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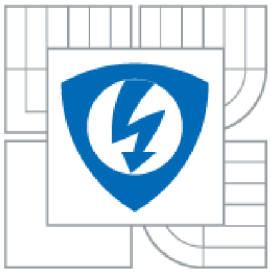

FAKULTA ELEKTROTECHNIKY A KOMUNIKAČNÍCH TECHNOLOGIÍ
ÚSTAV BIOMEDICÍNSKÉHO INŽENÝRSTVÍ

FACULTY OF ELECTRICAL ENGINEERING AND COMMUNICATION
DEPARTMENT OF BIOMEDICAL ENGINEERING

WIENEROVSKÁ VLNKOVÁ FILTRACE SIGNÁLŮ EKG

TITLE

DIPLOMOVÁ PRÁCE
MASTER´S THESIS

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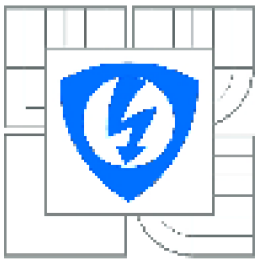

VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ

Fakulta elektrotechniky a komunikačních technologií

Ústav biomedicínského inženýrství

Diplomová práce

magisterský navazující studijní obor
Biomedicínské a ekologické inženýrství

Student:	Bc. Vasily Sizov	***ID:***	121671
Ročník:	2	***Akademický rok:***	2011/2012

NÁZEV TÉMATU:

Wienerovská vlnková filtrace signálů EKG

POKYNY PRO VYPRACOVÁNÍ:

1) Prostudujte problematiku filtrace s využitím vlnkové transformace. 2) Navrhněte wienerovský filtr uvedeného typu pro potlačení širokopásmových myopotenciálů v signálech EKG. K rozkladu signálu použijte osvědčené banky filtrů, zaměřte se na nalezení vhodné hloubky rozkladu a volby prahování při odhadu užitečného signálu, který wienerovský filtr vyžaduje. 3) Navržený filtr realizujte v prostředí Matlab. 4) Realizovaný filtr otestujte. Použijte signály EKG uměle rušené šumem s nastavitelnou úrovní a s výkonovým spektrem korespondujícím se spektrem reálných myopotenciálů. 5) Ověřte kvalitu filtru z hlediska poškození užitečného signálu vlivem filtrace. 6) Proveďte diskusi získaných výsledků.

DOPORUČENÁ LITERATURA:

[1] KOZUMPLÍK, J.: Multitaktní systémy. Elektronická skripta FEKT VUT v Brně, 2005.
[2] STRAMG, G., NGUYEN, T.: Wavelets and Filter Banks. Wellesley-Cambridge Press, 1996.

Termín zadání:	6.2.2012	***Termín odevzdání:***	18.5.2012

Vedoucí práce: doc. Ing. Jiří Kozumplík, CSc.
Konzultanti diplomové práce:

prof. Ing. Ivo Provazník, Ph.D.
Předseda oborové rady

UPOZORNĚNÍ:

ABSTRACT

This paper discusses the possibility of using wavelet transform applications dealing with noise suppression, especially in the area of filtering ECG signals. It is primarily to evaluate the influence of various parameters setting itself filtration, as is the way thresholding wavelet coefficients, setting thresholds and selection decomposition, and reconstruction filter banks.

Also there are the results of Wiener filtering, where the combination of banks used decomposition and reconstruction filters were tested. All filtration methods described here are tested on real ECG records with additive interference myopotencial noise and implemented in the Matlab enviroment.

Keywords: wavelet transform, ECG signal, wavelet filtering, wiener filter

ABSTRAKT

Tato práce se zabývá možností využití vlnkové transformace v aplikacích, které se zabývají potlačením šumu. Především se jedná o oblast filtrace signálu EKG. Úkolem je zhodnotit vliv různých parametrů nastavení samotné filtrace a zjistit jaký vliv má různé nastavení prahování wavelet koeficientů. Výsledkem práce je také stanovení hodnot prahů, stanovení nejlepšího způsobu rozkladu signálu a volba rekonstrukčních bank filtrů.

Text obsahuje výsledky Wienerovy filtrace, při které byly testovány různé banky rozkladových a rekonstrukčních filtrů.Všechny popsané filtrační metody byly testovány na reálných záznamech EKG s aditivním myopotenciálním šumem. Algoritmy byly realizovány v prostředí MATLAB.

Klíčová slova: vlnková transformace, EKG signál, vlnková filtrace, wienerovská filtrace

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Prohlášení

Prohlašuji, že svou diplomovou práci na téma "Wienerovská vlnková filtrace signalů EKG" jsem vypracoval samostatně pod vedením vedoucího diplomové práce a s použitím odborné literatury a dalších informačních zdrojů, které jsou všechny citovány v práci a uvedeny v seznamu literatury na konci práce.

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V Brně dne … .

.....
podpis autora (autorky)

PODĚKOVÁNÍ

Děkuji vedoucímu diplomové práce doc. ing. Jiřímu Kozumplikovi, CSc. za účinnou metodickou, pedagogickou a odbornou pomoc a další cenné rady při zpracování mé diplomové práce. Taky děkuji kamarádovi Ondřeji Macíčkovi za pomoc s formální stránkou mé diplomové práce.

V Brně dne .....

.....
(podpis autora)

Obsah

INTRODUCTION

Spontaneous electrical signals produced by the body is a kind of guidance for doctor in assessing the health status of patients. The most commonly measured and monitored signals are electrical brain activity - electroencephalogram (EEG), heart -electrocardiogram (ECG), muscles - electromyogram (EMG), stomach – elektrogastrogram (EEG). ECG signal is used to diagnose disorders such as heart rate, ventricular activation outside heart beat – extrasystoles, ischemic heart disease and its most severe forms – heart attack. When evaluating an electrocardiogram (ECG) is considered in particular the duration of each sections, their amplitude and changes the shape of waves and oscillations. It is therefore important to evaluate only useful signal without the interference that occurs in almost all ECG recordings.

Wavelet transform is a modern tool for signal processing. its application located mainly in the compression of images. Recently, due to its ability (eg capture rapid changes or discontinuities) is widely used to suppress noise in the signals. This paper is focused on the use of wavelet transform (with discrete time - DTWT) at filtering of electrocardiographic signals.

In first part of paper there are some theoretical bases about human's physiology. It is necessary to understand the process of electrokardiography, the one of the important subject of our work. Also we considered the main interferences of ECG signal.

The second part describe the theory of wavelets and wiener filtering. Here we considered discrete and inverse wavelet transform and their conditions. Also there is wiener filter application.

The last part summarizes the results obtained in different experiments with setting the parameters of wavelet filtering. They are listed here as a numerical value expressing the obtained from the output signal to noise ratio (SNR - Signal to noise ratio) and videooutputs filtration obtained in Matlab.

1.Theoretical bases

1.1 Electrical activity of the heart

Each heart contraction precedes the wave of electrical irritation, which begins in the sinoatrial (SA) node (Figure 1.1). The waves of electrical activity spreads through the chambers until they reach atrioventricular (AV) node. Minutes of the SA node has no permanent resting potential. What can be registered in contractile muscle cells. Spontaneous depolarization andrepolarizationSA node is unique, miraculous source of automatic impulses, whichactivate the AV node and atrium. This leads to impulses Tawar branch and they are activated muscle cells. In cardiomyocytes outside the SA node does not take plac eunder normal circumstances spontaneous depolarization, and therefore must be activated by impulses from the outside.

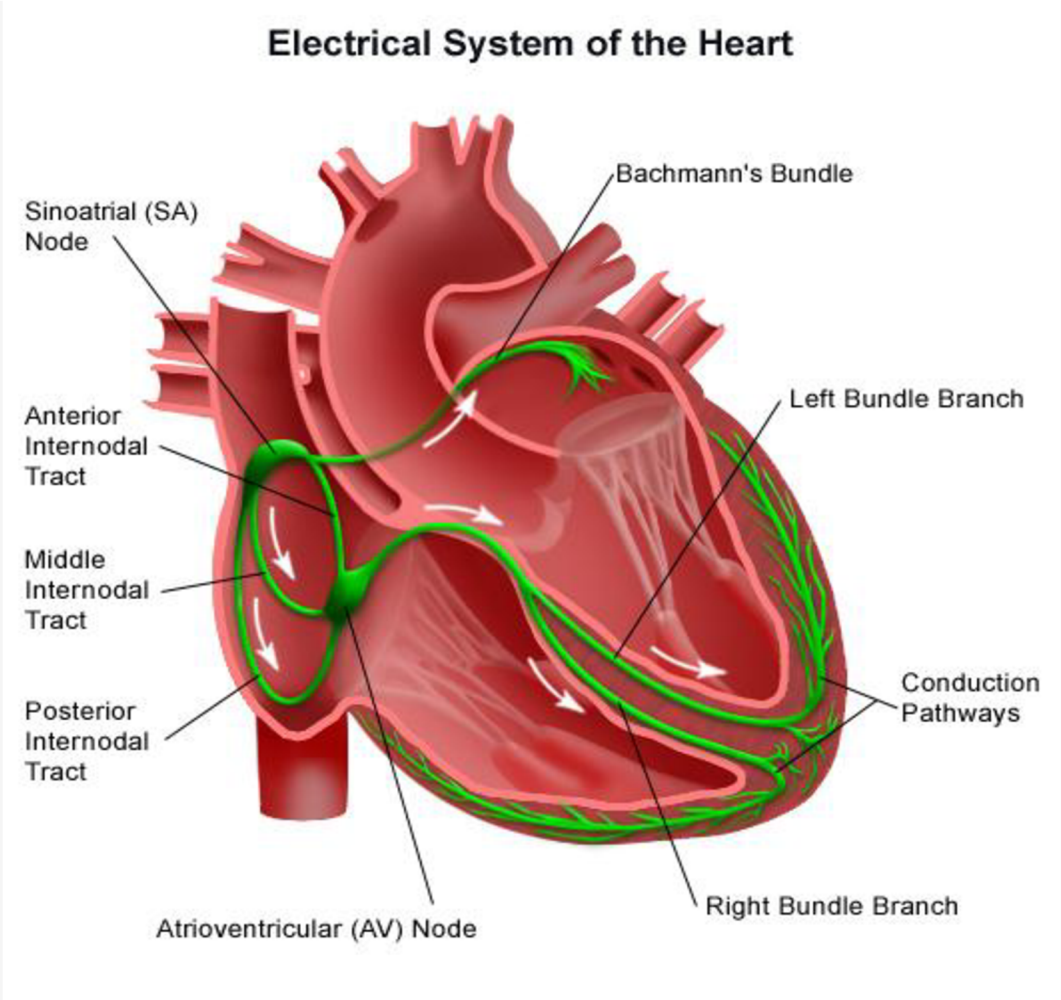


Figure. 1.1: Cardiac conduction system

1.2 Depolarization and repolarization

The resting heart muscle cell molecules dissociate into ions with positive charge on external and negative charge inside the cell membrane, the cell isin an electrically balanced, or vice versa polarized state. It works if the cell waveelectrical irritation, with negatively charged ions penetrate the surface of cells withpositivecharge inside the cell, this change of polarity is called depolarization. If the electrode is positioned so that the depolarization wave front is directed to the electrode, galvanometer deflection recorded positive. Directed the wave of depolarization from the electrode,writes the negative frequency.In the recovery phase with positive ions return to the outer surface of cells, while ions with a negative charge inside the cell. It restores the electrical balance of cells, this process is called repolarization. [4]

1.3 Action potential

In electrocardiography, the cardiac action potential is a specialized action potential in the heart, necessary for the electrical conduction system of the heart. The standard model used to understand the cardiac action potential is the action potential of the ventricular myocyte. The action potential has 5 phases (numbered 0-4). *Phase 4* is the resting membrane potential. This is the period that the cell remains in until it is stimulated by an external electrical stimulus (typically an adjacent cell). This phase of the action potential is associated with diastole of the chamber of the heart. *Phase 0* is the rapid depolarization phase. The slope of phase 0 represents the maximum rate of depolarization of the cell and is known as dV/dt_{max}. This phase is due to the opening of the fast Na^+ channels causing a rapid increase in the membrane conductance to Na^+ (G_{Na}) and thus a rapid influx of Na^+ ions (I_{Na}) into the cell; a Na^+current [6].

Phase 1 of the action potential occurs with the inactivation of the fast Na^+ channels. The transient net outward current causing the small downward deflection of the action potential is due to the movement of K^+ and Cl^- ions, carried by the I_{to1} and I_{to2} currents, respectively. Particularly the I_{to1} contributes to the "notch" of some ventricular cardiomyocyte action potentials.

Phase 2. This "plateau" phase of the cardiac action potential is sustained by a balance between inward movement of Ca^{2+} (I_{Ca}) through L-type calcium channels and outward movement of K^+ through the slow delayed rectifier potassium channels, I_{Ks}. The sodium-calcium exchanger current, $I_{Na,Ca}$ and the sodium/potassium pump current, $I_{Na,K}$ also play minor roles during phase 2. During *phase 3* (the "rapid repolarization" phase) of the action potential, the L-type Ca^{2+} channels close, while the slow delayed rectifier (I_{Ks}) K^+ channels are still open. [6]

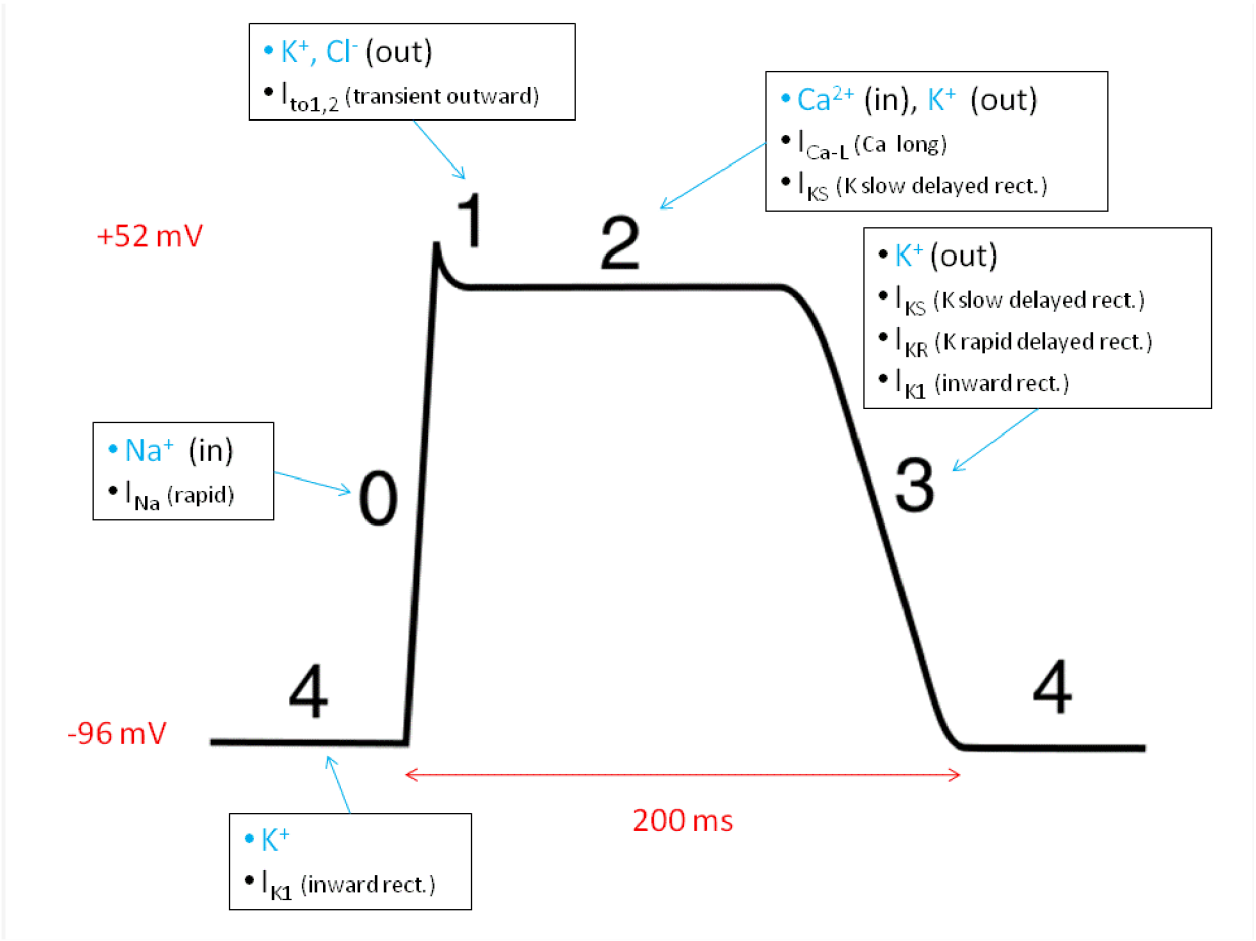


Figure. 1.2: Membrane action potential

1.4 Sinoatrial and atrioventricular node

The uniqueness of the SA node that it doesn't have no permanent resting potential. After completion of repolarization taking place in phase 4 spontaneous slow action potential depolarization occurs, which is cause of the SA node automaticity fibers. This provides a unique pacemaker automatic delivery of pulses driving the electrical activity of the heart and its contractions. The frequency of the SA node, typically 50-100 per minute, is influenced by vegetative nervous system, chemical and hormonal influences.

