Implementation of MATLAB Modular Processing System for Biological Signals

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ABSTRACT: *A biological signal is a weak signal, so it is necessary to find new or improve methods of its processing. The paper proposes the implementation of the modular signal processing system for processing and further analysis of the most commonly used biological signals in diagnostics, such as electrocardiogram, electromyogram, electroencephalogram, phonocardio-gram or pulse wave but it is possible to employ it also in other signal processing areas. Based on contemporary literature, a wide range of the processing and filtering methods are embedded (digital filters, adaptive filters, wavelet transform, independent and principal component analysis etc.) into user-friendly interface, serving for the testing of the accuracy and suitability of the individual techniques for the signal processing. The software is designed to ensure as greatest as possible area of the biological signal processing so that basic modifications or analysis of any one-dimensional biological signal can be made.*
Keywords: Biological Signal Processing, Digital Signal Processing.

I. INTRODUCTION

Because the biological signals are often corrupted by many types of artifacts or interference, the signal processing makes up the important part of their analysis and thus, facilitates a correct interpretation and a further diagnosis. The signal filtering and processing enables to eliminate or remove the undesirable components of the signal so that the more valuable information can be extracted. The sources of the noise can be physiologic (e.g. reciprocal influence of the different organs on each other, biological rhythms, patient's moving, movement of the electrode-electrolyte interface) or the environment where the signal recording takes place. The noise sources are typical for each individual biologic signal, depending on a way how a signal is measured, which sensors are used (e.g. different types of interference corrupt an electrical signal in the comparison with an acoustic signal, etc.) and also what is the frequency range of the signal.

In the last few years, there has been significant develop-ment of advanced methods of digital signal processing. The topicality of the issues examined the increase in the performance of the microprocessor technique (multi-core processors, field-programmable gate arrays). Just an inad-equate computing performance has been in the past the main limiting factor for the use of certain complex meth-ods. In addition, recently the new measurement methods have been occurred; the biolocation signals (sensing using the optical fibers, miniature sensors in the bloodstream, etc.) and in general, these new approaches also require the improvement of the signal processing methods. Taking into account developments in the last few years, it can be noted that today's time of changes is evoked by the performance parameters of available means of computing and is characterized by new trends in the signal processing area.

As a reaction on this development in biological signal processing, the software which can be available in clinical practice, is more and more evolved. This paper brings a description of the modular signal processing application created in MATLAB software, implemented mainly for the purposes of the education and testing of the several today well-known processing methods. These methods were cho-sen based on the research of the contemporary literature and includes digital filtration (Panda and Pati, 2012; Jag-tap and Uplane, 2012), adaptive noise canceller (Soedirdjo et al., 2015), principal and independent component analy-sis (Corradino and Bucolo, 2015; Velez-Perez et al., 2011; Romo-Vazquez et al., 2007), derivation, wavelet trans-form (Balasubramaniam and Nedumaran, 2009; Yavuz and Aydemir, 2016; Reaz et al., 2006), and empirical mode decomposition (Pang et al., 2016).

The implemented system represents a tool for the testing processing methods and enables the user to compare more techniques of the processing of the corrupted signal. The system offers the possibility to add a

