A Filtering technique based on a DLMS algorithm for ultrasonography video

Ermir PAPADHIMITRI[1], Nicola TESTONI[2], Luca DE MARCHI[3], Guido MASETTI[4]

[1] *Department of electronic, Informatics and statistics, University of Bologna, Italy*
Email: ermirpapadhimitri@hotmail.com – Phone: +355(692220221)
[2] *Department of electronic, Informatics and statistics, University of Bologna, Italy*
Email: nicola.testoni@unibo.it
[3] *Department of electronic, Informatics and statistics, University of Bologna, Italy*
[4] *Department of electronic, Informatics and statistics, University of Bologna, Italy*

ABSTRACT

It is well known that ultrasonography is a diagnostic method for visualizing inside human tissues by spreading ultrasounds and measuring their return time to the sensor. However, the interface between the human skin and this ultrasound transducer attenuates the received signal and the medical image quality deteriorates significantly. In this paper we propose a filtering technique in order to compensate this attenuation. A finite impulse response filter (FIR) based on a Delayed Least Mean Square (DLMS) was optimized and implemented. The main contribution of our work consists of finding the order and the coefficients of the filter that minimize the attenuation error. We validate our method first on simulated data and later on a reprogrammable FPGA device for a real time performance testing. Among others, we show that incrementing the order of the filter, not always is the best way to reduce image quality errors.

INTRODUCTION

Behind ultrasonography stands a simple physical phenomenon: the crystal of quartz, crossed by the current, generates ultrasonic waves. Knowing the speed of propagation and measuring the returning time of the waves, the machine is able to measure the distance of the object that generated the eco. Human bone, like a mirror, reflects all the ultrasound. A cyst filled with fluid, however, does not make any resistance and is easily crossed. Between these two extremes there is a wide gradation: there are structures of the human body that let go 'a bit' of ultrasound and send back others, such as occurs, for example the liver, muscles, thyroid and others. A computer transforms echoes in gray-scale images that move on the screen. This technique is used often in the field of internal medicine, surgery and radiology. Today, this method is considered as an examination of basic or filter compared to more complex imaging techniques like CT, magnetic resonance and angiography. An ultrasound machine consists of three main components:

• A probe that transmits and receives the signal.

• An electronic system that drives the transducer, generates the pulse transmission, receives the echo back from the sensor and processes the signal received.
• Display System.

The transducer alters the signal spectrum obtained, by introducing a modulation and thus compromising the quality of the signal itself. In this paper we will propose a way to clean up the signal from the noise introduced by the transducer

DLMS FIR ADAPTIVE FILTER

In order to clean up the video signal from noise, an adaptive filtering [1] system FIR (finite impulse response) can be used to make possible the deconvolution of the signal and the attenuation of the autoregressive component introduced by the transducer. The operation of a linear adaptive filter consists of two fundamental processes: a filtering process designed to produce an output response to a sequence of input data and an adaptive process that has the duty to provide a mechanism for updating the weights of the filter.

These two processes interact and the choice of a structure for the process has an essential effect for the correct operation of the algorithm. The ability of adaptive filters to work satisfactorily in an environment of unpredictable signals makes the adaptive filter a powerful tool for signal processing [2] and control applications. Adaptive process can be carried out very effectively and with a relatively low computational cost through the use of algorithms based on minimizing the least squares Least Mean Square (LMS) [3]. The LMS algorithm is well suited to software-based analysis but is not applicable to hardware implementation. Thus, Long et al. [4-6] developed and studied the characteristics of the DLMS algorithm such that the VLSI design of an approximate LMS adaptive finite impulse response (FIR) digital filter could be possible. In order to reduce the delay value, a tree-structure is first provided and applied in; however, there exist driving, modularity and local connection problems because the feedback error term needs to concurrently drive/update all the weights of the adaptive digital filter. In view of hardware design, finite driving/update eliminates the fan-out problem. Modularity is advantageous within a high regularity system such as an adaptive FIR digital filter since the layout of a module can be duplicated and reused, and the accurate timing sequence of the whole system can be easily checked.

In this work is used a pipelined DLMS architecture [7].