AV node slows the electrical current physiologically coming from the hall, thus gaining time for filling the chambers of the atrial systole, the period preceding the systole chambers. After passing through the AV node and bundle of His electrical pulse is veryquickly transfer all components of the chambers, left and right Tawara's branches and all the Purkinje fibers and muscle cells is depolarized. Depolarization spreads from the base to the tip of interventricular septum and then free left ventricular wall, always spreads from endocardium toward the epicardium. [4]

Fine peripheral branching arm of which creates a network of Purkinje fibers is anatomically located the endocardial cells. Temporary detention and leadership in slowing AV node has an important protective role in patients with atrial fibrillation and atrial flutter. In both these situations frequently come the fast AV node impulses from the atrial rate 300-600 per minute, this "barrier" decreases frequency of electrical impulses that reach the motorway network of chambers approximately 120-180pulses per minute, thereby preventing serious incidents tachycardia, which would compromise patient's life.

1.6 Electrocardiogram

Cardiac muscle is composed of many thousands (approximately 1010) of muscle cells. Each time depolarization and repolarization represents a large group of different phases of cell activity. The electrical activity of each component can be understood as a vector force.
The vector is defined as the force that has direction and magnitude. Sum of all instantaneous vectors produces cardiac electrical activity of heart. ECG records the sequence of instantaneous cardiac vectors. Cardiac muscle is composed of three muscle masses: interventricular septum, large muscle mass and left ventricular muscle mass much smaller chamber right. The size or amplitude of the recorded mass displacements is affected depolarize muscle and its distance from the electrodes registering.

A graphic record of electrical activity recorded by electrodes in the heart of strategic locations creates a body surface electrocardiogram (ECG). Record electrical currents, their direction and size, as well as the frequency of heart contractions, the instrument - an electrocardiograph. Its essence is the galvanometer, the deflection records the registration paper. ECG recording is thus obtained. For simple evaluation is sufficient to note
that captures the ECG (Figure 1.3):

• three prominent oscillations and waves: P wave, QRS complex oscillations and T wave

• two time intervals important in clinical practice: the PR interval and QRS duration

ST segment, the most important part of the ECG.

• The findings of ST segment abnormalities store allows early diagnosis of AMI and myocardial ischemia.

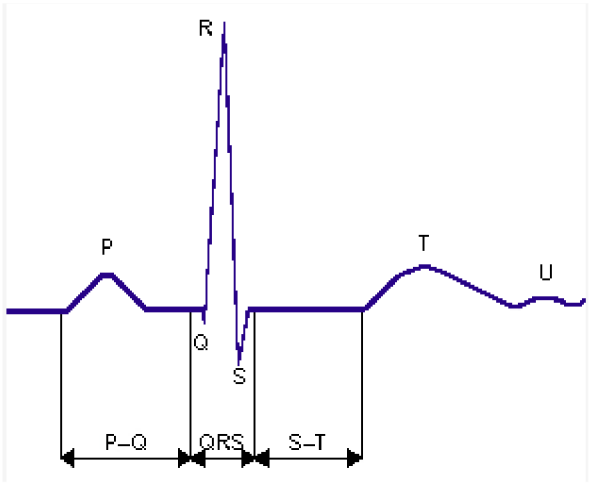


Figure. 1.3: The basic shape of the electrocardiogram

P wave

The first part of the P wave records the electrical activity of the right atrium. The central part of P wave arises at the completion of right atrial activation and early activation of the left atrium. The terminal portion of P wave consists of left atrium. P wave is the first deflection of the electrocardiogram, is a small, smooth rounded contour displacement before complex oscillations of QRS complex.

PR Interval

PR interval time information on who needs an electrical impulse from the atrium to the AV intersection node bundle of His, Tawara's branches and Purkinje fibers to the beginning depolarization of muscle cells.

QRS complex

QRS complex is the image of the electrical activation of the ventricular myocardium and electric power resulting in depolarization of ventricular muscle in the ECG register as sharp oscillations. Sharp scissors oscillations are referred to as the QRS complex regardless of whether they are mostly positive (directed upward) or negative (downward).

The origin of the QRS complex

QRS complex formation makes the three vectors. The electrical impulse that spreads from the SA node,activates the hall and there is a P wave, the first wave of the

electrocardiogram. Procedure electric impulse slows briefly at the AV node and then quickly spread bundle of His, right and left Tawara's branches and the Purkinje fibers into the ventricular myocardium.Dissemination electrical impulse ventricular septal myocardium is called depolarization, and that is the cause oscillations of the QRS complex on ECG.

ST segment

ST segment lies between the end of the QRS wave and the beginning of T. inform the moment in which all parts of the ventricles is depolarized, or the phase in which they are aligned electric power and incipient depolarization ended repolarization, which are mutually offset (neutralize). The course of ST segment may be affected in varying degrees early repolarization. The point at which the ST segment withdraws from the QRS complex is called J (Junction). ST segment normally flows into the ascending part of the T wave and has no place quite horizontally, nor with ascending part of the T wave to create sharp angle.

T wave

T wave, broad rounded wave shape, resulting from the electrical recovery, repolarization chambers. T wave following each QRS complex and is separated from the QRS time interval, which is constant for each ECG. Given that the recovery Chambers is the direction of their activation, polarity of the resulting vector is similar to T polarity of the QRS vector. T wave arises at the time of mechanical systole ventricles, the QRS complex it immediately precedes it.Processes associated with the emergence of the T wave of energy-in the development QRS energy is consumed. Metabolic activity of muscle cells and energy is necessary for repolarization during movement of ions in this process. Repolarization and configuration of the T wave may therefore be influenced by some metabolic, haemodynamic and physiological circumstances. According to Levine, there are approximately 67 causes of T wave shape changes, like drinking ice water, swallowing food, exercise, starvation, infection, fever, tachycardia, anoxia, shock, electrolyte disturbances, acidosis, alkalosis, hormonal disorders, subarachnoid hemorrhage and the influence of drugs or alcohol.

U wave

The U wave is a wave that follows the T wave is seen on the ECG records only for some individuals. Its voltage is low, in some leads, it can be difficult to find. Its origin is unclear.

1.7 Lead systems

According to the site to capture leakage distinguish between different systems:

- standard 12-lead system (leads I, II, III, aVR, aVL, aVF, V1-V6) using 10 electrodes,
- orthogonal discharge system according to Frank (leads X, Y, Z) uses eight electrodes
- modified systems for stress ECG.

1.7.1 The standard 12-lead system

Classic mode is ECG registration 12 lead system. It consists of both bipolar leads, through which we register the potential difference between two points, and both unipolar leads. Unipolar leads potentials recorded from a single location due to the zero potential (indifferent electrode). Bipolar limb are leads I, II, III, the other leads are unipolar. For a standard form 12 lead system ECG bipolar limb leads the Einthoven triangle. The combination of limb electrodes using the same resistance is obtained Wilson's terminal, which is virtually constant, zero potential to form a reference point against which to measure the potential of the unipolar chest and limb leads enlarged.

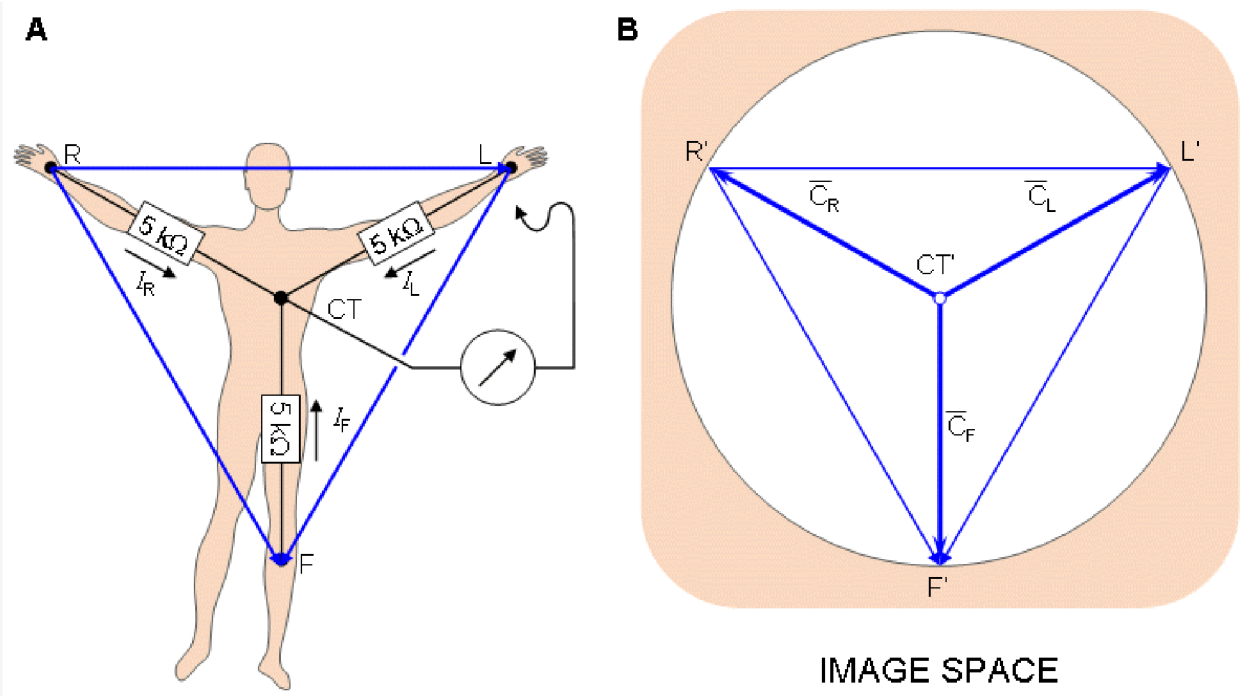


Figure. 1.4: (A) The circuit of the Wilson central terminal (CT).
(B) The location of the Wilson central terminal in the image space (CT'). It is located in the center of the Einthoven triangle.

Electrodes limb leads is the best place on the inside of the forearm or leg where the skin is less resistance than on the outside. Of course, after soaking or applying a small amount of paste according to the type of ECG electrodes. Localization of electrodes the limb leads is not essential, it means that they can be attached the arm or thigh, possibly on the shoulders ofpatients after amputation or significant tremor. The correct location is shown in Figure 1.5

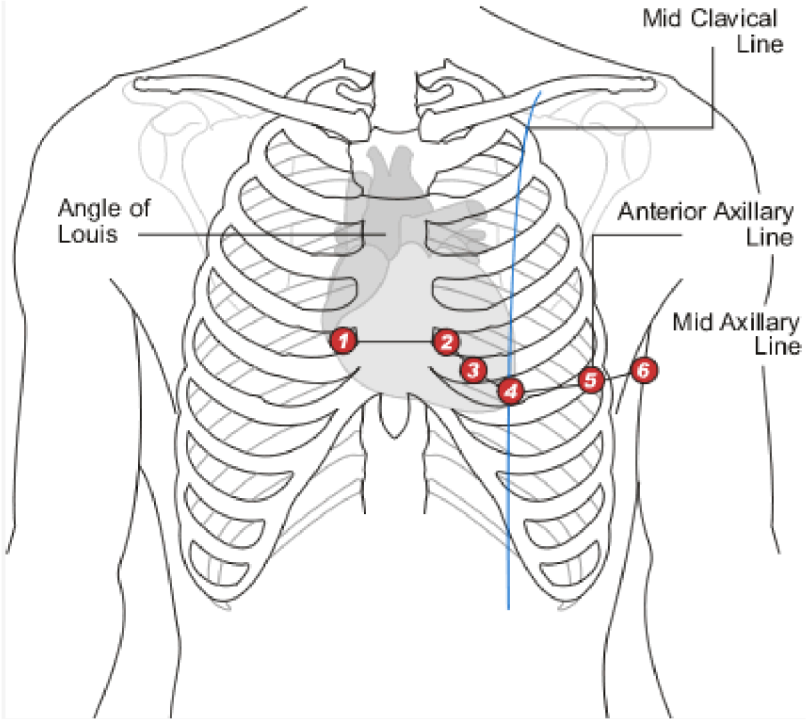


Figure. 1.5: Positioning of the 6 chest leads

Location chest leads:

- V1 = 4 intercostal space to the right of the sternum
- V2 = 4 intercostal space at left sternal
- V3 = on a halfway between V2 and V4
- V4 = 5 intercostal space in midclavicular line (center of the germ)
- V5 = 5 intercostal space in the front axillary line
- V6 = 5 intercostal space in mid axillary line

1.7.2 Orthogonal lead system

Taking orthogonal leads is not very widespread in Czech Republic. They provide a

continuous image vector in three mutually perpendicular planes: frontal, sagittal and horizontal. Electrodes for sensing orthogonal leads are placed differently from conventional ECG. The most common is lead system according to Frank. Recording of cardiac vectors can be perform either a scalar, ie oscillations of ECG, or flat. In scalar views we get three leads, X, Y and Z. When we receive the printed display vector loop which form the essence vektokardiografie. Unlike the scalar ECG display can vektokardiografie obtained using planar display the size and direction of each vectors. Displaying horizontal in the frontal and sagittal plane and so we obtain a spatial orientation (Figure 1.6).

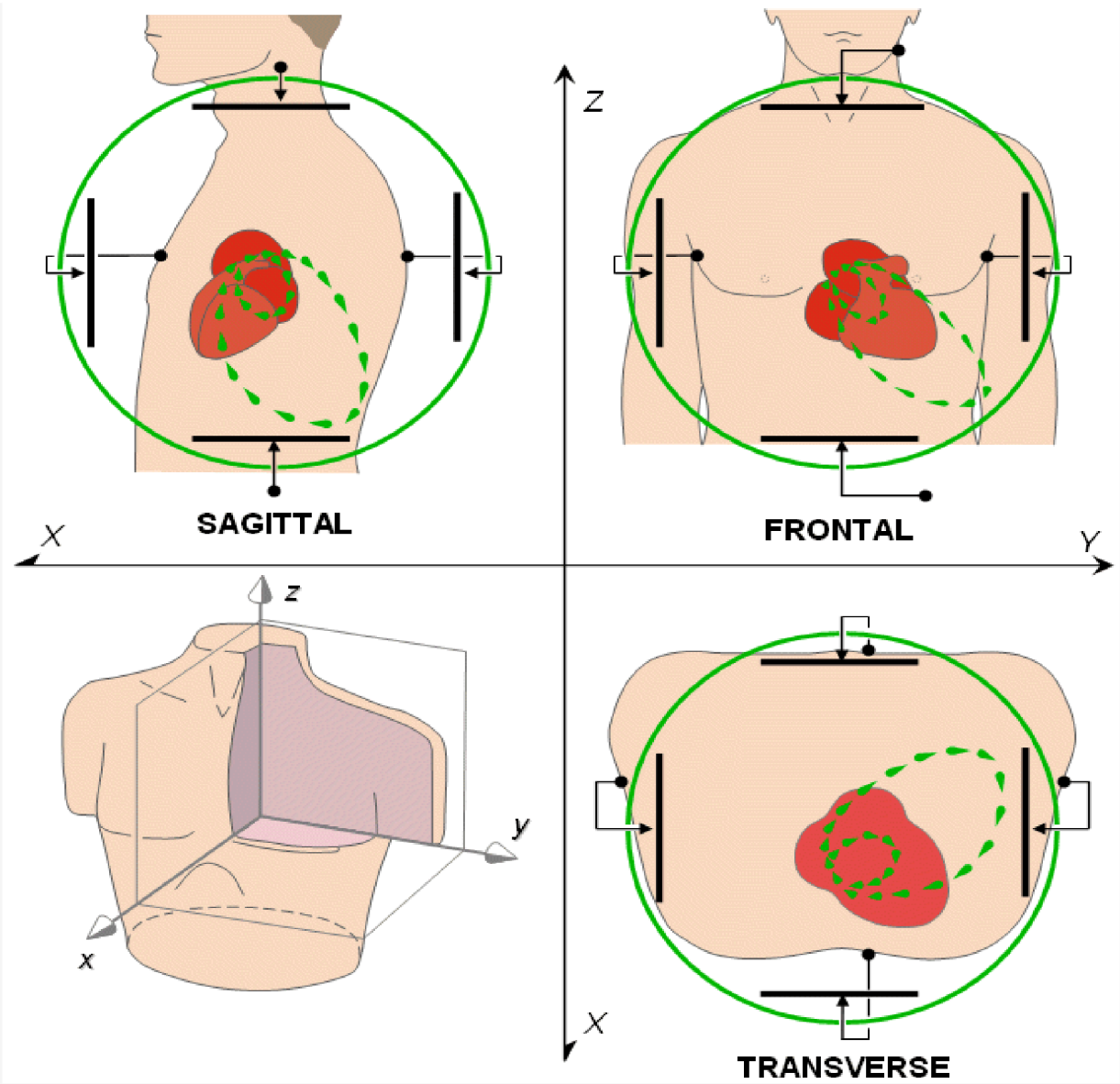


Figure 1.6. Orthogonal lead system

1.7.3 Intracardiac leads

They represent no special invasive investigative method by which we can information about the shape of the electric potential in the individual heart sections. It helps in the diagnosis of arrhythmias during catheterization informs us about the position the catheter in the heart. The implementation for permanent pacing electrodes, which can simultaneously serve as an electrode sensing, potentials can be recorded from the right heart and to assess the correct location. An important diagnostic method is the potential scan of His bundle. It is the structure of the conduction system connected to the atrioventricular node. They are divided into part joint and the arm, formerly known as the bundle. Bundle of His is an important from the electrophysiological point of view. Its cells are endowed with the ability of spontaneous excitation and thus produce rhythm. We talk about junctional ectopic contractions (junction - the area connection). Electrogram of His bundle gives detailed information on the atrioventricular conduction time.

