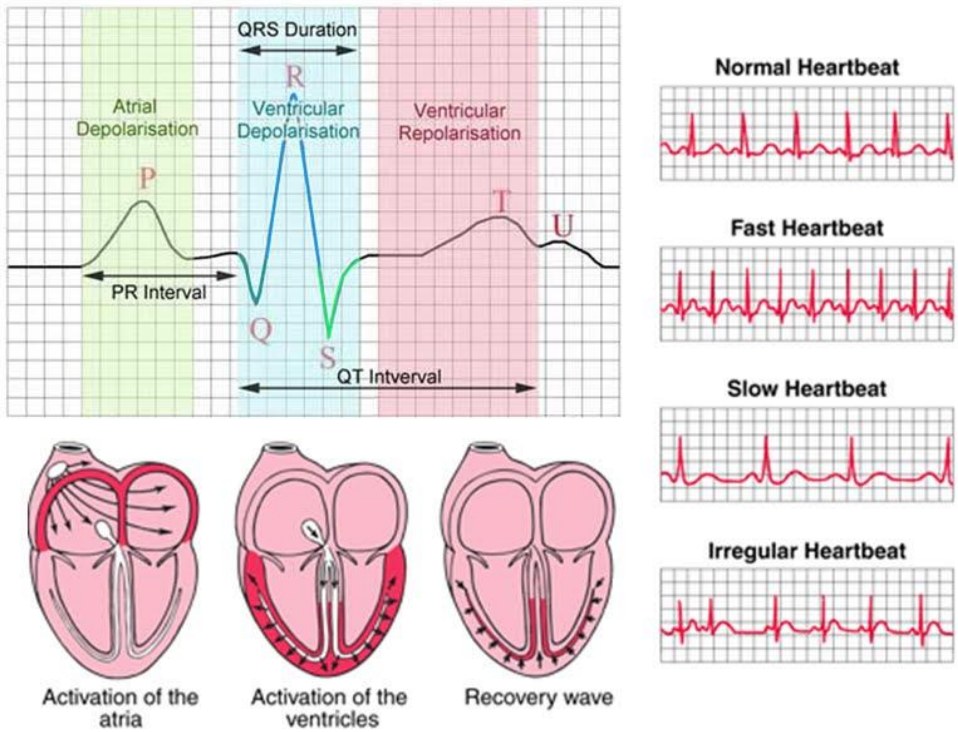


Figure 1: ECG signal with description and scheme of changes inside heart [9.]

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

While heart rhythm is regulated entirely by the sinoatrial node under normal conditions, heart rate is regulated by sympathetic and parasympathetic input to the sinoatrial node. Sympathetic nervous system (SNS) by releasing hormones increases hear rate (f_c.) 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 (Figure 2).

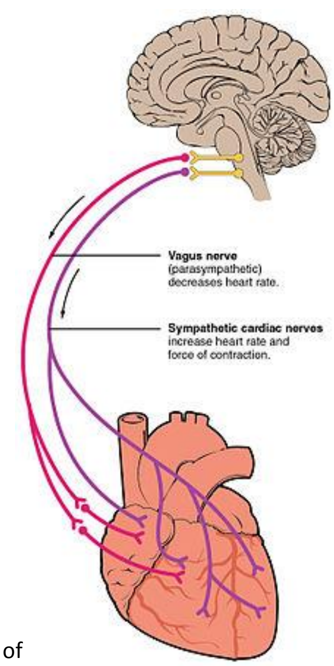


Figure 2: HRV as a consequence of continuous interplay of SNS and PNS

Hart rate plot is achieved by calculating $1/T_{RR}$ 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. Their physiological origins are much less defined but probably include thermo regulation, blood pressure regulation, humoral and metabolic regulation ect. [1.]

From all things mentioned, follows that SNS activation presents as slow increase of f_c meaning also reduction in HRV, while PNS activation indicates as fast decrease of f_c 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.

3 Wavelet transform

Many methods for signal analysis exist but most famous one is Fourier transform, which breaks down signal into sum of sinusoids of different frequencies. It shifts representation of signal from time to frequency domain and this frequency content of the signal is often very important information. But drawback is that during the transformation temporal information about signal is lost, so it is impossible to say when some event (e.g. change of main frequency) happened. For this reason it is mainly used for stationary signals which don't change much in time.

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. It is often represented as that there is a window of certain width, and this window moves along time axis. This maps signal into two dimensional signal where it is possible to determine when something happened and what was frequency content at this moment. However this information can be obtained only with certain resolution which is determined by the size of window. Drawback is that once you choose a particular size for the time window, 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 3comparison of FFT, STFT and WT is graphically represented. Wavelet transform is called that way because it uses a waveform instead of sinusoid function as in Fourier transform. Wavelet is waveform of effectively limited duration that has an average value of zero. Also, it can be noticed that wavelet analysis does not use a time-frequency region, but rather a time-scale region. This is because wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original wavelet.

Scaling a wavelet means stretching (or compressing) it where small scale is very compressed signal and large scale is very stretched signal. Scale is related to the frequency of the signal in a way that smaller scale means larger frequency and vice versa. Shifting of a wavelet means delaying it in time.

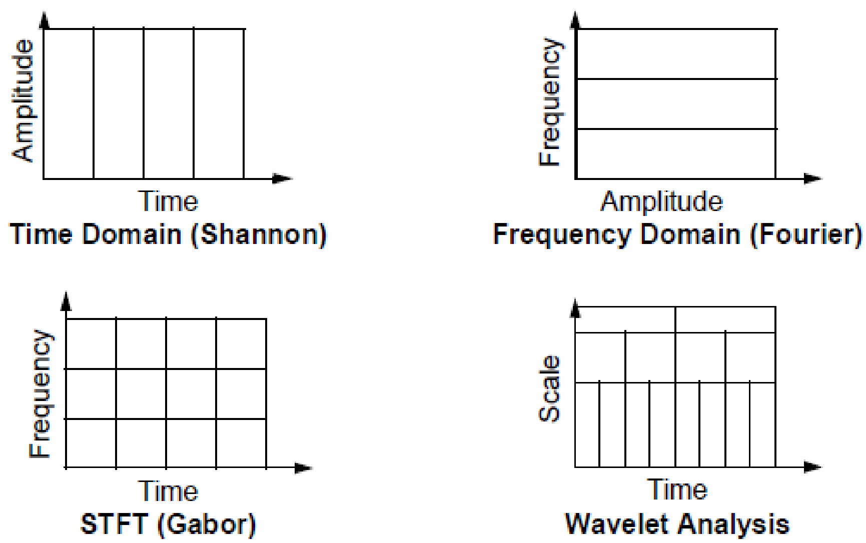


Figure 3: Comparison of temporal and frequency resolution of FFT, STFT and WT [8.]

In order to describe wavelet transform more clearly it can be divided into five steps [4.]

1. Take a wavelet and compare it to a section at the start of the original signal.
2. Calculate a number C that represents how closely correlated the wavelet is with this section of the signal. The higher C is, the more the similarity. Note that the results will depend on the shape of the wavelet you choose.
3. Shift the wavelet to the right and repeat steps 1 and 2 until you've covered the whole signal.
4. Scale (stretch) the wavelet and repeat steps 1 through 3.
5. Repeat steps 1 through 4 for all scales.

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 some coefficients. This will be shown later. 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).

3.1 Continuous wavelet transform - CWT

Continuous wavelet decomposition can calculate correspondence with signal for any scale of wavelet function. It is done in a way that scaled wavelet function is shifted smoothly along the signal and correlation with that signal section is measured. If similarity is larger the coefficient for that time and scale is also larger.

Here continuous wavelet decomposition was made for all scales which correspond to frequencies that we are interested in (Table 1). Graph in Figure 5a) shows coefficients for each frequency level. For lower frequencies smaller resolution of scales was used in order to speed up the calculation. In Table 2 boundary scales and corresponding frequencies for each frequency band are listed. Also resolutions of scale used for each frequency band are noted. This means that in HF band coefficients for only 11 scales were calculated. Unfortunately this has to be adapted for every signal if the sampling rate of the signal is changed, because relation between scale and frequency depends on the sampling rate. Even though most popular mother wavelets for CWT are wavelets from Daubechies family (Figure 13), “mexh” (so called “mexican hat”) mother wavelet was used because this way it could be compared with CWTFT method.

Table 2: Scales, corresponding frequencies and resolutions for frequency bands with CWT method

	HF	**LF**	**ULF**
Scale boundaries	300- 850	850-3050	3050 - 41350
Frequency boundaries [Hz]	0.416- 0.156	0.156- 0.041	0.041 - 0.0032
Resolution	50	200	2000

3.2 Continuous wavelet transform using FFT - CWTFT

Problem with continuous wavelet transform 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. In order to be able to reconstruct only high frequency (HF) or LF part of the signal continuous wavelet transform using FFT algorithm is used. 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. Since Daubechie’s wavelets mostly don’t satisfy this condition, popular “mexh” (so called “mexican hat”) wavelet was used. In Figure 5b) coefficients for all frequencies are shown. It differs from the ones in Figure 5a). when CWT was used. In HF frequency range there is almost no difference, but as approaching to ULF frequencies differences increase. Unfortunately, appropriate explanation for that is not found but it is believed that it is because of some constraints of CWT function for very low frequencies. In Table 3 list of scales, corresponding frequencies and resolutions for all frequency ranges is shown.

Table 3: Scales, corresponding frequencies and resolutions for frequency bands with CWTFT method

	HF	LF	ULF
Scale boundaries	300- 800	800 - 3000	3000 - 43000
Frequency boundaries [Hz]	0.417- 0.156	0.156- 0.0417	0.0417 -0.0029
Resolution	50	100	1000

3.3 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 and positions 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 4 [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. Here is signal decomposed in 19 levels (chosen because of the length of the signal), and for every level (scale) corresponding frequency is calculated. After that, levels are distributed in belonging frequency range. Since frequencies decrease by factor of two, usually only two or three levels are in each frequency range which can be seen in Table 4. Here "db10" wavelet was used for decomposition, because it is not possible to use "mexh".

