

FPGA based noise reduction in ECG signal using adaptive filters

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ABSTRACT

Adaptive filters have become much more common and are now routinely used in devices such as mobile phones and other communication devices, camcorders and digital cameras, and medical monitoring equipment. Suppose a hospital is recording a heart beat (an ECG) which is being corrupted with noise. A static filter is needed to remove all the noise frequencies, which could excessively degrade the quality of the ECG since the heart beat would also likely have frequency components in the rejected range. To circumvent this potential loss of information, an adaptive filter is used. The adaptive filter takes the input from the patient and compares it with the reference input. Such an adaptive technique generally allows a filter with a smaller rejection range which means in our case that quality of the output signal is more accurate for medical diagnoses. The adaptive filter here is trained using LMS algorithm and RLS algorithm. The algorithms are implemented using Simulink as a reference model where the blocks are taken from Xilinx block set. The system generator (sysGen) token is used to convert the blocks to bit file which can be downloaded to Virtex5 FPGA. The simulation output in MATLAB and Virtex5 FPGA hardware implementation results are quite promising.

Keywords: noise cancellation, adaptive filter, least mean square(LMS), recursive least square(RLS).

INTRODUCTION

The FIR filter computations play an important role in the DSP systems. The FIR filtering is a convolution operation which can be viewed as the weighted summation of the input sequences. The large amount of multiply and accumulate operations attracts many researchers to study this issue. The FIR Filter consists of shifters, adders, and multipliers. These constituents can be chosen on the demand of the designer. As the FIR filter alone can't solve the problem of non stationary noise, there is a great need for making the filter adaptive. There are number of possible algorithms available for designing of adaptive filter. One of the most popular adaptive algorithms available in the literature is the stochastic gradient algorithm also called least-mean-square (LMS). Its popularity comes from the fact that it is very simple to implement. As a consequence, the LMS algorithm is widely used in many applications. Least-Mean -Square (LMS) adaptive filter is the main component of many communication systems; traditionally, such adaptive filters are implemented in Digital Signal Processors (DSPs). Sometimes, they are implemented in ASICs, where performance is the key requirement. However, many high-performance DSP systems, including LMS adaptive filters, may be implemented using Field Programmable Gate Arrays (FPGAs) due to some of their attractive advantages. Such advantages include flexibility and programmability but most of all availability of tens to hundreds of hardware multipliers available on a chip.

Adaptive filtering constitutes one of the core technologies in digital signal processing and finds numerous application areas in science as well as in industry. In this project LMS algorithm is used to reduce the error at the output of the system. A VHDL implementation is developed for a LMS adaptive filter. It has been proven that LMS Algorithm has good behavior. The method used to cancel the noise signal is known as adaptive filtering. Adaptive filters are dynamic filters which iteratively alter their characteristics in order to achieve an optimal desired output. An adaptive filter algorithmically alters its parameters in order to minimize a function of the difference between the desired output $d(k)$ and its actual output $y(k)$. This function is known as the objective function of the adaptive algorithm.

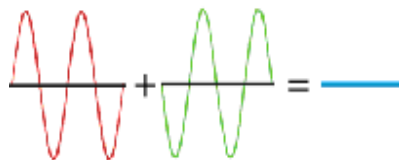


Fig.1. Destructive interference

Adaptive Noise Cancellation (ANC) is a widely applicable set of noise attenuating technique. Unlike simple filtering, ANC techniques attenuate noise through the addition of an "anti-noise" signal with 180-degree phase difference, thereby dampening the energy of the noise waves. Active

feedback via an embedded microphone facilitates targeted noise cancellation without any requisite a priori knowledge about the signal transmitted or the noise present. There are several algorithms used to calculate the “anti-noise” signal.

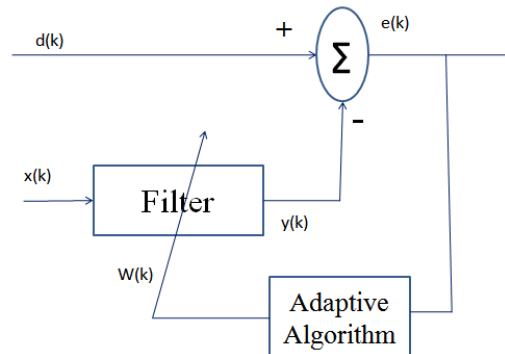


Fig. 2. Adaptive Filter Process

LMS ALGORITHM:

The Least Mean Square (LMS) algorithm, introduced by Widrow and Hoff in 1959 is an adaptive algorithm, which uses a gradient-based method of steepest decent. LMS algorithm uses the estimates of the gradient vector from the available data. LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which eventually leads to the minimum mean square error. Compared to other algorithms LMS algorithm is relatively simple; it does not require correlation function calculation nor does it require matrix inversions. The optimum tap-weights of a transversal (FIR) Wiener filter can be obtained by solving the Wiener-Hoff equation provided that the required statistics of the underlying signals are available.