1.7.4 Special Lead Systems

12-lead electrocardiogram represents a classic fundamental electrocardiographic examination. For more accurate diagnosis is sometimes necessary to supplement the examination of other leads, which can provide us with valuable information. Complementary to conventional ECG leads as leads V3R, V4R, which register from the right side of chest. Similarly, we continued to record leads V7, V8, V9, left axillary line between the back and spine at the level of leakage V6. With esophageal electrode can record high atrial potentials, better assess the electrical activity of fibrillation and its relation to ventricular electrical activity.Using the indicated in the differential-diagnostic resolution of atrial and ventricular arrhythmias. Scanning is simple. Esophageal electrode is introduced through the nose or mouth to a depth of 35-40 cm from the teeth and the registration form is evaluated ECG atrial potential.

Monitoring leads .We use them to monitor arrhythmias, usually in patients in bed. This is a manifold bipolar, with the placement of electrodes usually on the front chest. Monitoring leads are also used in some investigations of stress, such as stress echocardiography or during endurance training at high-risk persons.

1.8 Electrodes

All electrodes have one thing in common, despite all the diversity. It is metal-electrolyte combination. Metal is the material of electrodes, an electrolyte solution may take the form, gel can be formed or body fluids. What features will this pair will be depend both on the

electrode material, as well as on the chemical composition of the electrolyte.

Capture and record an electrocardiogram (ECG) from the body surface is performed in principle.

Three types of electrodes:

a) The standard large-scale metal electrodes made of an alloy of zinc, copper and nickel. They are used for short-term ECG recording signals from limb leads. They are applied with a thin layer of electrode gel or aqueous electrolyte consisting of sodium chloride and potassium chloride. Are fixed to the skin elastic bandage or spring clamp.

b) Suction electrodes used for sensing short-thoracic leads ECG signal, which are easily movable. They have the shape of hollow metal goblet. The skins fix the rubber suction blower through a layer of electrolyte.

c) Floating electrodes Ag / AgCl. The electrodes are made of metal ceramic with silver and coated with a layer of silver chloride. Bulging discs are placed in plastic sleeve with space for gel or polyurethane foam saturated gel. Fixation to the skin is carried out double-sided adhesive tape. Electrodes are among unpolarized and are suitable for application in long-term monitoring.

Division of electrodes can be made according to various criteria. According to the polariability electrode polarity and non-polarity, according to the location of the electrode surface and electrodes placed inside the body. Another division can be for example the shape or method of use. Some types of electrodes are shown in Fig 1.7

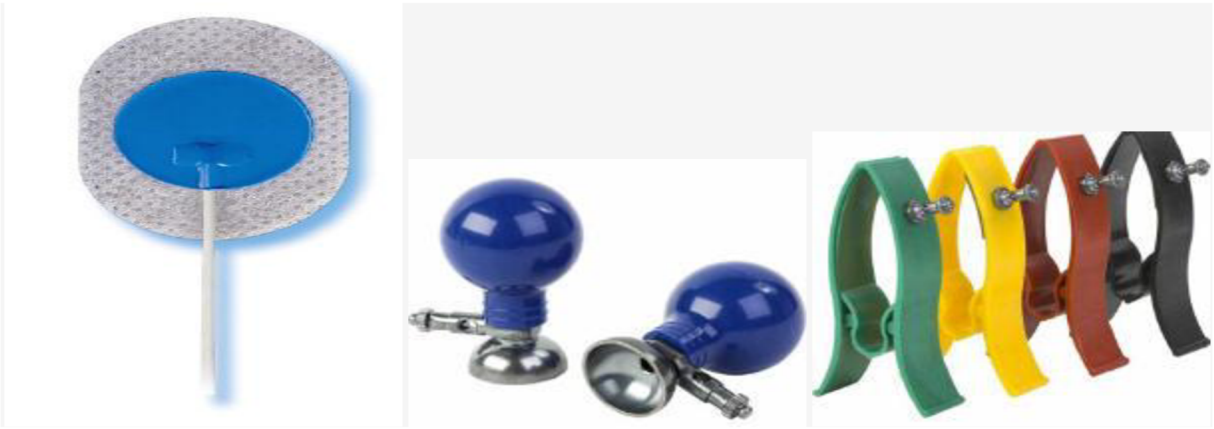


Figure. 1.7: Children electrode, suction chest electrodes, limb electrodes

2. Basic types of ECG interference

2.1 Sources of ECG Monitoring Artifact

The electrical activity of the heart is sensed by monitoring electrodes placed on the skin surface. The electrical signal is very small (normally 0.0001 to 0.003 volt). These signals are within the frequency range of 0.05 to 100 Hertz (Hz.) or cycles per second. Unfortunately, other artifactual signals of similar frequency and often larger amplitude reach the skin surface and mix with the ECG signals.[9,12] Artifactual signals arise from several internal and external sources. Internal or physiologic sources of artifact are: (1) signals from other muscles (electromyographic signals) and (2) signals produced in the epidermis. External or non-physiologic sources of artifact are: (1) 60 Hz. Pickup, (2) offset signals produced by the electrode itself, (3) signals produced by the interaction of body fluids and the electrode gel, and (4) lead wire and patient cable problems. [14]

2.2 Physiologic Sources of ECG Artifact

Electromyographic (EMG) Signals - All muscle activity produces electrical signals. Signals from muscles other than the heart are called EMG signals and appear on the monitor as narrow, rapid spikes associated with muscle movement. These signals are sufficiently dissimilar to the ECG signals that they can be electronically reduced or "filtered" from the trace. This filtering is readily observed by reduction in the size of EMG signals as the monitor is switched from the diagnostic mode to the monitor mode (in monitors so equipped). [14]

Epidermal Signals - The skin is a source of electrical signals which produce motion artifact. Studies have revealed that a voltage of several millivolts can be generated by stretching the epidermis, the outer layer of the skin. This stretching is the primary source of movement-related (motion) artifact. This type of artifact is visible as large baseline shifts occurring when the patient changes positions in bed, eats or ambulates. Epidermal artifact is more troublesome than other types of artifact because: (1) it is difficult to filter electronically and (2) its amplitude is often larger than the ECG signal. [14]

2.3 Non-Physiologic Sources of ECG Artifact

50 Hz. Pickup - This type of artifact, also called 50 Hz. Interference, produces a wide, fuzzy baseline. It is related to poor electrode contact associated with poor skin preparation techniques, dried electrode gel, or defective patient cables or lead wires. [14]

The source of 50 Hz. pickup is the 50 Hz. current which supplies power to the electrical wall outlets. The 50 Hz. energy "radiates" from the electrical wiring in the patient's room and is received in the lead wires and by the patient. The source of radiation cannot be eliminated, but modern monitors can reduce 50 Hz. pickup by filtering and by an electronic technique called common mode rejection. This technique requires good skin contact by all electrodes. One or more electrodes with poor contact will result in the wide fuzzy baseline. [14]

Offset Potentials - An offset potential is a voltage that is stored by the electrode. This stored voltage will add to the ECG signal and interfere with it. (The offset potential causes the disappearance of the ECG after defibrillation.) The amount of offset potential and the length of time required for it to dissipate are determined by the materials used for the electrode and the gel. Certain combinations of metals and gels generate large voltages (up to 200 millivolts) with the ability to hold this voltage for long periods of time. Electrode materials such as silver-silver chloride do not allow significant buildup of offset potential, whereas stainless steel electrodes have poor offset characteristics. Most electrodes used for ECG monitoring today are made of silver-silver chloride. With the common use of the silver-silver chloride electrode, offset potentials are no longer considered to be a significant problem. [14]

Electrode Gel - until recently, movement of the electrode gel under the electrode was thought to be the primary cause of motion artifact; however, studies have revealed that this effect is minimal.[8,12] The electrode gel does, however, significantly affect the transmission of signals from the skin to the electrode. The lack of sufficient electrode gel, frequently due to evaporation caused by improper storage, results in 50 Hz. pickup and extremely unstable traces. This type of artifact is easily identified by very high electrode impedances. [14]

Lead Wire and Cable Problems - Breaks in the wires and connections between the electrode and the monitor will always be a source of monitoring problems. Poor contact at any snap connection, loose pins at the cable end of the lead wire, and breaks in the conductors of the lead wire or patient cable can cause intermittent loss of the ECG tracing, 60 Hz. pickup, or trace instability. [14]

2.4 Electrode Impedance

In order for ECG signals to pass from the body to the electrode, an electrically conductive path between the skin and electrode must be established. The conductive ability of this path is referred to as electrode impedance or contact impedance. Electrode impedance is measured in ohms. High impedance decreases the conduction of the ECG signal. Low impedances improve

this conduction. The major factors affecting electrode impedance are: (1) the quantity and quality of gel between the electrode and the patient and (2) the degree to which the outer layer of the epidermis (the stratum corneum) has been bridged by the conductive gel.

Proper site preparation (as described below) will produce contact impedances of 10,000 ohms or less in 90% of patients.[9] Less than 5,000 ohms is a good target value. Improper site preparation will usually produce contact impedances as high as 100,000 to 200,000 ohms. [14]

3. ECG processing

3.1 Basic functions

It is simpler to explain a basis function if we move out of the realm of analog (functions) and into the realm of digital (vectors) (*). Every two-dimensional vector (x,y) is a combination of the vector (1,0) and(0,1). These two vectors are the basis vectors for (x,y). Why? Notice that x multiplied by (1,0) is the vector (x,0), and y multiplied by (0,1) is the vector (0,y). The sum is (x,y). [13]

The best basis vectors have the valuable extra property that the vectors are perpendicular, or orthogonal to each other. For the basis (1,0) and (0,1), this criteria is satisfied. Now let's go back to the analog world, and see how to relate these concepts to basis functions. Instead of the vector (x,y), we have a function f(x). Imagine that f(x) is a musical tone, say the note A in a particular octave. We can construct A by adding sines and cosines using combinations of amplitudes and frequencies. The sines and cosines are the basis functions in this example, and the elements of Fourier synthesis. For the sines and cosines chosen, we can set the additional requirement that they be orthogonal. How? By choosing the appropriate combination of sine and cosine function terms whose inner product add up to zero. The particular set of functions that are orthogonal and that construct f(x) are our orthogonal basis functions for this problem. [13]

A basis function varies in scale by chopping up the same function or data space using different scale sizes. For example, imagine we have a signal over the domain from 0 to 1. We can divide the signal with two step functions that range from 0 to 1/2 and 1/2 to 1. Then we can divide the original signal again using four step functions from 0 to 1/4, 1/4 to 1/2, 1/2 to 3/4, and 3/4 to 1. And so on. Each set of representations code the original signal with a particular resolution or scale. [13]

3.2 Some examples of wavelet form

Wavelet transforms comprise an infinite set. The different wavelet families make different trade-offs between how compactly the basis functions are localized in space and how smooth they are. Some of the wavelet bases have fractal structure. The Daubechies wavelet family is one example

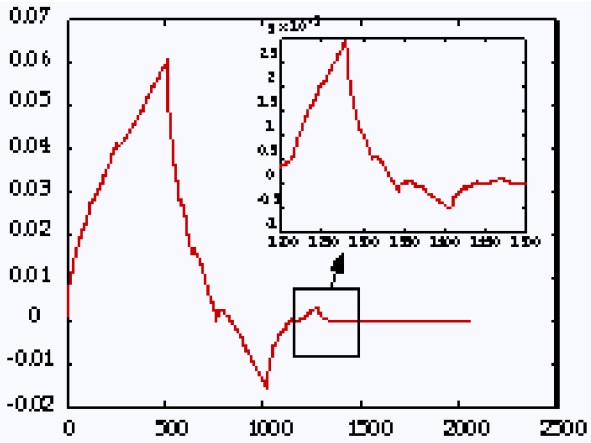


Fig. 3.3 The fractal self-similiarity of the Daubechies mother wavelet

This figure was generated using the WaveLab command:

```
wave=MakeWavelet(2, -4, 'Daubechies', 4, 'Mother', 2048).
```

The inset figure was created by zooming into the region x=1200 to 1500.

Within each family of wavelets (such as the Daubechies family) are wavelet subclasses distinguished by the number of coefficients and by the level of iteration. Wavelets are classified within a family most often by the number of vanishing moments. This is an extra set of mathematical relationships for the coefficients that must be satisfied, and is directly related to the number of coefficients .For example, within the Coiflet wavelet family are Coiflets with two vanishing moments, and Coiflets with three vanishing moments. In Figure 3.4, I illustrate several different wavelet families. [13]

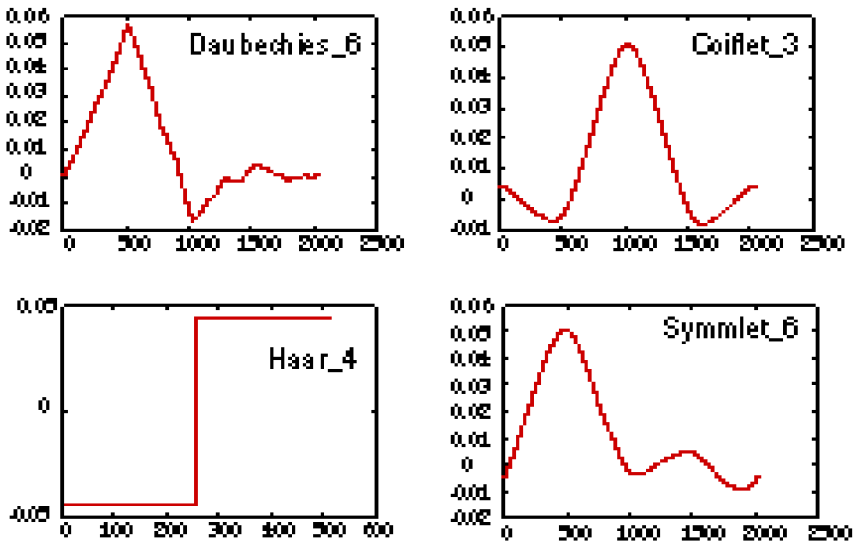


Fig. 3.4 Several different families of wavelets

The number next to the wavelet name represents the number of vanishing moments (A stringent mathematical definition related to the number of wavelet coefficients) for the subclass of wavelet. Note: These figures were created using WaveLab, by typing:

```
wave = MakeWavelet(2,-4,'Daubechies',6,'Mother', 2048);
wave = MakeWavelet(2,-4,'Coiflet',3,'Mother', 2048);
wave = MakeWavelet(0,0,'Haar',4,'Mother', 512);
wave = MakeWavelet(2,-4,'Symmlet',6,'Mother', 2048);
```

3.4 Wavelet filtering of ECG signal

Scanned ECG signal is a mixture of useful signal and (almost entirely additive) interference spectrum of additive interference mingle with the useful signal spectrum. Classical linear filtering is applied for suppression of narrowband interference (drift and mains hum), the suppression of broadband myopotentials linear filters is problematic.The spectrum of useful signal occupies a band from about 1 to 125 Hz (lower limit is determined by heart rate).

The quality resting ECG signal spectrum occupies myopotentials region above 100 Hz, less good records (especially in very young children ECG), however, extends to muchlower frequencies. The presence complicates computing season's myopotential signal, especially finding the start and end of QRS complexes. Resting ECG signals preprocessing linear filters leads to extreme cropping cycles in breach of the QRS complex and sharp transitions at the beginning and end of QRS.

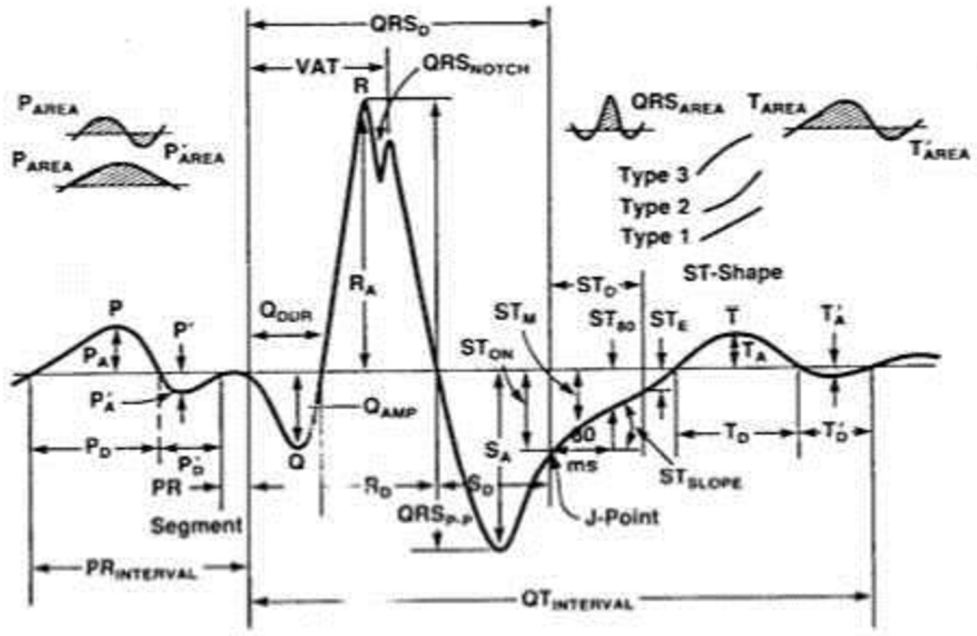


Figure 3.5 Example of a possible shape of the cycle of the ECG signal indicating the voltage andtime data, which is measured as a basis for subsequent interpretation.[2]

3.5 Signal filtration with DTWT

Signal filtering is to modify the wavelet coefficients resulting from direct application DTWT and their reconstruction using inverse DTWT. The whole process is nonlinear because of the use of non-linear thresholding of these coefficients.

