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Performance Analysis of LMS, NLMS and PSO Algorithm

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Abstract: **The Adaptive digital filters have been used for several years to design of linear adaptive filters based on FIR filter structures is well developed and widely applied in practice. However, the same is not true for more general classes of adaptive systems such as linear infinite impulse response adaptive filters and nonlinear adaptive systems. System identification in noisy environment has been a matter of concern for researchers in many disciplines of science and engineering. In the past the least mean square algorithm (LMS), genetic algorithm (GA) etc. have been employed for developing a parallel model. During training by LMS algorithm the weight rattle around and does not converge to optimal solution. This gives rise to poor performance of the model. Although GA always ensures the convergence of the weights to the global optimum but it suffers from slower convergence rate. To alleviate the problem we propose a novel Particle Swarm Optimization (PSO) technique for identifying nonlinear systems. The PSO is also a population based derivative free optimization technique like GA, and hence ascertains the convergence of the model parameters to the global optimum, there by yielding the same performance as provided by GA but with a faster speed. Comprehensive computer simulations validate that the PSO based identification is a better candidate even under noisy condition both in terms of convergence speed as well as number of input samples used. Weights to the global optimum but it suffers from slower convergence rate. To alleviate the problem we propose a novel Particle Swarm Optimization (PSO) technique for identifying nonlinear systems. The PSO is also a population based derivative free optimization technique like GA, and hence ascertains the convergence of the model parameters to the global optimum, there by yielding the same performance as provided by GA but with a faster speed. Comprehensive computer simulations validate that the PSO based identification is a better candidate even under noisy condition both in terms of convergence speed as well as number of input samples used.**

Key Words: Adaptive filter; LMS; Variable step size; VSS

1. INTRODUCTION

Adaptive filtering has got may application in the field of signal processing such as control system, system identification and communication network. Several commercial applications for instance noise-cancelling headphones, active mufflers, and the control of noise in air conditioning ducts and videoconference [1, 2]. To reduce the noise there are methods such as adaptive algorithms, belonging to the family of least mean square (LMS), genetic algorithm and particle swarm optimization (PSO) are most useful because of low-cost real-time implementations, robustness and low computational complexity [3,4].By previous work it is known that LMS based algorithms depends directly on the choice of the step-size parameter. If the step size is larger it speeds up convergence rate, if smaller step-sizes tend to improve steady-state performance at the cost of a slower adaptation. Variable step-size (VSS) strategies are frequently sought after to provide both fast convergence and good steady-state performances [5–11]. In general, the step-size should be large in the early adaptation, and have its value progressively reduced as the algorithm approaches steady-state. The rate at which the step-size is reduced depends on the strategy employed and on the system variables that control such strategy. Different strategies usually lead to distinct performance levels.

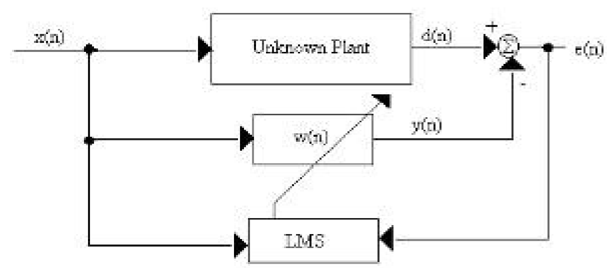

Fig 1: Block diagram of ANC Control System Using LMS Algorithm

The LMS, [9,11] algorithm is a stochastic gradient algorithm which iterates each tap weight and tap length the filter in the direction of the gradient of the squared amplitude of an error signal with respect to that tap weight. The LMS algorithm was devised by Widrow and Hoff in 1959. The objective is to change (adapt) the coefficients of an FIR filter, **w**(n), to match as closely as possible to the response of an unknown system, **p**(n). The unknown system and the adapting filter process the same input signal x[n] and have outputs d[n] (also referred to as the desired signal) and y[n] respectively.

LMS algorithm and the weights of the filter are modified based on the LMS algorithm. It is assumed that all the impulse responses in this paper are modeled by those of finite impulse response (FIR) filters. d(n) has the primary noise to be controlled and **x**(n) is the reference about the noise.

2. RELATED WORK:

In this work we introduced a novel method to obtain an optimal step-size and an algorithm for LMS. The algorithm runs iteratively and convergence to the equalizer coefficients by finding the optimal step-size which minimizes the steady-state error rate at each iteration. No initialization for the step-size value is required. Efficiency of the proposed algorithm is shown by making a performance comparison between some of the other LMS based algorithms and optimal step-size LMS algorithm [1] .A variations of gradient adaptive step-size LMS algorithms are presented. They propose a simplification to a class of the studied algorithms [2]. Adaption in the variable step size LMS proposed by [3] based on weighting coefficients bias/variance trade off. Authors in [4] examine the stability of VSLMS with uncorrelated stationary Gaussian data. Most VSLMS described in the literature use a data-dependent step-size, where the step-size either depends on the data before the current time (prior step -size rule) or through the current time (posterior step size rule).It has often been assumed that VSLMS algorithms are stable (in the sense of mean square bounded weights), provided that the step-size is constrained to lie within the corresponding stability region for the LMS algorithm.

