

Implementation of Adaptive Filters for Biomedical Applications

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Abstract. In biomedical signal acquisition like electrocardiography ECG or electroencephalography EEC one of the main problems is to separate the small input signals from noise and disturbances caused by the 50 Hz power supplies, high frequency interference and random body voltages. Different types of analogue and digital filters are used to remove the unwanted spectral parts. In most applications the filter bandwidth of those filters are fixed and will not adapt to changing interference patterns.

Adaptive filter techniques are required to overcome this problem. Different adaptive filter types have been analyzed. Finite Impulse Response (FIR) filters are preferred because of their better stability. An adaptive filter was implemented which suppresses known noise sources in an ECG application. Simulations were done with MATLAB and VHDL. The filter was coded in VHDL and tested on a FPGA.

A 50 Hz interference on the ECG input signal was attenuated by 50 dB. The convergence time for the adaptive algorithm was less than 3 sec. The filter implementation needed 9500 equivalent gates and worked with $7.1 \mu W$ for a filter clock speed of 1.8 kHz.

1 Introduction

In many applications for biomedical signal-processing the information-bearing signals are superposed by further components. Thus signals get distorted and the extraction of information is complicated. In electrocardiography interferences may have a technical source, for example a power supply unit, or a biological source, for example respiration.

Commonly frequency-selective filters with fixed coefficients are used to suppress a specific frequency range of a signal. If the frequency spectrum of signal and interference overlap or the characteristic of the interference is time dependent or not exactly known, filters with fixed coefficients can hardly meet the demands. Often the filter's transfer behavior can't be specified sufficiently exact or those spectrals of the ECG which fall in the filter's cut-off region get lost [1], [2].

These difficulties can be handled using an adaptive filter, a system with variable instead of fixed coefficients. This is a time-variant systems which is able to adapt its coefficients to the environment during operation. In contrast to frequency-selective filters adaptive systems enable direct gripping of the eliminated signal.

If it is not exclusively an unwanted signal, the included information can be processed where required.

The 50 Hz power line hum resulting from power supply units is commonly eliminated from the ECG by using notchfilters. In this paper an alternative in the form of an adaptive filter is presented.

2 Methods

The concept of interference cancellation with adaptive filters is shown in Fig. 1. Starting point is a mixture of signals $d[n]$ consisting of the information-bearing ECG signal $ekg[n]$ and an interfering component $noise[n]$. Having a reference signal which is correlated with $noise[n]$ and uncorrelated with $ekg[n]$, it is possible to eliminate the interference using an adaptive filter. In order to suppress the 50 Hz power line hum, the reference signal $x[n]$ is gripped at the power supply. It has the same frequency, but different amplitude and phase compared to $noise[n]$. Unlike using frequency-selective filters the adaptive filter is applied to $x[n]$ instead of the primary input $d[n]$. The filter output $y[n]$ is an estimate of $noise[n]$. Subtracting this from the underlying signal $d[n]$ we get the dejamed signal $e[n]$, an estimate of $ekg[n]$.

Adaptive filters are preferably designed as FIR filters known for their good stability properties and simple cost function.

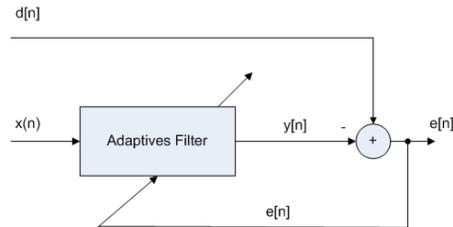


Fig. 1. Concept of interference cancellation

In order to minimize the power of $e[n]$ different cost functions as functions of the filter coefficients are possible. One is the MSE³-criterion that leads to the following optimization problem:

$$J = E\{e^2[n]\} = (d[n] - y[n])^2 \rightarrow \min .$$

For a filter with filter order N this results in a quadratic cost-function with a global minimum. R is the autocorrelation matrix according to $x[n]$ and p is the

³ Minimum square error

crosscorrelation-vector between $x[n]$ and $d[n]$.

$$J = E\{e^2[n]\} = E\{d^2[n]\} - 2w^T p + w^T R w .$$

with

$$w = (w_0, w_1, \dots, w_{N-1})^T: \text{filtercoefficients}$$

There are several algorithms to solve the minimization problem. Due to the simple implementation the LMS⁴-algorithm was considered. It is derived from the gradient-method by using stochastic instead of exact gradients.

