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ECG SIMULATION AND INTEGRATION OF KALMAN FILTER IN CARDIO PEDIATRIC CASES

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ABSTRACT

This article will show an overview of the model and simulations of general cardio pediatrics cases. To avoid simulated interference, Kalman and lowpass filter blocks are placed. In pediatric cases normal ECG (Electrocardiogram) curve is a bit different in relation to the middle-age persons. In cardio pediatric is represented especially the ECG curve with higher beats/min. Depending on the age of the child's heart rate is variable. Therefore, identifying irregularities of the heart rate in children should be implemented a particular type of filter to eliminate rough measurement error on measurement signals. The model is obtained computationally shown in the examples of simulation in LabView and Java application programming interfaces. The model realization of the ECG signal is based on a few methods. Therefore, it selected only one method to display a simulated ECG signal. Installation of additional software filters allows us for realistic expectations after hardware integration. The real practical case is provided by a developed system with compiled firmware in the microcontroller. Firmware defines the behavior of the ECG signal after the integration of Kalman and the lowpass filter. Some cardio pediatric cases are processed with the method which can be applied Kalman or lowpass filter.

KEY WORDS

ECG model, ECG Simulation, Kalman filter, low-pass filter, smart city

CLASSIFICATION

JEL: Q53, R41

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INTRODUCTION

The realization of the ECG signal simulator for cardio pediatric cases requires the development of the model. With additional model possibilities like parameter adjustment, a waveform of the ECG curve is defined. The model parameters depend on a lot of specifics that can occur in children's cases e.g. one of the specificities of the right ventricular hypertrophy is when V1 is different and changes with ages. How the heart grows, operational frequency is reduced and minute volume is held. Specificity can be seen in the T wave, which is the subject of electrolyte status activity of the autonomic nervous system. Transition to the ST segment does not contain significant changes or specifics unless a child has ischemia. That case is then defined by the pressure or volume load of the right ventricle in the right precordial leads. Using V4, V5 and V6 (left leads) can be displayed when the left ventricle is loaded, then is a case of aortic stenosis difficult. Very important parameters for simulation of the ECG curves in cardio pediatric cases are V1, V2, V3, and V4 lead. Negative or inverted signals are characteristic of cardio pediatric cases and children's cases for up to 12 years. This is the case for V1 – V4 leads. Later, after 12 years of the child may remain inverted signal in V1 and V2 leads. Between 17 – 18 years usually lead V1 becomes positive, non-inverted. Some people have a whole life negative/inverted V1. Pleasantly we call them in discussions forever young.

During measurements of heart rate, results show different frequencies at various ages and lifetime of child Table 1. The fluctuation of heart rate is in the age range from 3 30 days and 1 – 3 months. There occur of the highest frequency because the fiber of muscle on the heart is formed. For the knowledge of the heartbeat and creating/simulate curves, it is necessary to recall the appearance of the heart (ventricle and atrium) and the ideal/basic global curve of ECG waveform signal Figure 1 a) and b).

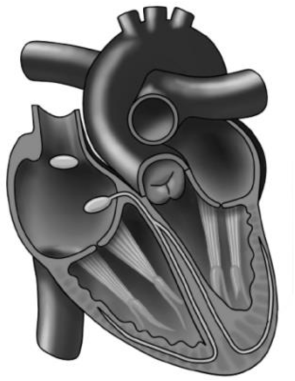
Table 1. Heart rate by children ages.

	Heart rate (bpm)	
Age	**Mean**	**Range**
< 1 day	119	94-145
1-7 days	133	100-175
3-30 days	163	115-190
1-3 months	154	124-190
3-6 months	140	111-179
6-12 months	140	112-177
1-3 years	126	98-163
3-5 years	98	65-132
5-8 years	96	70-115
8-12 years	79	55-107
12-16 years	75	55-102

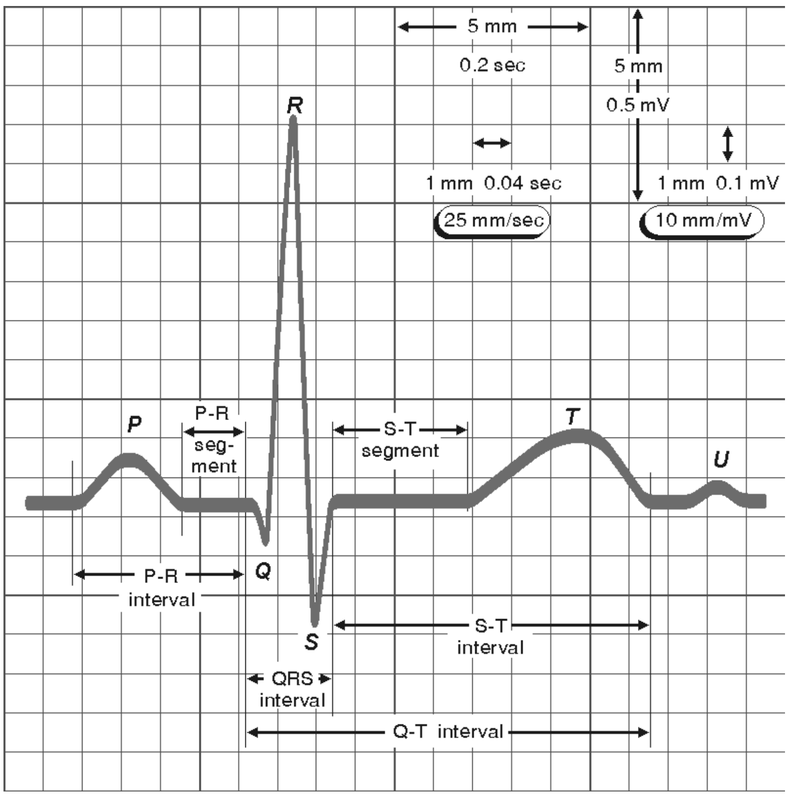
The model of the ECG signal is manifested thought a 3D model of the heart [1]. The Mash network of lines on the model defines density and tissue form [1]. To form a 3D image/model of the heart is necessary to make a mathematical model [1-3]. Substituting the parameters in a mathematical model, it is created dynamically model and emulation of the heartbeat.

Important criteria used to observe the specificity of right ventricular hypertrophy when is the R more than 20 mm in V1 through all the years, R/S ratio more than 6.5mm and upright T wave in V4 after 72 h of life. Also, the presence of a Q wave in V1 is part of the criteria. Left ventricular hypertrophy is defined when the S is more than 20 mm in V1, R more than 20 mm in V6, and Q wave more than 4 mm in V5 and V6. Also, T wave inversion in V5 and V6 characterize these criteria [4-7].

