



## An FPGA Implementation of an Adaptive Algorithm for Data Reduction in Wireless Sensor Network

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**Abstract :** Power saving is a major concern in wireless sensor network and researcher, engineers are working hard to solve energy related problem in wireless sensor network. The wireless sensor network is wireless network with each node consist of a wireless node i.e. wireless transceiver and a sensor witch picks up the information such as temperature, light, humidity, voltage, radiation etc and send it to sink node. Sink node receive the information from the source node which is connected to the sensor and forward it to the main data processing machine which ultimately utilized the sensed information. Here we proposed that the Data transmission between Source node and sink node can be reduced if we deploy a predictive filter at the both end i.e. transmitter side and a receiver side so the data reported to sink node will be reduced drastically and hence power can be saved and battery operated node transmitter can work for longer duration. Here FPGA design for predictive filter is shown the code are written in VHDL using Xilinx ISE tool.

**Index Terms :** Adaptive filters, Digital signal processing, FPGA, LMS filter, Simulink model, Wireless sensor Network, Xilinx ISE tool.

### I. INTRODUCTION

Sensor nodes are battery powered, and therefore contain a limited supply of energy. Moreover the sensor nodes are getting smaller in size, lowering the capacity of the battery even more. Despite this scarcity of energy, the sensor network is expected to operate for a relatively long time. Replacing batteries is most often an impossible task, hence one of the primary design goals is to use this limited amount of energy as efficiently as possible.

The aim of a data reduction algorithm is to drastically reduce the amount of reporting done by a sensor node without imposing any hardware constraints which may lead to expensive nodes. The cost of a sensor network depends on the amount of hardware each sensor node contains. Hence complex hardware should be avoided as this will increase the cost of a sensor network and its up keeping. The sensor node must be inexpensive such that if it fails, due to insufficient energy or physical damage, it would be more feasible to discard that node rather than replacing its battery pack on site. It must be appreciated that most of the WSN applications require that they work in harsh and hostile environments which are inaccessible to humans. For Data transmission reduction we deploy the predictive LMS ( least mean square ) filter / algorithm.

LMS algorithm is similar to the method of steepest descent in that it adapts the weights by iteratively approaching the Mean Square Error (MSE) minimum. Widrow and Hoff invented this technique in 1960 for use in training neural networks.

The data reduction employed was proposed by Santini et al. and Nicholas Paul Borg et. al. in [1], [2]. This approach exploits the Least Mean Squares (LMS) adaptive algorithm. This algorithm is used since it provides an important trade-off between complexity and convergence time. It is very simple and it requires a few computations and a small memory footprint. However it provides excellent performance. Moreover, this approach does not require a

priori knowledge or statistical modeling of the observed signals. This paper discusses theory behind the LMS filter, its simple simulink model, The VHDL code is written for predictive LMS filter under Xilinx ISE tool and implemented on Spartan-3 FPGA kit the sensor nod node is customized using LM35 temperature sensor and 0804 analog to digital converter IC. The RF trans-receiver is used for actual data reduction demonstration.

### II. THEORY

Adaptive filters are typically used in applications where the statistical characteristics of the signals to be filtered are either unknown a priori or are slowly time-variant (non-stationary signals) [3]. The generic structure of an adaptive filter is shown fig 1.

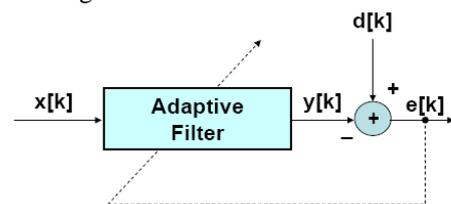


Figure. 1 General structure of Adaptive filter.

In fig 1 as shown Input signal is =  $x[k]$   
Output of the filter is =  $y[k]$  is given by

$$y[k] = \sum_{i=0}^{N-1} w_{i+1}[k] * x[k-i] \quad (1)$$

Reference signal or Desired signal =  $d[k]$

Error signal  $e[k]$ , the difference between desired signal and output of the filter is given by equation no 2

$$e[k] = d[k] - y[k] \quad (2)$$

We can convert the Adaptive filter into predictive filter by replacing its reference signal by input signal and input signal is delayed by unit delay. The structure of the Predictive filter is shown in the fig 2.

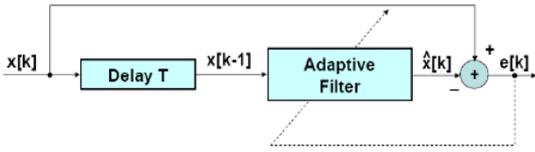


Figure 2. Adaptive filter as a predictive filter.

In predictive filter the input to the filter is unit delayed signal i.e.  $x[k-1]$  (previous sample ) and the reference is the current signal i.e.  $x[k]$  So error signal is nothing but difference between the present sample/signal and past signal i.e. delayed signal  $x[k-1]$ . Here LMS algorithm try to adjust the weight of the filter such that depending upon the two input one is present input  $x[k]$  and past input  $x[k-1]$  it predict the future value of input or output will be as close as possible to the next input.