For each iteration step the filtercoefficients for the next step $w(n+1)$ are computed the following:

$$w(n+1) = w(n) + \mu e[n]x(n) .$$

In order to guarantee convergence for the LMS-algorithm, μ has to be adapted to the maximal amplitude of the reference signal ($ma(x)$). An upper bound can be defined:

$$\mu_{max} = \frac{2}{3N \cdot ma(x)^2} .$$

The LMS-algorithm does not converge to the exact solution but to a sufficient good approximation. As a measure for the deviation between approximation and exact solution the so called misadjustment M is introduced. It depends on the average power of the reference signal ($power(x)$) and the stepsize μ . In order to achieve a small misadjustment a small stepsize is required.

$$M = \frac{\mu}{2} \cdot N \cdot power(x) .$$

But a small stepsize leads to a large convergence time. The convergence time τ can be expressed like the following where α is the applied stepsize normalized to the maximum possible μ_{max} . λ_{max} is the largest, λ_{min} the smallest eigenvalue of R .

$$\tau \approx \frac{1}{4\alpha} \kappa(R) .$$

with

$$\kappa(R) = \frac{\lambda_{max}}{\lambda_{min}} \quad \text{conditon number}$$

So the speed of convergence also depends on the condition number of R and therefore on the character of the reference input $x[n]$. The LMS-algorithm shows

⁴ Least Mean Square

slow convergence for signals with non-smooth and fast convergence for signals with uniformly distributed spectrum.

Among suiting the parameters N and μ to the problem, several optimization strategies can be applied in order to improve the behaviour of the LMS-algorithm. Different strategies lead to different filter types. Normalization of the stepsize μ according to signal power in each step or reducing $\kappa(R)$ via orthogonal transforms are just a selection of possibilities. Above all the hardware complexity has to be considered.

The 50 Hz power line interference noise(t) only has a frequency component at 50 Hz and is assumed to be a sine. It can be expressed as follows:

$$\begin{aligned} \text{noise}(t) &= a_n \sin(\omega t + \varphi) \\ &= a_n (\sin(\omega t) \cos(\varphi) + \cos(\omega t) \sin(\varphi)) \\ &= a_n \cos(\varphi) \cdot \sin(\omega t) + a_n \sin(\varphi) \cdot \sin(\omega t + \Delta) \\ &= w_0 \sin(\omega t) + w_1 \sin(\omega t + \Delta) \end{aligned}$$

According to this the filter order has been set to $N = 2$. Because of the small filter order the LMS-filter was designed without one of the mentioned optimization strategies. Both for $d[n]$ and the outputs $y[n]$ and $e[n]$ a 16-bit-representation is used, whereas for $x[n]$ a 8-bit-representation is required.

First simulations of the filter behaviour were done with MATLAB. At this stage the influence of μ on the signal quality of $e[n]$ and $y[n]$ was established. After choosing μ the filter was coded in VHDL and simulated with Modelsim on different levels of abstraction. To monitor quantisation effects the MATLAB-filter was used as a reference-model for the VHDL-models in each level. Using a simulation environment developed for this application, both models were simulated parallel and results were compared. Finally the filter was tested on a FPGA with ECG signals.

3 Results

The ECG of an healthy adult has a fundamental frequency from about 60 bpm⁵ up to 80 bpm. For certain disease patterns fundamental frequencies down to 20 bpm occur. At physical stress frequencies up to 200 bpm are observed [4]. The adaptive filter was tested for ECG signals with different fundamental frequencies. For frequencies up to 160 bpm good results were achieved, whereas the signal quality is downgrading for higher frequencies. Furthermore the filter was applied to ECGs with a power line interference of different frequencies. For interfering frequencies from 30 Hz to 100 Hz the filter turned out to be well suitable. The influence of the amplitude of the superposed signal was also studied. Interfering components with amplitudes from 0,05% to 100% relating to the maximum ECG amplitude can be extracted. Depending on the amplitude of the superposed signal, the interference was damped by 4 dB up to 50 dB. Convergence time of the

⁵ beats per minute

adaptive algorithm is less than 3 sec.

For a VIRTEX E FPGA [3] from Xilinx the filter realisation needs 9500 equivalent gates and the calculated power loss is $7.1 \mu W$. Using a sampling frequency of 256 Hz for the ECG the filter clock speed is 1.8 kHz.

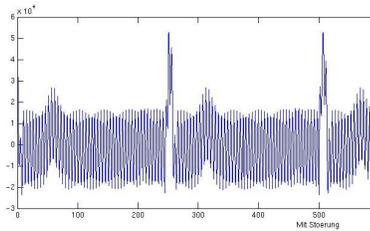


Fig. 2. ECG before filtering

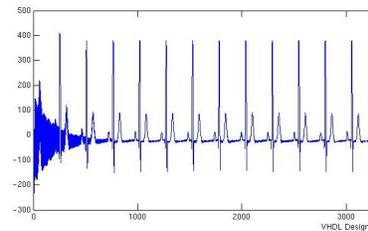


Fig. 3. ECG after filtering

4 Conclusions

Commonly notchfilters with fixed coefficients are used to suppress the 50Hz power-line interference in ECG signals. The alternative introduced in this paper has the advantage of better flexibility compared to frequency-selective filters. The disturbance is also eliminated if its frequency is shifted. One disadvantage of the developed adaptive filter are worse results with increasing ECG's fundamental frequency. The degradation of signal quality is noticeable from a fundamental frequency of 160 bpm. Before applying the designed adaptive filter to higher frequencies occurring in stress ECG the design would have to be adjusted. Furthermore unlike frequency-selective filters adaptive systems need a proper reference signal for the interference. But this also opens an interesting method to search for a known signal in distorted or superposed signals.

References

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