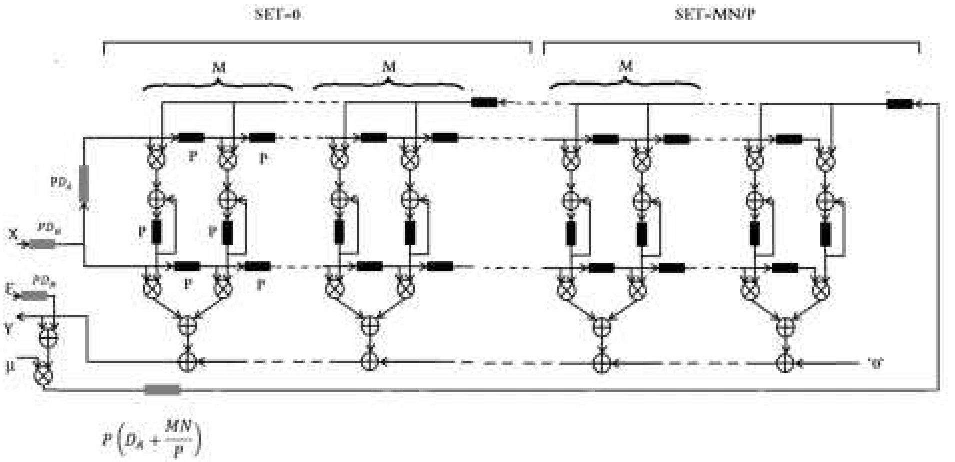

Figure 1. A pipelined DLMS adaptive FIR filter architecture

The architecture is synthesized by using a number of functions preserving transformations on the signal flow graph representation of the delayed LMS algorithm [8] as shown in Figure 1. This architecture is derived from the standard representation of the DLMS algorithm [7] by applying the holdup, associatively, retiming and slowdown transformations.

D_A and D_H are two parameters that depend from the multiplicator's (Tm) and adder's (Ta) execution time:

$$D_A = \left\lceil \frac{Tm + [\log 2M] * Ta}{Tc} \right\rceil \tag{1}$$

$$D_H = \left\lceil \frac{Tm}{Tc} \right\rceil \tag{2}$$

P is the delay introduced by the shift registers. N is the filter's order and M is the pipeline [9] factor. The generic FIR filter formula is:

$$y = \sum_{k=1}^{k=N} x(k) W_k \tag{3}$$

W_k has the following expression:

$$W_k = W_k(M, N, P, D_H, D_A, \mu, n) + x(n,k) \cdot \varepsilon(n,k) \tag{4}$$

The constant μ multiplies the filter's weight update mechanism and stands as a calibration tool with the purpose to help the convergence of the output signal to the desired response.

In this architecture Y is the output, X and ε are inputs, respectively the ultrasonographic signal and the difference between X and Y. M, N, P and μ are parameters to optimize depending on the application that the filter is going to be used. To measure the error computed, the FIR filter was implemented in a predictive configuration as shown in Figure 2. X is the input signal from the probe, Y is the output from the DLMS FIR filter and Z^{-1} is the delay introduced from a shift register.

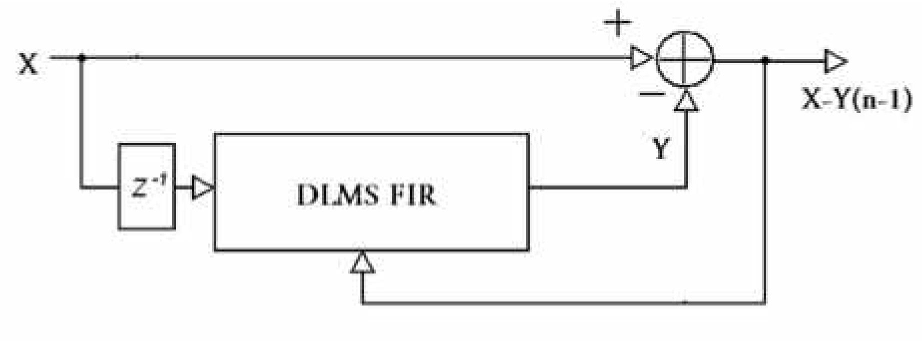

Figure 2 A predictive configuration of the adaptive filter

Simulations

MATLAB was chosen as the software platform for the simulations. MATLAB (short for Matrix Laboratory) is an environment for the numeric calculation [10] and uses a programming language (interpreted) created from The MathWorks [11]. To ensure right statistical results for the filter, the elaboration of 17 images was simulated, each of which is interpreted as a matrix 2500 × 1996. The mean square error E_{ms} [12] of the prediction was used as benchmark for the optimization. The functionality of the filter was simulated for various combinations of N, M, P and values of µ. To be noticed that not all sets of three natural numbers can be used because the value of (MN)/P must be also a natural number. There were not made simulations for P greater than 12 as this would compromise the response time of the filter. In fact, as shown in figure 1, the value of P delays the input of the filter as well as the calculation of the filter's weights.

Results

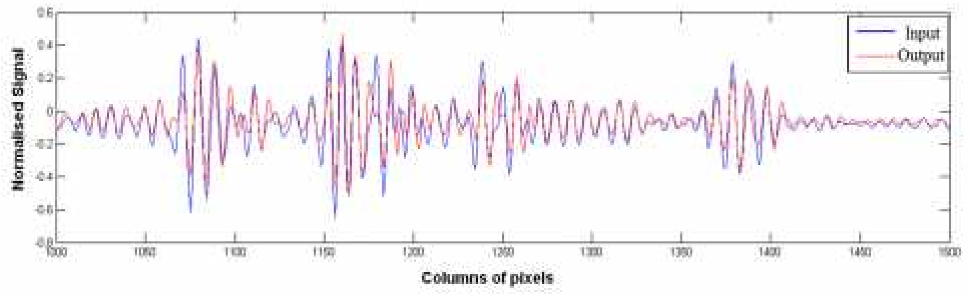

Figure 3 The normalized Input and output of the filter in a simulation with N=4, P=4, M=1 and μ=0.0025 for a succession of 500 pixels.