In cardio pediatric cases is included several forms of normal rhythms of heartbeats such as at normal sinus rhythm, normal sinus rhythm at arrhythmia and sinus tachycardia. Characteristic description of normal sinus rhythm describes regular regularity at 60-100 bpm (beats per minute). Also, the QRS complex is less than 120 ms. The only difference in sinus arrhythmia is irregular regularity. The characteristic of sinus tachycardia is that regularity is regular but the heart rate is greater than 100 bpm. Except for those phenomena, fast and slow rhythm is also represented [8].



a)



b)

Figure 1. a) Appearance of the heart, b) Ideal/basic global curve of ECG waveform signal.

3D MODEL OF HEART AND ECG SIGNAL SIMULATION

3D MODEL OF HEART

Mathematical modeling of ECG is known as the forward problem of electrocardiography. There are three basic types of the model; a model for electrical activity of heart, model calculating torso and heart-torso coupling model of conditions. With space and time discretization numerical results are obtained [2].

The dynamical model creates and generates a trajectory in a three-dimensional space. Applying integral equations to mathematical models, 3D models are obtained, Figure 2. Through six frames is shown characteristic appearances like membrane potential, TNNP (Tusscher-Noble-Noble-Panfilov) ionic model and repolarization or relaxation of the ventricles in T wave, Figure 2. According to the fractal behavior method for the dynamical model is possible to be dimensioned. Similar methods of identification of processes, recursively repeated with small phase shifts, describes cardiac nature. Precisely, these phase shifts are defined by the nature of acceleration and deceleration of the heartbeat [9].

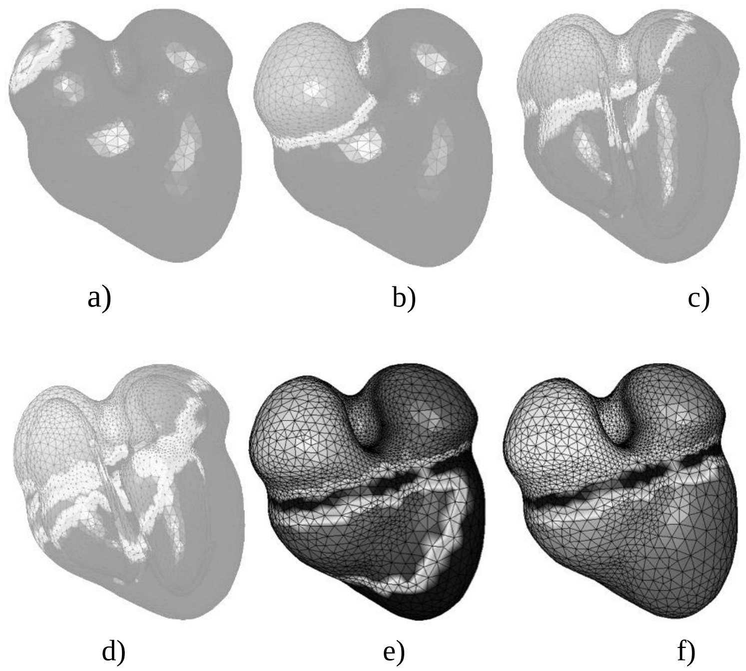


Figure 2. Heart 3D model (dynamics of behavior).

ECG SIMULATION

To accurately simulate the ECG curve in cardio pediatric cases it is necessary to create a simulator that has the option of entering parameters. Besides the basic parameters that characterize the ECG curve, sometimes is added to simulation: temperature, main pressure, diastolic pressure, systolic pressure and oxygen saturation. The important parameter used in LabView ECG simulator is “spacer width” which may lead to the characteristic movements that are essential for cardio pediatrics. Exactly this parameter is included as a slider in a graphical interface that the ECG curve can be faithfully simulated. Throughout the paper, we use two simulators. Primary ECG simulator over which is made modifications with filter block using LabView interface. A secondary ECG simulator is implemented in Java and interference has not eliminated in that case.

The basic interface for configuring the simulator defines the appearance of the ECG curve Figure 3. A block diagram of the global system design of the ECG signal is shown in Figure 4. Design of white noise and other parameters in blocks that simulate real interference has been achieved in the waveform of ECG signal in Figure 5. To see the difference in the simulated signals, the scenario is divided into three segments with different heartbeats. Thus are defined 68 bpm, 115 bpm and 155 bpm.

Basic simulated ECG signal with 68 bpm with a graphic interface for setting the parameters is shown in Figure 6. Figure 7 a) and b) represents a curve of ECG signals with 115 and 155 bpm. The integration of block diagram to generate white noise and amplitude amplification for virtual emulation of artifacts produced an effect on the curve that improves Kalman or lowpass filter, Figure 8 a) and b).

For reduction of the white noise has been used lowpass filter. To remove the component of motion artifacts during the measurement is used Kalman filter. In the third subtitle is defined lowpass and integration of Kalman filter. After signal omission, an ideal model of signals is obtained and faithful to the original signals.

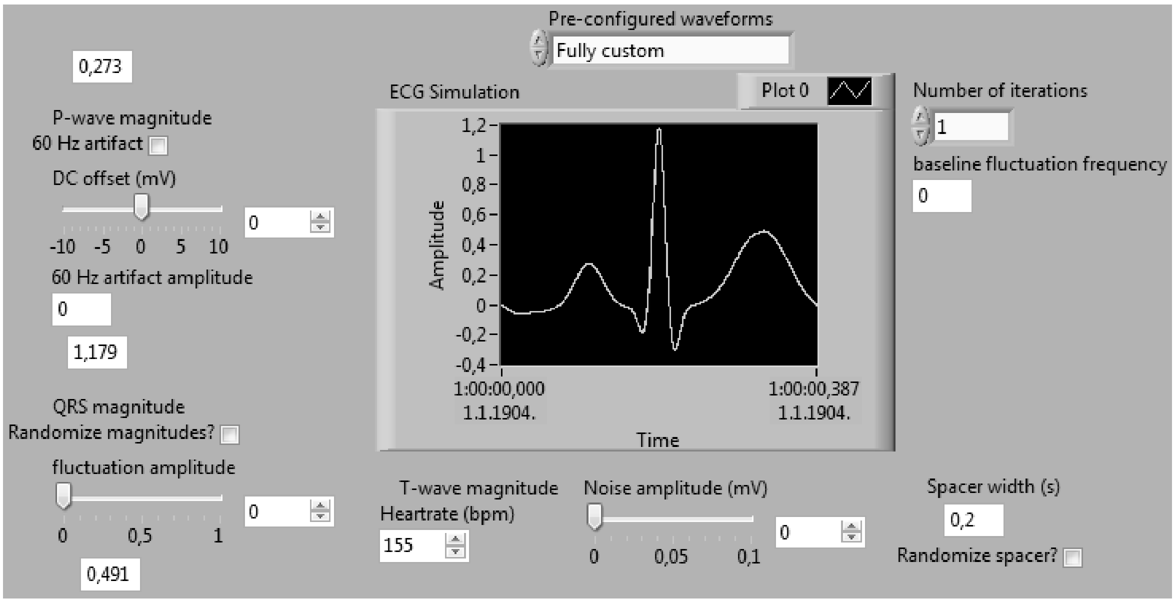


Figure 3. Basic interface for ECG curve design.