Table 4: Scales, corresponding frequencies and resolutions for frequency bands with DWT method

	HF	LF	ULF
Scales	1024 and 2048	4096 and 8192	16384, 32768 and 65536
Frequencies [Hz]	0.334 and 0.167	0.0835 and 0.0417	0.0208, 0.0104 and 0.0052
Levels	10 and 11	12 and 13	14, 15 and 16

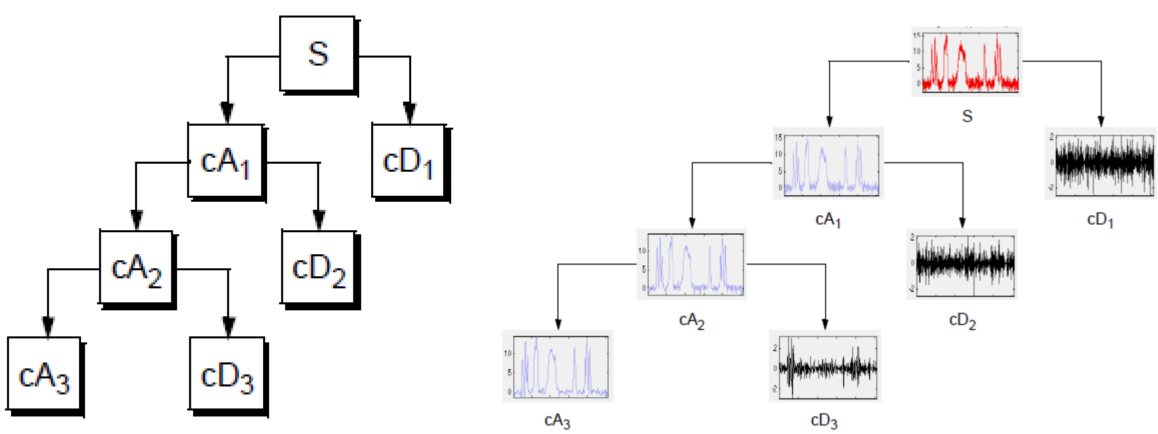


Figure 4: Wavelet decomposition tree [4.]

4 Comparison of methods

It is not easy to compare coefficients and results that are achieved with CWT, CWTFT and DWT because firstly coefficients depend of the type of wavelet even if type of transform is the same. Here same wavelet function couldn't be used for all transforms because of restrictions of some transforms. Because of discretized scale levels for CWTFT and DWT not exactly the same range of frequencies for ULF, LF and HF range is used in all transforms.

In Figure 5 coefficients for all frequency levels for CWT and CWTFT method are shown. The difference is visible. In HF frequency range there is almost no difference, but as approaching to ULF frequencies differences increase. Unfortunately, appropriate explanation for that is not found but it is believed that it is because of some constraints of CWT function for very low frequencies. Also some differences could be caused by slightly different boundary frequencies for frequency bands.

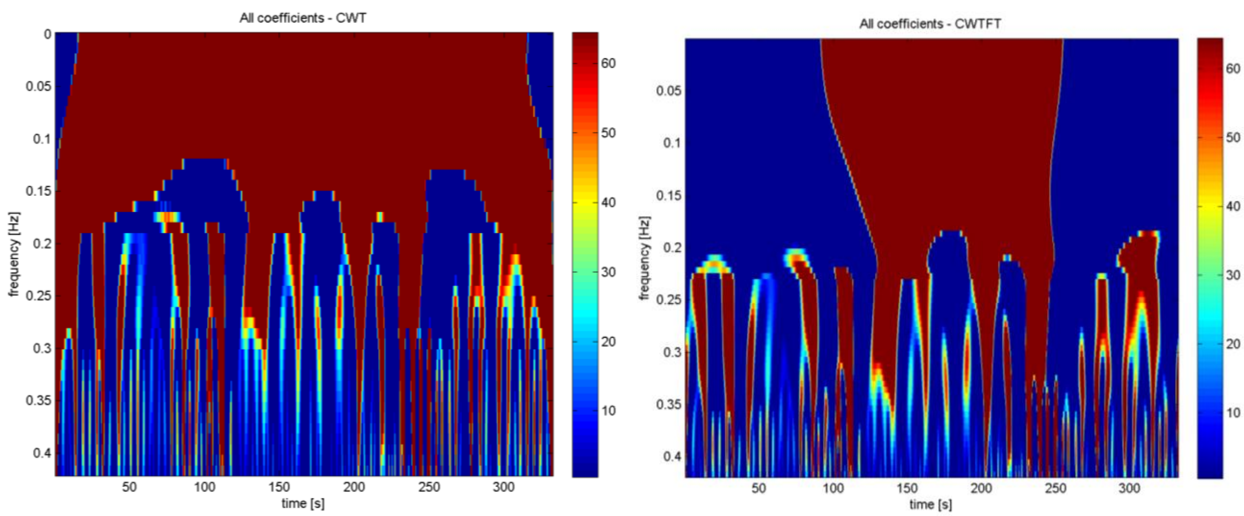
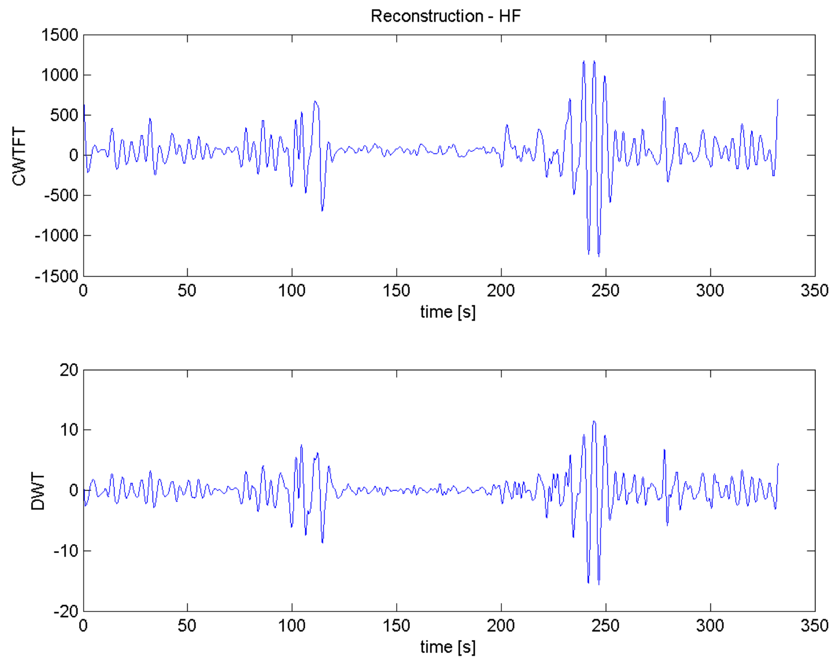


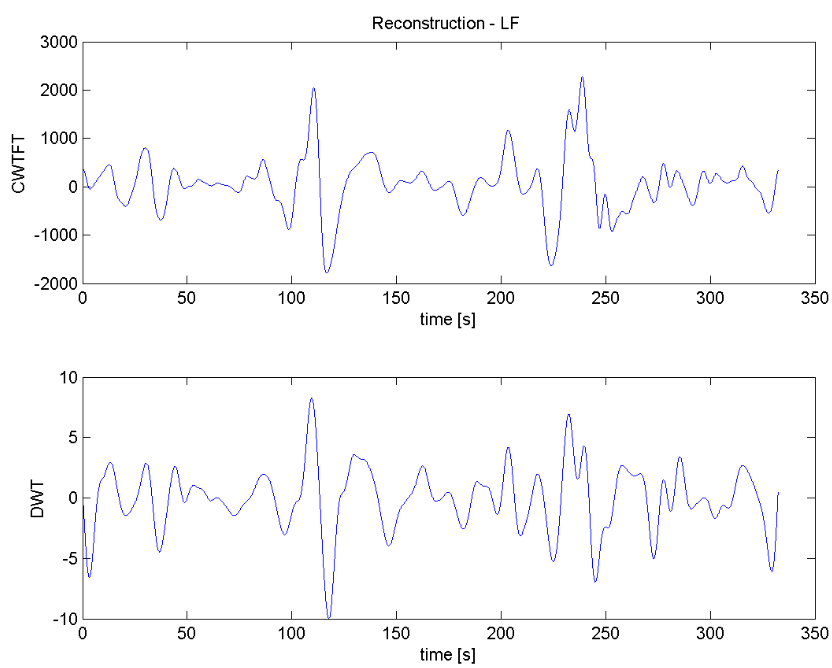
Figure 5: CWT and CWTFT decomposition for range of frequencies that are important for HRV