The results of the all calculations are reported in Table 1.

Table 1 Results from the simulations. Min(E_{ms}) is the minumum error varying μ

N	P	M	min(E_{ms})
4	4	1	0.0412
8	4	1	0.0416
12	4	1	0.0444
16	4	1	0.0440
20	4	1	0.0459
24	4	1	0.0451
28	4	1	0.0453
32	4	1	0.0464
16	8	1	0.0405
16	8	2	0.0431
16	8	4	0.0457
2	2	1	0,0385
3	3	1	0,0369
5	5	1	0,0287
6	6	1	0,0370
7	7	1	0,0344
8	8	1	0,0338
9	9	1	0,0285
10	10	1	0,0335
11	11	1	0,0283
12	12	1	0,0315
13	13	1	0,0349

In the Figure 4 is shown the relation between μ and the mean square error for four sets of M, N and P. Finally was simulated an adaptive FIR filter using a simple

LMS updating architecture with order 11 and it was found a mean square error 0.0295.

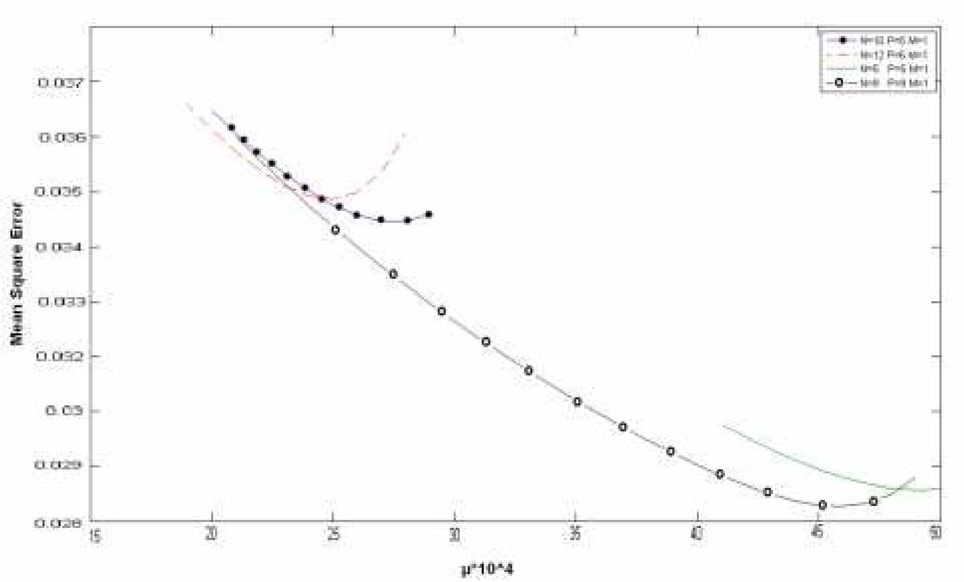

Figure 4 Relation between the value of μ and the value of mean square error

Discussions

The results showed that the minimum error is gained through an implementation with M=1. The filter convergence behaviour and tracking capability do not allow us to increment the delay factor P. As predicted, in the before values greater than 13 would compromise the convergence of the signal. However the configurations with M=1 showed three relative minimums of the error: P=11, P=9 and P=5. From the simulations results shown in Table 1, maintaining constant M and P and increasing the order of the filter did degrade the performance. The dependence of the error from the coefficient μ showed one absolute minimum almost for all sets of N, M and P. Optimizing the coefficient, generally depends from the other parameters and specifically increasing the order of the filter increase also the value of μ. The values of the coefficient μ presents the minimum error in the range between 1,5 10^{-3} and 5,5 10^{-3} [13]. The DLMS architecture with N=11, M=11, P=11 compared to a LMS architecture with order 11 showed 4% decrement of the error. A future optimization of the filter would be implementing a dynamic coefficient that can vary depending on statistical predictive knowledge of the video signal.

CONCLUSION

A DLMS pipelined FIR architecture was optimized for ultrasonographic applications. The simulations made for 22 sets of parameters and varying the calibration coefficient μ showed that the most efficient filter architecture for ultrasonographic applications has an order N= 11, a pipeline factor M=1, a delay factor P=11 and a calibration coefficient μ=0.00452. Using this configuration was found that the mean square error of the filter in a predictive configuration is 0.0283.

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