International Journal of Scientific & Technical Development(A Peer-Reviewed Bi-Annual Journal) ISSN 2348-4047

DEVELOPING AN ADAPTIVE FILTER FOR SYSTEM RECOGNITION

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Abstract

The purpose of this paper is to study the adaptive filters theory for the noise cancellation problem. Firstly the paper presents the theory behind the adaptive filters. Secondly it describes three most commonly adaptive filters which were also used in computer experiments, the LMS, NLMS and RLS algorithms. Furthermore, the study explains some of the applications of adaptive filters, the system identification and prediction problems. It also describes some computer experiments conducted by the author within a general problem, providing its solution by using the LMS, NLMS and the RLS algorithms and comparing the results. Moreover, the work focuses on one of the classes of application of the adaptive filters: the active noise cancellation problem, presenting a general problem, the three different algorithm solutions and a comparison between them.
Keywords— Centre of Mass (CoM), adaptive filter, LMS, RLS Algorithm

Introduction

Digital signal processing (DSP) has been a major player in the current technical advancements such as noise filtering, system identification, and voice prediction. Standard DSP techniques, however, are not enough to solve these problems quickly and obtain acceptable results. Adaptive filtering techniques must be implemented to promote accurate solutions and a timely convergence to that solution.

Discrete-time (or digital) filters are being everywhere in today's signal processing applications. Filters are used to achieve desired spectral characteristics of a signal, to reject unwanted signals, like noise or interferers, to reduce the bit rate in signal transmission, etc.

The notion of making filters adaptive, i.e., to alter parameters (coefficients) of a filter according to some algorithm, tackles the problems that we might not in advance know, e.g., the characteristics of the signal, or of the unwanted signal, or of a systems influence on the signal that we like to compensate. Adaptive filters can adjust to unknown environment, and even track signal or system characteristics varying over time.

An adaptive filter is a filter that self-adjusts its transfer function according to an optimization algorithm driven by an error signal. Because of the complexity of the optimization algorithms, most adaptive filters are digital filters. By way of contrast, a non-adaptive filter has a static transfer function. Adaptive filters are required for some applications because some parameters of the desired processing operation are not known in advance. The adaptive filter uses feedback in the form of an error signal to refine its transfer function to match the changing parameters.

System Identification

System identification, also popularly called as mathematical modeling is a category of adaptive filtering that finds a huge range of applications particularly in the areas of communication. Adaptive filter is used to provide the linear model which represents the best fit of the unknown plant. In this configuration, the plant and the adaptive filter are connected in parallel form and driven by the same input. The plant output is called as desired response of the system. The error signal is obtained by subtracting the adaptive filter output from the desired output. If the plant is dynamic, then adaptive filter will also be time varying or non stationary.

LMS Algorithm

The research work on adaptive filtering can be traced back to 1950s when a number of researchers were independently working on the different applications of adaptive filters. From this study, LMS algorithm emerged as a simple yet effective algorithm for the purpose of adaptive filtering. It was devised by Bernard Widrow, Professor of Stanford University and his doctoral research scholar, Ted Hoff in 1959. LMS algorithm is known as a stochastic gradient algorithm. This means that it iterates each tap weight of transversal filter in the direction of the gradient of the squared magnitude of error with respect to the tap weight. The filter is only adapted based on the error at the current time. LMS algorithm is closely related to the concept of the stochastic approximation developed by Robbins and Monro in 1951. The primary difference between the two is LMS algorithm uses the fixed convergence rate parameter to update the tap weight of the filter whereas stochastic approximation method uses the convergence parameter that in inversely proportional to the time n or power of n. There is another stochastic gradient algorithm which is closely related to LMS. This algorithm is called as Gradient Adaptive Lattice (GAL) developed by Griffiths in 1977. The difference between the LMS and GAL is only in underlying filtering structure, LMS uses transversal structure and GAL uses lattice structure. The LMS algorithm has an inherent limitation that it can search local minima only but not global minima [8]. However, this limitation can be overcome by simultaneously initializing the search at multiple points. This algorithm is derived as follows. The LMS algorithm is an approximate version of SDA which simply approximates R and p by replacing the expectation operator by instantaneous value. Thus,

$$R = E[x(n)\, x^T(n)] \approx x(n)\, x^T(n) \quad (1)$$

$$p = E[d(n)\, x(n)] \approx d(n)\, x(n) \quad (2)$$

Substituting (1) and (2) in Steepest Descent algorithm given in (15) gives,

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

By separating out the common factor,

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

Using the relationship

$$y(n) = x^T(n)w(n)$$

and $e(n)=d(n)-y(n)$,

above equation can be written as

$$w(n+1) = w(n) + \mu\, x(n)\, e(n) \quad (3)$$

This equation represents popular LMS algorithm equation. This algorithm is of O(N) and requires 2N+1 multiplication and 2N addition per iteration. For stability of LMS algorithm convergence rate parameter μ satisfies the relationship.

