High Speed System Identification Using Adaptive FIR Filter and Effect on Performance of Variable Step Size

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Abstract—System identification is one of the important applications in adaptive filters, particularly for LMS algorithm due to easy implementation and low complexity. Depending on the error signal LMS algorithm corrects the output of FIR filter and approaches towards the desired output. In this paper a second order system is taken as the desired system and this system is identified using a known system of 5th order. Effect of different values of step size are analyzed and discussed in this paper. MATLAB (2014 b) is used for the practical realization and result analysis that proves it to be a fast system identification. Different results like filter coefficients and system output etc. are also concluded in this paper.

Index Terms—Least Mean Square (LMS), Finite Impulse Response (FIR).

I. INTRODUCTION

Adaptive filters prove their ability in different fields of signal processing like system identification, channel equalization, echo cancellation etc. Among the different adaptive algorithms available in the literature, most popular one is the stochastic gradient algorithm. This algorithm is also called least-mean-square (LMS) [1], [2]. Adaptive algorithms are also having a large range of applications like in adaptive filters, in smart antennas (for beam formation) [1], in hearing aids applications for patients to develop a low power hearing machine [3], in filters which uses adaptive fuzzy dividing frequency control mechanism for reduction of harmonics and in power factor [4], in power system for estimation of low frequency power modes [5] etc. There are different adaptive algorithms in which LMS has maximum applications due to its simplicity [6]. Easy implementation makes LMS algorithm so popular. As a consequence, the LMS algorithm is widely used in many applications. Some advantages of FPGA, like reprogramming ability and flexibility makes LMS adaptive filters to be tested again and again on these FPGAs for different applications of these filters. The coefficients of the filter are updated by the equations as:

\[ w(n+1) = w(n) + \mu x(n)r(n) \]  
\[ r(n) = d(n) - w(n)^T x(n) \]

In above \( x(n) \) is input vector and \( w(n) \) is coefficient update vector at particular iteration for example at \( n^{th} \) iteration

\[ x(n) = [x(n), x(n-1), ..., x(n-N+1)]^T \]  
\[ w(n) = [w_n(0), w_n(1), ..., w_n(N-1)]^T \]

Where the desired response is denoted by \( d(n) \). and response of filter is denoted by \( w(n)^T x(n) \). \( r(n) \) is difference between desired and filtered response at \( n^{th} \) iteration. Conventional implementation of above equation is shown in Fig.1.

Different properties such as robust behaviour when implemented infinite-precision hardware, well understood convergence behaviour and computational simplicity for most situations as compared to least square methods [7] of LMS adaptive filters makes this algorithm most desirable. Unknown system identification has been a central issue in various application areas such as control, channel equalization, echo cancellation in communication networks and teleconferencing etc. Identification is the procedure of specifying the unknown model in terms of the available experimental evidence, that is, a set of measurements of the input output desired response signals and an appropriately error that is optimized with respect to unknown model parameters. Figure 2 shows the basic block diagram of system identification.

Figure 1 Conventional Adaptive LMS Filter

Figure 2. General Adaptive System Identification
identification. Adaptive identification refers to a particular procedure where we learn more about the model as each new pair of measurements is received and we update the knowledge to incorporate the newly received information. The Least Mean Square (LMS) adaptive filter is a well-behaved algorithm which is generally used in applications where a system has to adapt to its environment. Architectures are analyzed in terms of the following parameters: speed, power consumption and FPGA resource usage. Modern FPGAs contain many resources that support DSP applications which are implemented in the FPGA fabric and optimized for high performance and low power consumption [8].

II. BRIEF ON SYSTEM IDENTIFICATION AND PROBLEM FORMULATION

System Identification is the process of defining a method which describes arithmetical tools and algorithms that build dynamic models from predefined data. It can be done by adjusting parameters within a given system till its output matches with the measured filter response. Applying system identification to structural models and engineering mechanics provides an efficient means of validating structural models and design assumptions and many other more. A system is referred as a structure or a part of a structure in case of engineering. Inputs and outputs are dynamic excitations and structural responses respectively and they are sampled at discrete instants of time from real world when they can be contaminated with unwanted disturbances i.e, noise.

One of the important applications of adaptive filter is to use adaptive filters to identify unknown system. This can be understood as the response of an unknown communications channel or frequency response of an auditorium, an utilization in system identification. Other applications include noise cancellation, channel identification. In the figure 2, unknown system is placed in parallel with adaptive filter. This layout represents one of the many possible structures. The shaded area is adaptive filter system. In the figure when e(k) is sufficiently small, in that case the filter response is nearly equal to the desired one.

From the figure 2 it is clear that same input signal is feed to both the systems as in known system as well as in unknown system. The necessary equations for formulation of system identification is shown under as

If the system input at time $t = x(t)$

The output response of system on common input is $y(t)$. Then the basic equation between the input and output of the system is given as

$$y(t) + a_1y(t - 1) + \cdots + a_ny(t - n) = b_1x(t - 1) + \cdots + b_mx(t - m)$$

Another useful way to view it as determining the next output value as

$$y(t) = -a_1y(t - 1) - \cdots - a_ny(t - n) + b_1x(t - 1) + \cdots + b_mx(t - m)$$

These equations are modeled in vector form to implement in the MATLAB environment.

III. RESULTS AND DISCUSSION

MATLAB is used as coding tool in this work. For implementation point of view the second order unknown system is considered. An Unknown system of order 5 is taken. Step size plays an important role in determining and adjusting the filter weights. Careful choice of step size makes the better estimation of unknown system. In this paper the values of step size is taken as 0.32 and 0.15, and accordingly the results are shown below in the figures.

In this work 2000 samples are taken and the output of true and estimated system is calculated. In the figure 3 both these values are shown. At the simulation time error signal is calculated which helps in convergence of the algorithm to achieve the desired response. In the figure 4 graph of estimated error on different samples of time is shown.
When the algorithm for system identification evaluates the responses for different samples, filters weights are calculated; these are shown in figure 5. Both actual and estimated weights are shown in the figure. Discreet values of system coefficients for different instant of samples are shown in the figure 6 which shows that comparable coefficients are obtained when compared to true values.

Further figure 7-9 shows the behaviour of adaptation of unknown system for different values of step size (μ). As we increases the step size from 0.02 to 0.09 we can see that red graph is increased and it does not identifies the required system output. When μ=0.02 then better system identification is achieved comparable to μ=0.09 In the figures red graph shows the estimated values of system output which traces the unknown blue graph.
IV. CONCLUSION

In this paper system identification is shown using Adaptive Filter in which LMS Algorithm is utilized. For simulating this identification we used a system of order 2 as the unknown system and the known system is of order 5. The quality of system identification depends on various factors such as the quality of the inputs, which are under control of a systems engineer and the correctness of the output response. Among the different factors, step size is considered here and the effect of different values of step size on system identification is concluded in this work. When step size is relatively small, then system identification is better with large amount of adaptation time. Similarly when we use relatively larger values of step size, LMS algorithm convergence in system identification is poor.

REFERENCES