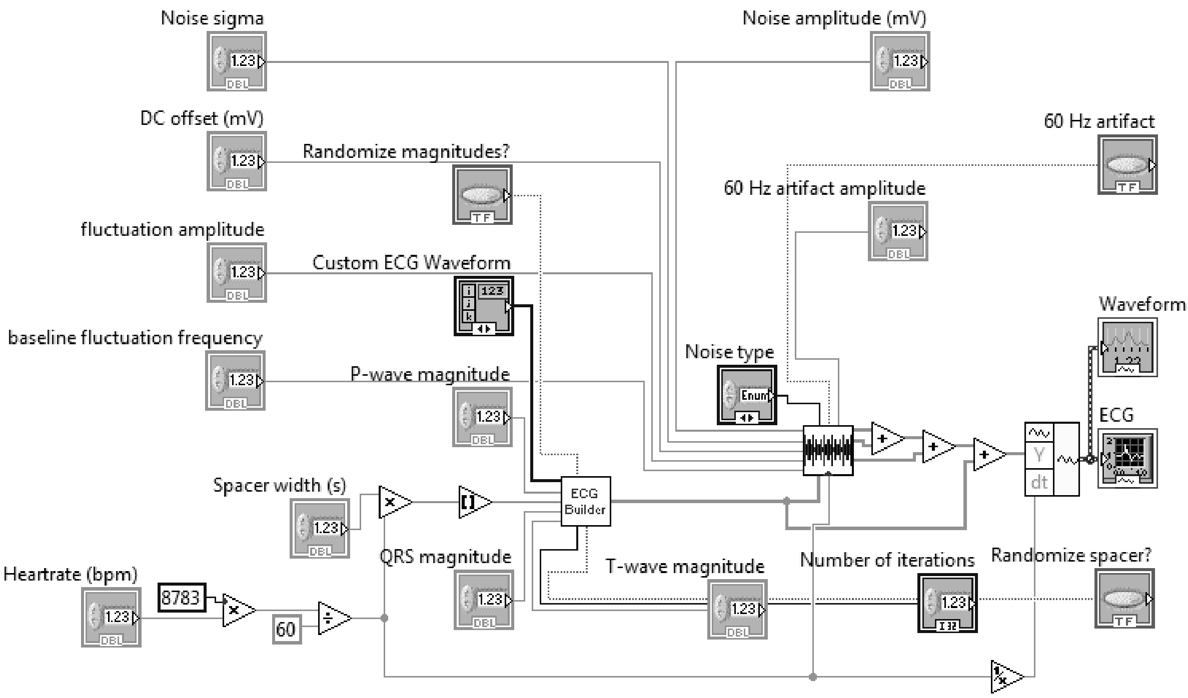


Figure 4. Block diagram of global simulation design of ECG signal.

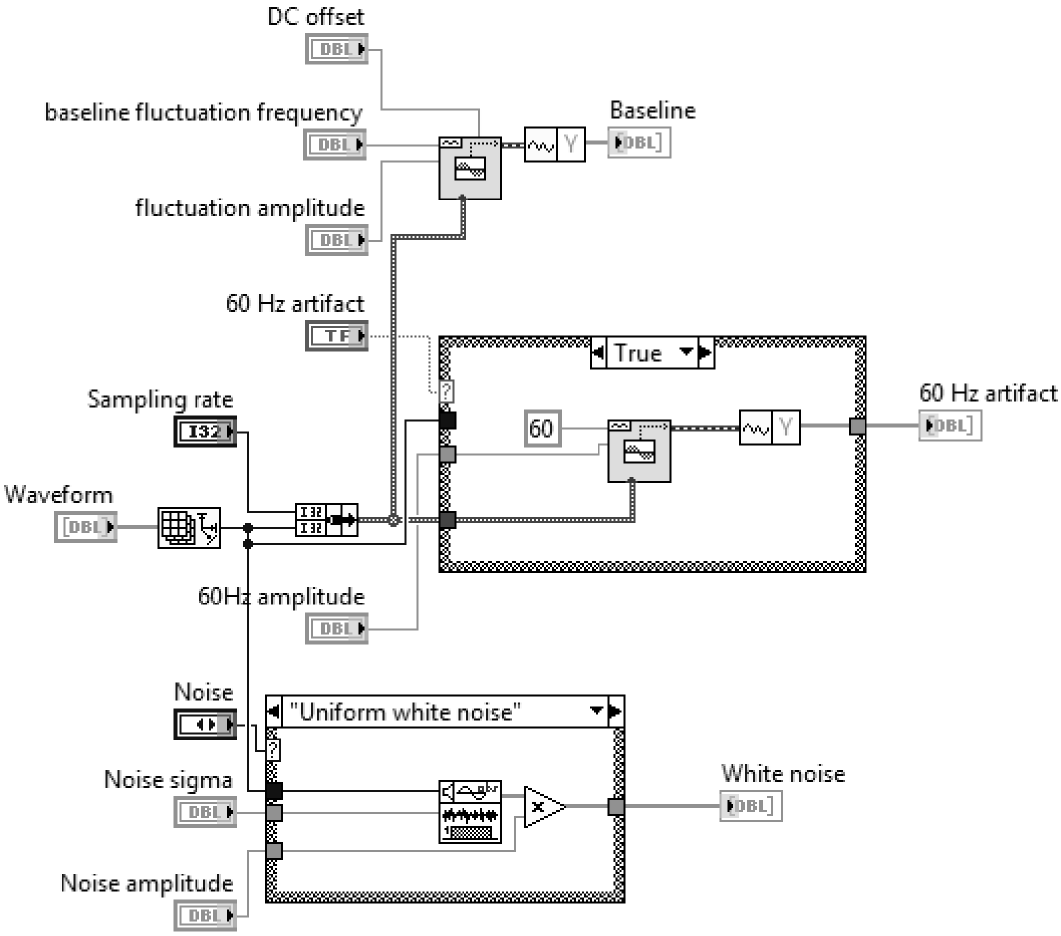


Figure 5. Block diagram of noise.