mixture of the available types of interference to the processed signal and evaluate the precision of the processing by computing of the signal-to-noise ratio (SNR) and determining the shape distortion of the signal during the filtration by correlation coefficients. After each change of the processed
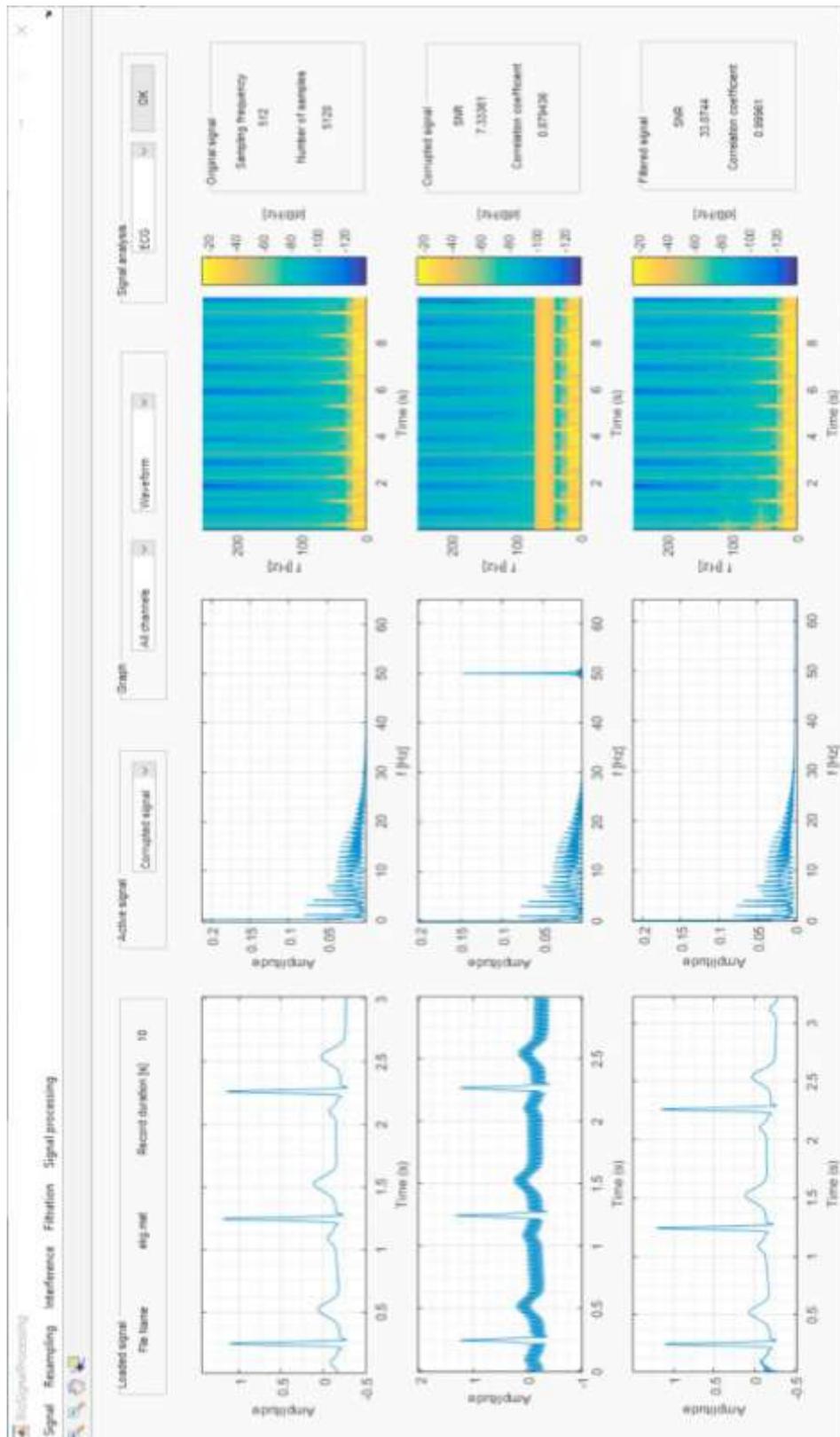
Fig. 1. The user interface of the main window of the implemented software, where the user can modify the original and corrupted signals.

signal (e.g. adding the interference or filtration), these criteria are computed and the user can compare the values of the original signal, corrupted signal and filtered signal, when also the graphic representation is displayed
- time waveforms of the signals, their frequency spectra and spectrograms which shows frequency distribution in time (see Fig. 1). A whole function of the application is described in the following sections.

II. BIOSIGNAL PROCESSING

The whole program contains five basic parts: loading a signal, it's resampling, adding an interference, filtration or other processing methods and last, analysis. The general function of the software is designed in Fig. 2. Summary of the options when working with signals is described in Table 1.