RLS Algorithm

The recursive-least-squares (RLS) algorithm is based on the well-known least squares method. The RLS algorithm recursively solves the least squares problem. In the following equations, the constants λ and δ are parameters set by the user that represent the forgetting factor and regularization parameter respectively. The forgetting factor (λ) is a positive constant less than unity that is roughly a measure of the memory of the algorithm; the vector wˆ represents the adaptive filter's weight vector and the M-by-M matrix P is referred to as the inverse correlation matrix. The vector π is employed as an intermediary step to computing the gain vector k. This gain vector is multiplied by a priori estimation error ξ (n) and added to the weight vector to update the weights. Once the weights are updated the inverse correlation matrix is recalculated, and also the training resumes with the new input values. A summary of the RLS algorithm follows: Initialize the weight vector and the inverse correlation matrix P.

$\hat{w}^H(0) = \bar{0}$

$p(0) = \delta^{-1} I$ For each instance of time n = 1, 2, 3 …, compute:

An adaptive filter trained with the RLS algorithm can converge up to an order of magnitude faster than the LMS filter at the expense of increased computational complexity

Adaptive Noise Cancellation System

In adaptive noise cancellation, the adaptive filter is usually designed as a transversal FIR filter structure. The transversal filter consists of three basic elements; unit delay elements, multipliers and adders as shown in Figure. The unit delay elements are designed using the unit delay operator. The output of the Unit-delay operator z-1 is a delayed copy of its

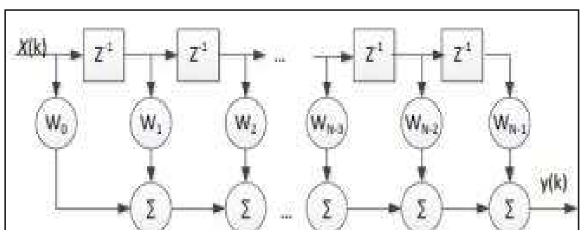


Figure The Transversal FIR Filter Structure input. The number of delay elements represents the filter order.

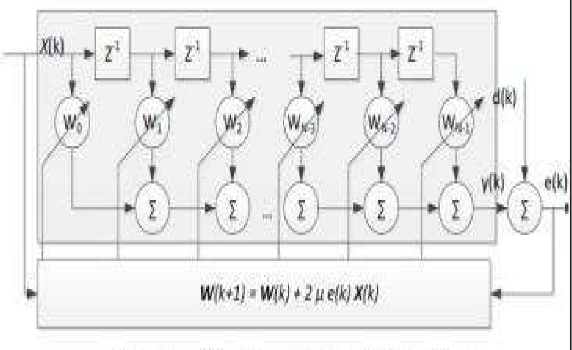
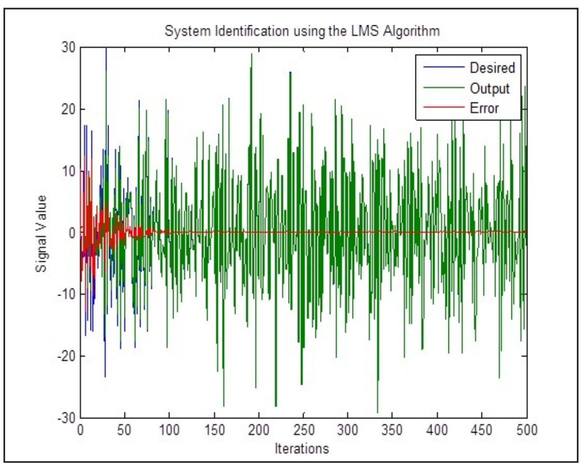


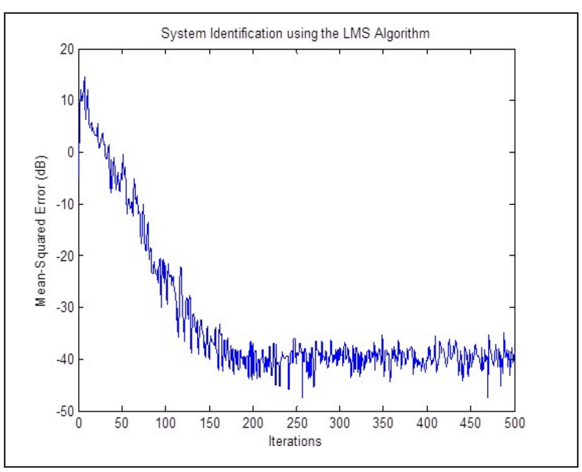
Figure . Adaptive noise cancellation filter

The adaptive noise cancellation filter employing the LMS algorithm can be implemented as shown in following Figure