M-1

$$\begin{aligned} Y(n) &= \sum_{i=0}^{M-1} W_i(n) * x(n-i); \\ E(n) &= d(n) - y(n) \\ W_i(n+1) &= W_i(n) + 2\mu e(n) x(n-i) \end{aligned}$$

In this equations, the tap inputs $x(n), x(n-1) \dots x(n-M+1)$ form the elements of the reference signal $x(n)$, where M-1 is the number of delay elements. $d(n)$ denotes the primary input signal, $e(n)$ denotes the error signal and constitutes the overall system output. $W_i(n)$ denotes the tap weight at the n th iteration. In equation (3), the tap weights update in accordance with the estimation error and scaling factor μ is the step-size parameter μ controls the stability and convergence speed of the LMS.

RLS ALGORITHM:

The RLS algorithms are known for their excellent performance when working in time varying environments but at the cost of an increased computational complexity and some stability problems. In this algorithm the filter tap weight vector is updated using the Delta rule for the update of the coefficients, we obtain the following equation where μ is the learning rate:

$$w_{n+1} = w_n + \mu \cdot \tanh[\beta \cdot e(n)] \cdot x_n$$

The intermediate gain vector used to compute tap weights are as given below:

$$\begin{aligned} k(n) &= U(n) / (\lambda + x^T(n)u(n)) \\ u(n) &= w_{n-1}^T(n-1)x(n) \end{aligned}$$

Where: λ is a small positive constant very close to, but smaller than 1.

The filter output is calculated using the filter tap weights of previous iteration and the current input vector as shown below:

$$\begin{aligned} \bar{y}_{n-1}(n) &= \bar{w}^T(n-1)x(n) \\ \bar{e}_{n-1}(n) &= d(n) - \bar{y}_{n-1}(n) \end{aligned}$$

In the RLS Algorithm, the estimate of previous samples of output signal, error signal and filter weight is required that leads to higher memory requirements.

HARDWARE CO-SIMULATION:

System Generator provides accelerated simulation through hardware co-simulation. System Generator will automatically create a hardware simulation token for a design captured in the Xilinx DSP block set that will run on one of over 20 supported hardware platforms. This hardware will co-simulate with the rest of the Simulink system to provide up to a 1000x simulation performance increase.

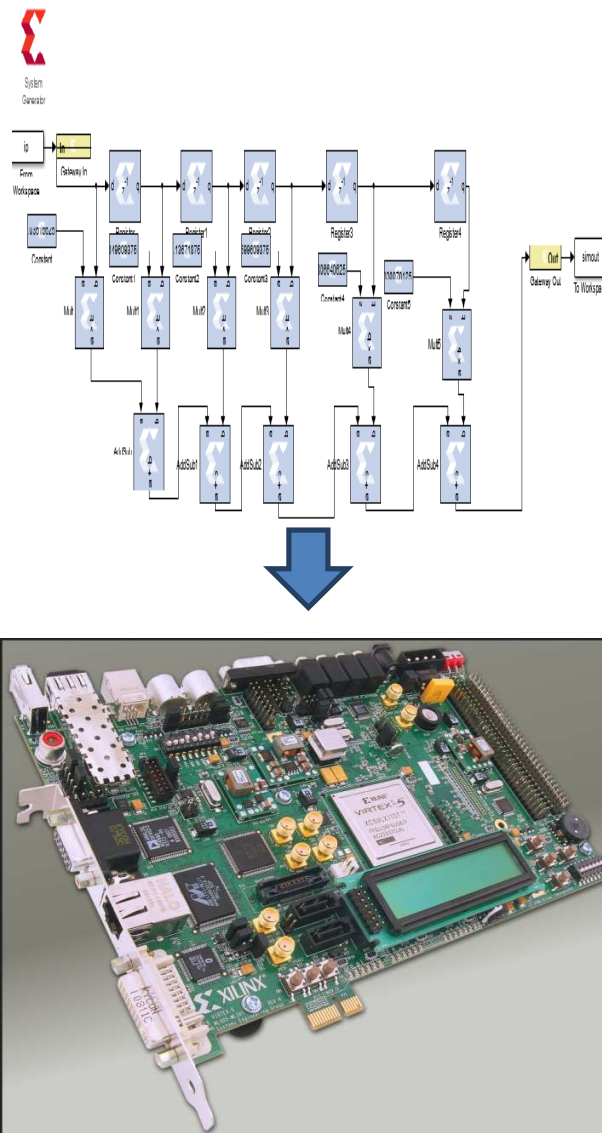
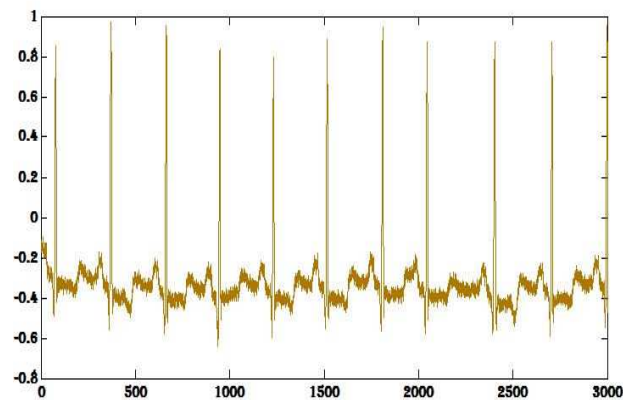