Start

Main window

no
Loaded signal exists   Loading of signal

yes

Active signal
choice

Analyse signal
no   yes   Analysis module
Edit signal

yes   no
Signal processing   no

Save signal
module

yes

no   Save signal Saving of
signal

yes
Saving   of
signal

End
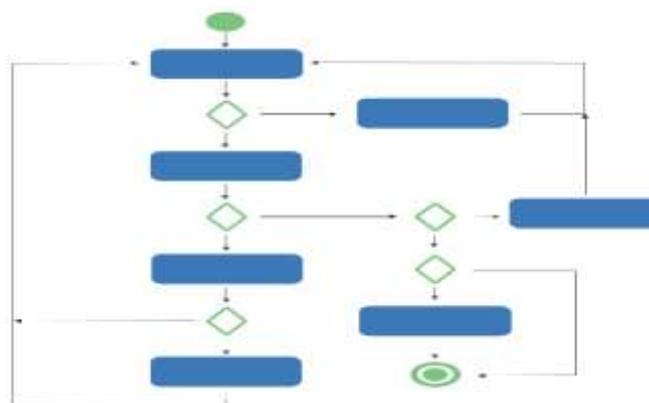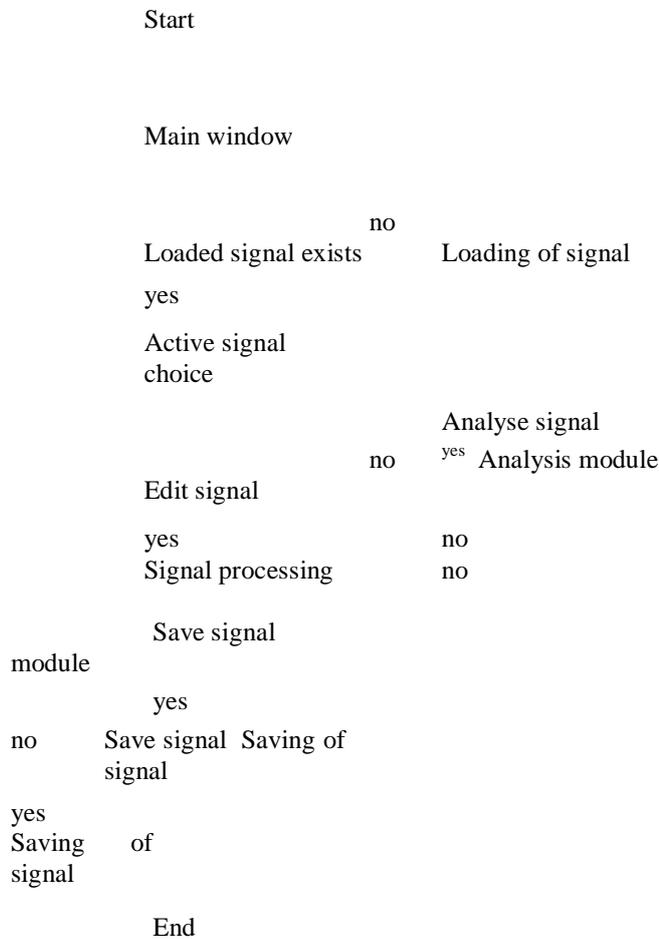
Fig. 2. UML diagram of the application.

2.1 Signal Loading

The software allows loading a signal in the .mat format. The system can work both with signals single-channel and multi-channel when each channel is saved in one row of the matrix. For the successful loading of the signal, the user has to type a sampling frequency or the time duration of the signal. The next step is to select the desired time segment of the signal and channels of the signal, which would be loaded into the system. This signal is saved as an original signal in the main window of the application.

2.2 Resampling

Signal resampling is used when the sampling frequency originally used is not high enough for some specific types

Table 1. Summary of the software functions.

Sampling	Interference and Noise	Filtration	Processing	Analysis
Linear	Power line interference 50/60 Hz	FIR filter	WT	Fixed peak detector
Nearest neighbor	Gauss trend	IIR filter	EMD	Adaptive peak detector
Cubic	Linear trend	Moving average	Derivation	Frequency power
Cubic spline	Random noise	filter Notch	ICA	Envelope
	Low-frequency drift	ANC	PCA	
	White noise			

of analysis (e.g. ECG duration of RR or ST interval, the width of T or P waves, etc.), or vice versa when the high resolution is not needed when analyzed. Thus, the sampling frequency is reduced to allow faster, although less accurate signal processing.

The resampling process is carried out by different inter-polation techniques (Srikanth et al., 1998). The user can select the type of interpolation, such as linear, nearest neighbor, cubic and spline interpolation. The resampled signal is saved also as the original signal.

2.3 Interference and Noise

In this step, the user can add to the signal power line interference, low-frequency drift, Gauss or linear trend, random high-frequency noise or white noise. So, the op-tions include simulation of the different states of the signal, non-depending on the type of signal or the way of its measurement. For example, high-frequency noise can simulate effect of electromagnetic fields but also poor electrode-skin contact, muscle potentials or acoustic noise; low-frequency drift or trends can represent slow motion ar-tifacts occurring from patient's breathing or limb moving. Due to these opportunities, the system can also simulate pathological phenomena by

combining all these types of interference (Watford, 2014; Costa et al., 2012; Elgendi, 2012; Luca et al., 2012; Abbaspour and Fallah, 2014). All types of noise can be modified in amplitude, power line interference and slow trends above that in frequency. The signal with added interference is saved as the corrupted signal to the main window.