The analysis of these VSLMS algorithms in the literature typically precedes in two steps [5], [6], [7].Block diagram of the basic adaptive structure which is FIR in nature, is shown in Fig. 1. Here depending on the error signal adaptive algorithm controls the tap-length and tap-weights as well and determine the fittest one. This tap-length is updated using PSO style algorithm and for every individual tap-length, tap-weights are updated using LMS algorithm. Generally both these parameters of a system are affected in a time varying environment. The proposed technique updates three technicques efficiently. In conventional PSO, crossover and mutation are performed among fittest parent and new population always replace current population. Typical values of PSO parameters are: population size=50, crossover rate=0.9, mutation rate=0.05. But in the proposed technique the conventional PSO is modified as shown in the flow chart chart 1. To achieve better convergence and therefore named as PSO style.

3. ALGORITHMIC VIEW OF EP APPLIED IN EVSSLMS

(i). Generate initial population of μ individuals and set k=1, each individual is taken as a pair of real valued vectors (x_i , η_i) , $\forall$ i={1, … … .μ}

(ii). Evaluate the fitness score of each individual (x_i , η_i) , $\forall$ i={1, … … .μ} of the population based on the objective function (x_i)

(iii). Each parent (x_i , η_i) , i={1, … … .μ} creates a single offspring (x_i', η_i') by:

4. SIMULATION RESULTS

In this section presents three examples to illustrate the properties of LMS, NLMS and EVSSLMS algorithm. All examples compare with LMS, NLMS and EVSSLMS algorithm. In general the mean square error has to reach zero as soon as possible. But in practice, because of random nature of various phenomena makes it difficult for the automated systems to serve the purpose. The basic algorithm in the adaptive filtering, the LMS, initializes the process of predicting the unknown system or channel. But because of same step size the LMS takes considerable amount of time as well as complexity, modification of LMS in different ways are proposed in the literature. The performance of LMS algorithm is shown in the part a figures 2, 3 and 4. In fig. 5, the Mean Square Error (MSE) is plotted with respect to number of iterations with inherently represents the time to converge. As can be observed, in the case of LMS, the maximum value of MSE is around 0.45. The MSE is under 0.05 after 50 iterations. But even after 500 iterations also the error is not less than 0.01. In the Normalized LMS algorithm on the other hand the MSE has a maximum value around 0.85.

The MSE is greater than 0.05 even till 100 iterations. From that point onwards the MSE is less than even 0.01. In the case BSSLMS, the maximum value of MSE is around 0.45. The MSE is less than 0.05 by 25 iterations itself. From 50 iterations onwards the MSE is less than 0.01. In the case EVSSLMS, the maximum value of MSE is around 0.38. The MSE is greater than 0.1 even till 50 iterations. From 100 iterations onwards.

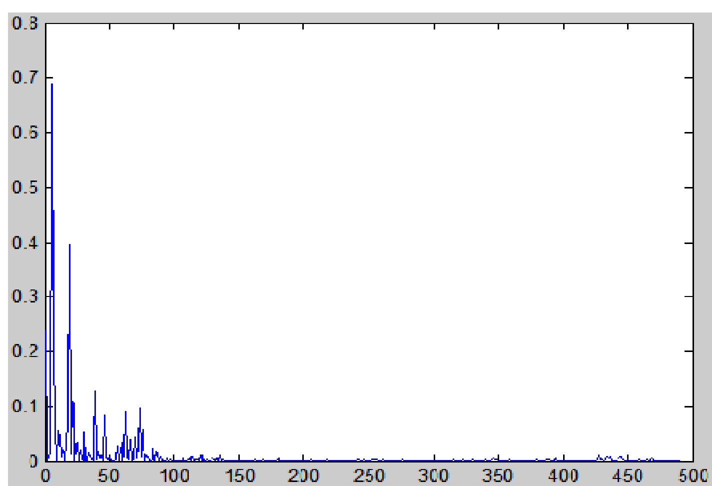

Fig 2. Performance of NLMS Algorithms (MSE Vs No. (MSE Vs No. Iterations (0-500)