4.1 Reconstruction for different frequency bands

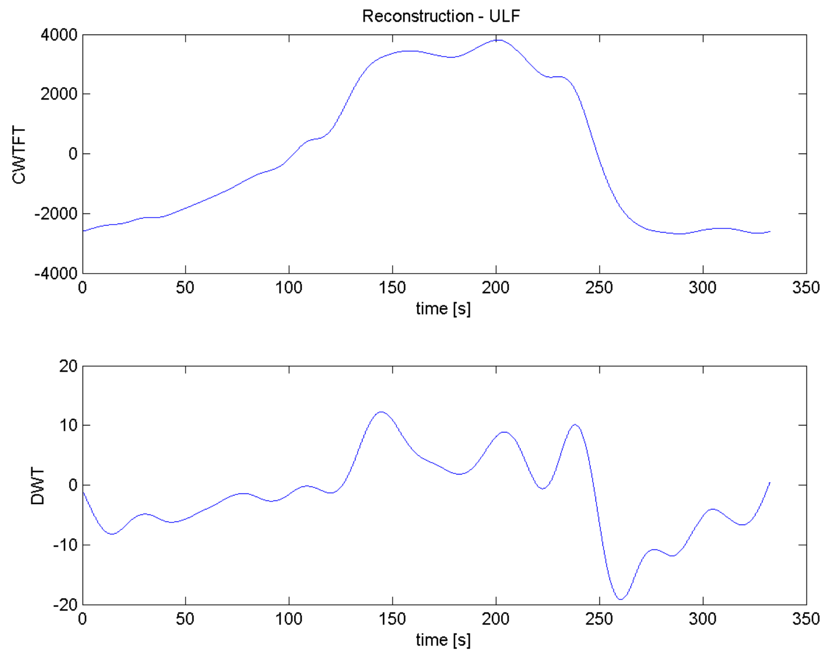
Signal was reconstructed using coefficients for each frequency band separately. This was only possible to do in CWTFT and DWT method. Results are separated for HF, LF and ULF and shown in Figure 6. Difference is very small for high and low frequencies. Only for ultra-low frequencies difference is more visible, but even then main trends are the same.



a) Reconstruction of high frequency coefficients of signal



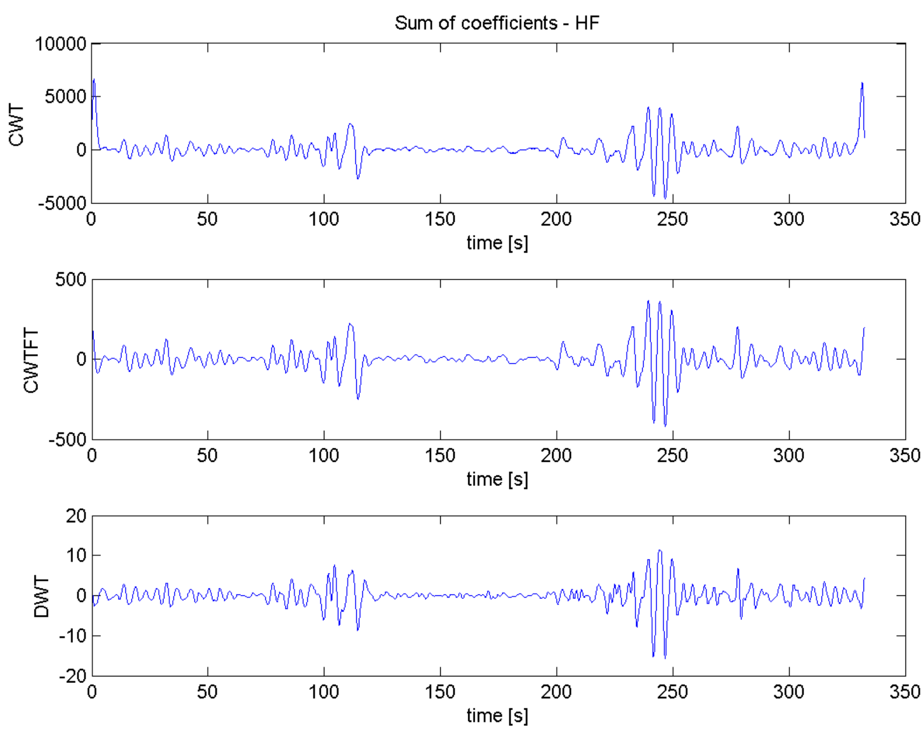
b) Reconstruction of low frequency coefficients of signal



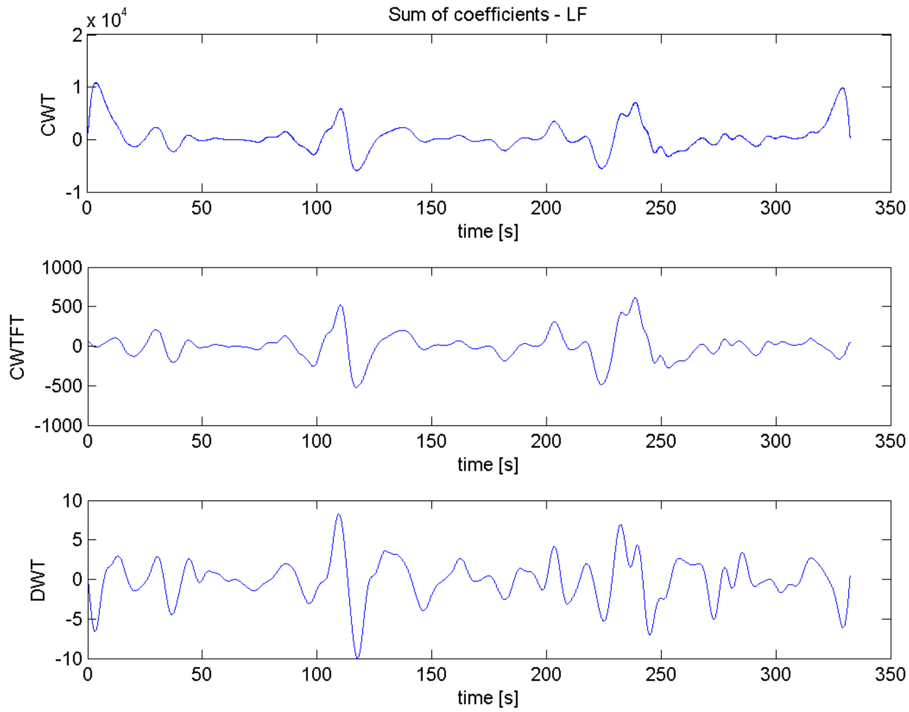
c) Reconstruction of ultra-low frequency coefficients of signal

Figure 6: Reconstruction of different frequency bands (HF, LF, ULF) coefficients of signal with CWTFT and DWT method

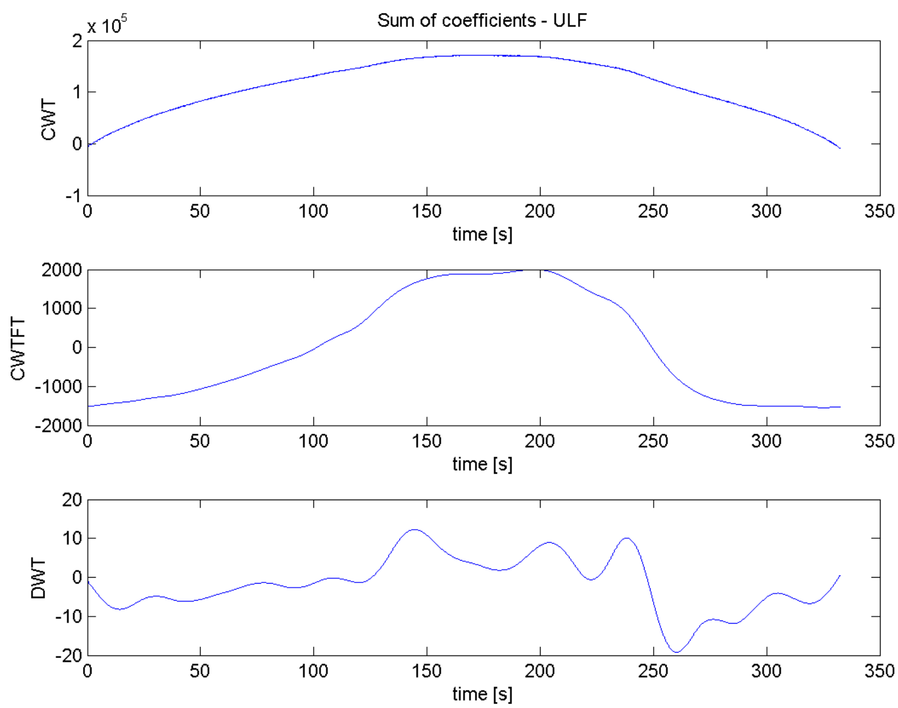
4.2 Sum of coefficients



a) Sum of high frequency coefficients of signal



b) Sum of low frequency coefficients of signal



c) Sum of ultra low frequency coefficients of signal

Figure 7: Sum of coefficients of different frequency bands (HF, LF, ULF) achieved with CWT, CWTFT and DWT methods

Since it is not possible to do the reconstruction of the signal based on coefficients for CWT, only sum of all coefficients for every frequency band was studied. This way all three methods could be compared as shown in Figure 7. Results are very similar for all three methods with only minor differences for HF and LF band. Only for ULF band larger difference for CWT is noticed. The same effect is seen in Figure 5, even though reason for such difference of CWT for ULF is not clear.