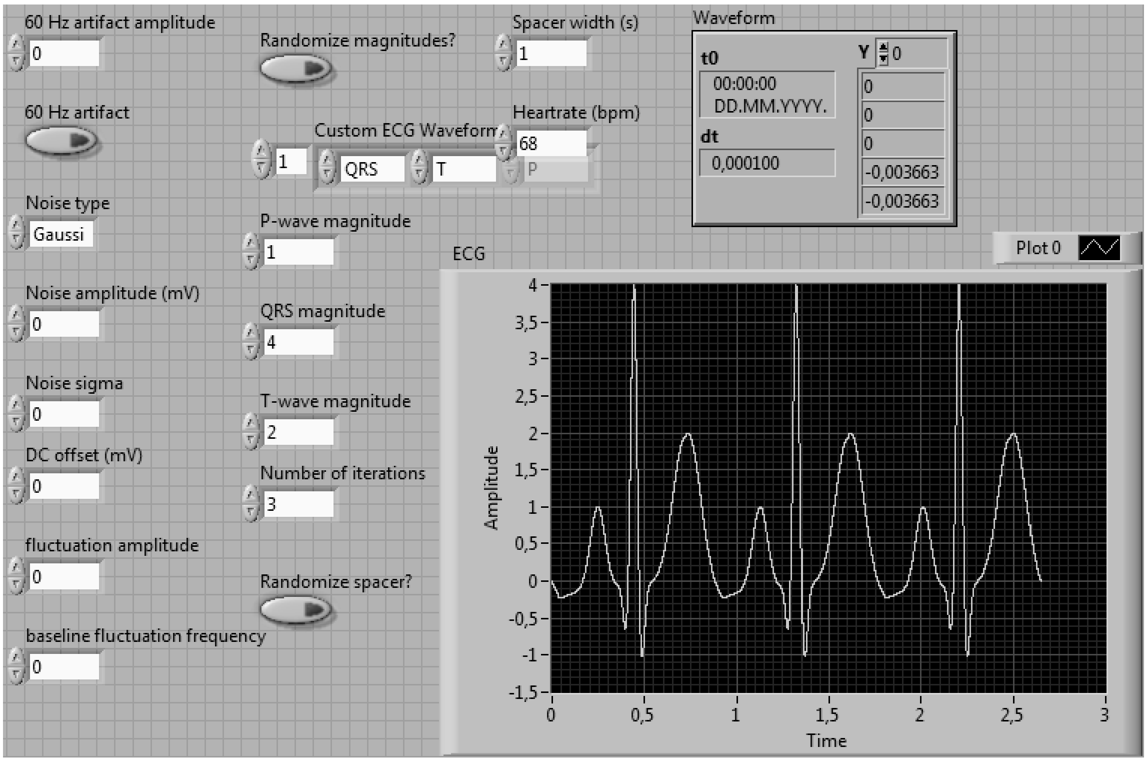
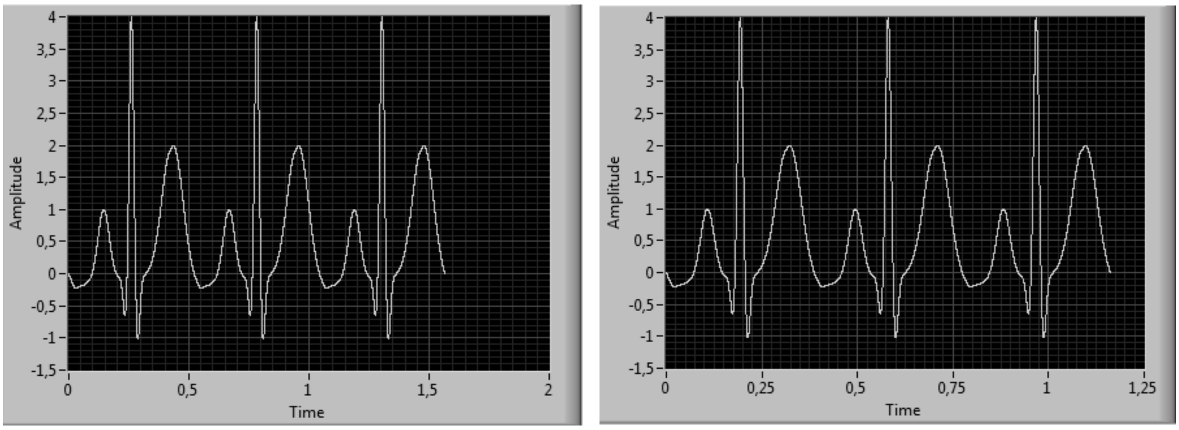
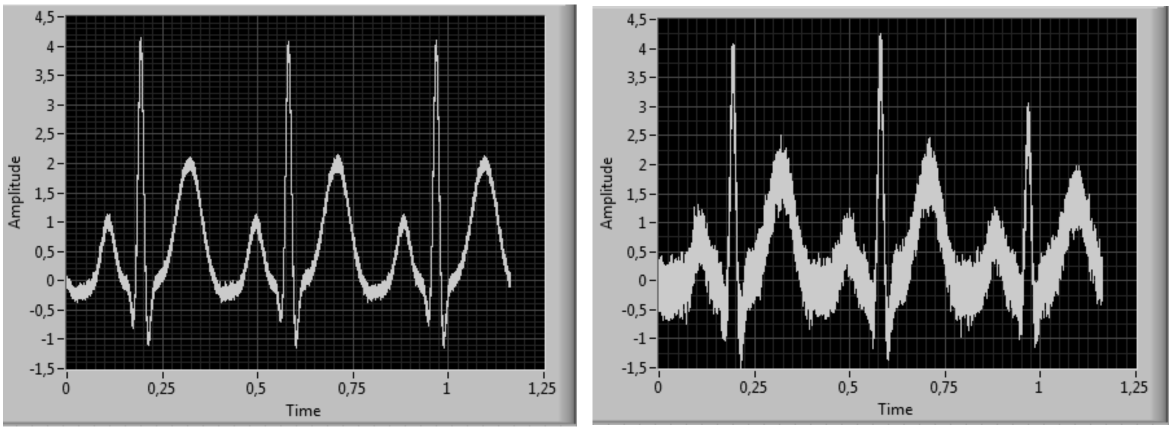


Figure 6. Secondary graphical interface for parameter adjustment (68 bpm).



a) b)

Figure 7. ECG signal a) at 115 bpm, and b) at 155 bpm.



a) b)

Figure 8. ECG signal a) at 155 bpm with white noise, and b) at 155 bpm with 2 mV amplitude noise.