2.4 Processing

From the processing methods, IIR (infinite impulse re-sponse) filters, FIR (finite impulse response) filters, mov-ing average, adaptive noise canceller (ANC), principal and independent component analysis (PCA and ICA), derivation, wavelet transform (WT) and empirical mode decomposition (EMD) are implemented. As wide as pos-sible range of properties of each method is included in the user interface, so it is possible to examine all the options and choose the most appropriate one, e.g. different types of filters, wavelets etc. Each processing method has
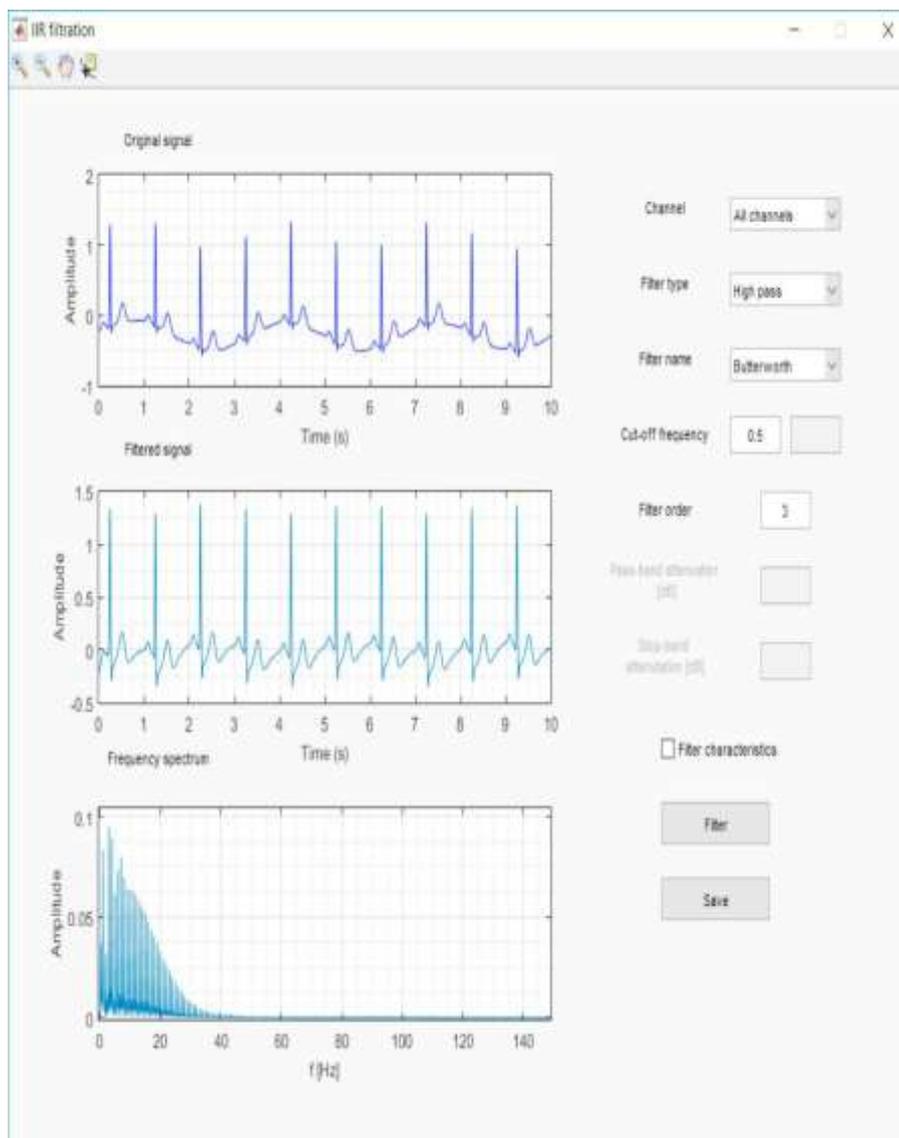
Fig. 3. Example of the filtration module.

its own module (Fig. 3) in the implemented system so that the user can decide during editing the signal if the changes will be saved for the next adjustments or not. The software always shows the graphic representation of the signal to control the changes of the signals during their processing; time waveform and frequency spectrum, eventually spectrogram. All signals edited in one of the modules of processing are saved as the filtered signal in the main window. The processing methods are described in details in the following subsections.

a) Digital Filters

Frequency-selective filters contain the filters types low-pass, high-pass, band-pass and band-stop or notch depend-ing on which frequencies should be eliminated or passed. The digital filter can be split into two main groups: FIR and IIR filters. These filters were well-established in the analogue domain and thanks to the bilinear transforma-tion, they found the application in the digital domain.

Filter IIR requires minimal one feedback loop. Its ad-vantage is a low order of the transfer function, relativelylow delay during the processing of the input sample and low requirements on memory during the calculation of the coefficients. Contrary, the disadvantage may be the problem with stability and a non-linear phase characteris-tic (Rangayyan, 2015; Bruce, 2001).

In the proposed application, three types of IIR filter are implemented: Butterworth filter, which is very often used type of the filter thanks to its simplicity and maximal straight and monotonous frequency response, Chebyshev filter and elliptical filter. Another often-used filter is notch filter, which is popular in the filtering of only one frequency from the signal frequency range (e.g. when removing power line interference) and it behaves as a band-stop filter with just one stop frequency.

Conversely, FIR filter is always stable, has no feedback loops, can have linear phase response and high order of the transfer function. Its disadvantage is the lower steepness of the transient band. Three types of filtering windows are implemented: Hamming, Hanning, and Blackman. The special type of the FIR filter is also themovingaverage

filter, which is also labelled as a filter in time domain and is represented by the window of the certain length moving through the signal (Rangayyan, 2015; Bruce, 2001).