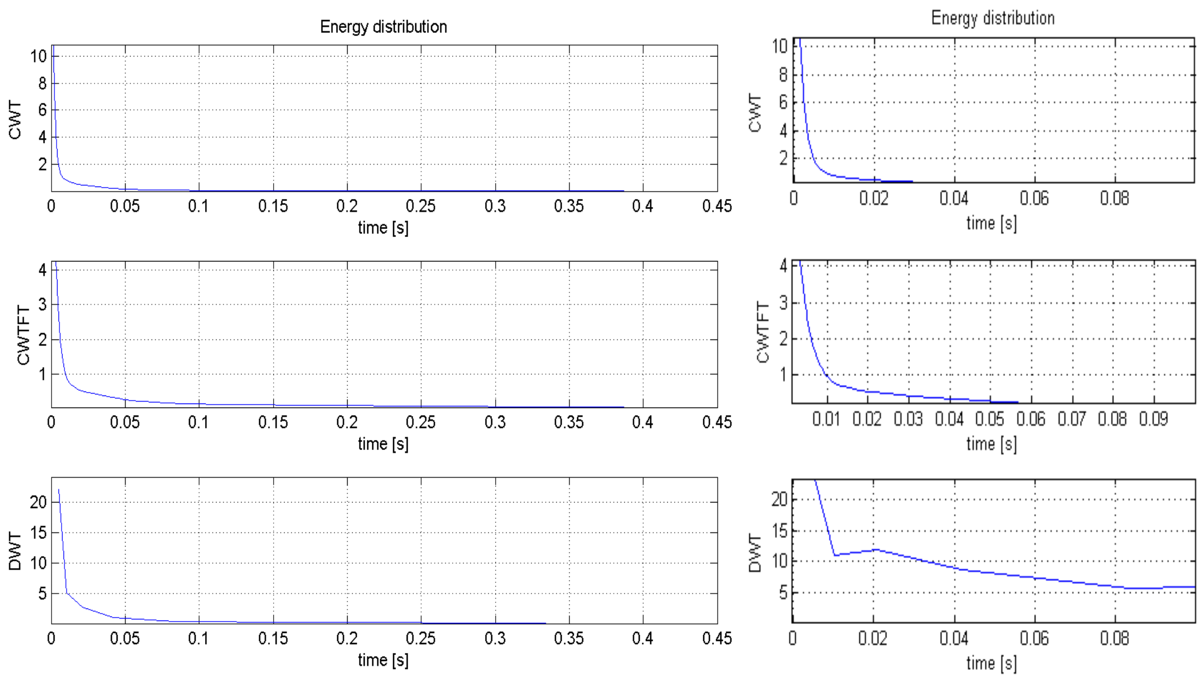
4.3 Energy distribution

Distribution of energy through different frequencies was studied in order to compare methods with Fourier decomposition of signal. Values don't have to be the same but global tendencies should be the same. This can be seen in Figure 8 where energy distribution for all three methods is shown and from Figure 9 where FFT of the signal is plotted. This shows very good correlation.

4.4 Calculation time

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

DWT is best method for the wavelet decomposition of signal for several reasons: time and CPU power consumption, simplicity of decomposition and reconstruction and the quality of decomposition and reconstruction itself.



a) All frequencies b) Zoomed for ULF and LF

Figure 8: Sum of coefficients of different frequency bands (HF; LF, ULF) achieved with CWT, CWTFT and DWT methods

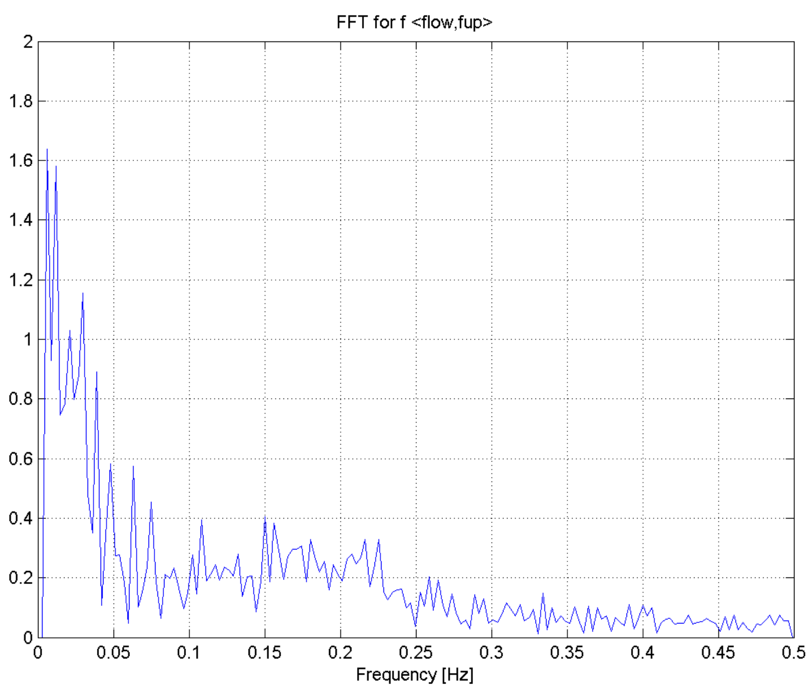


Figure 9: FFT of the signal

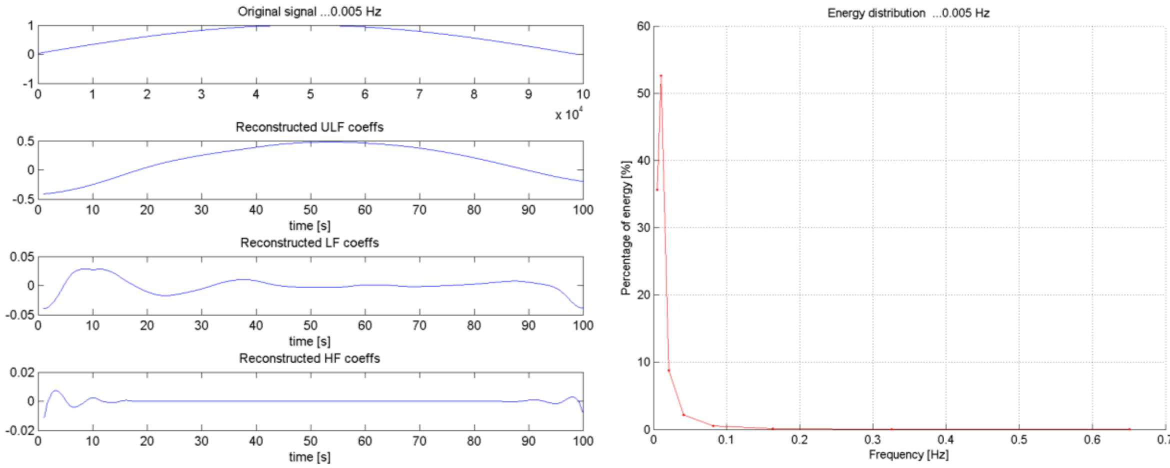
5 DWT method analysis

5.1 Quality of decomposition

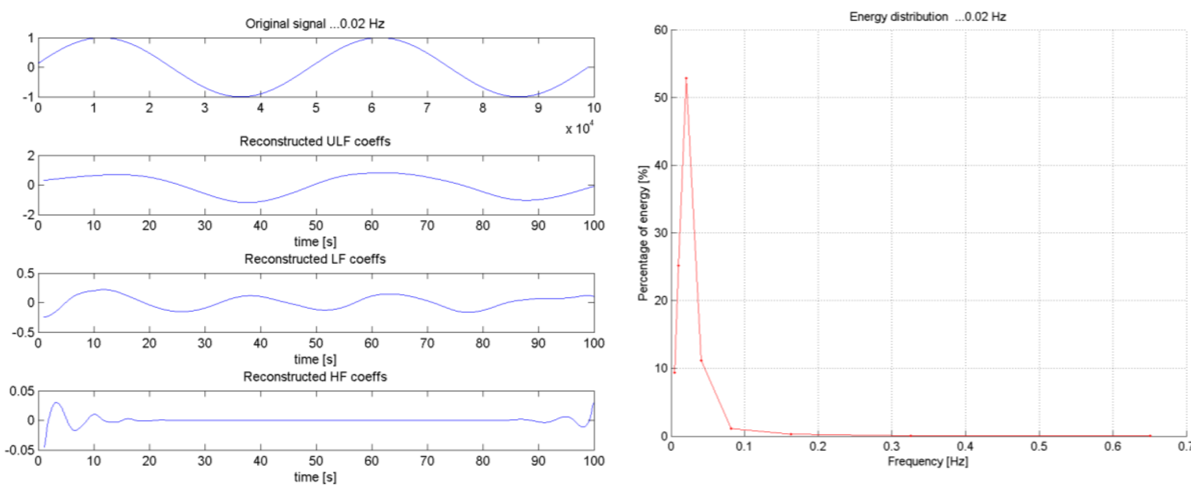
In order to quantitatively determine how good discrete wavelet transform decomposes signal on HF, LF and ULF frequency bands it was tested on artificial (known) signal. Idea was to use signal that consists of sinusoids of three different frequencies, one from each frequency band. But before that sinusoids of different frequencies were used to observe decomposition in more details. Energy distribution globally and how well the peak of maximal energy corresponds to the frequency of sinusoid in signal were studied. Also reconstruction using separately HF, LF and ULF frequencies was observed too. In Figure 10 reconstruction and energy distribution for sinusoids of different frequencies is shown. In Figure 10a) where frequency is 0.005Hz it can be seen on reconstruction graphs that this frequency is very well detected as a ULF band and also energy distribution frequency of peak agrees to the input frequency very well. In Figure 10b) frequency of 0.02Hz is used which is still in ULF band but closer to the border of ULF and LF band. Sinusoidal shape is recognized on both band levels ULF and LF, and also frequency of peak agreed very well. In Figure 10c) frequency 0.07Hz, which is in LF band, is used. On reconstruction it is also detected under LF band. In Figure 10d) frequency 0.1Hz is used, which is still in LF band but closer to HF band. Again, in reconstruction graph it is detected in both bands: LF and HF. In energy distribution graph it can be seen that frequency of peak is not very precisely detected. This is because DWT uses "dyadic" distribution of frequencies, which means every two consecutive frequencies increase as factor of 2. For this reason the peak belongs to the frequency which is closest to the input frequency.

In Figure 10e) and f) frequencies 0.3 and 0.5 Hz respectively were used. They are nicely reconstructed in corresponding HF frequency band. Again, if frequency is not exactly one of decomposition level frequencies then peak is not precisely detected. For larger frequencies resolution is smaller so the error is larger.