Smaller quantization in hardware is monitored and filtered by setting a limit of real filter, while developed simulation at the same clock data is faster processed. Comparing to the existing simulators, Figure 9, which has integrated parameters such as body temperature, surface skin temperature, pressure, etc. It is possible to display a more faithful signal [10]. Very important parameters for adjustment in the existing simulator are heart rate, oxygen saturation and PPG (Photoplethysmograph) which we can bring from additional hardware mobile measurement devices called oximeter [11-13]. With SPO2 (Saturation of peripheral Oxygen) and mounting real oximeter, with additional measurements is easier to determine the condition of the patient. Another simulator of ECG signals was realized through Java compiled and uploaded an online interface where we can also change parameters, Figure 10. Changing values of parameters for different waveforms with simultaneous creation of logging files is achieved [14-15]. Then such a file can be analyzed separately and we can use null-points for simulated curves. Elements inserted for adding artifacts impairments include the low voltages that modulate to the ideal ECG curve.

Figures 11 and 12 represent the Java online simulator of ECG signals with an amplitude noise of 0,2 mV and 0,5 mV. Filtering, in this case, is not realized in Java programming code. Creating additional program code form in shape of "for" loop, counting to 10 and with fragmentation system can eliminate undesirable interference and characterizes the case behavior of the Kalman filter effect. White noise is possible to integrate with the function "randomize" where the number of offsets limit can be constrained by software.

Filtering white noise in the same simulator software can be provided graphically in LabView or with standard Java code. Kalman has two types of integration of filter; matrix and with "for" loop where is loop options mostly used for integration into embedded devices.

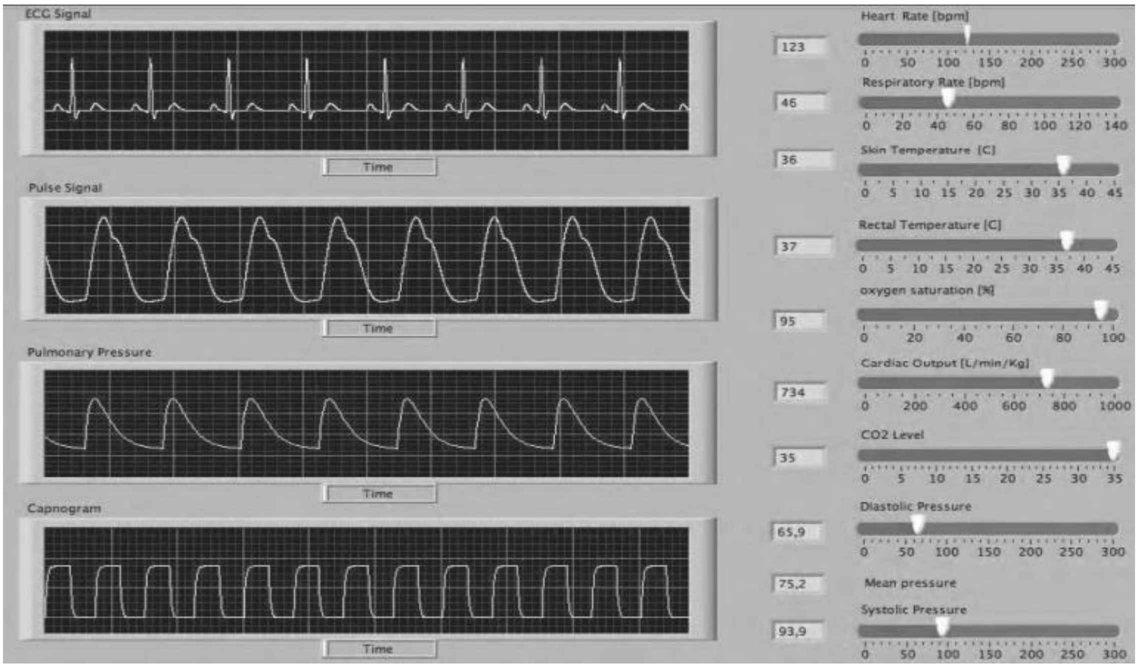


Figure 9. Existing ECG simulator without filtering and modeling noise.

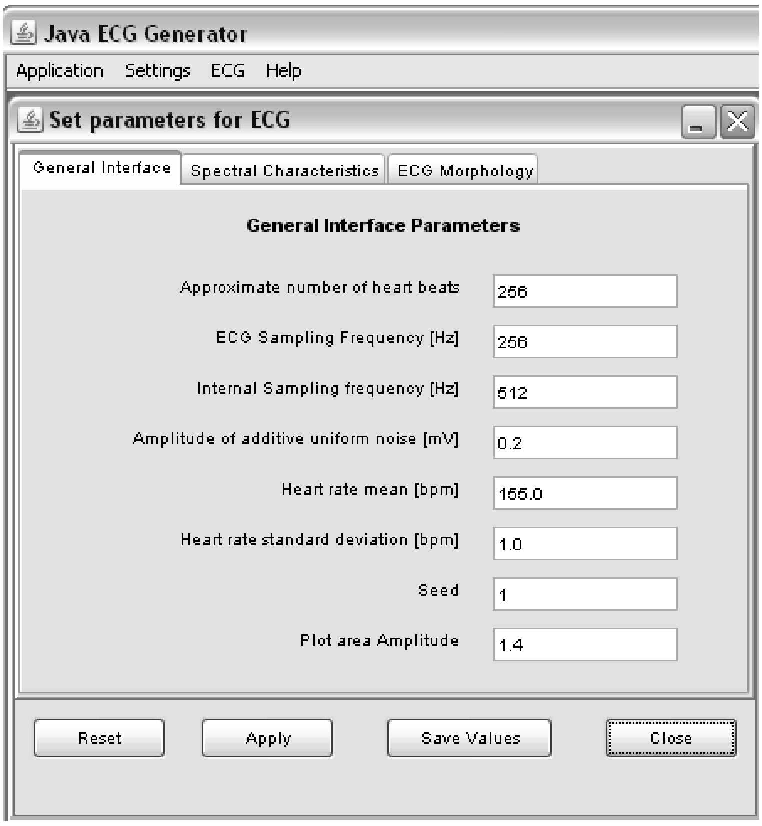


Figure 10. Java ECG simulator/generator [14, 15].