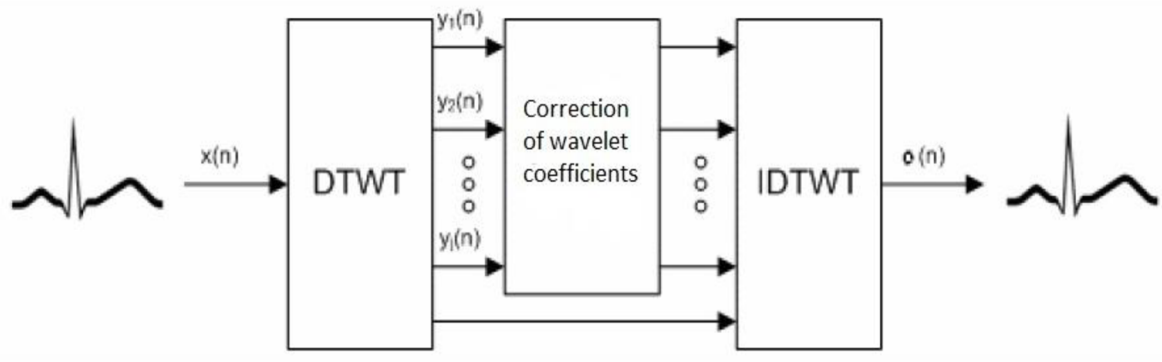


Fig. 3.6 Wavelet filtration principle [2]

Where $x(n)$ is a signal with additive noise component, $y_i(n)$ is divided into signals different frequency bands and $o(n)$ are filtered output signal.

3.6 Thresholding of wavelet coefficients

3.6.1 Hard thresholding

Hard and soft thresholding is one of the basic types of thresholding coefficients DTWT. Let the input value as $y(n)$ as a threshold λ and the output value as ${}^{\lambda}y$. Then for hard threshold applies:

$$ {}^{\lambda}y(n) = \begin{cases} y(n) & pro\ |y(n)| > \lambda \\ 0 & pro\ |y(n)| \le \lambda \end{cases} . \tag{3.1} $$

This means that all the coefficients $y(n)$, which are smaller than the specified threshold will be reset.

3.6.2 Soft thresholding

For the soft thresholding we can apply:

$$ {}^{\lambda}y(n) = \begin{cases} sign[y(n)][|y(n)| - \lambda] & pro\ |y(n)| > \lambda \\ 0 & pro\ |y(n)| \le \lambda \end{cases} . \tag{3.2} $$

This means that all the coefficients *y (n)*, which are smaller than the specified threshold will be reset (as well as the hard thresholding), but also to move the remaining coefficients size threshold toward zero.

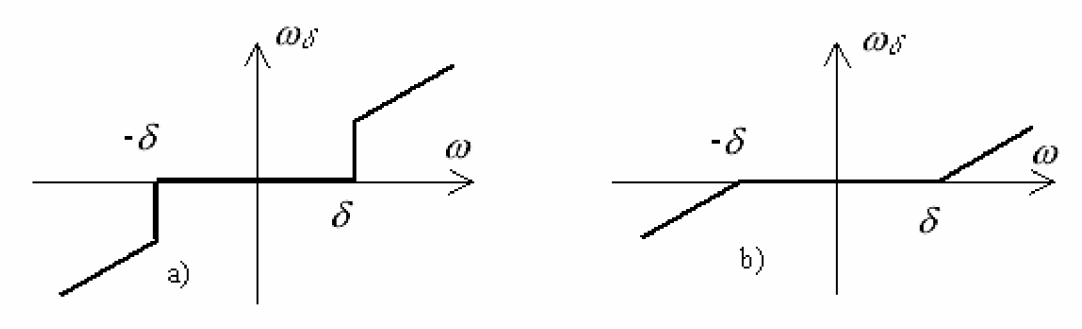


Fig. 3.7 Principle of thresholding: a) hard, b) soft

3.6.3 Determination of thresholding values

Threshold depends on the input noise level when the input is highthe ratio of signal to noise threshold is higher. Noise level *w* is represented by σ_w standard deviation or by dispersion $\sigma.^2$Assuming an additive mixture of *x (n)* of the useful signal *s (n)* and noise *w (n)*:

$$x(n) = s(n) + w(n) \tag{3.3}$$

If we denote the coefficients DTWT input signal *x (n)* as y_m *(n)*, the useful signal u_m *(n)* and noise $v_m(n)$ where n is the index of the coefficient of *m-th* level of decomposition, thanks linearity DTWT we can write:

$$y_m(n) = u_m(n) + v_m(n) \tag{3.4}$$

Next, suppose that the noise component of the input signal is represented by white noise, i.e a stochastic signal which is characterized by three features:

- zero mean value

$$\mu_w = E\{w(n)\} = 0, \tag{3.5}$$

- medium output which equals to dispersion

$$P_w = E\{w^2(n)\} = E\{(w(n) - \mu_w)^2\} = \sigma^2{}_w \tag{3.6}$$

- autocorrelation sequence

$$r_{ww}(n) = \sigma^2{}_w\delta\ (n), \text{ where } \delta\ (n) = 1 \text{ for } n=0,\ \delta\ (n) = 0, \text{ for } n \neq 0, \tag{3.7}$$

from which it is clear that it is not correlated.

3.6.4 Universal threshold

Universal method of threshold determination was created by Donoho and Johnstone [8]. Based on number of samples N and the standard deviation of additive white noise σ_w, we calculate the value λ that minimizes the risk of deviations from the optimal (but unknown) threshold values.

$$\lambda = \sigma_w \sqrt{2\ln(N)} \tag{3.8}$$

Thresholding is then performed for all the wavelet coefficients. The method can be used for soft, hard and hybrid thresholding.

3.6.5 Empirical threshold

Empirical threshold is used in cases where the use of universal threshold does not achieve the desired results. This is the multiplication of noise by standard deviation with empirical constant K, and the result is the threshold value

$$\lambda = K\sigma_w \tag{3.9}$$

or threshold values for every band separately

$$\lambda_m = K_m\sigma_m \tag{3.10}$$

3.7 Wiener Filtration

Wiener filter is used in cases of appreciable diffusion noise spectrum components$w\ (n)$ and the spectrum of useful signal $s\ (n)$. Assuming that the input signal $x\ (n) = s\ (n) + w\ (n)$, i.e a mixture of both additive (uncorrelated components), Wiener filter in frequency domainis an optimal correction factor $H_{opt}\ (\omega)$ for the correction of the spectrum $X\ (\omega)$, for

$$Y(\omega) = X(\omega) \cdot H_{opt}\ (\omega) \tag{3.11}$$

being optimal approximation for the spectrum $S(\omega)$ of useful signal in the meaning of the smallest standard deviation of $y(n)$ from $s(n)$, here: $y(n) = s(n) + e(n)$, where $E\{e^2(n)\} \rightarrow min$Wiener's correction factor has the form:

$$H_{opt}(\omega) = \frac{R_{ss}(\omega)}{R_{ss}(\omega)+R_{ww}(\omega)}, \tag{3.12}$$

where $R_{ss}\ (\omega)$ is a useful signal power spectrum and $R_{ww}\ (\omega)$ is the noise power spectrum. This expression contains the original signal power spectrum, which in practice often not occur, that's why it has relationship (3.13) and more practical form:

$$H_{opt}(\omega) = \frac{R_{xx}(\omega) - R_{ww}(\omega)}{R_{xx}(\omega)}, \tag{3.13}$$

because expected non-correlation of separated components leads to the possibility of expression power spectrum $R_{xx}(\omega)$ input as $R_{xx}(\omega) = R_{ss}(\omega) + R_{ww}(\omega)$. The correction factor becomes always fair value from the interval $<0, 1>$ for each specific value of frequency ω.

There is also an analogy to the above method of filtering, in which the appropriate correction factors multiplied by the individual coefficients DTWT. We define analog (3.11) correction factors that are looking for $g_m(n)$ such that the adjusted values of the coefficients DTWT

$$^{\lambda}y_m(n) = y_m(n)g_m(n) = g_m(n)[u_m(n)+v_m(n)] \tag{3.14}$$

were optimal approximation of coefficients $u_m(n)$ of useful signal in the meaning of the smallest standard deviation of $^{\lambda}y(n)$ from $s(n)$, here $^{\lambda}y(n) = s(n) + e(n)$, where $E\{e_2(n)\} \rightarrow min.$ In [2] this Wiener correction factor is defined as

$$g_m(n) = \frac{u_m^2(n)}{u_m^2(n)+v_m^2(n)}. \tag{3.15}$$

Unfortunately we do not know the value of noise coefficients $v_m(n)$ in the *m-th* band, because they are part of an additive mixture of wavelet coefficients $y_m(n)$, but their square can bereplaced by estimation in the form of dispersion of noise in the *m-th* band, so we get

$$g_m(n) = \frac{u_m^2(n)}{u_m^2(n)+\sigma_m^2(n)}. \tag{3.16}$$

3.7.1 Hybrid threshold

This threshold is about estimation of useful signal coefficients $u_m(n)$, according to the example

$$u_m^2(n) = \max|k \cdot y_m^2 - \sigma_v^2, 0| \tag{3.17}$$

from [2]. After achieving the form [3.16] we will find the correction factor $g_m(n)$in the form:

$$g_m(n) = max\left[1 - \frac{\sigma_v^2}{k \cdot y_m^2(n)}, 0\right]. \tag{3.18}$$

To find the correct coefficients of DTWT $^{\lambda}y_m(n)$let us multiply factor on “brutal” coefficients $y_m(n)$ according to (3.14)

$$\lambda_y(n) = y_m(n)g_m(n) = max\left[y_m(n) - \frac{\sigma_v^2}{k \cdot y_m(n)}, 0\right]. \tag{3.19}$$

If $y_m(n) - \frac{\sigma_v^2}{k \cdot y_m(n)} \leq 0$ than $^{\lambda}y_m(n) = 0$,

if $y_m(n) - \frac{\sigma_v^2}{k \cdot y_m(n)} > 0$ than $^{\lambda}y_m(n) = y_m(n) - \frac{\sigma_v^2}{k \cdot y_m(n)}$.

It is possible to derive, that there is a coefficient's thresholding of $y_m(n)$ with threshold

$\lambda_m = \frac{1}{\sqrt{k}}\sigma_v$ and conditions $\lambda_y(n) = \begin{cases} y_m(n) - \frac{\lambda_m^2}{y_m(n)} & for\ |y_m(n)| > \lambda_m \\ 0 & for\ |y_m(n)| \le \lambda_m \end{cases}$ (3.20)

Retrieved thresholding process defined above is shown in Fig. 3.8. It forms a sort of compromise between soft and hard thresholding. Coefficients whose values will be close to the threshold value will be affected (adjusted)substantially more than the coefficients with significantly under-threshold value.

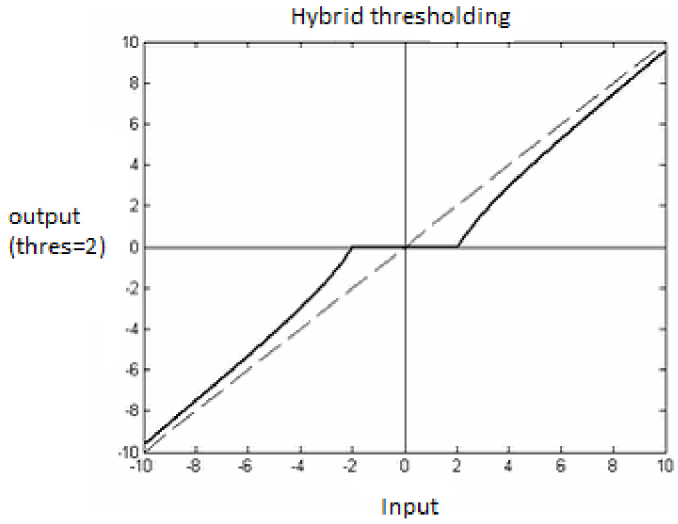


Fig. 3.8 Hybrid thresholding according to (3.20) for λ_m=2.

3.7.2 Pilot estimation method

Another possibility to obtain the coefficients u (n) m is a useful method for the pilot signal estimate, which is described in [2], [9]. Its principle is outlined in Fig. 3.9 upper branch scheme used to obtain a pilot signal *s(n)* which should as far as possible correspond to a useful signal without noise. WT1 contains transformation, followed by treatment coefficients in block H and the inverse transformation IWT1. Transformation WT2, which is the basis Wiener wavelet filtering, is subject to both the input signal (electrocardiogram) and a pilot signal s (n). Both outputs are processed by hardware block, in which the correction factor is applied

$$\bar{g}_m(n) = \frac{\bar{u}_m^2(n)}{\bar{u}_m^2(n) + \sigma_{v_m}^2} \tag{3.21}$$

where $\overline{u_m^2}$ *(n)*are quadrates of useful signal coefficients from the pilot estimate $\bar{s}$ *(n).*

There is a bug in the calculation of adjusted coefficients ${}^{\lambda}y_m(n)$ due to disagreement between optimal (from the pilot estimate) and the estimated coefficients of *m-th* band useful signal. This error is considered in detail in [2].

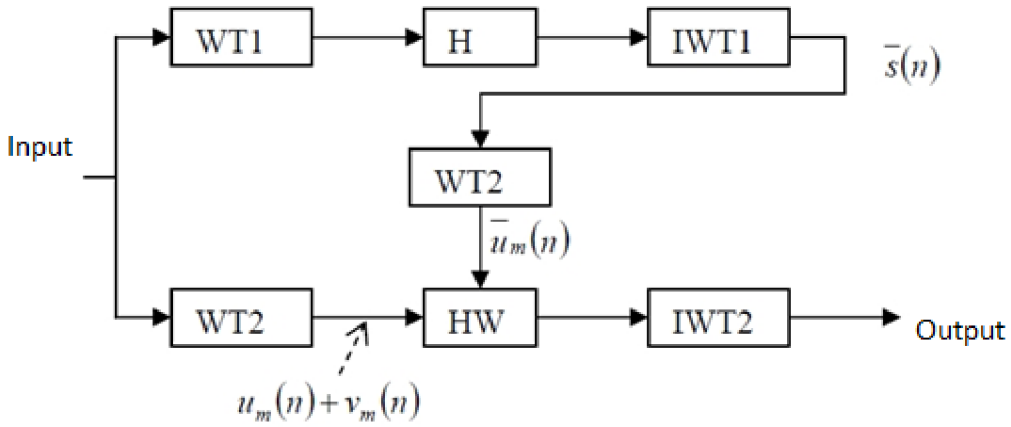


Fig.3.9 Wiener filtration with pilot estimate method [2]

Appropriate adjustment of wavelet coefficients in a block of H is described in [2]. In the case when useful coefficients significantly higher than the noise coefficients is preferable to use hard thresholding. Otherwise, use a hard thresholding resulted in preservation under-threshold values with a high proportion of noise and estimate the values of the pilotwill beaftertransformation WT2 mistakenly misrepresented as coefficients useful. For this reason, there will be more suitable to use soft thresholding, or choose a compromise in the form of hybridthresholding.