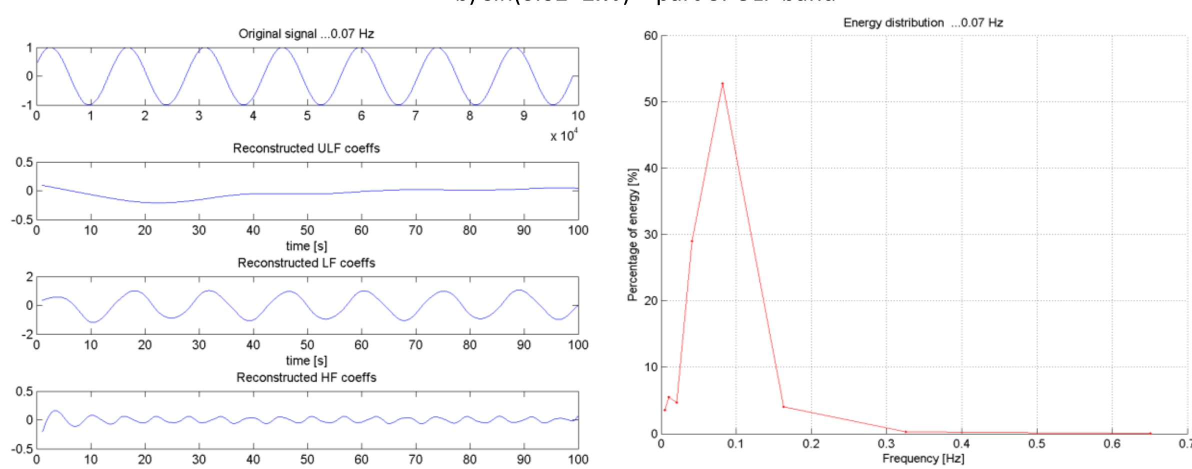
In all these graphs two things can be noted. Detection to which band some frequency belongs, based on reconstruction is precisely detected only for frequencies which are in the middle for the frequency band and further from the boundaries. As getting closer to the boundaries other bands detect these frequencies too. 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.



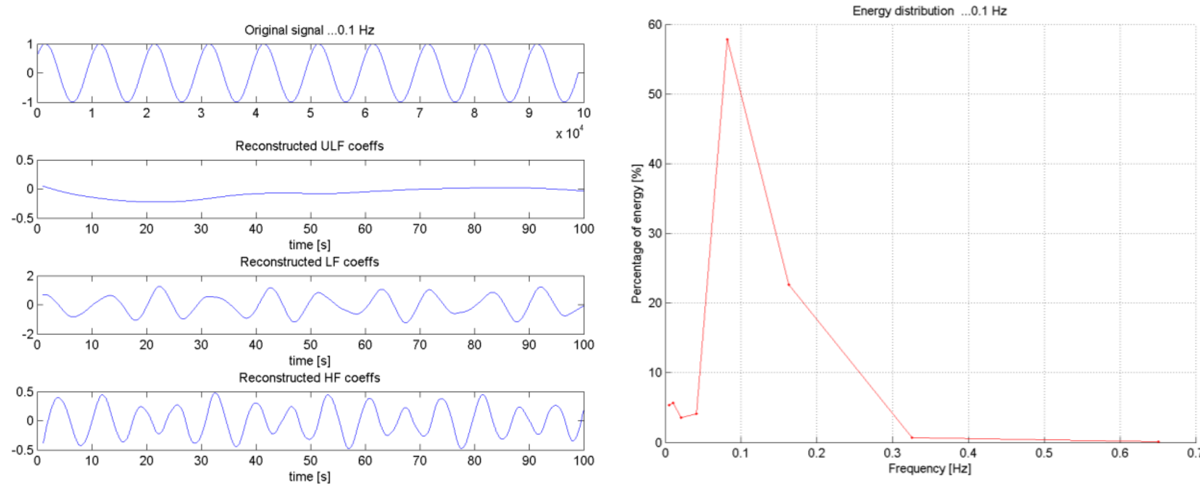
a) sin(0.005*$2\pi t$) – part of ULF band



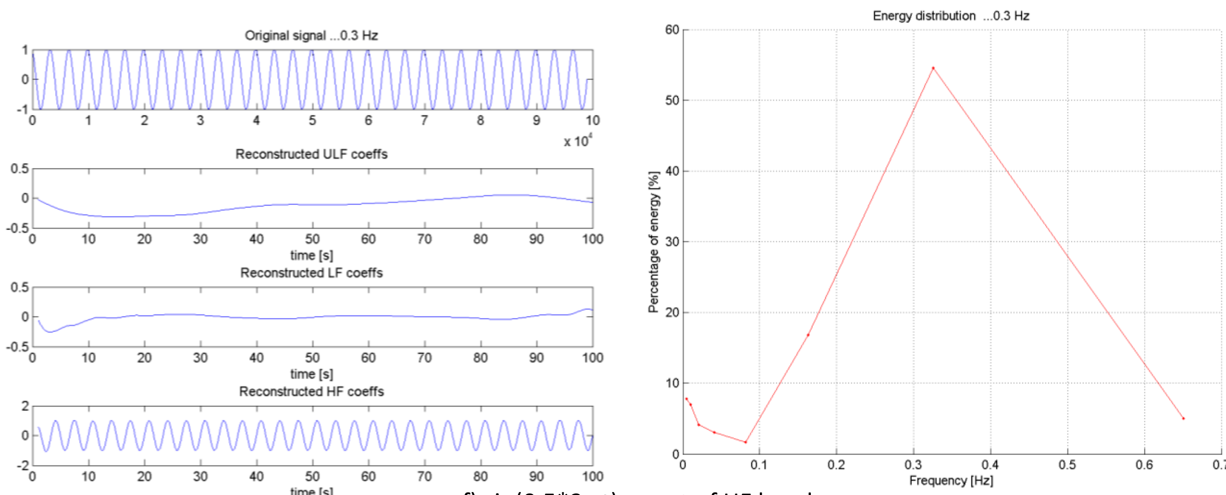
b) sin(0.02*$2\pi t$) – part of ULF band



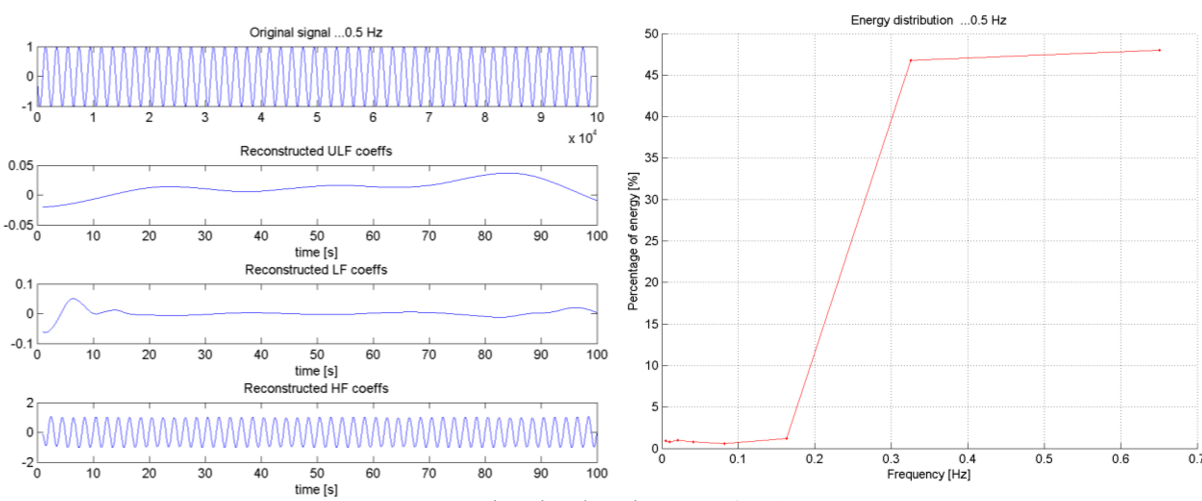
c) sin(0.07*$2\pi t$) – border between ULF and LF band