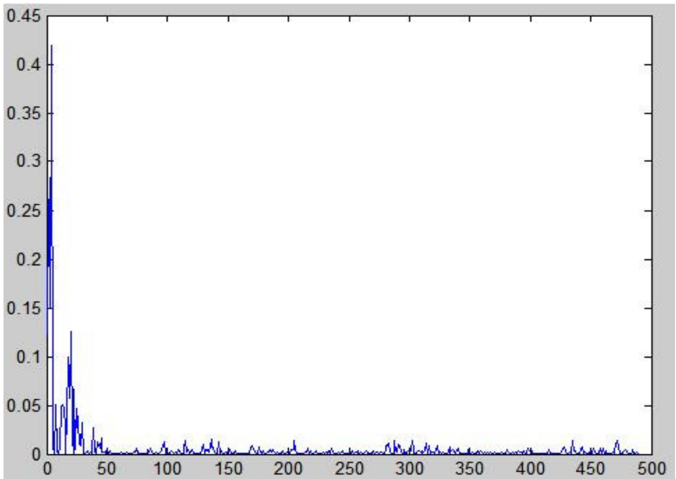

Fig 3. Performance of LMS Algorithms (MSE Vs No. Iterations (0-500)

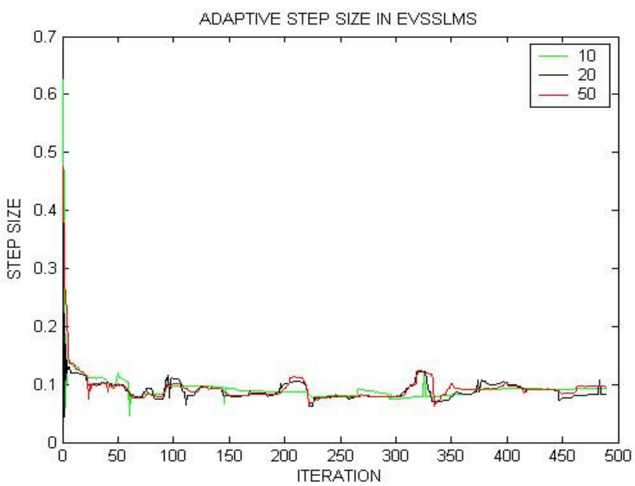

Fig 4. Defined step size by EVSSLMS for different population size

5. CONCLUSION

The problem of optimal variable step size integrated with LMS algorithm has solved with the involvement of evolutionary programming. Presented method is robust and does not require the statistical characteristics of input signal as in the case of other existing solutions. Very good convergence and tracking capability can be achieved automatically by presented method. Performance of proposed EVSSLMS also checked with different population size and it has shown that with less population performance is also equally well and in result higher speed of solution.

REFERENCES

[1] S. Haykin, Adaptive Filter Theory, second ed., Prentice-Hall, nglewood Cliffs, NJ, 1991.

[2] C. Breining, et al., Acoustic echo control. An application of very-high-order adaptive filters, IEEE Signal Process. Mag.16 (4) (July 1999) 42–69.

[3] Wee-Peng Ang Farhang-Boroujeny, B," A new class of gradient adaptive step size LMS algorithm" "Signal Processing, IEEE Transactions on,2001, Volume: 49 Issue: 4 , page(s): 805 – 810.

[4] Krstajic, B. Stankovic, L.J. Uskokovic, Z. "an approach to variable step size LMS algorithm". : Electronics Letters , Aug 2002 ,Volume: 38 Issue: 16,On page(s): 927 – 928.

[5] Solmaz, C.O.; Oruc, O.; Kayran, A.H.; " Optimal step-size LMS equalizer algorithm ".Signal Processing and Communications Applications (SIU), 2011 IEEE . April 2011,page no. 853 - 856 .

[6] Krstajic, B. Stankovic, L.J. Uskokovic, Z. "an approach to variable step size LMS algorithm". : Electronics Letters , Aug 2002 ,Volume: 38 Issue: 16,On page(s): 927 – 928.

[7] Wee-Peng Ang Farhang-Boroujeny, B," A new class of gradient adaptive step size LMS algorithm" "Signal Processing, IEEE Transactions on,2001, Volume: U page(s): 805 – 810.

[8] Saul B. Gelfand, Yongbin Wei, James V. Krogmeier, ," The Stability of Variable Step-Size LMS Algorithms" IEEE TRANSACTIONS ON SIGNAL PROCESSING, VOL. 47, NO. 12, December 1999

[9] R. Kwong and E. W. Johnston, "A variable step size LMS algorithm," *IEEE Trans. Signal Processing*, vol. 40, pp. 1633–1642, July 1992.

[10] V. J. Mathews and Z. Xie, "A stochastic gradient adaptive filter with gradient adaptive step size," *IEEE Trans. Signal Processing*, vol. 41,pp. 2075–2087, June 1993.

[11] Tao Dai; Shahrrava, B.," Variable step-size NLMS and affine projection algorithms with variable smoothing factor "Circuits and Systems, 2005. 48th Midwest Symposium on , Aug. 2005 , page(s): 1530 - 1532 Vol. 2.