The software enables the following options to choose:

- Type of the filter approximation (Butterworth, Cheby-shev, elliptical) or window (Hamming, Hanning, Blackman),
- Type of the filter (low-pass, high-pass, band-stop, band-pass),
- Cut-off frequencies,
- Filter order (increasing order increases the efficiency of filtration),
- Ripple of passband or stopband (Chebyshev and elliptical filters).

b) Adaptive Noise Cancellation

The ANC method represents a way how to remove a noise which is not stationary, i.e. it changes in time, and which overlaps with the desired signal significantly (e.g., ECG signal of mother and fetus). The spectrum of the signal is then the combination of the same or similar frequency ranges, thus they cannot be separated by fixed filtration.

The ANC uses two input signals - the desired signal with

a   noise x(n) and the reference signal r(n) which is in correlation with noise. The filter modifies the reference so that the signal very similar to the noise y(n) is gained and the output signal e(n) is obtained as its difference with the input signal. The connection of the output and the locked loop of the filter assures the minimal output power and also a small power of the noise in the output signal (Fig. 4) (Rangayyan, 2015).
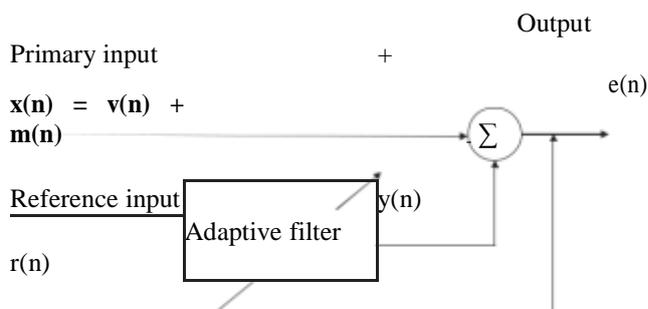
Fig. 4. Schema of ANC function.

The proposed module for the ANC processing contains a selection of the reference signal, which can be generated directly in the application, such as white noise or power line interference, or loaded from the file when the user can choose the time segment of the desired reference signal (this option simulates the situation of

measuring with two sensors - one is the desired signal with the added noise and the second records only the interference).

c) Wavelet Transform

Due to many limitations of the Fourier transform when used in the processing of the non-stationary signals, the methods of the time-frequency processing are found. The idea of the WT is the suitable changing of the maternal wavelet's width in time, so to gain the optimal ratio between time and frequency distinguishability. For the lower frequencies, it is recommended to use the narrower maternal wavelet and on the contrary, for the higher frequencies, the wider one. The WT technique is very often used in the processing of the non-stationary signals but also in other cases, because of the extensive selection of the maternal waves, whose shape often responds to their main characters (e.g. QRS complex of ECG) (Abbaspour and Fallah, 2014).

The options implemented in the application contain the selection of the type of maternal wavelet (Daubechies, Coiflet, Symlet, Meyer) in their all practicable widths and a level of decomposition, which is very important prop-erty of the WT filtering; the low level could remove the insufficient amount of noise but too high decomposition level can distort an original signal and lost the important information, which becomes illegible.

d) Empiric Mode Decomposition

The EMD is a method of the decomposition of the complex non-stationary signal into the given number of the simpler signals, so-called intrinsic mode functions (IMFs). This process is based on the calculation of the local characteris-tics of the signal and it is used most often for a detrending. The process of the EMD algorithm is:

- Finding the points of all extremes of the given signal x(n),
- Interpolating between minimums for creating the low envelope of the signal and between maximums for computing the high envelope of the signal,
- Calculating the mean of both envelopes $x_m(n)$,
- Subtracting the calculated mean, when obtaining modal signal $s(n) = x(n) - x_m(n)$,
- If s(n) fulfils a condition of IMF, defining c(n) = s(n) and saving IMF; if not, defining x(n) = s(n) and repeating whole process,
- The first IMF is calculated, the remaining signal is marked as x(n) − c(n) and the process is re-peated (Flandrin et al., 2004).

The original signal is the sum of all found IMFs. For the filtering applied, the user selects only several of IMFs which characterize the signal. The noise IMFs can be removed.

e) PCA and ICA

In the field of biological signals, it is very common to measure signals from different sources or multiple channels when some of them cause independent information or redundant data. When analyzing multi-channel measure-ments, it is necessary to solve the relationship between individual channels, the potential existence of their cor-relation, presence redundancy and quality of information obtained. It is, therefore, necessary to divide this signal mixture into individual signals components and remove those unwanted ones. There are two methods, one of which deals with PCA and another ICA.