d) sin(0.1*2πt) – part of LF band



f) sin(0.5*2πt) – part of HF band



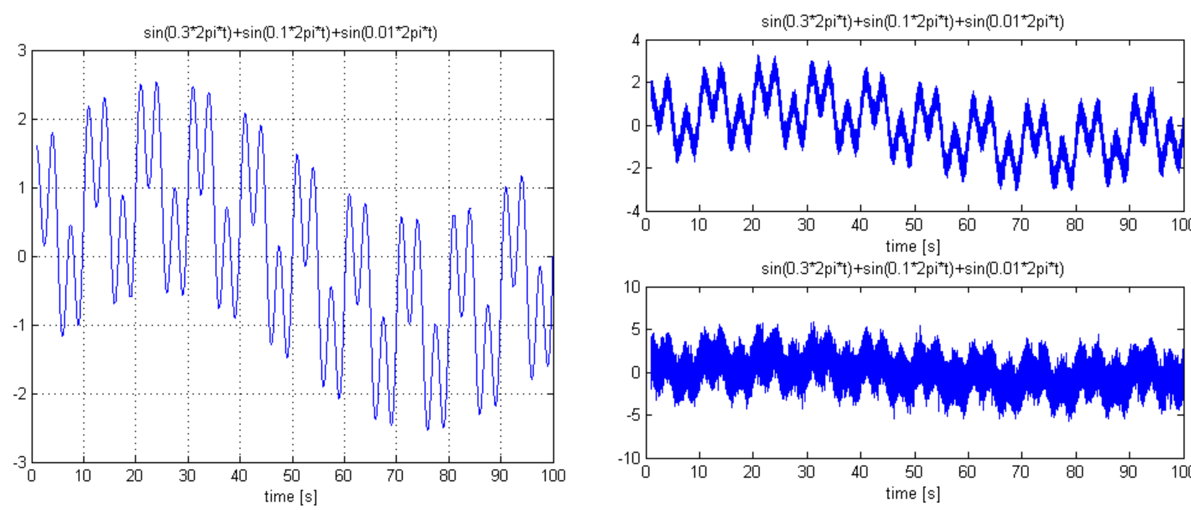
e) sin(0.3*2πt) – part of HF band

Figure 10: Energy and decomposition for sinusoids of different frequencies

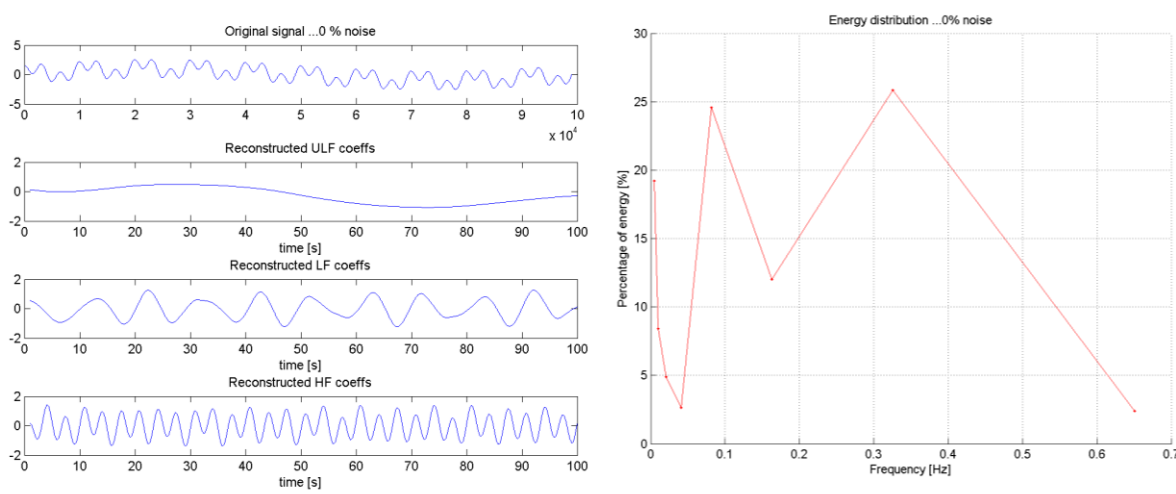
5.2 Noise influence

In Figure 11a) signal which consists of sinusoid waves of three different frequencies is shown on the left, and the same signal with added Gaussian noise of two different amplitudes on the right. Influence of noise on DWT decomposition, reconstruction and energy distribution is studied. In Figure 11b) reconstruction and energy distribution for signal without noise is represented. Energy distribution graph reveals three peaks, and their frequencies are close to real frequencies of the sinusoids in signal. Error is due to discrete scale and frequencies used in decomposition, as was explained in previous section. Also, reconstruction is very well if periods of signals for ULF, LF and HF are observed. Even though shape is not completely sinusoidal, periods match very well with initial frequencies.

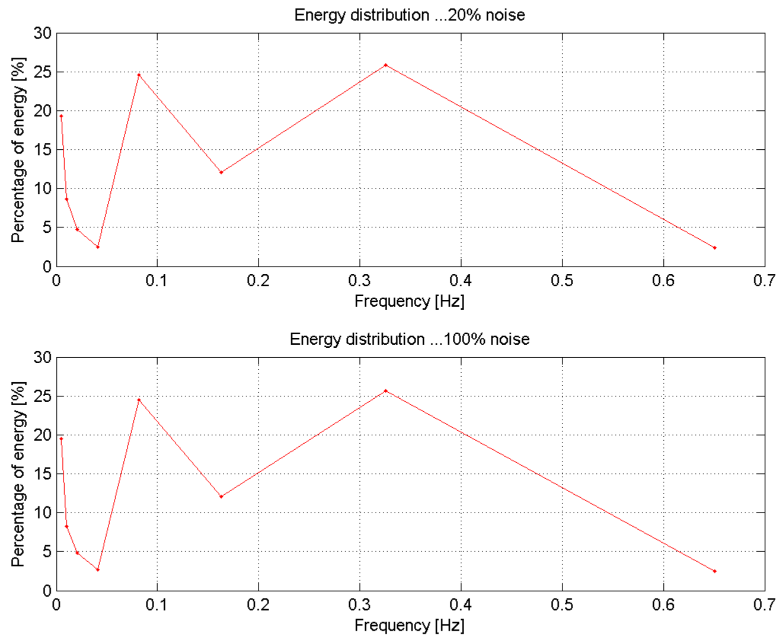
Figure 11c) shows energy distribution for signal with two levels of noise . Even though distribution is not completely the same, positions of peaks remained the same. Furthermore, observing Figure 11d), where reconstruction for these two cases is shown, it is visible that noise didn't influence decomposition and reconstruction even when amplitude of noise was in range of signal amplitude. This is another very positive property of DWT transform.



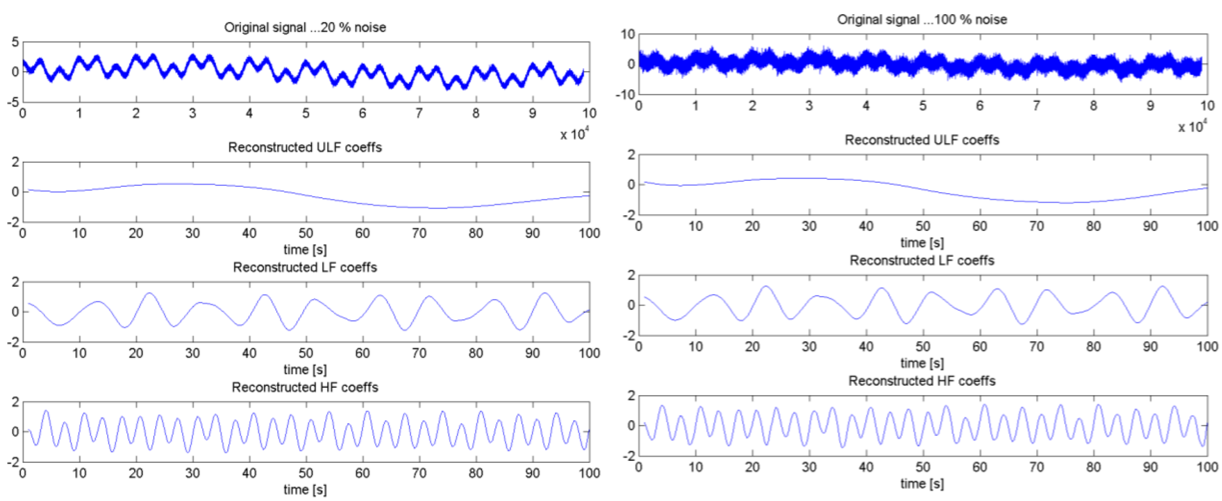
a) Sinusoid of three different frequencies without and with two level of noise



b) Decomposition and energy distribution without noise



c) Energy distribution with noise: 20% of signal amplitude – upper graph, and 100% of signal amplitude – lower graph



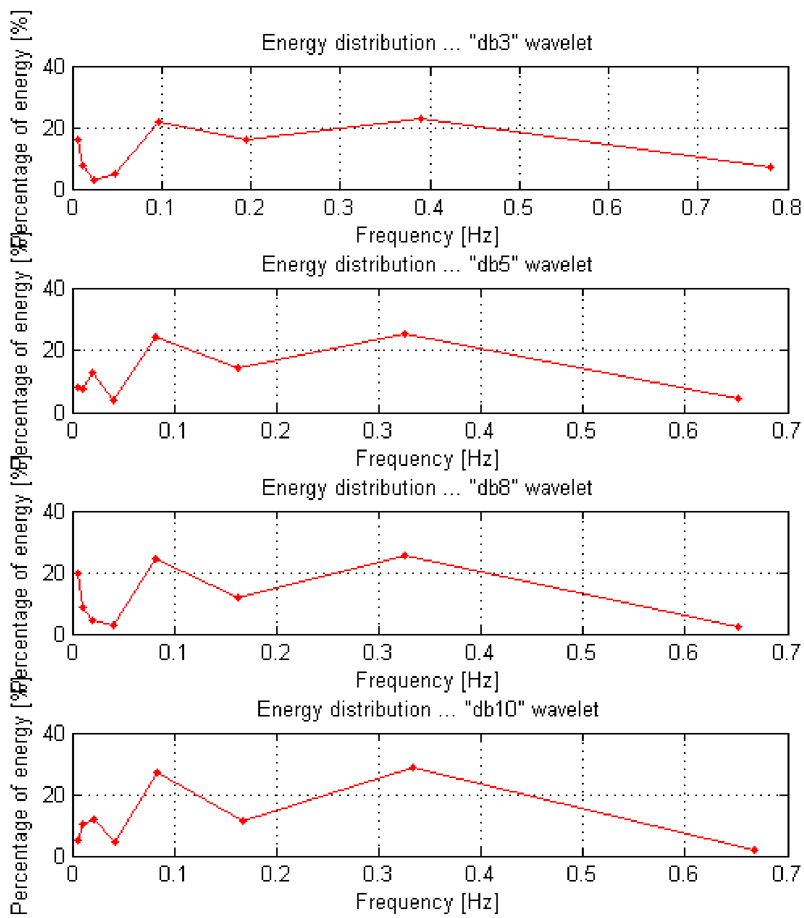
d) Decomposition with noise: 20% of signal amplitude – left and 100% of signal amplitude – right