3.7.3 Wiener filtering with FFT

There are a lot of tasks in numerical processing, which are based on Fourier techniques. One of these is filtering to remove a noise from "corrupted" signals. Let us consider, that there is some underlying, uncorrupted signal *u(t)* that we want to measure. The measurementprocess is imperfect, however, and what comes out of our measurement device is acorrupted signal *c(t)*. The signal *c(t)* may be less than perfect in either or both of two respects. First, the apparatus may not have a perfect "delta-function" response, so that the true signal *u(t)* is convolved with (smeared out by) some known responsefunction *r(t)* to give a smeared signal *s(t)* [11],

$$S(f) = R(f)U(f) \tag{3.22}$$

where *S, R, U* are the Fourier transforms of *s, r, u*, respectively. Second, the measured signal *c(t)* may contain an additional component of noise *n(t),*

$$c(t) = s(t) + n(t) \tag{3.23}$$

We divide *C(f)* by *R(f)* to get a deconvolved signal. Now we want to treat a problem, when there is a noise. The task is to construct optimal filter *Φ(f)*, which will estimate true signal *U* by [11] :

$$\hat{U}(f) = \frac{C(f)\Phi(f)}{R(f)} \tag{3.24}$$

How $\hat{U}$ can be close to *U*? We want them be close in the least-square sense

$$\int_{-\infty}^{\infty} |\hat{u}(t) - u(t)|^2 dt = \int_{-\infty}^{\infty} \left|\hat{U}(f) - U(f)\right|^2 df \text{is minimized} \tag{3.25}$$

Substitutions equations (3.24) and (3.23), the right hand side of (3.25) becomes

$$\int_{-\infty}^{\infty} \left|\frac{[S(f) + N(f)]\Phi(f)}{R(f)} - \frac{S(f)}{R(f)}\right|^2 df$$
$$= \int_{-\infty}^{\infty} |R(f)|^{-2}\{|S(f)|^2|1 - \Phi(f)|^2 + |N(f)|^2\,|\Phi(f)|^2\}df \tag{3.26}$$

The signal *S* and the noise *N* are uncorrelated, so their cross product, when integrated over frequency *f*, gave zero.(This is practically definition of noise). Obviously (3.26) will be minimum if and only if the integrandis minimized with respect to *Φ(f)* at every value of *f*. Let us search for such asolution where *Φ(f)* is a real function. Differentiating with respect to *Φ*, and settingthe result equal to zero gives

$$\Phi(f) = \frac{|S(f)|^2}{|S(f)|^2 + |N(f)|^2} \tag{3.27}$$

This is the formula for optimal Wiener filter *Φ(f)* [7]

4. ECG processing. Practical part.

4.1 Choice of DTWT type.

For tests carried out in other chapters is good to select the appropriate option DTWT. From studies carried out in [2] it is clear that 4 levels of decomposition is the most suitable, but in this paper we will consider 5 types of decomposition: from 2-level to 6-level.

4.2 Choice of threshold value

Wavelet coefficients are modified depending on the chosen threshold value. Determination of the threshold level has a significant influence on the outcome of filtration itself. Its value should be calculated for each m band separately and its value may be based on the levelofinterference(standard deviation or variance) in this band[1] [2]. In this paper the level of threshold is defined by two methods: empirical and universal threshold (according to equations (3.8), (3.9)).

4.3 Tested signals

We have tested 5 signals from ECG database *physionet.org* [12] . This website includes a lot of ECG signal number, with different shape,they were taken from different people.

We assume that all signals have zero noise component, i.e waveforms contain only useful signal. This assumption we will use in evaluating different methods of filtering by signal / noise ratio (SNR below). To evaluate the proposed methods of filtration in the ratio of the SNR is necessary to have a folder useful signal (ECG database) and noise component. Filtration methods are designed to get the best results in suppressing of myopotencial interference ("motion artifact"), so that's why spectral interference properties of the model should have myopotencial character. Frequency content of myopotentials is upwards of 10 to 500Hz with the dominant frequencies of 20 to 250Hz, useful signal spectrum has a band approximately 1 - 250Hz (where the bottom line is affected heart rate), [2].

One of the most important criteria of signal filtration quality is SNR. The output SNR will be calculated according to equation:

$$SNR_{výst} = 10 \cdot \log_{10} \frac{\sum_{n=1}^{N-1} [s(n)]^2}{\sum_{n=1}^{N-1} [y(n) - s(n)]^2} \quad [dB]. \tag{4.1}$$

Another outcome measure will be changes in the shape of filtered signals compared to the original signals. The primary area will be as a rule beginning and end of the QRS complex, a Q wave and S wave, the process can be considerably influenced by the higher threshold. Also the size of the R wave will be rated, but it can be cut off, filtration may also be the reason of the QRS complex dilatation.

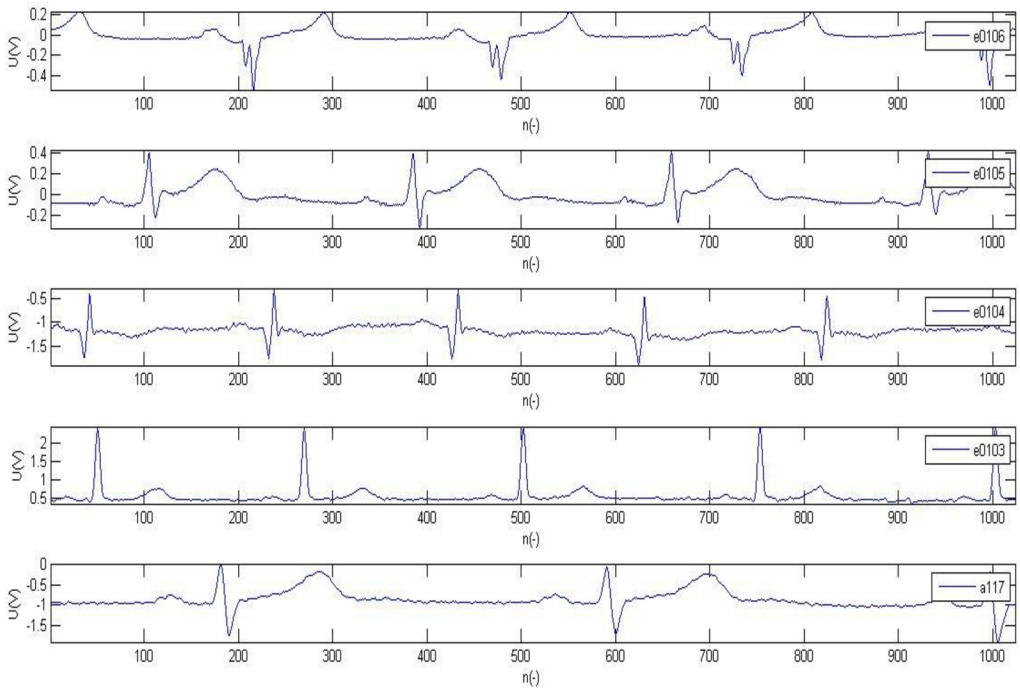


Fig. 4.1 Example of tested signals

4.4 Threshold experiments

There are results from three type of thresholding. 4-level decomposition DTWT was used.

Tab. 4.1 Values of output SNR for different thresholding

EKG signal	Input SNR [dB]	Output SNR [dB]		
		Hard thres.	Soft thres.	Hybrid thres.
a117	10	16,42	9.89	13.77
e0103	10	17,88	11,15	14.95
e0104	10	19.04	13,13	16,11
e0105	10	18,33	12,24	15,78
e0106	10	17,45	11,23	14,88

Hard thresholding

Hard thresholding method is quite radical. Weighted coefficient remaining after DTWT will be either left without change or will be reset. This has its advantages – strong suppression of noise components, minimal damage (distortion, dilatation), QRS high oscillation complex, but also disadvantages in terms of leaving a sharp noise pulses. This method of thresholding was, according to Tab. 4.1 as the best resultobtained in terms of output SNR.

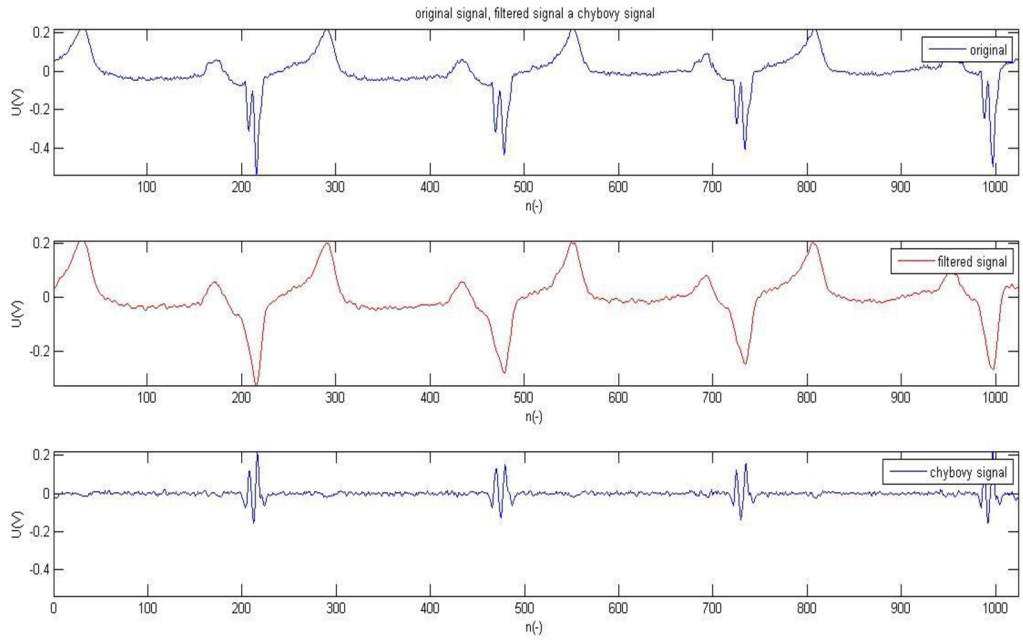


Fig.4.2 the results after hard thresholding (signal *e0106*, universal threshold, filtr*Haar*)

Soft thresholding

When using soft thresholding we can achieve "more smoothly" impression from the output signal that lacks sharp transitions.On the contrary, to some extent offset above-threshold coefficients, which is reflected especially with cropping of high frequencies of QRS complex. The values obtained in the tab. 4.1 by this soft method are not very convenient, the main reason is a universal threshold.

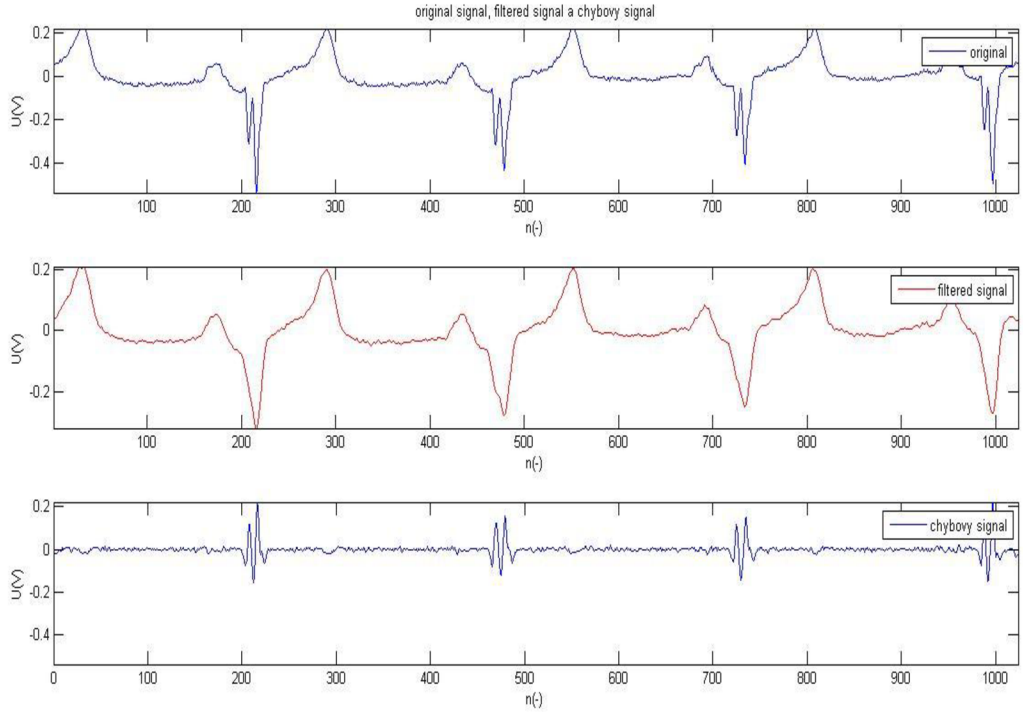


Fig.4.3 the results after soft thresholding (signal *e0106*, universal threshold, filtr*Haar*)

Hybrid thresholding

This threshold constitutes a compromise between hard and soft thresholding method. It combines the advantages of both previous methods i.e. suppression and random interference pulses cropping and minimal dilatation of the QRS complex. Similarly, the range satisfactory results with respect to the output SNR (see Tab. 4.1).

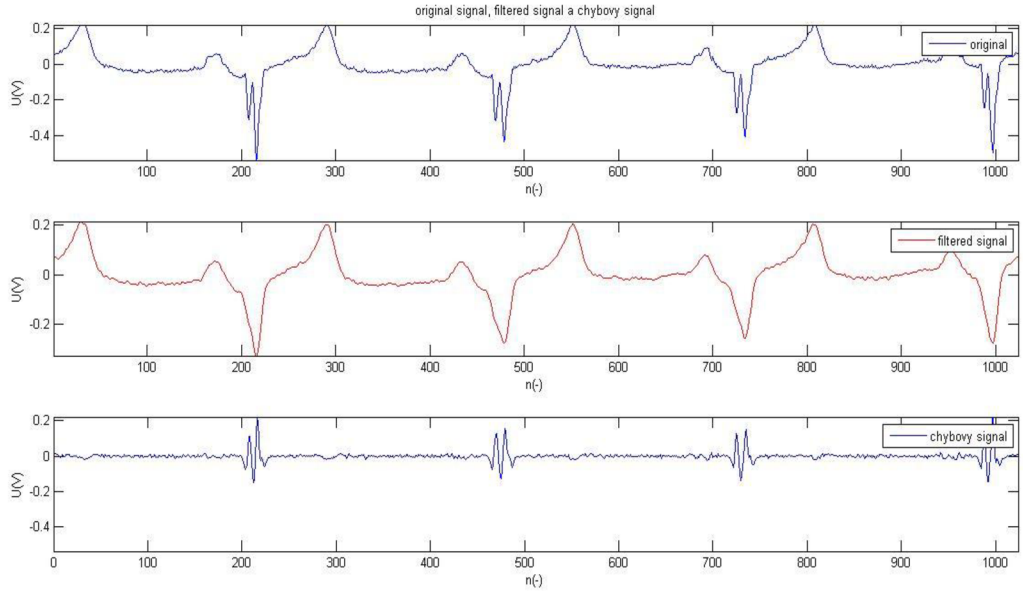


Fig.4.4 the results after hybridthresholding (signal *e0106*, universal threshold, filtrHaar)

4.5 Wiener filtration with different level of DTWT decomposition

Let us consider the problem of choice of level DTWT decomposition. There are 5 possible variants: 2.3.4.5 and 6 levels. In this chapter we will use only hybrid threshold, like the most suitable for ECG filtration.

Six-level DTWT decomposition

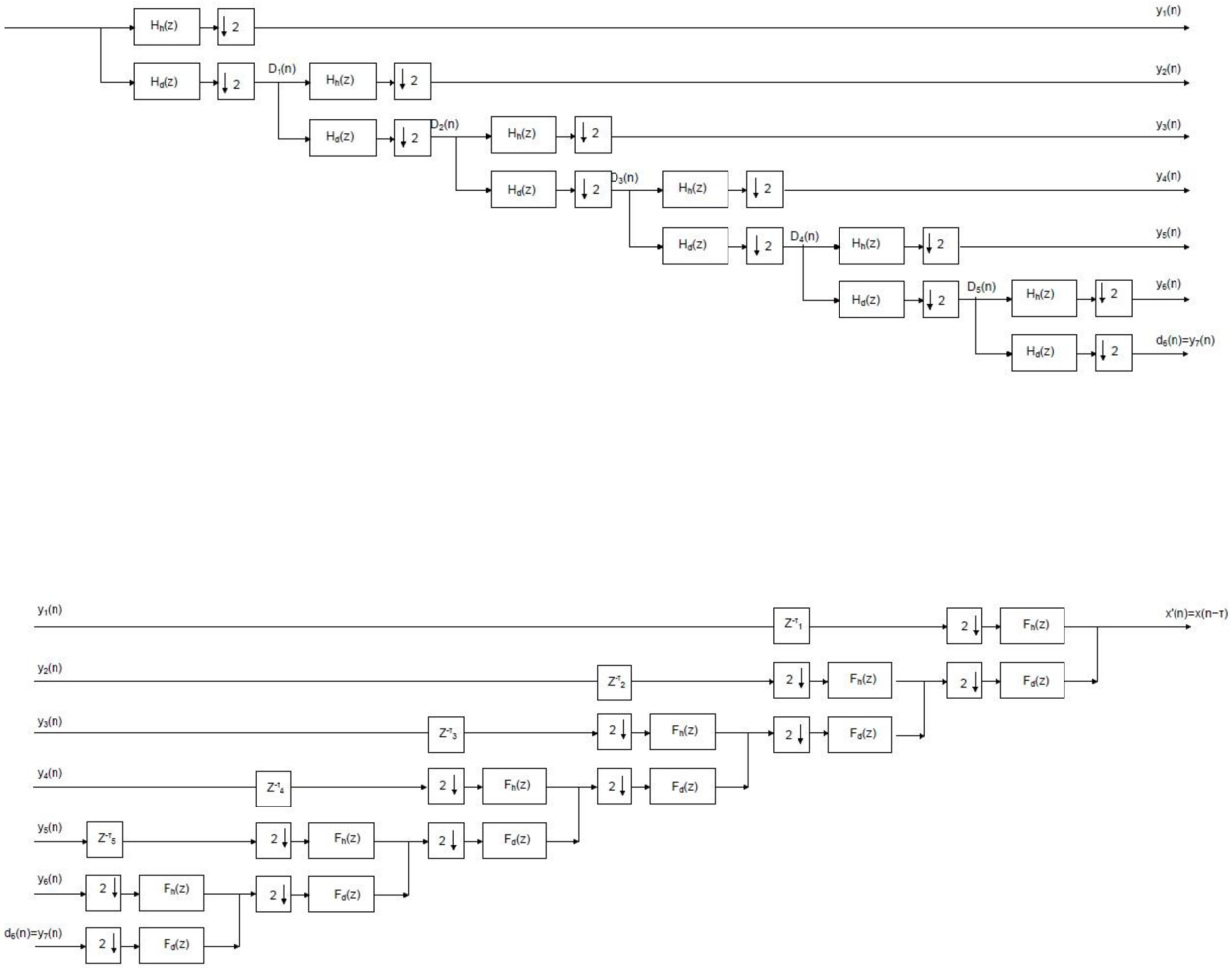


Fig. 4.5 Realization of six-level DTWT and IDTWT decomposition

Realization in MatLab is obtained due to command *swt*, which performs a multilevel 1-D stationary wavelet decomposition using specific wavelet decomposition filters. From [2], we know that the best mixture of filters WT1 and WT2 are ‘haar’ and ‘db3’.