### III. LEAST MEAN SQUARES ALGORITHM

Many adaptive algorithms have been developed. The choice of one algorithm over another depends on the trade-off among different factors, including convergence speed, robustness, stability and computational complexity. One of the simplest, yet successful, adaptive algorithm is the Least-Mean-Square algorithm (LMS). The advantage of the LMS is that despite its low computational overhead it provides very good performance in a wide spectrum of applications. The LMS algorithm is defined through three equations that are listed in table 1.

Table 1 . LMS algorithm equations.

Filter output	$y[k] = \underline{w}^T[k] \underline{x}[k]$
Error signal	$e[k] = d[k] - y[k]$
Weights adaptation	$\underline{w}[k+1] = \underline{w}[k] + \mu \underline{x}[k] e[k]$

$W[k]$  is the weight of the filter, Parameter  $\mu$  is the step-size which tunes the convergence speed of the algorithm where  $w[k]$  and  $x[k]$  denote  $N \times 1$  column vectors, the  $w[k]$  and  $x[k]$  denoted by the following equation.

$$w[k] = [w1[k], w2[k], \dots, wN[k]]^T \quad (3)$$

$$x[k] = [x[k - 1], x[k - 2], \dots, x[k - N]]^T \quad (4)$$

The filter computes an estimation  $\hat{x}[k]$  of the input signal at the step  $k$ , as a linear combination of the previous  $N$

Readings.

$$\hat{x}[k] = \sum_{i=1}^N w_i[k] * x[k - i] \quad (5)$$

The prediction error,  $e[k]$ , is then computed and fed back to adapt the filter weights. The adaptation process depends on two parameters: the step-size  $\mu$  and the filter order  $N$ . Step-size  $\mu$  tunes the convergence speed whilst filter order  $N$  is a measure of the computational load and memory size of the filter. From equations 3 to 5 it is straightforward to realize that the LMS algorithm requires  $2N + 1$  multiplications and  $2N$  additions per iteration.

### IV. SIMULINK MODEL OF LMS PREDICTIVE FILTER

A model of predictive filter can be developed in a Simulink tool which a part of the MATLAB software. The

online help received from Matlab official website [4]. In MATLAB software there are many inbuilt tools available through which one can create his own model and simulation can be done. In simulink tool there is Signal processing Block set in which there is a filtering option and in filtering there are several inbuilt Adaptive filter available and one can select any filter as per his requirement. A simulink model of predictive filter using LMS filter can be developed and tested as given in the fig.3.

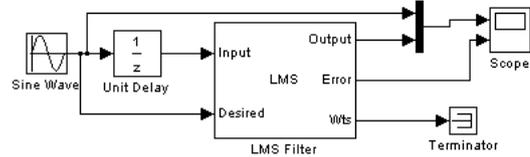


Figure.3 Predictive filter Simulink Model using LMS filter.

The output of the LMS filter tries to catch the input value and the error between the desired signal i.e.  $e(t)=d(t)-y(t)$  tries to become zero can be seen from the output signal on the scope as shown in Figure 04.

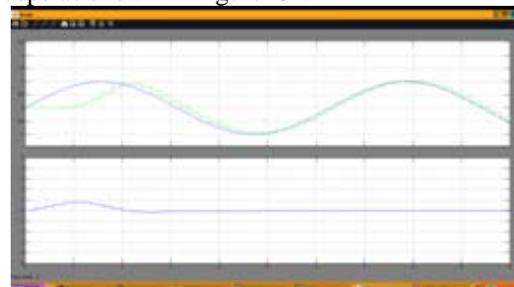


Figure 04. The Simulink model output on Scope Desired signal and predicted value Error signal on 2nd axis.

The first signal shows the input and output signal to the LMS filter and second signal the error output which tries to become zero.

### V. IMPLEMENTATION

Fig 5 illustrates two sensor nodes, a data source (A) and a data sink (B). Data source (A) holds a stream of sensor data,  $\{x[k]\}$ , that has to be transmitted to data sink (B). A minimal error budget (accuracy)  $\epsilon_{max}$  is given and known by both the source and the sink, such that the sink requires to know a value in the range  $x[k] \pm \epsilon_{max}$  rather than the exact value  $x[k]$ .



Figure 5. Communication between source A and Sink B

Instead of transmitting the complete data stream  $\{x[k]\}$  from source to sink, the data reduction algorithm selects a subset of sensor readings that is transmitted to the sink, such that the original observation data,  $\{x[k]\}$ , can be reproduced within the given accuracy. The data reduction is achieved by introducing identical predictive filters (shown in Fig 2) both in the source and in the sink. The prediction filter produces an estimate of the next sensor reading in the data stream. This estimate depends on the previous sensor readings and on the adaptation weights which the LMS algorithm

calculates from the resultant errors. Both the sensor node and the sink apply the same prediction algorithm, hence computing the same prediction of the upcoming reading. Since the sensor node holds the actual sensor value, it is able to compute the prediction error and compare it with the user-defined error threshold  $\epsilon_{max}$ . The sensor node only reports the actual value to the sink node when the threshold is exceeded. Otherwise, the sensor node does not transmit its reading. The sink interprets the missing reporting as a confirmation that the predicted sensor value lies within the error budget. Therefore it includes this value in its memory instead of the actual reading. Similarly, the sensor node discards the real measurement and also stores the predicted value. This scheme ensures that at any time instant  $k$ , both the sensor node and the sink node share the same knowledge of the observed physical phenomenon.