Figure 11: Energy and decomposition for signal with and without noise

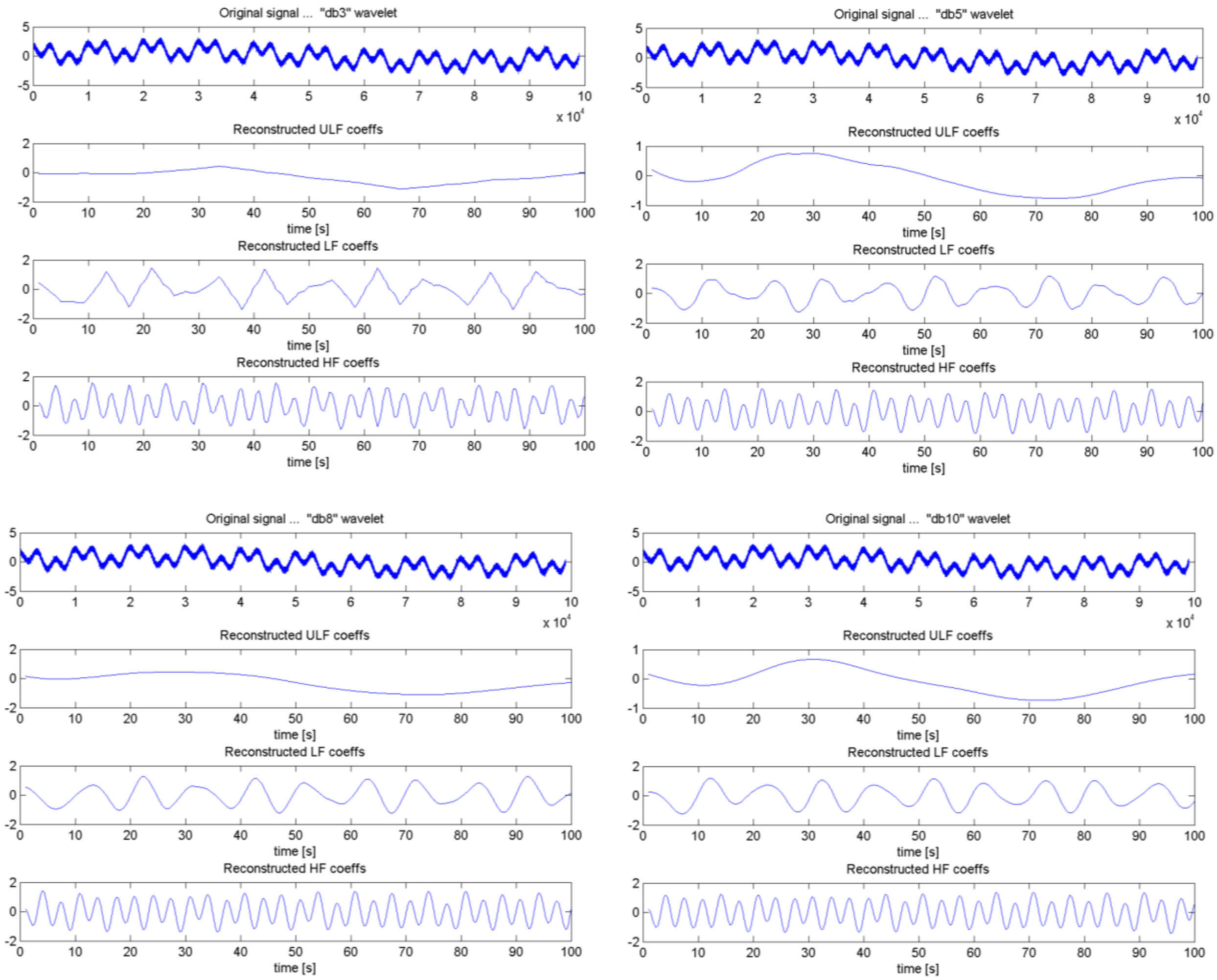
5.3 Influence of chosen wavelet function

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". It can be noticed in Figure 12a) that difference is very small for LF and HF band, but for ULF there are noticeable differences. Since there is no trend for ULF peak as increasing Daubechie function it is hard to conclude what is the reason. In Figure 12b) differences between reconstructions when different wavelet functions were used can be mostly seen on ULF and LF band signal. For LF and HF, reconstruction signals look very similar especially for “larger” Daubechie wavelet functions. Since “db1” is actually step function and “larger” Daubechie’s functions are more complex ones, but more similar to each other, as can be seen in Figure 13 this could be explanation for smaller difference of decomposition with “larger” Daubechie’s family wavelet functions. For this reason it is not necessary to use “db10” for analysis, just some enough “large” one.

Last thing to notice is that reconstructed signals in each band are not sinusoid functions as one may expect. This is (as explained in Chapter 5.1) due to the fact that borders of band pass filters that are “simulated” in DWT are not very precise.

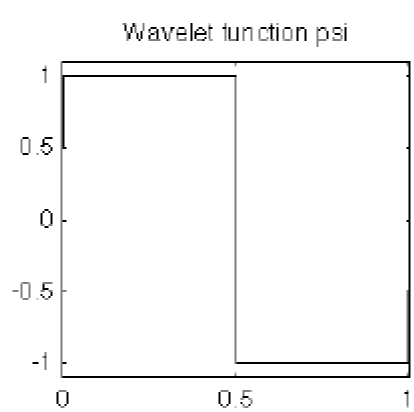


a) Energy distribution for different wavelet functions used

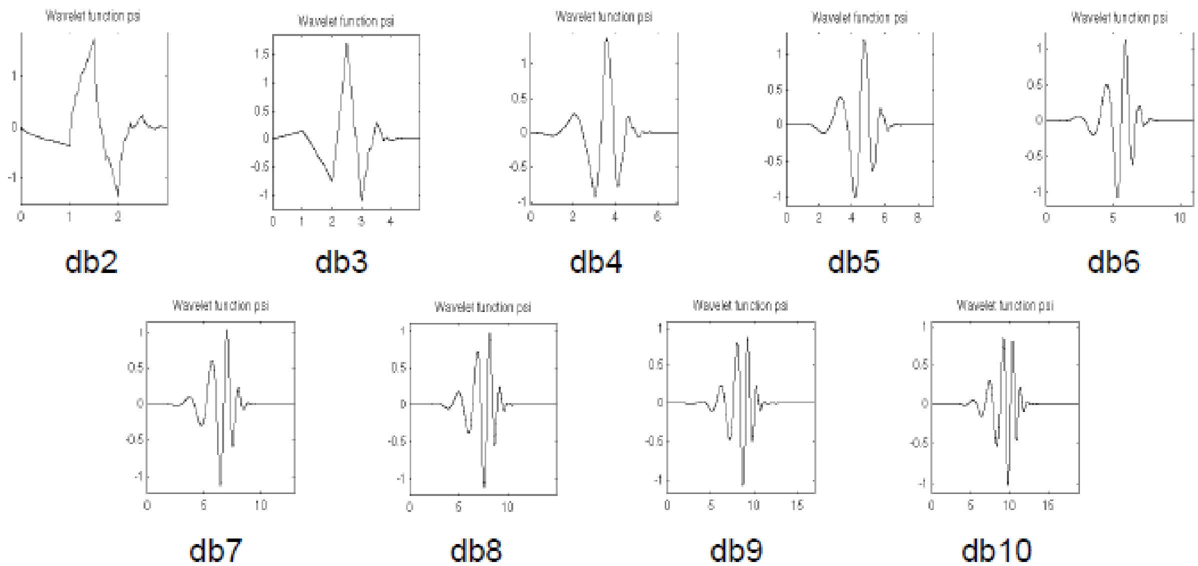


b) Decomposition for different wavelet functions used

Figure 12: Energy and decomposition for different wavelet functions used



a) "Db1" wavelet function

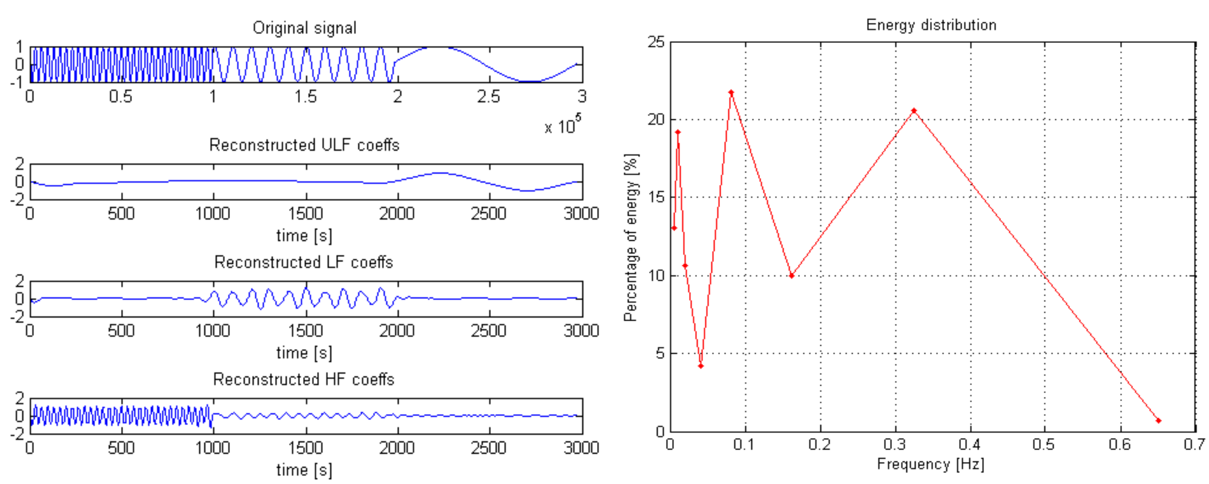


b) “Db2” to “Db10” wavelet functions

Figure 13: Daubechies wavelet family [8.]