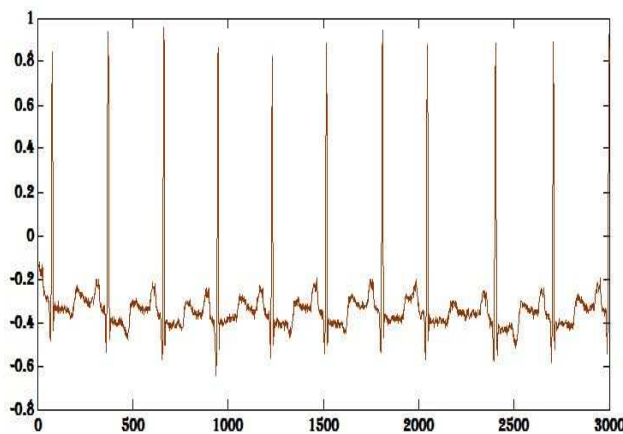
Fig.3. Hardware Co-Simulation

SIMULATION RESULT

An ECG signal with noise is given as an input i.e., $x(n)$, and the desired signal is $d(n)$ which is the original signal. The blocks set are created for both the LMS and the RLS algorithms of an adaptive filter. The ECG signal is added with a known amount of noise to calculate the convergence rate and thus to obtain the resource utilized by the hardware virtex5 FPGA. The process is similar to that of the flow chart shown in figure. Once the compilation is done the JTAG is created for the corresponding algorithm to which the inputs and outputs are connected and this is loaded as a bit file to the virtex5 FPGA. The process is carried on in the hardware and the output is shown in the MATLAB software. The compilation status also provides the resource utilized by the FPGA and is compared for both the algorithms. Thus the results are as shown below:



INPUT X(n)



LMS & RLS filter output.

The Xilinx system generator creates a bit file which can be downloaded to the FPGA. This bit file created provides the design summary of each process and thus for the above two algorithms the results are tabulated.

CONCLUSION

The development of algorithm design and implementation, for an ECG signal is presented in MATLAB Simulink block set and Xilinx software. Adaptive filter is a filter that which varies with time, adapting its coefficients to some reference using algorithms like LMS, RLS etc., The problem of estimating an unknown random signal in the presence of noise is often faced. Adaptive filters minimize the error in the estimation according to a certain criterion. The RLS for adaptive filters gives a higher quality in the disturbance and noise cancellation. The LMS algorithms

are simpler in evaluation process, but they attain lower quality in the cancellation of disturbing signals. RLS algorithm achieves a higher quality in the disturbing signal cancellation, but they have large numerical claims for RLS filter coefficient evaluation, thus the utilized resources and time taken for the completion process are also high when compared with the LMS algorithm.

Design summary	LMS	RLS
No of slice registers	90	307
No of flip flops	90	307
No of bounded IOB's	35	37
No of DSP48 slice	6	10
Power utilized	0.500 W	0.525 W
Clock speed	0.807	1.54
Xst completion time	7.39 sec	9.31 sec
Memory usage	298668 KB	308524 KB

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