Implementation of Adaptive Filters for ECG Data Processing

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Abstract – One of the main problems in biomedical data processing like electrocardiography is the separation of the wanted signal from noises caused by power line interference, high frequency interference, external electromagnetic fields and random body movements and respiration. Different types of digital filters are used to remove signal components from unwanted frequency ranges. It is difficult to apply filters with fixed coefficients to reduce random noises, because human behavior is not exactly known depending on the time. Adaptive filter technique is required to overcome this problem. In the article two types of adaptive filters are considered. Results of simulations in MATLAB are presented. Filters were coded in MPLAB C Compiler and tested on a digital signal processor of Microchip family dsPIC30F6014, based on the results of modeling.

I. INTRODUCTION

Electrocardiogram (ECG) is one of the most important parameters for heart activity monitoring. A doctor can detect different types of deflections by the full form analysis of the ECG signal. Method of registration of electrical potentials generated on the surface of a body as a result of heart contraction is called electrocardiography. In many applications for biomedical signal processing the useful signals are superposed by different components. Interference may have technical sources, for example, power supply harmonic 50 Hz, high frequency noises and electromagnetic fields from other electronic devices, and biological sources, such as muscular reaction, respiratory movements and changing parameters of the direct contact between electrodes and the skin [1]. So, extraction and analysis of the information-bearing signal are complicated, caused by distortions from interference. Using advanced digital signal processing this task can be shifted from the analogue to the digital domain [2].

At the Fraunhofer IIS the direct conversion of ECG-signals with high resolution Delta Sigma Converters is suggested. Only a single Low Noise Preamplifier is used at the electrodes to generate a high impedance input [3, 4].

The input signal $x[n]$ consists of the information-bearing ECG signal $ecg[n]$ and an interfering part.
noise[n]. The presented adaptive filter does not use a reference artificial signal, which is correlated with noise[n] and uncorrelated with ecg[n], as in most implementations. The input distorted signal is defined either a useful signal or the reference. Therefore the criterion of coefficients assessment u[n] is different from the conventional LMS algorithm.

The adaptive filter output e[n] is an estimation of the input noise noise[n]. The estimation e[n] is calculated according to the following equation:

\[ e[n] = \sum_{i=0}^{N-1} w_n(i) \cdot x_{n-i} ; \]  

with N – the filter order; \( w = (w_0, w_1, ..., w_{N-1}) \) – filter coefficients.

The useful ECG signal is derived by subtraction of the estimated noise e[n] from the input signal x[n]:

\[ \text{ecg}[n] = x[n] - e[n] . \]  

To minimize the power of noises e[n] it is necessary to solve an optimization problem of Minimum Square Error (MSE) minimization [1]:

\[ J = (x[n] - e[n])^2 \rightarrow \min . \]  

There are several approaches to solve the minimization problem. The most simple and wide-spread way is the LMS-algorithm. But to derive a sufficiently good approximation it is necessary to use a reference signal, because one of the important parameters is the maximum amplitude of the reference signal. Therefore it is supposed to calculate the parameter u[n], using the following equation:

\[ u[n] = \sum_{i=0}^{N-1} (x_{n-i} - e_n)^2 . \]  

For each iteration step, filter coefficients for the next step are computed as a ration of the input signal x[n] to the u[n]:

\[ w[n+1] = \frac{x[n]}{u[n]} . \]  

B. An adaptive filter on the base of FFT

A new approach to adjust the filter coefficients is based on the calculation of the frequency spectrum of the input signal using Fast Fourier Transform FFT [2].

Concept of noise cancellation with using FFT adaptive filter is presented in Fig. 3.

The transfer function H is given by:

\[ H = \frac{N}{N-1} \left( \frac{S_x}{S_y} - \frac{1}{N} \right) . \]  

N input samples are averaged and the spectrum of the average \( S_x \) is found. Then the average of the spectrum of N input periods is taken. The filter is then applied to the new time period. The adaptive filter with finite impulse response is used because of the greater stability and smaller sensitivity to finite resolution effects.