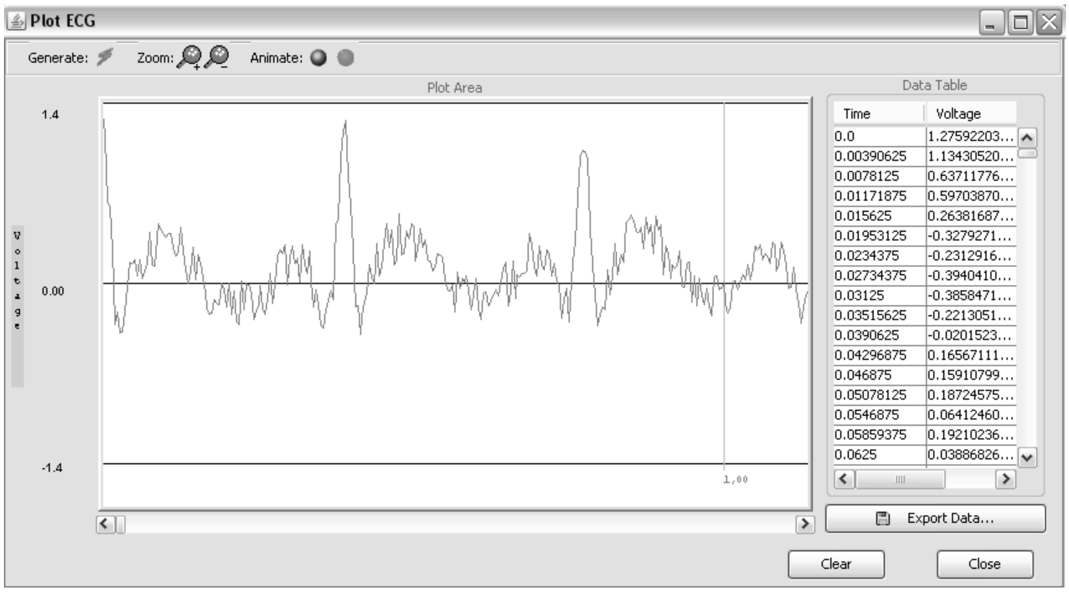


Figure 11. Java ECG simulator with amplitude noise 0,2 mV.

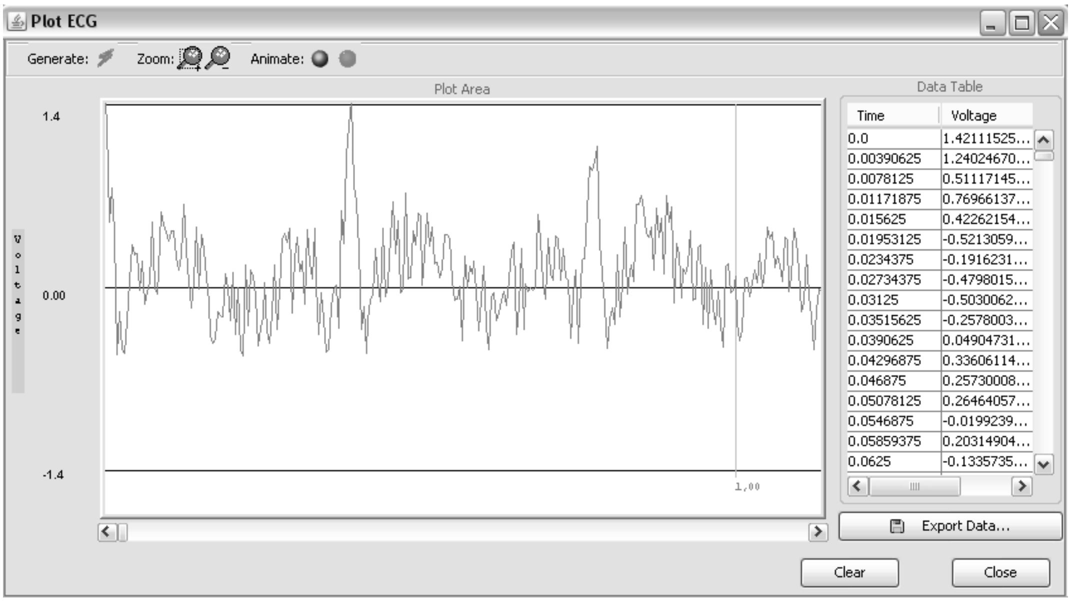


Figure 12. Java ECG simulator with amplitude noise 0,5 mV.

INTEGRATION OF LOWPASS AND KALMAN FILTER IN SIMULATOR

Kalman filter integration in LabView simulator requests known process frequency. Kalman filter is used for parameterization of various processes and is applied in this simulator. Many processes use Kalman filter such as calculation of the angle of multirotor/quadcopter [16-18]. During logging and processing, all three axes of accelerometer, gyroscope, and magnetometer must be filtered signals. Also, e.g., a self-balancing vehicle with an accelerometer and gyroscope have integrated Kalman filter to reduce the effect of drift [19, 20]. Scenarios where variables are not linear its used Extended Kalman filter. Signal analysis of previous applications bringing us to the conclusion that such application of filter brings very good results in the processing of ECG signals. Besides the simulator, the idea is to integrate the filter into the firmware of the embedded device.

To analyze and process the signal, it is necessary to make discretization. Using inverse delta function $d(k)$ with characteristic adjusted amplification, adder processes output value for Kalman filter, Figure 13.

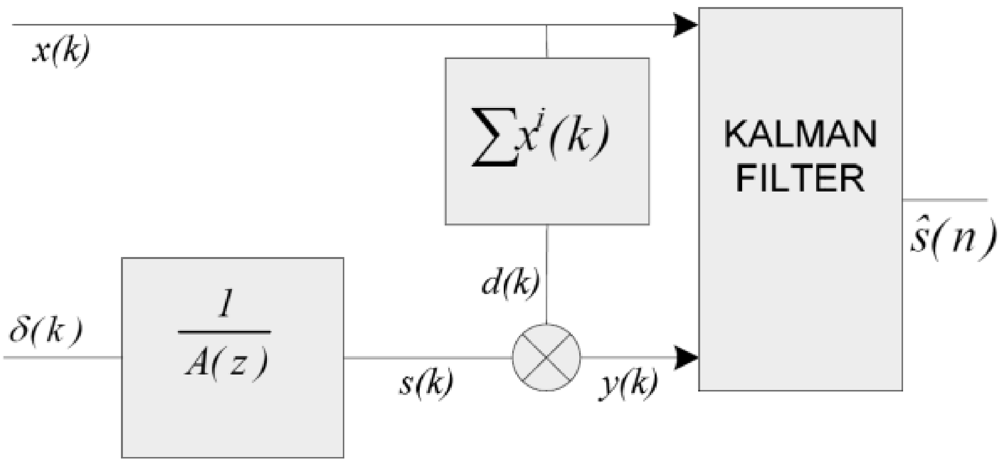


Figure 13. Model of signal value preparation for Kalman filter processes.

Presented filter block can be realized using a matrix of discrete mathematical relations or by using loops inside the software. This software can be integrated into a computer simulation and incorporated into the firmware of an embedded microcontroller device. Application of ECG simulator in LabView was used for filtering systems on Kalman/matrix principle, Figure 14. Possibilities for filtering can be processed with "for" loop counting to 10. "Shredding" of the signal in this way is less obtained, accurate and filtered response. How it is difficult to incorporate matrix form in an embedded device, preparation for future work is installing a filter in measuring system of ECG via loop principle. After taking ten samples of measurements at a much higher frequency, the variable is bit shifted and divided by ten.