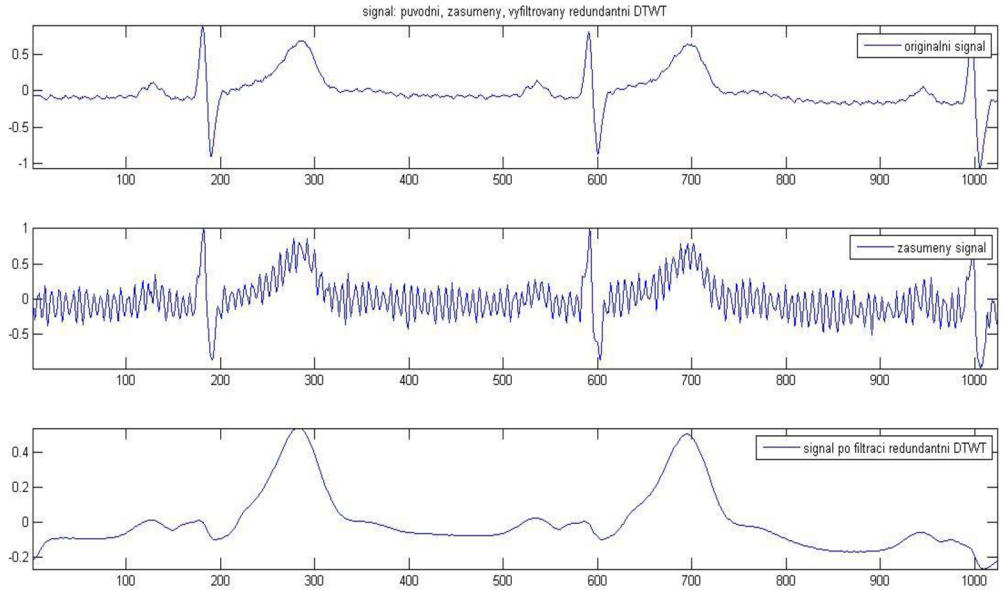


Fig. 4.6 Signal *a117*after 6-level decomposition

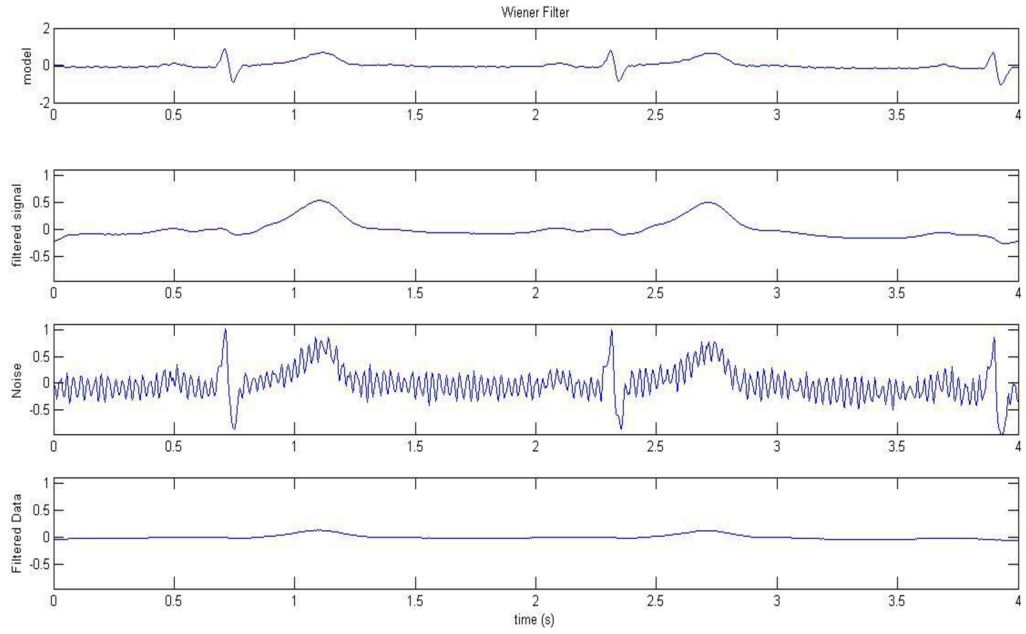


Fig.4.7 Signal *a117* after Wiener filter

As we can see on fig. 4.7 the 6-level decomposition of DTWT is not very good variant for obtaining satisfaction results. A lot of useful information were lost during the first step – decomposition on bands WT1. After that we obtained a signal without QRS complex and big P wave. Then Wiener filter's coefficients smooth this signal, but nevertheless it has lost useful data.

5-level of DTWT decomposition

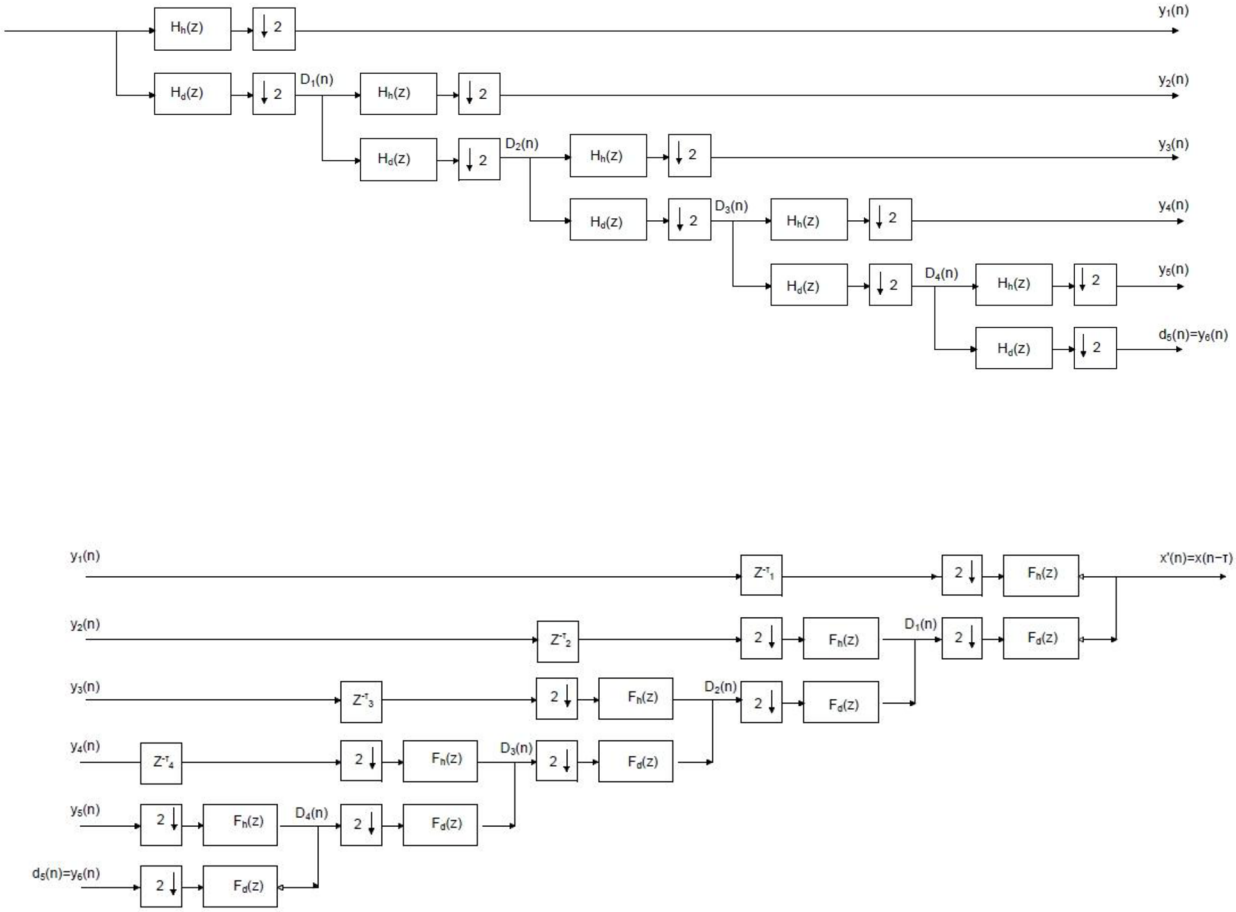


Fig. 4.8 Realization of five-level DTWT and IDTWT decomposition

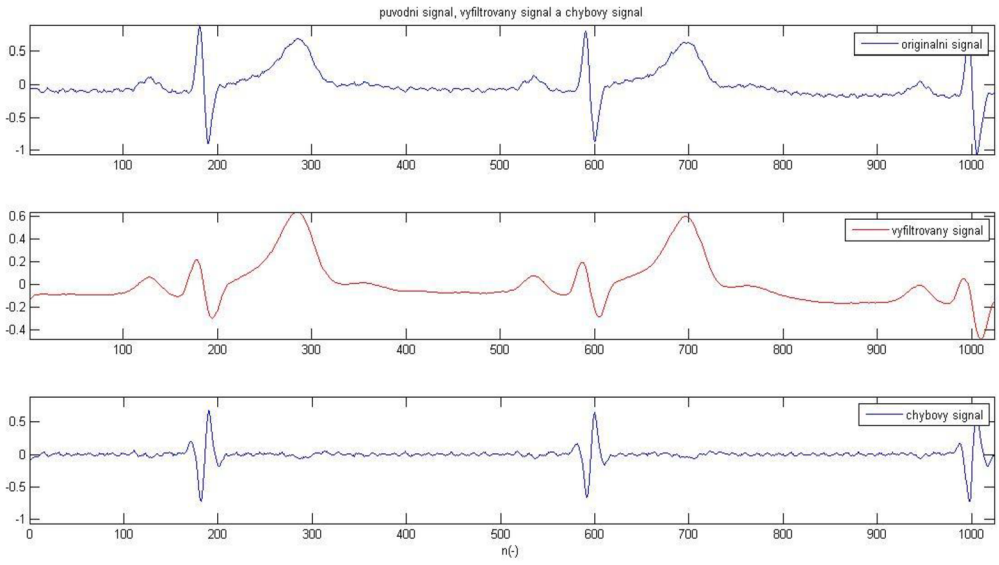


Fig. 4.9 Signal a117 after 5-level decomposition, universal threshold

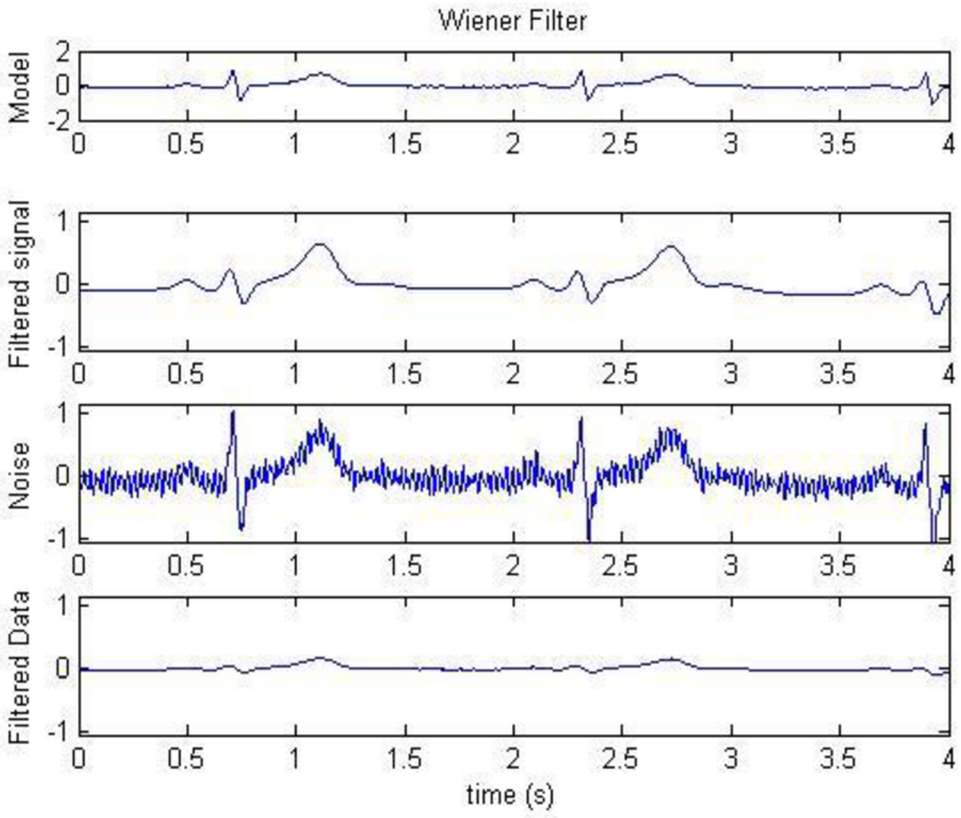
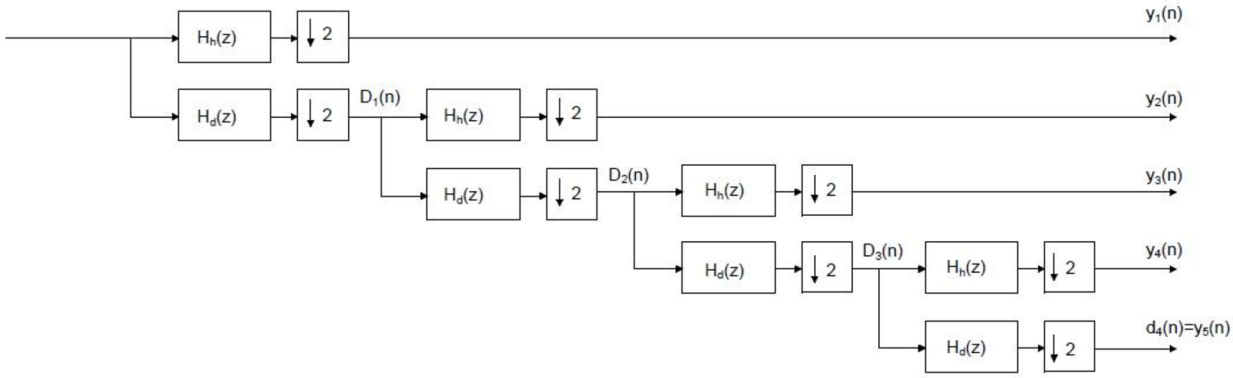


Fig. 4.10 Signal *a117* after Wiener filter, 5-level decomposition.

As we can see on fig.4.9 and especially on fig.4.10, 5-level decomposition is going better, than the previous one. But it is also far from ideal, for example the wave T has a bigger value than any point of QRS complex. If we know the initial signal (our case), it is clear, that this filtration can be much better.