The output of the FFT adaptive filter is calculated according to the equation:

\[ y[n] = \sum_{k=0}^{N-1} H(k) \cdot x_{n-k} . \]  

The filter implementation described above shows strong smoothing effects. It is recommended to select a filter order which is less than a half the number of samples for a period. Since the ECG signal is pseudo-periodical, the period of a QRS complex is used to compute the filter order N:

\[ N = \frac{1}{2} \cdot \frac{F_s}{F_{QRS}} ; \]  

\[ F_s \] – the sampling frequency;

\[ F_{QRS} = \frac{1}{T_{QRS}} ; \]  

\[ T_{QRS} \] – the duration of QRS complex.

The duration of QRS complex is 0.11 s approximately, so for a sampling frequency 512 Hz, the filter order is equal 28. To find the moving average with a symmetric output it is required to use the odd number of samples, therefore the filter order is set equal 27 or 29.

It is necessary to use a set of FFT points similar with the filter order N. Therefore we can’t perform the FFT with 1024 points for instance simultaneously with using the filter core equal 27 or 29. So, an optimization problem appears. On the one hand, a large number of FFT points greatly increases computing accuracy of the power spectral density. On the other hand, a big filter core causes distortions of the output signal and the loss of...
valuable diagnostic information. The optimization problem is to find the optimum order for the transfer function.

The behaviour of the adaptive FFT filter was estimated by modeling in MATLAB. On the first run, the set of FFT points and the filter order were selected empirically. The conclusion was that the quality of the output signal depends in total on the right choice of the filter core but in the next sequence on the quantity of FFT points. So, on the next step, the transfer function order was calculated according to the equation (8). Results of modeling are presented below.

The FFT adaptive filter requires significantly more convergence time than the LMS adaptive filter. The reason is necessity to use a greater number of input samples for computing of the spectral density. In the modeling 2048 input samples were used. Therefore, for the sampling frequency 512 Hz the convergence time constitutes 4 second. The standard [1] requires the convergence time must be not more than 2 seconds. So, for the practical application it needs to use not more than 1024 input samples simultaneously with the sampling rate 512 Hz or to increase the sampling rate.

### III. RESULTS

An ECG data acquisition device was developed on the base of a digital signal processor (DSP) of Microchip family dsPIC30f6014. The embedded ADC in the DSP was used for analog-to-digital conversion of the input ECG signal with a sampling frequency 512 Hz. Data from the ADC output, saved in DSP memory, were read and used for simulations of the adaptive filters behaviour, done in MATLAB. Model of the input signal is shown in Fig. 4.

![Fig. 4. Standard ECG input signal with 180 beats per minute](image)

The output of the adaptive filter, realized with LMS algorithm, is shown in Fig. 5 as time domain signal and as corresponding FFT. The filter core is equal 8. The filter increases the signal to noise ratio (SNR) by 19.64 dB. The convergence time is 78.4 ms approximately.

![Fig. 5. The output of the adaptive filter, realized with LMS algorithm](image)

The output of the adaptive filter, realized with FFT, is shown in Fig. 6.

The filter core is equal 27. The filter improves the signal to noise ratio by 32 dB. SNR is the attitude of spectral densities of the 3 Hz component (useful signal) and the 42 Hz part (noise). To access the improvement of the SNR it is necessary to calculate the SNR for the input and the output signal, then to find the difference between in dB units.

![Fig. 6. The output of the adaptive filter, realized with FFT](image)
Real data from the DSP memory, obtained by using the adaptive LMS filter are presented in Fig. 7.

The adaptive FFT filter was only simulated in MATLAB because of the great requirements for the hardware resources. Future work will concentrate on this.

IV. CONCLUSIONS

The adaptive filter, realized with FFT, ensures better results compared to the filter based on LMS. But the algorithm of Fast Fourier Transformation is more difficult to implement and requires more time and hardware resources. Therefore, if hardware with automatic FFT computing is applied, the FFT adaptive filter implementation is preferable. In other cases the LMS adaptive filter is better because of the simple and reliable algorithm and small convergence time. The proposed LMS adaptive filter has one more merit: it doesn’t require an artificial reference signal, correlated with noises, so additional sensors are not needed in the measurement equipment.

REFERENCES