The PCA method decomposes the signal into its uncorre-lated components when keeping as low as possible number of dimensions. The goal is to find a variable which brings as much as possible useful information. The resulting prin-cipal components are sorted in descending order.

The ICA algorithm is based on the assumption of the linear combination of independent sources. The basic properties of the ICA method are the confusion of the indexes of separated components (the separated sources are obtained
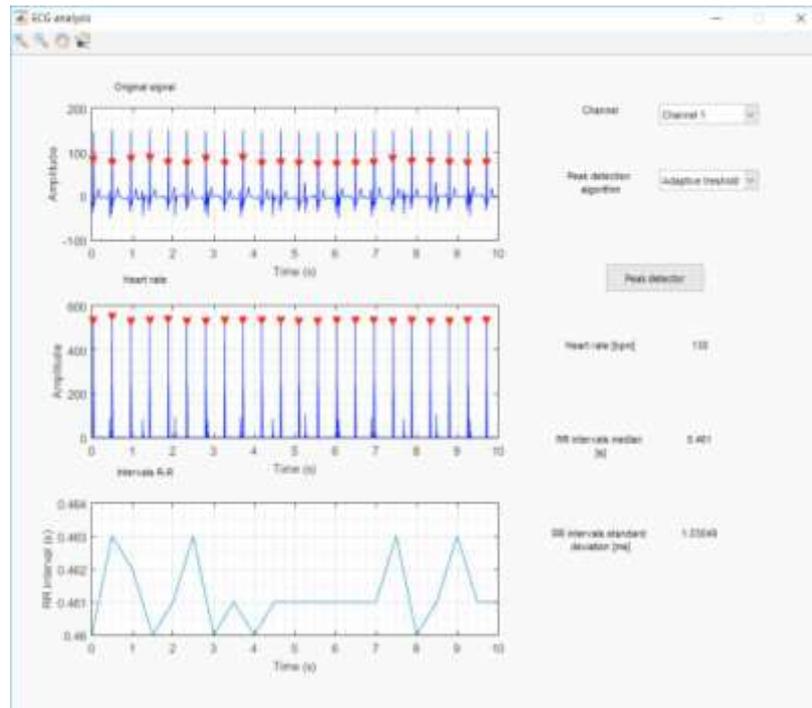
Fig. 5. Example of the analysis block (peak detector).

in the reverse order than of the original sources) and amplitude distortion of the separated signals (Potter and Kinsner, 2001; Rangayyan, 2015).

The modules of PCA and ICA processing allow the user to select a number of separated components, and one certain component which will be saved for the further processing or analysis.

2.5 Analysis

The last step of the process offered by the application is a signal analysis. The implemented software works with the biological signals most used in diagnostics; electrocardio-gram (ECG), electroencephalogram (EEG), electromyo-gram (EMG), phonocardiogram (PCG) and pulse wave (PPG) which the analyzing blocks are made for, but the processing methods allow editing any one-dimensional data. For each type of the signal was created a different form of the analysis; for the heart monitoring and pulse wave (ECG, PCG, PPG), the peak detector was imple-mented (Fig. 5). The two algorithms of the peak detector are used; with the fixed threshold and adaptive threshold. The heart rate, median and standard deviation of the intervals between the obtained peaks are calculated, as the indexes of the heart rate variability, which means a very important part of the diagnostics of heart and also neural diseases (Electrophysiology, 1996).

In the case of the brain activity (EEG), the autoregressive model of the fundamental frequency bands (delta, theta, alpha, beta) and the median of the power in these bands are computed. The distinction of bands power is important for the detection of the pathological states of the different parts of the brain.

On the contrary, the muscular activity (EMG) is analyzed mainly in the time domain; the envelope of the signal, time segments when the signal does not reach zero and maximum amplitude are computed but also the frequency spectrum is shown, and the maximum signal power is calculated (Rangayyan, 2015).

III. EXPERIMENTS

For the verification of the application function, several experiments were done. In the paper, as an example, the elimination of the power line interference from ECG signal using ANC filtration is described.

The ECG signal generated from LabVIEW biomedical toolkit was corrupted by power line interference on the frequency of 50 Hz so that the SNR was -10 dB and correlation 0.244. The ANC is a very effective tool for the elimination of power line interference because this noise is quite easy to simulate in the reference signal. After adding a noise, signal is saved and then filtered by ANC with the sinus reference signal and order 1, which offered the best SNR improvement and correlation coefficients.

The signal before and after filtration can be seen in Fig. 6 and Fig. 7. As spectrograms show, the ANC filtration suppressed power line interference sufficiently, only at the beginning of the signal, there is visible remain of the noise, which can be caused by the delay of the algorithm. The SNR value after filtration reached 21.5 dB and correlation coefficient increased to 0.995.