4-level of DTWT decomposition

So according to the [2], we should get good result. First of all let see the scheme:



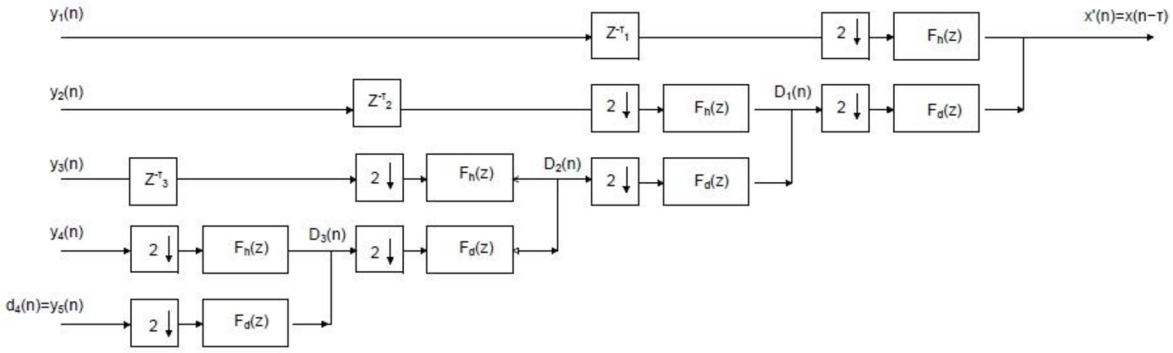
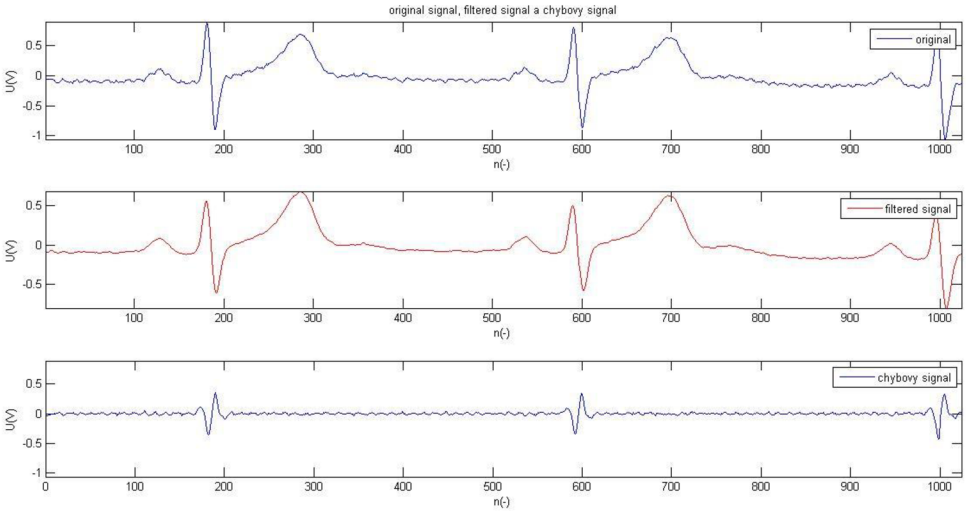


Fig. 4.11 Realization of four-level DTWT and IDTWT decomposition



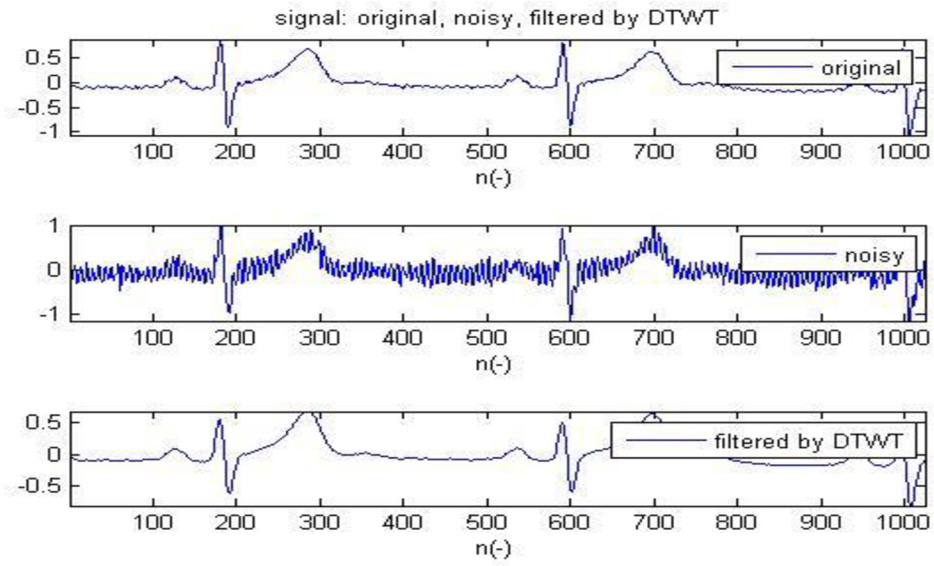


Fig. 4.12 Signal *a117* after 4-level decomposition, universal threshold

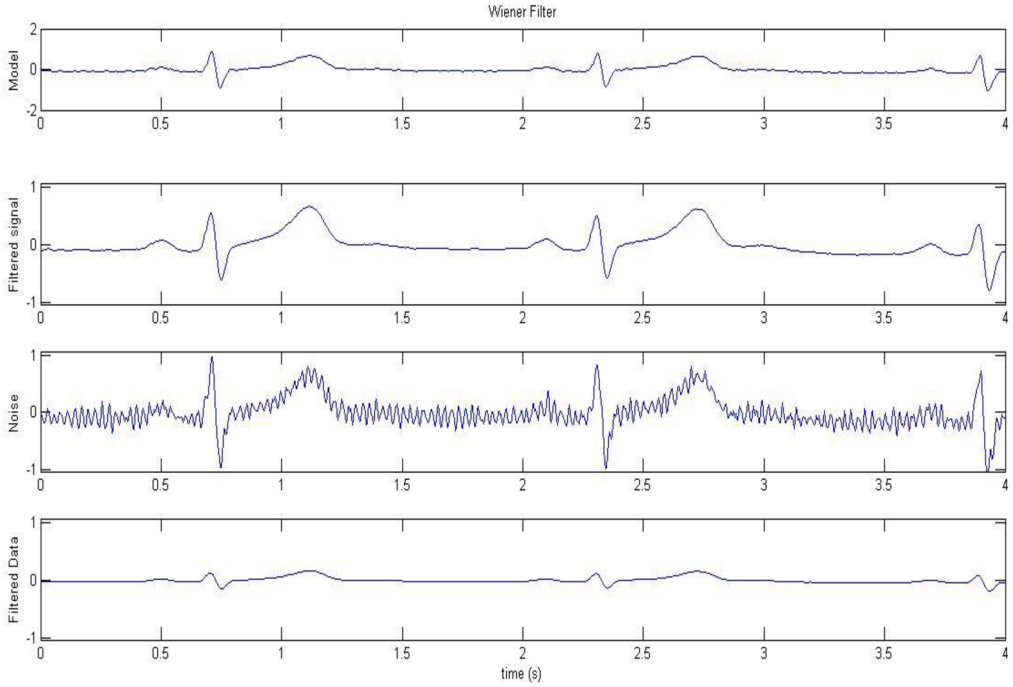
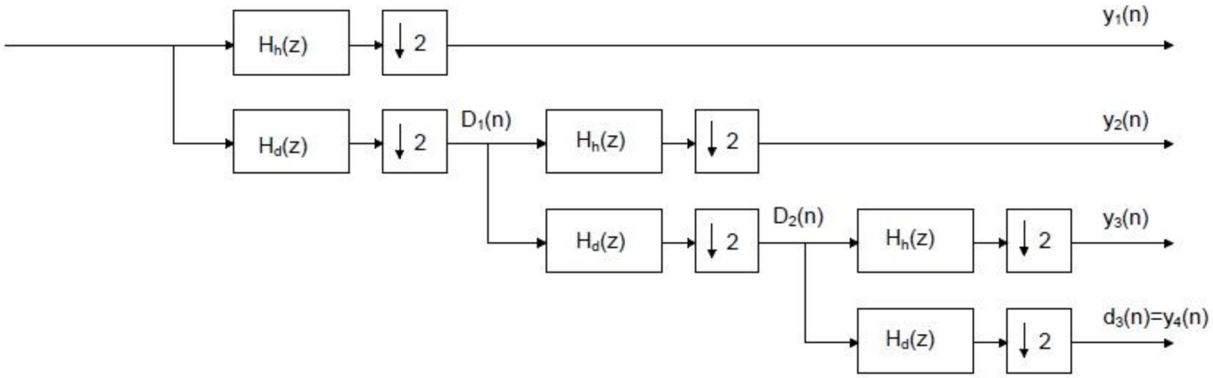


Fig. 4.13 Signal *a117* after Wiener filtration, 4-level decomposition

As we can see, this type of decomposition is much more better than other previous, even after first part (I mean hybrid thresholding of signal *a117*), it seems to be good. The signal is smooth, without any peaks and another interferences. After Wiener filtration the max.values of the wave T is almost equal to the values of QRS complex.

3-level of DTWT decomposition

Let us consider next step – 3-level of DTWT decomposition. Here is its scheme:



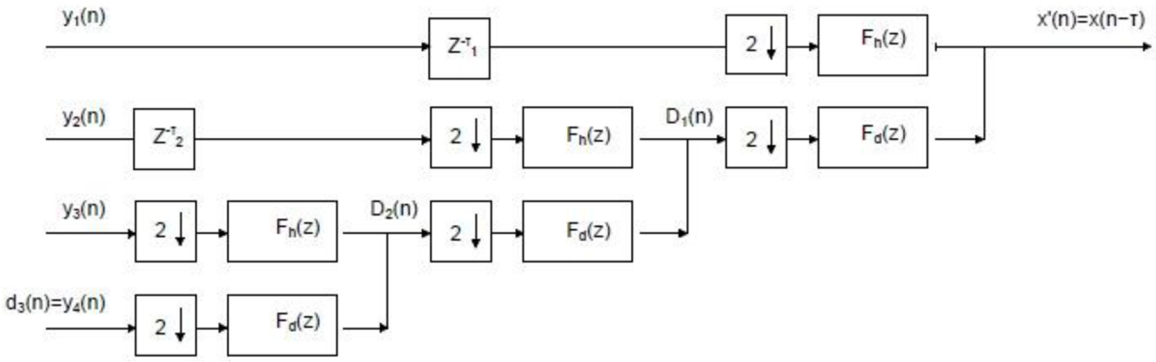


Fig.4.14 Realization of three-level DTWT and IDTWT decomposition

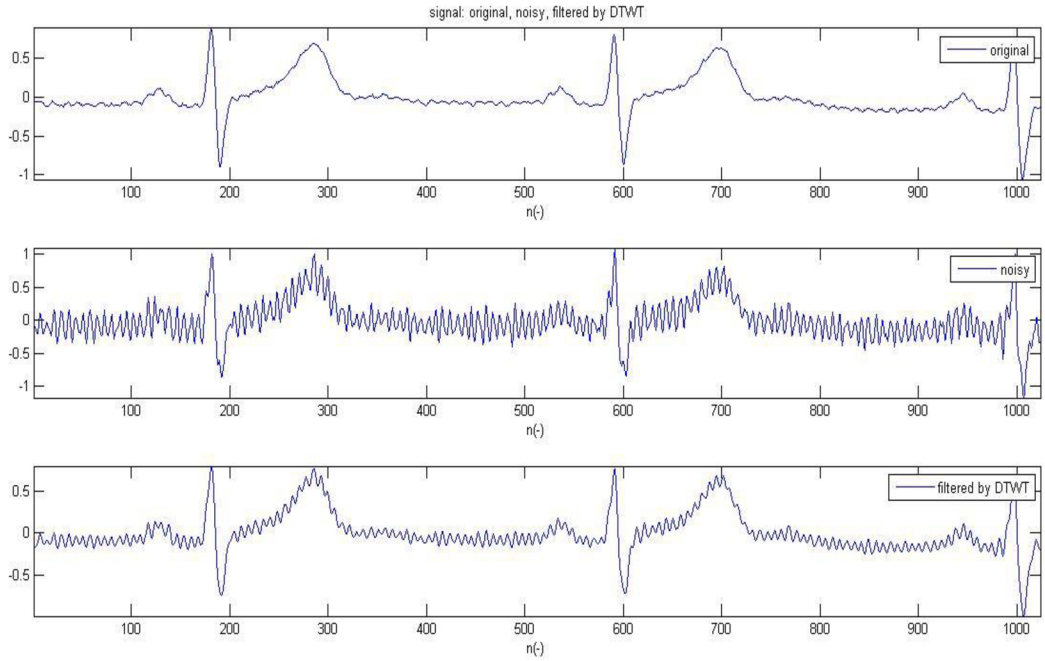


Fig.4.15 Signal *a117* after 3-level decomposition, universal threshold

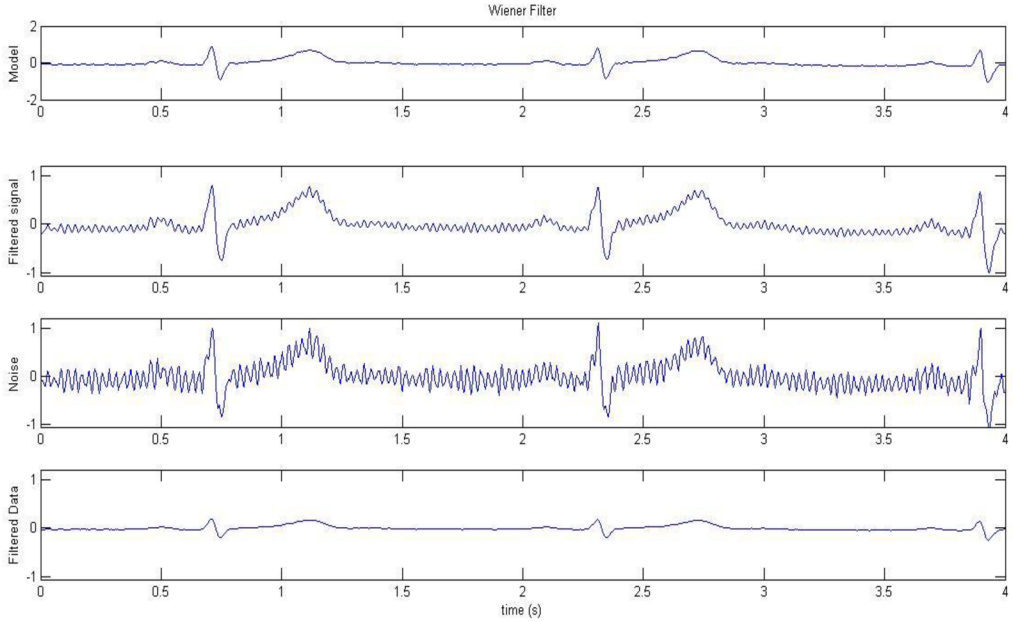


Fig. 4.16 Signal *a117* after Wiener filtration, 3-level decomposition

As we can see on fig. 4.15 and 4.16, 3-level decomposition is not suitable for denoising of ECG signal. There are a lot of un-denoised myopotentials, which lead to bad quality of output signal.

2-level of DTWT decomposition

This is the last try to get good results, now there are only 2 levels. First of all scheme:

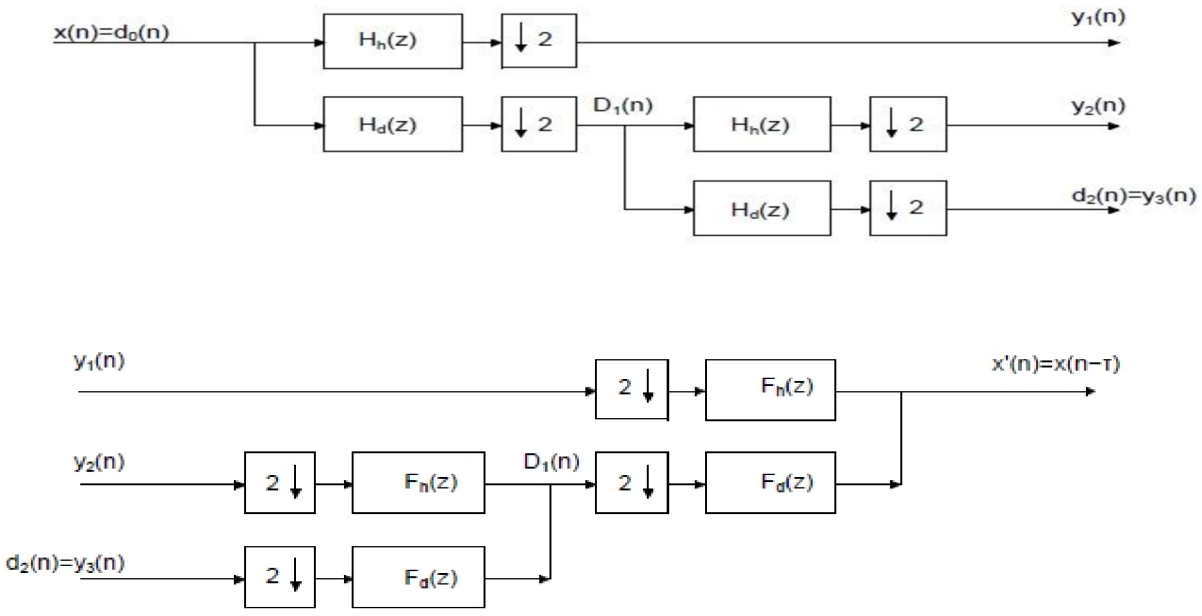


Fig.4.17 Realization of two-level DTWT and IDTWT decomposition

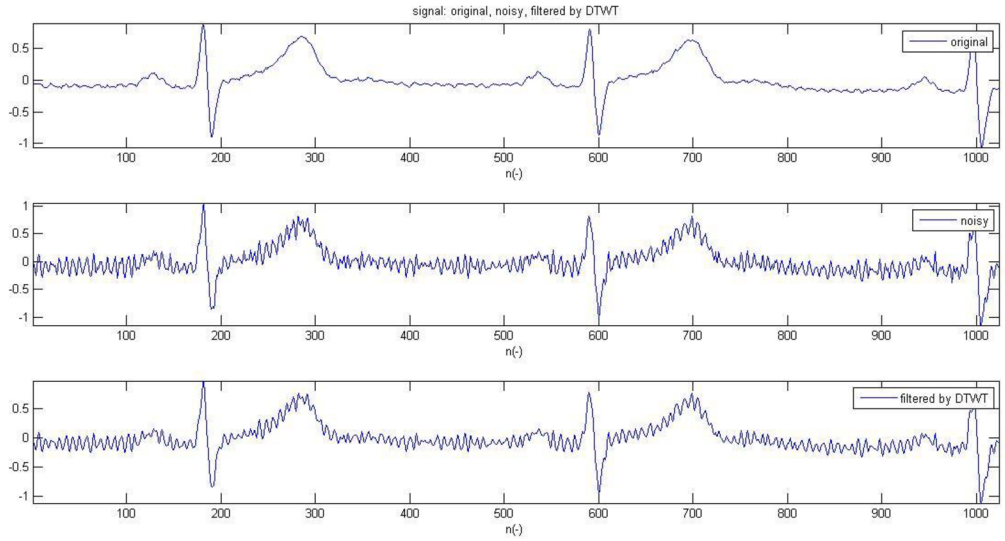


Fig.4.18 Signal *a117* after 2-level decomposition, universal threshold

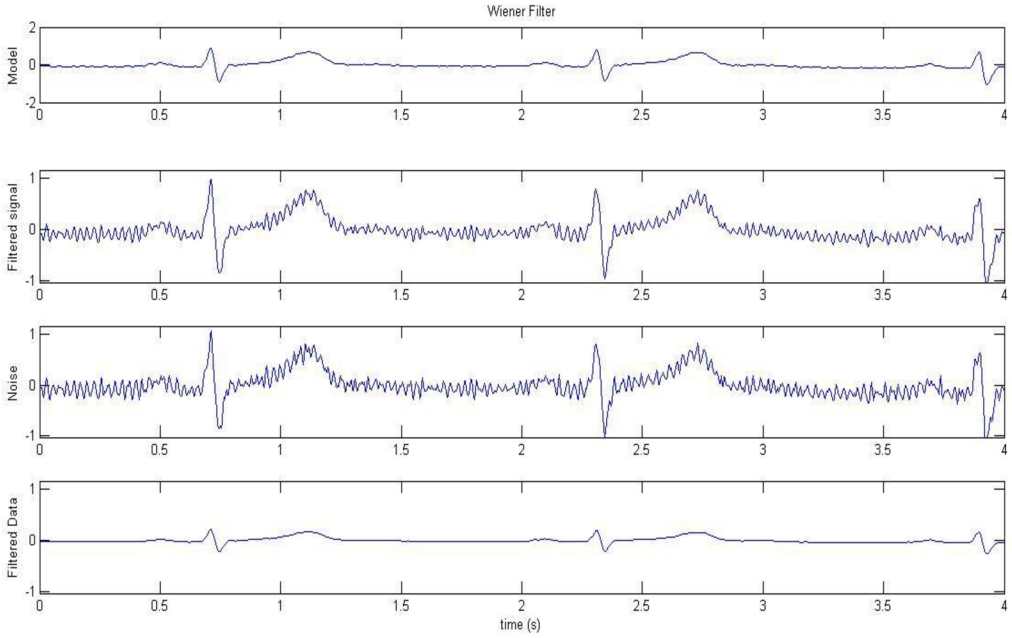


Fig. 4.19 Signal *a117* after Wiener filtration, 2-level decomposition

It seems that this algorithm almost doesn't work. Even after Wiener filtering, noise and other artifacts don't disappear. There some positive moments in QRS complex, but they are not so bright and evident.

Now we can make a conclusion, that the most suitable form for ECG denoising is 4-level decomposition.

Let us consider other 4 signals, which will be tested with Wiener filter with 4-level decomposition of DTWT and IDTWT.

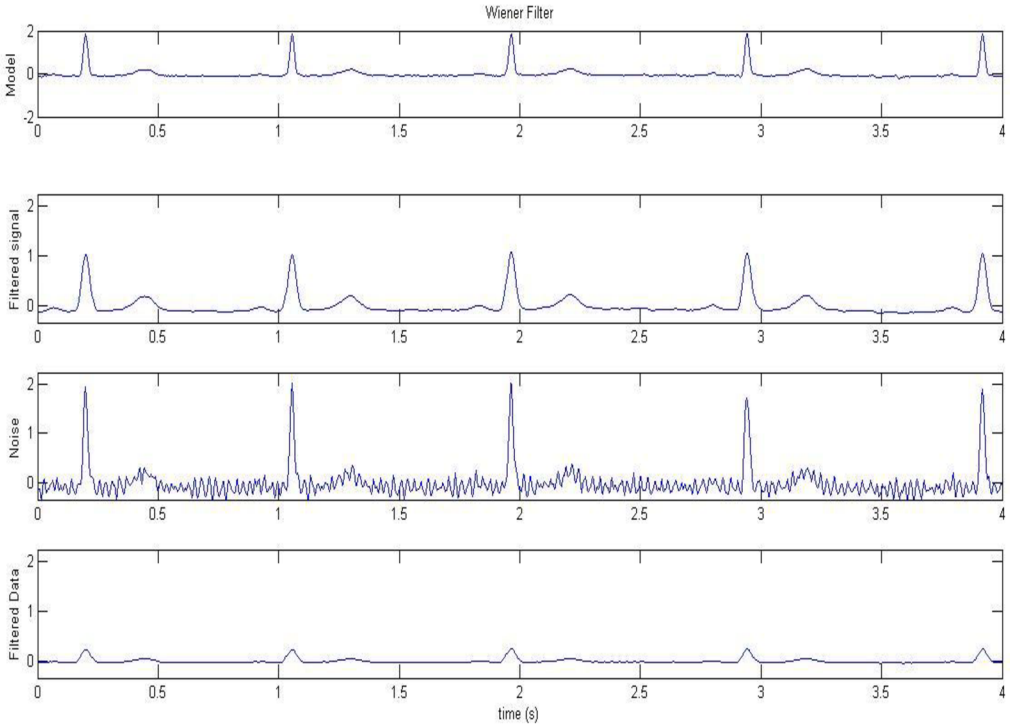


Fig. 4.20 Signal *e0103*after Wiener filtration, universal threshold, hybrid thresholding

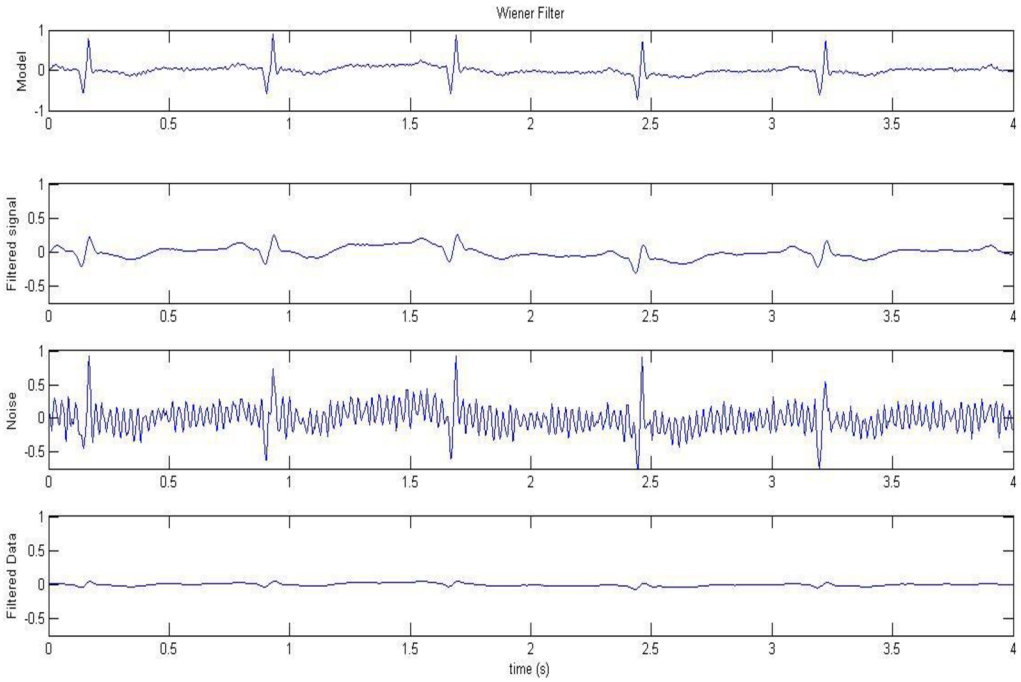


Fig. 4.21 Signal *e0104*after Wiener filtration, universal threshold, hybrid thresholding

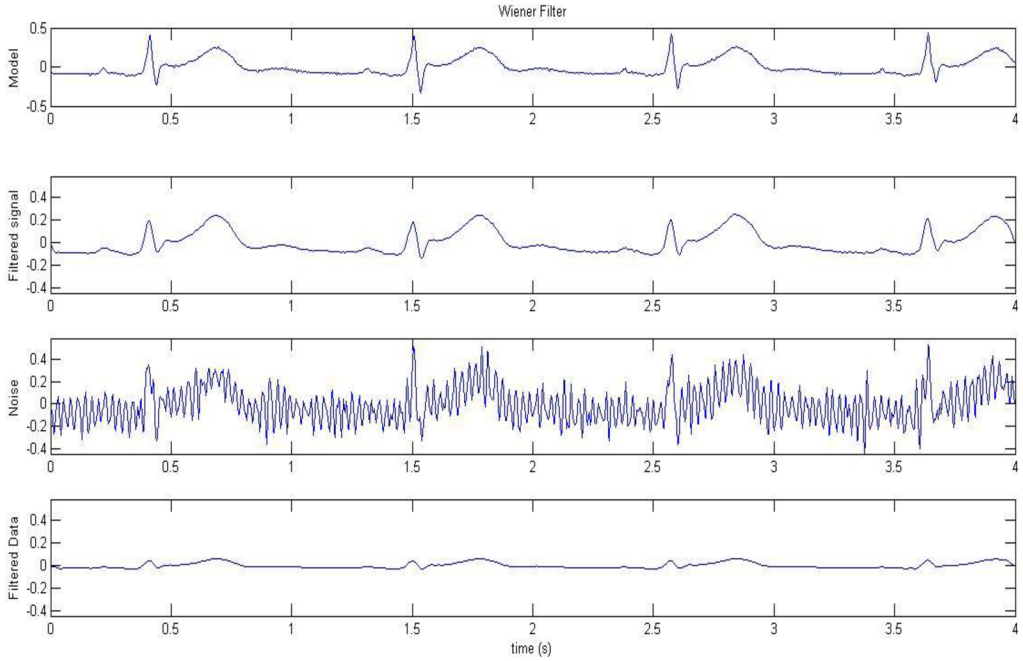


Fig. 4.22 Signal *e0105*after Wiener filtration, universal threshold, hybrid thresholding

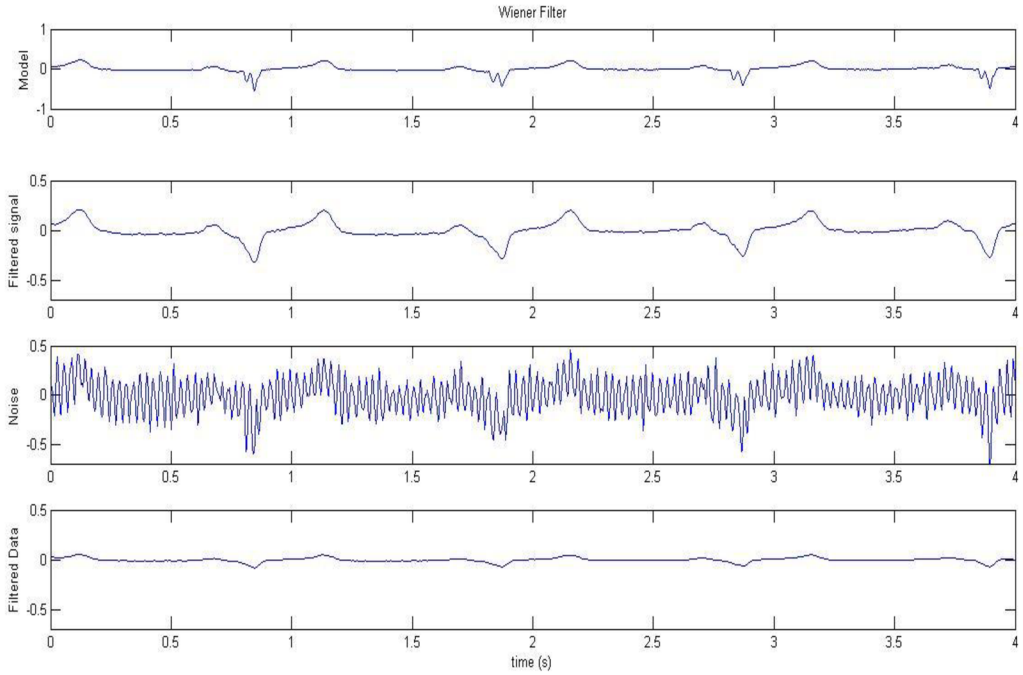


Fig. 4.23 Signal *e0106*after Wiener filtration, universal threshold, hybrid thresholding

5. Discussion

Before I started to work on this paper, I had thought that it would be much easier. But than during finding of good knowledge resources, I understood, that these theme of ECG Wiener filtering is not so popular and not a lot of people work with it. That's why for me it seemed much more interesting, try to implement Wiener filtering to the medical signal and also make some experiments with wavelet transformation and filtration.

Now let me consider some results of my work with other researchers who are interested in this theme. One of the basing kriteria is signal – to noise ratio[dB]. For example [10] have got SNR_{out}=17,5 dB for hard threshold, while [3] have got value about 20 dB. So even my expeirence in MatLab and in signal processing is very small, my SNR_{out} =16.3 for hard threshold, and I think it is not bad result.

Also it is very interesting to see on level of decomposition of other authors. So in this paper I made a conclusion, that 4-level of decomposion is the most suitable. Other researches for example [3] has also the same opinion. But there are also good results with 5 and 6 level of decomposition, it means that you can properly set a suitable threshold for every signal

There is also another question – choise of filter for wavelet transform. Some works dealing with this issue for example, [10] prefer the use of filters with a short pulse characteristics for the position of WT1. Filters with longer impulse characteristics cause the emergence of oscillations at the beginning and end of QRS complexes.Recommended filters for the position of WT2 [10], they even have a longer pulse char. because of better frequency resolution. In this field there are bid number of variants, you need just to choose the most suitable one.

Of course, this method of Wilter wavelet filtering is not the last point. There is another, which is more complicated method called „ Adaptive Wavelet Wiener Filtering Method " (AWWFM). Our method is improved by adding the block for the noise estimate (NE) (fig. 5.1)

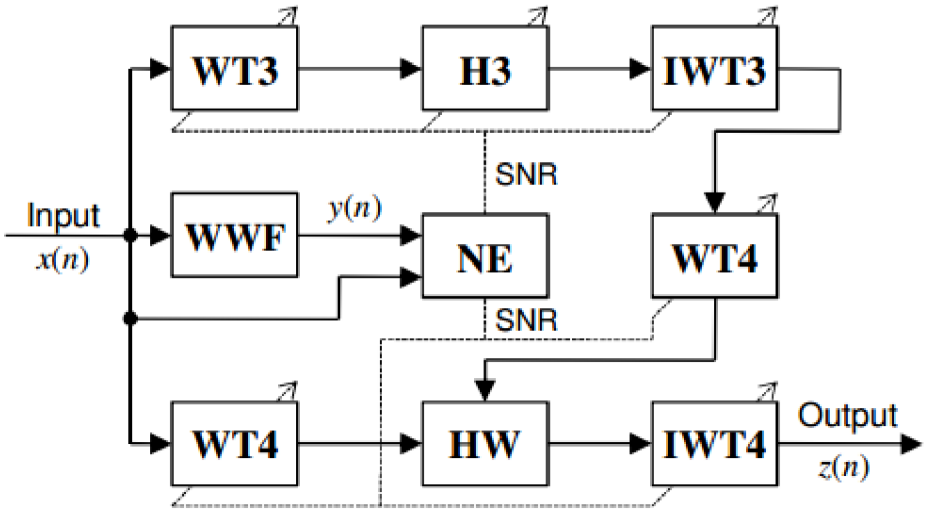


Fig. 5.1 The block diagram of the AWWFM method [3].

So the using of this method may be the logical continuous of my work and if in future I will decide to stay in this area, AWWFM method may be first aim to reach good results.

CONCLUSION

This paper describes various methods and their modifications suitable for filtering noisy signals, especially the real ECG records.

The choice of hard thresholding method of wavelet coefficients DTWT filtration brings fair value of the output signal to noise ratio and significantly harm QRS complex, but leads to the occurrence of sharp noise pulses formed above-threshold DTWT coefficients. With appropriate setting of thresholds can these soft thresholding completely suppress the artifacts, but, unfortunately, there is a reduction of peak waves of a certain R. Compromise is to use a hybrid thresholding, which with a suitable minimum threshold cuts peaks of QRS waves and to some extent able to suppress the above-threshold noise DTWT coefficients.

The selection threshold is appropriate to combine the chosen threshold. Some combinations such as hard thresholding with universal threshold (as well as with empirical threshold at which it is chosen too high constant K) whose value is based is too high does not bring good results. It is suitable for the selected thresholding experiment with the settings of the empirical constants at threshold. Selection of filter banks for wavelet transform is evaluated according to two aspects similarly to the selection threshold. From the group of orthogonal filters achieved in terms of output SNR better filters with shorter impulse characteristic, which have smaller ripple output signal at the end of the QRS complex. The lower level of the input SNR perform better biorthogonal filters longer impulse response at higher SNR at the input, the resulting values are comparable. The output signal waveforms at biorthogonal filters is evident that a shorter impulse response better to suppress ripple end of the QRS complex.

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ATTACHMENTS

In the back of the plates is accompanied by a CD with an electronic edition of the files needed to run the test program created in the programming environment Matlab version 7.10.0.499 (R2010a).