5.4 Temporal resolution

Figure 14 shows signal reconstruction and energy distribution for signal whose frequency content changes in time. 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. Also from Figure 14b) it is noticed that energy distribution hasn’t changed in comparison to the image in Figure 12a) where all three components were present in input signal, all the time. This confirms DWT ability to analyze signal in frequency and time domain.



a) Signal reconstruction

b) Energy distribution

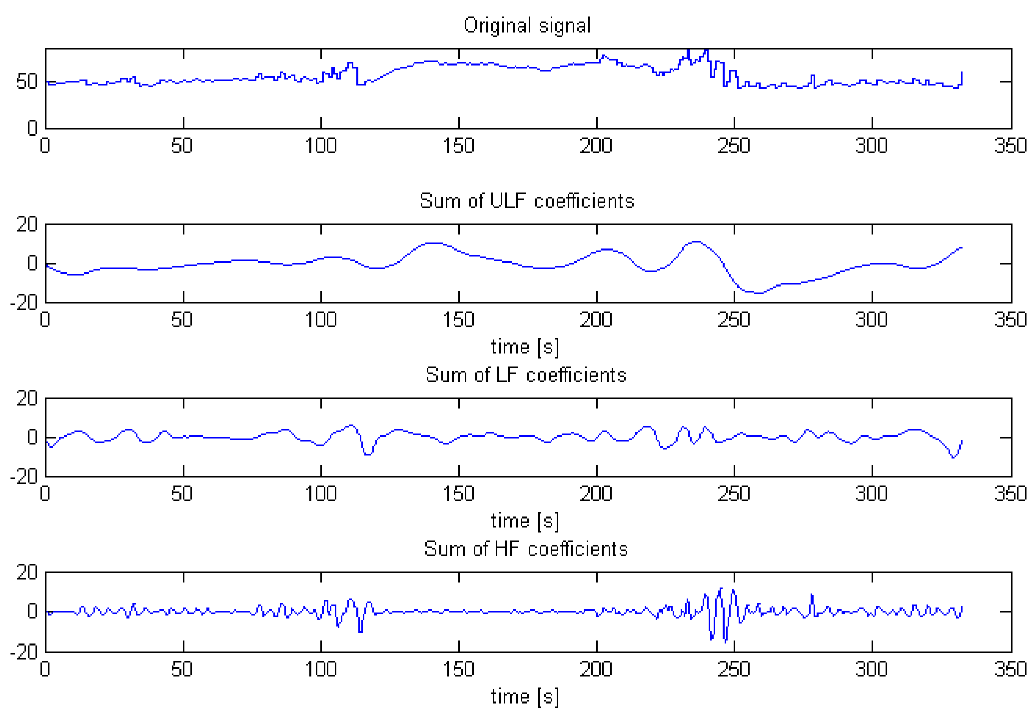
Figure 14: Test of temporal resolution of DWT

6 HRV analysis example

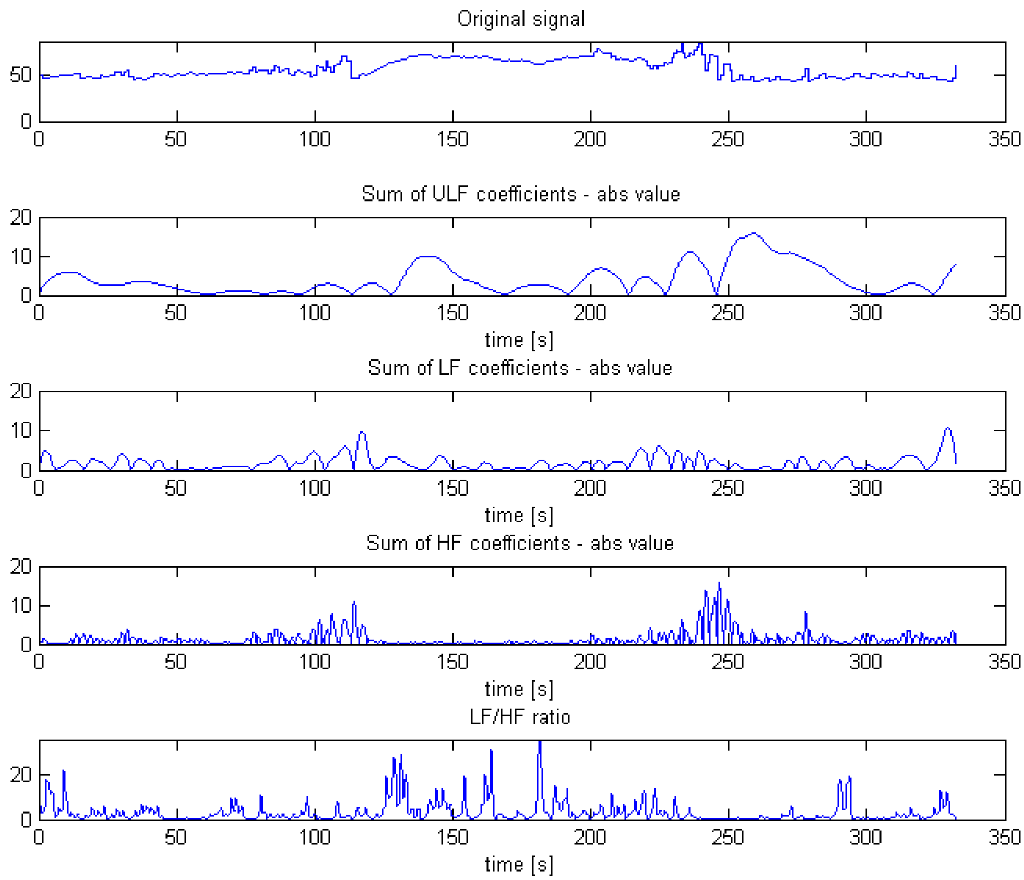
Five minute signal of heart rate sampled with 500 sample/s is used to present input and output data of HRV analysis using DWT method. Interpretation of results is given at the end. In Figure 15a) original signal (top one graph) and DWT coefficients separately for ULF; LF and HF frequency band are presented. On x axis is time in seconds and on y axis is arbitrary unit of amplitude of coefficients that is dependent on the transfer function of acquisition system, but it can be interpreted as normalized. Coefficients can have negative values which means that signal similar to the wavelet function but with inverse amplitude.

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 15b), absolute values of coefficients are plotted.



a) Heart rate signal decomposition on three frequency bands using DWT (with "db8")



b) Absolute values of coefficients and LF/HF ratio

Figure 15: Heart rate signal decomposition using DWT for HRV analyses

There are many possible causes of ULF, LF and HF component activation and it is very hard just to conclude what is exact reason for change in one specific case, just from coefficient changes in time. Possible reason for (for example) large LF/HF ratio depends largely on situation when was signal recorded. If the signal length is only few minutes it's not very likely that change happened because of different stages in sleep. If it is a long term recording it can be signal measuring changes of sleep stages, stress during working hours or even physical activity during day. In order to conclude something from DWT decomposition (or most other methods for HRV analyzes) conditions under which signal was recorded has to be known. Also it's much easier to find something if you know what you are looking for.

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 15b) 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.

7 Conclusion

In this seminar, possibility to analyze heart rate variability (HRV) with wavelet transform was investigated. First heart rate variability, its importance and main parameters that control it are presented. After that wavelet transform was explained dividing it on three types: continuous wavelet transform (CWT), continuous transform using Fourier transform (CWTFT) and discrete wavelet transform (DWT). After that, three methods were compared using reconstruction for different frequency bands, comparing coefficients for every frequency band, energy distribution per frequencies and in computational time needed to conduct decomposition. Decomposition quality showed very similar (except for smaller differences) for all three methods, but DWT showed to be the best one from several reasons: time and CPU power consummation, simplicity of decomposition and reconstruction and in the end quality, it was tested further.

Quality of decomposition, noise influence and mother wavelet type influence and time resolution were observed. Concerning quality of decomposition: detection to which band some frequency belongs, based on reconstruction is precisely detected only for frequencies which are in the middle for the frequency bands and further from the boundaries. As getting closer to the boundaries other bands detect these frequencies too. 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. This is another very positive property of DWT transform. In order to achieve precise decomposition and reconstruction some “large” mother wavelet function from Daubechies family can be used. Temporal resolution was shown to be very precise, which confirms DWTs’ ability to analyze signal in frequency and time domain.

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.

8 Literature

[1.] E. Kaniusas: Biomedical sensors and signals I, Springer 2012.

[2.] L.G.Gamero, M. Risk, J.F.Sobb, A.J.Ramirez, J.P.Saul: Heart rate variability analysis using wavelet transform,IEEE Computeirs in Cardiology 1996.

[3.] C.A.Garcia, A. Otero, X. Vila, D.G.Marquez: A new algorithm for wavelet-based heart rate variability analysis, 2014

[4.] I. Szollosi, H. Krum, D. Kaye, M. T. Naughton: Sleep Apnea in Heart Failure Increases Heart Rate Variability and Sympathetic Dominance, Sleep Journal, 2007.

[5.] V. Demchenko,R. Čmejla, J. Vokřál: Analysis of heart rate variability during respiration

[6.] Task Force of the European society of cardiology and the North American society of pacing and electrophysiology: Heart rate variability - Standards of measurement, physiological interpretation, and clinical use, European Heart Journal, 1996

[7.] M.Misiti, Y.Misiti, G.Oppenheim, J.M.Poggi: Wavelet Toolbox for use with Matlab, The Mathworks, 1997

[8.] M.Misiti, Y.Misiti, G.Oppenheim, J.M.Poggi: Wavelet Toolbox™ 4 - Getting Started Guide, The Mathworks, 1997

[9.] http://4.bp.blogspot.com/_5Nslwo9F6bI/S_EU-Kcs4DI/AAAAAAAAAg4/5f0VSazrcN4/s1600/ECG+trace+%26+basics.jpg, access 5.12.2015.