Original signal

Corrupted signal
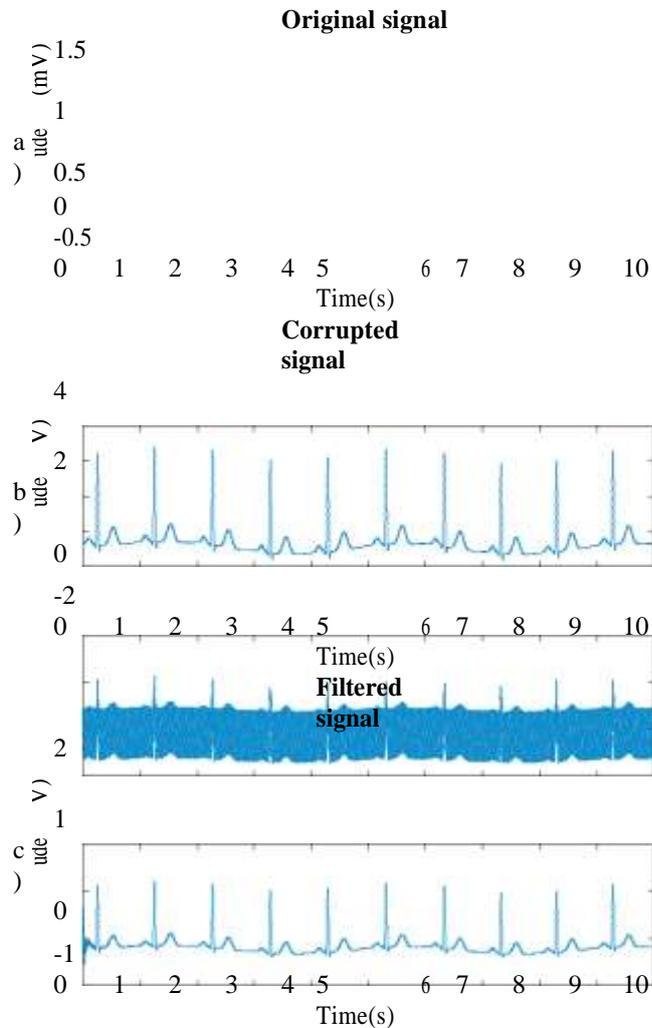
Filtered signal

Fig**. 6**. Time waveforms of the original, corrupted and filtered ECG signals.

Then, the Bland-Altman analysis (Fig. 8) was made for the evaluation of the accuracy of the implemented filtra-tion and following parameters were calculated: accuracy (ACC), sensitivity (SE), positive predictive value (PPV) and harmonic mean of SE and PPV (F1) according to (1)-

(4). The method proved to be very sufficient for the elim-ination of the power line interference from the signal ac-cording to the calculated parameters reaching values above 99 % and a number of the false negative and false positive values only 37, while a number of true positive values reached 5083. All results of the filtration are summarized in Table 2.

$$ACC = \frac{TP}{n} \cdot 100 = \frac{TP}{TP + FP + FN} \cdot 100 \ (\%), \quad (1)$$

Original signal

Time (s)

Corrupted signal

Time (s)

Filtered signal

Time (s)
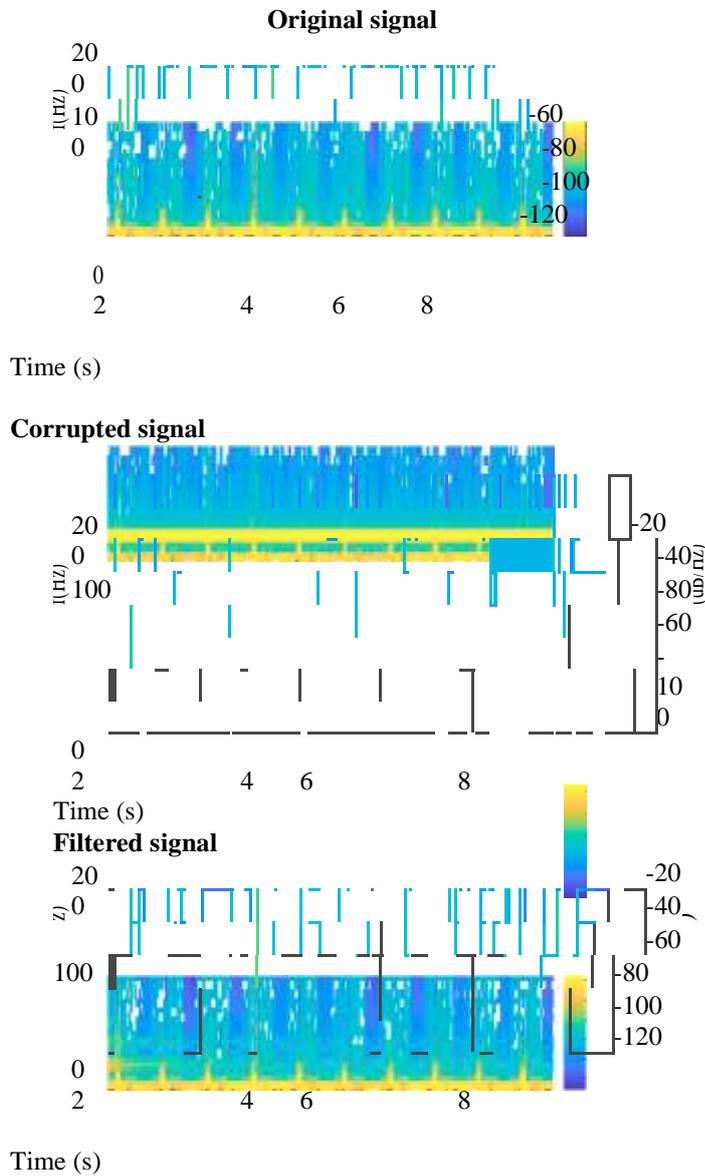
Fig. 7. Spectrograms of the original, corrupted and filtered ECG signals.