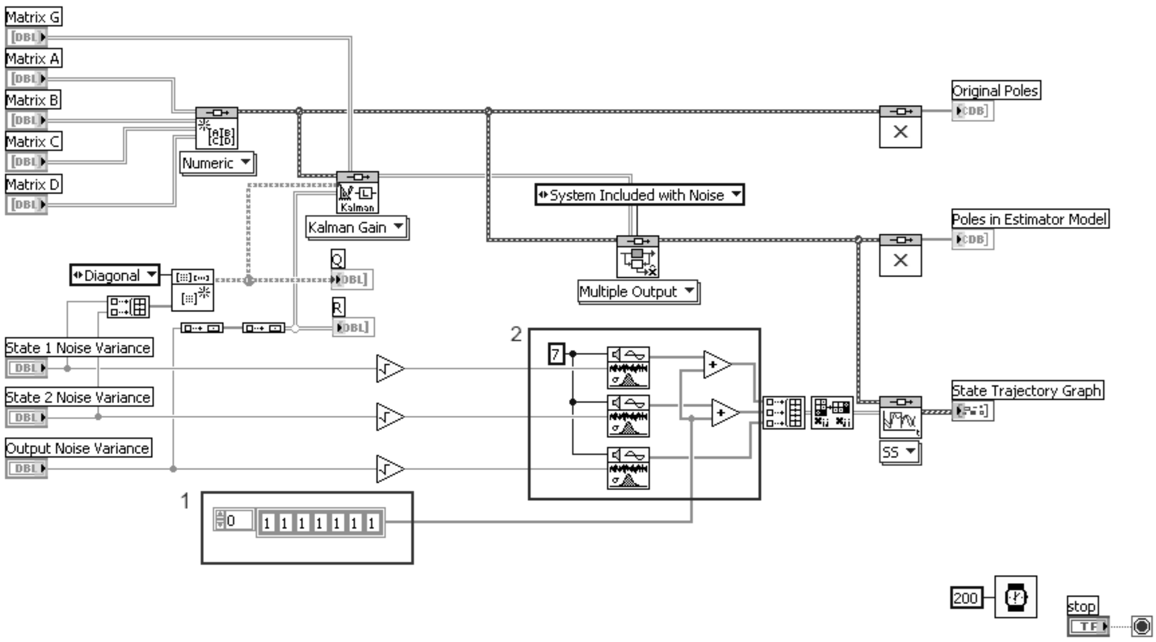


Figure 14. Matrix principle of integrated Kalman filter in ECG simulator.

Earlier mentioned matrix principle uses some additional operation over the matrix-like transposing. Integration to the planed embedded device is not suitable for this operation because is necessary to ensure bigger processor power on higher frequencies.

Lowpass filter integration can be efficiently designed in software and hardware. Function integration in software simulation separates characteristic frequencies while in hardware is passive electronic used with resistor and capacitor integrated on each channel. The lowpass

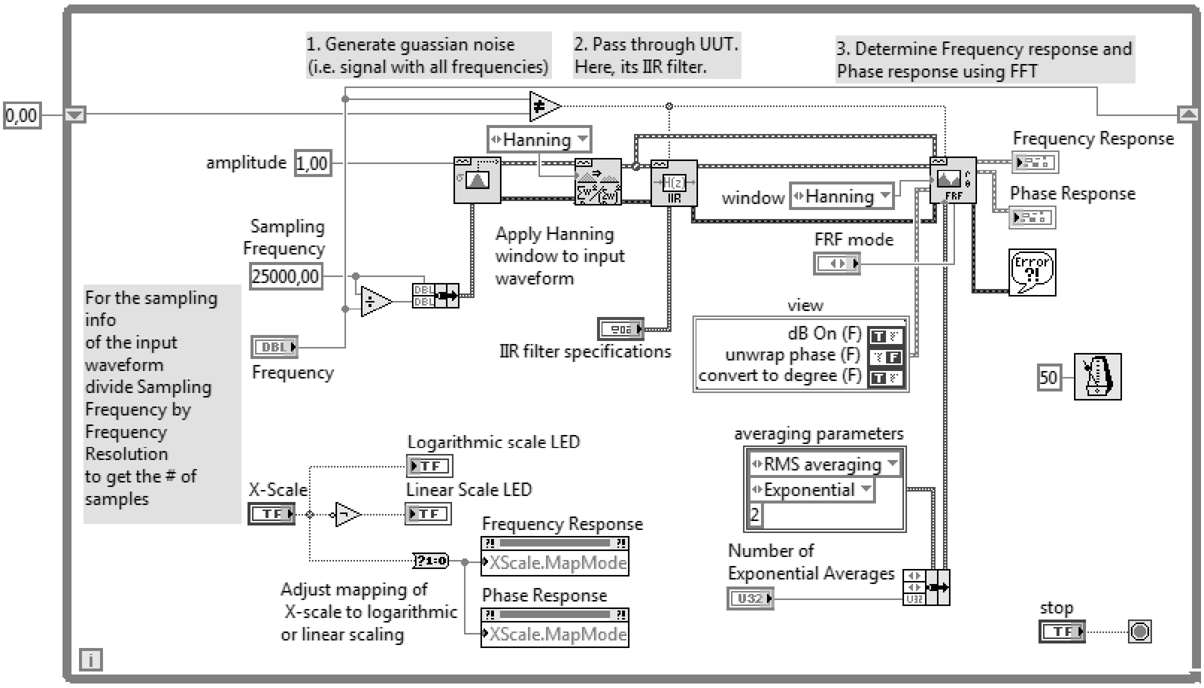


Figure 15. Design of Butterworth lowpass and bandpass filter

filter is usually used for isolating harmonic from the power network. There appears a frequency of 50 Hz or 60 Hz with the prescribed tolerance in Hz, and their presence, because electromagnetic compatibility must be isolated as rough measurement error. Figure 15 represents the design of two integrated filters based on the Butterworth principle. Integration of Butterworth lowpass filter is for the elimination of low frequencies like mentioned, 50 Hz and 60 Hz.

Figure 16 represents a Butterworth lowpass filter, while Butterworth bandpass filter is finally integrated because our muscles and natural movements represent high frequencies. For elimination of these frequencies is necessary to integrate high pass filter. With this solution with bandpass filter integration, Figure 17 was achieved and prepared for the installation of a dynamic Kalman filter. Prescribed frequencies that are specified for measuring ECG signals are 100-150 Hz. With an obligatory sampling of the signal during measurement on mobile embedded devices its between 1-2 kHz minimum. Industrial devices, designed for hospitals and clinics, must have higher sampling frequency.