### VI. FPGA IMPLEMENTATION DEVICE AND TOOL INFORMATION

FPGA implementation of Adaptive filter was discussed by Mrs. S S Godbole *et al* in [5]. Here Spartan 3 kit is used to implement the FPGA module of LMS predictive filter. There are other method to implement predictive filter on FPGA discussed in [6], [7], [8]. Spartan-3 Starter Kit board, which includes the following components and features:  
 200,000-gate Xilinx Spartan-3 XC3S200 FPGA in a 256-ball thin Ball Grid Array package (XC3S200FT256)  
 4,320 logic cell equivalents  
 Twelve 18K-bit block RAMs (216K bits)  
 Twelve 18x18 hardware multipliers  
 Four Digital Clock Managers (DCMs)  
 Up to 173 user-defined I/O signals  
 2Mbit Xilinx XCF02S Platform Flash, in-system programmable configuration PROM.  
 1Mbit non-volatile data or application code storage available after FPGA configuration

### VII. HARDWARE DETAILS

The sensor hardware circuit is interfaced with Spartan-3 kit, the LM35 temperature sensor is connected to analog to digital converter IC 0804, it is self clocked 8 bit analog to digital converter 20 pin DIP package, the 8 bit data is interfaced with FPGA kit. Only start of conversion and end of conversion control line is used. The 8 bit data is fed to LMS filter the 16 bit output is fed to parallel to serial converter which is ultimately connected to asynchronous 9600 baud rate transmitter. The TxD line is carrying serial data from FPGA is connected to wireless transmitter [9] low power radio device which operate at 433MHz. the transmitted data can be easily received through radio receiver on the other end.



Figure 6. RTL view of LMS filter core

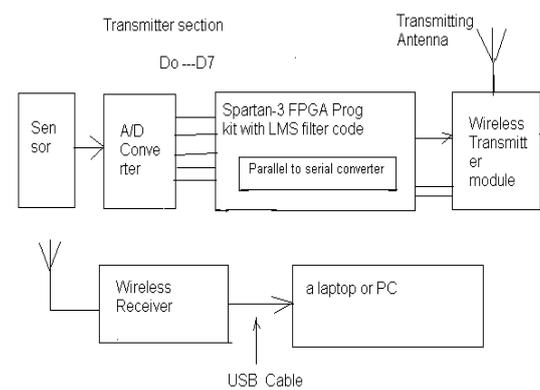


Figure. 7 Hardware setup used for demonstration includes transmitter and receiver section

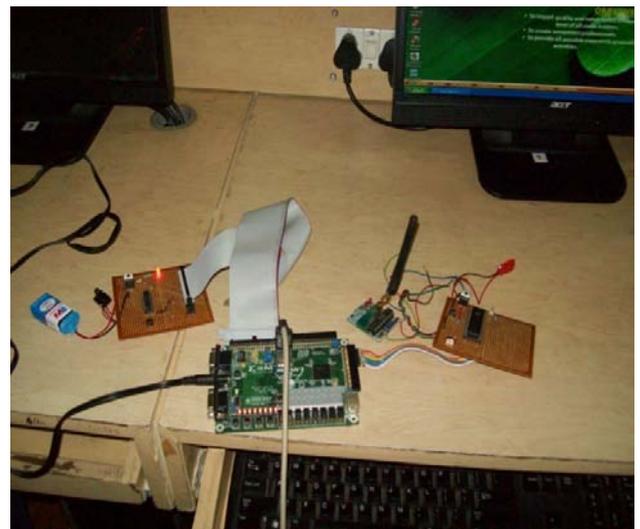


Figure 8. Sensor Circuit is interfaced with the Spartan3 FPGA kit the output of the filter is connected to the serial RF transmitter.

### VIII. CONCLUSION

To reduce data transmission a predictive filter is added at the transmitter side as well as receiving side but question may arise that when we are increasing extra hardware how the power consumption is reduced the answer is the maximum power is consumed during transmission of data and when transmitter is in idle mode it consume negligible power and even if we add extra hardware it take little power and the battery life of the transmitter sensor will go up by 1000 times. If we look at typical rating of normal wireless transmitter takes around 18mA when it operate in normal data transmission mode, in standby mode it take only 800nA and if we add the power consumed in predictive filter the total current may not go beyond 18 micro ampere. Hence maximum power is consumed during transmission of data and reducing transmission will increase power saving.

### IX. ACKNOWLEDGMENT

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