$$SE = \frac{TP}{TP + FN} \cdot 100 \ (\%), \quad (2)$$

$$PPV = \frac{TP}{TP + FP} \cdot 100 \ (\%), \quad (3)$$

$$F1 = 2 \cdot \frac{SE \cdot PPV}{SE + PPV} = \frac{2 \cdot TP}{TP + FP + FN} \cdot 100 \ (\%), \quad (4)$$

where TP is a number of true positive values (samples in the original signal that are preserved also in the filtered signal), FP is a number of false positive values (samples appeared in the filtered signal but not contained in the original signal) and FN is number of false negative values (samples that would appear in the filtered signal but do not).

Table 2. Results of the ANC filtration of ECG signal.

SNR improvement (dB)	31.53
Correlation improvement (-)	0.751
TP (-)	5083
FP (-)	19
FN (-)	18
ACC (%)	99.28
SE (%)	99.63
PPV (%)	99.65
F1 (%)	99.64

If interested in other results of filtering by the implemented system, such as other filtration methods applied for the removing of the power line interference in ECG and EMG signals, see (Ladrova et al., 2019b,a)
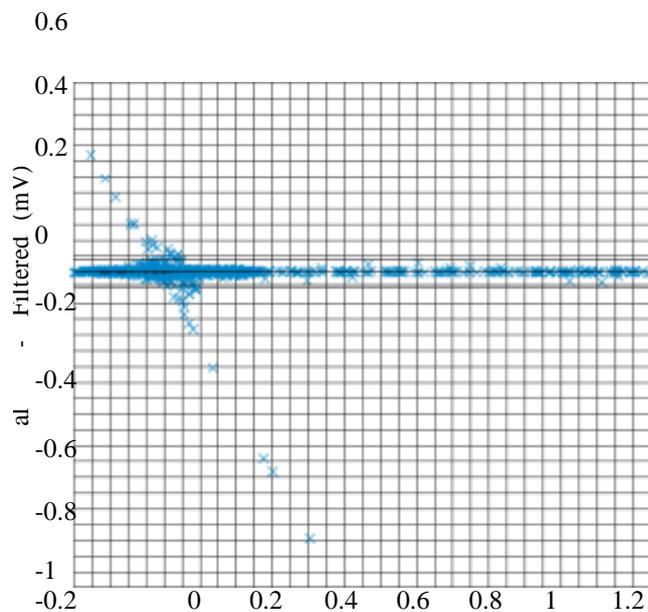
(Original + Filtered)/2 (mV)

Fig. 8. Bland-Altman graph of the ANC filtration of the ECG signal.

IV. CONCLUSION

The presented paper proposed an implementation of the modular system in MATLAB for biological signal pro-cessing. The proposed software is unique due to the wide range of the processing methods contained in one easy-to-use and well-arranged application serving as a tool for the preliminary research and other purposes. The software is modular, which means that all changes in the signal are made separately and also, the researcher can work with every stage of the signal (original, corrupted, filtered) individually. It brings the opportunity to compare different well-known signal processing methods in different cases of signal corruption. The system enables to add some of the implemented kinds of interference to the plain signal, choose an appropriate filtering method and observe an improvement in the power of the noise contained in the signal and the level of the signal distortion. The researcher can then evaluate, which techniques of processing would be suitable for the individual need and which results could the specific method reach. On the other hand, the system can also be used for the signal processing of the real-measured signals which are corrupted by noise from their origin. The system can serve as the educational tool of the signal processing, when bringing the overview of the

most frequently-used processing techniques and their effect on the signals, including its clear graphic representation.

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