ECG signals sometimes in real conditions has a dynamic component of interference or noise. Superelevation or some doctors say overshoot, after filtration by ordinary filters in characteristic points, can lead to making the wrong diagnosis, especially in the ST segment. To avoid this situation, Kalman filter with very low latency/delay of filtering, (below 1ms), in this application provides real-time measurement. Referring to the dynamic ECG model [21, 22], it is possible to use EKF (Extended Kalman Filter). The basic feature of the EKF is nonlinearity compared to standard Kalman filter as is mentioned before. To linarite nonlinear dynamic model must be linearized model through state-equations [2, 3, 7, 22]. Estimation of signal trough EKF requires parameterization [22-23]. In practice, when after measuring the ECG signal is integrated, EKF proved to be further improved in readings [24-26]. Through practice it turned out that older cardiologists and cardio pediatricians have been well adapted to the nuisance so-called; offset that can be understood without the need for additional integration into small portable devices. In professional desktop devices, which is used to measure ECG signals, such EKF is integrated for additional analyzes.

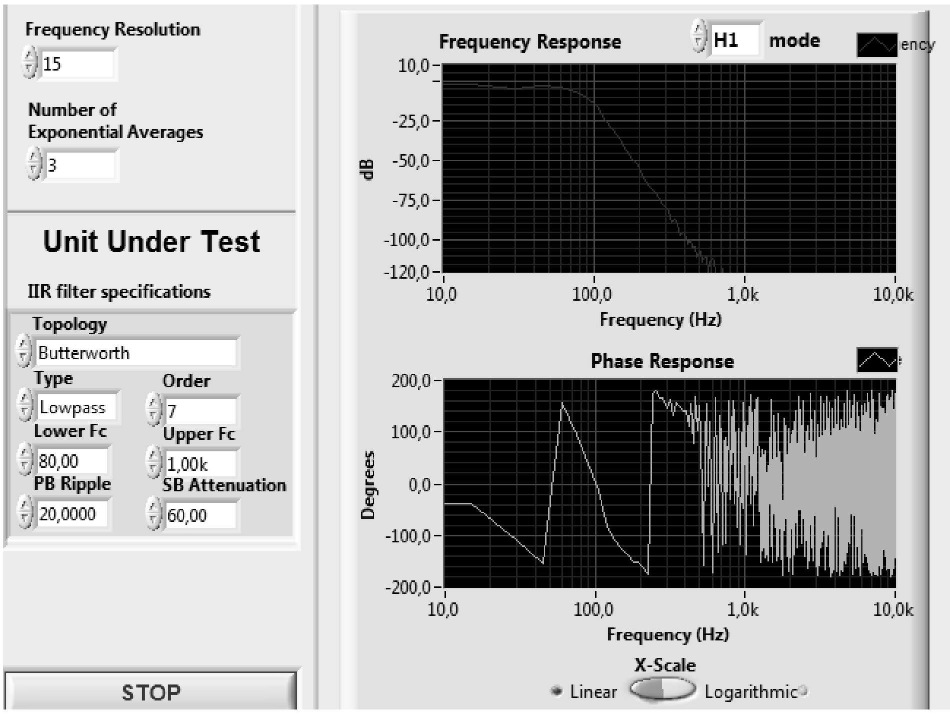


Figure 16. Butterworth lowpass filter.

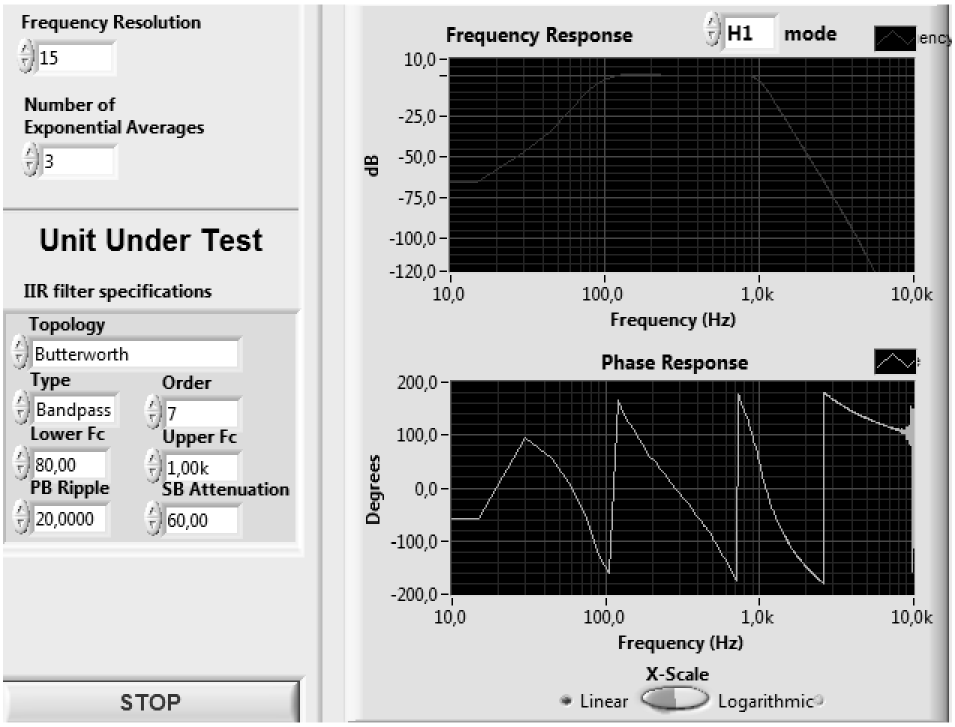


Figure 17. Butterworth bandpass filter.

CONCLUSION

During the development of ECG signal simulation, we took into consideration existing mathematical models of the heart. 3D model of the heart is shown through isometrics dynamic events, Fig. 2. During the elimination of interference, first was used Butterworth bandpass filter. The second filter in real-time analysis, for assumed embedded device integration is used on the Kalman filter “loop” principle. Kalman filter is shown through the matrix form with matrix transposition while it is taken into consideration the standard

Kalman "loop" method for easier integration in embedded devices. Upper classes, such as the ability to use FPGA (VHDL programming), allow us for the integration of matrix Kalman filter, but in such cases, it is used Extended Kalman filtering (EKF). Simulation results show average R-RF time between 7-8 ms at 60 heartbeat rate, while the R-R segment is 735 ms. The integration of all filters is considered for implementation in an embedded microcontroller device for wireless monitoring. The same principle is used in Holter devices but without Kalman "loop" filter integration. Thus, achieving off-line analysis with recording 24-hour log on SD card. ECG simulations and filter integration provide us with techniques to integrate and work in real-time on an embedded wireless device. By Kalman filter is achieved the elimination of superelevation/overshoot and less time is necessary for filtering (below 1ms). Results represent a very small delay compared to existing solutions. This method of filter implementation in cardio pediatric cases exactly is suitable for a larger number of beats because the method precisely enhances analysis and diagnosis creation of the patient.

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