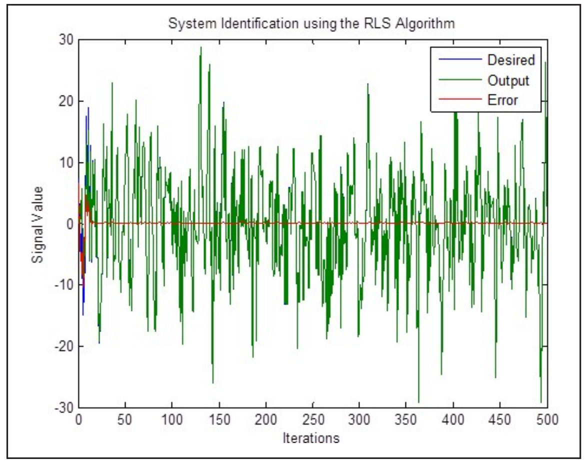
Software Simulation Results

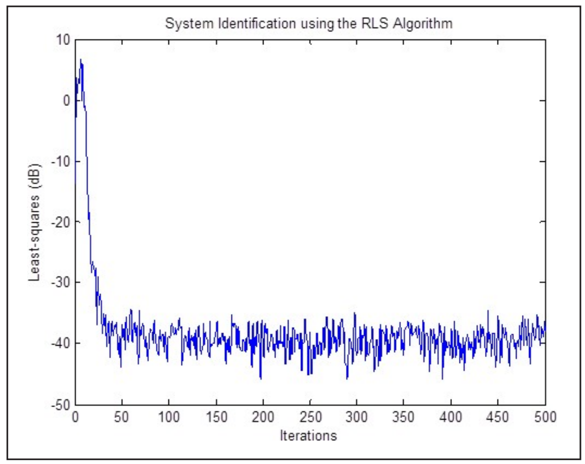
Adaptive noise cancellation is designed by using both LMS algorithm and RLS algorithm. In this we have taken input as sinusoidal signal plus 3 types of noises. Those are uniform noise,





Gaussian noise and additive white Gaussian noise.





LMS Solution

RLS Solution

Comparison of Results

In real-time applications, it is very important to analyze all the important details before we choose an adaptive algorithm. A small difference could result in elevated cost of implementation, or in a weak system, which is not stable in all variable changes, or even the solution is impossible to be implemented. The choice between using one algorithm instead of another, to the system identification problem, depends mainly on the following factors:

- Rate of Convergence: number of iterations required by the algorithm, to converge to a value close to the optimum Wiener solution in the mean-square sense. If the algorithm has a fast rate of convergence, it means that the algorithm adapts rapidly to a stationary unknown environment.
- Computational cost: when we talk about

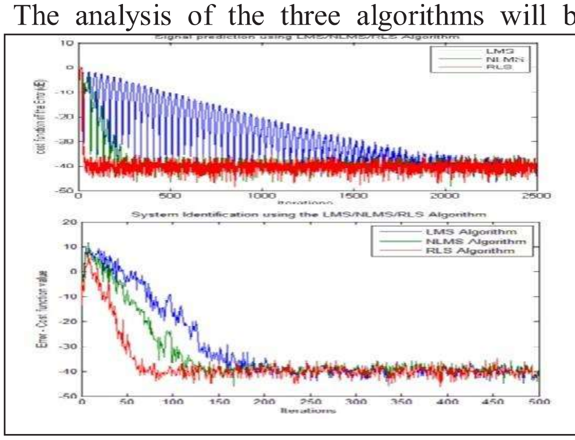
computational cost, it includes implementation cost, amount necessary to implement the algorithm in a computer and the number of arithmetic operations. The order of the operations is also important as well as the memory allocation, which is the space necessary to store the data and the program.

- Tracking: capacity of the algorithm to track statistical variations in a stationary unknown environment.

In this particular application, those three factors have has been analyzed. The tracking factor has been analyzed in two stages, one after a few hundred of iterations and the other after a few thousand iterations.

The figure shows a comparison between the rates of convergence of the three proposed algorithms. Investigating the results shown in figure, it can be detect that the rate of convergence of the RLS algorithm is faster than the other two. Indeed, it can be twice faster than the NLMS and three times faster than the LMS algorithm

The analysis of the three algorithms will be

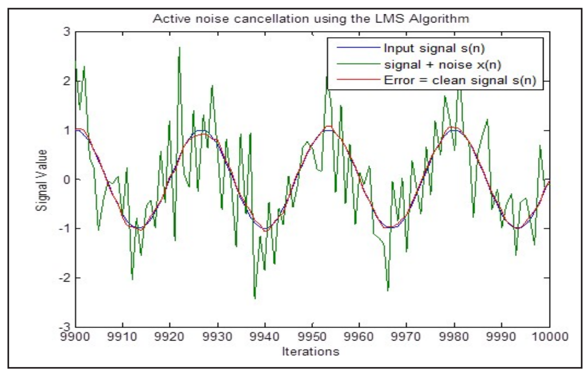


performed according to the factors presented in Subsection 4.1.5, which are: the rate of convergence, the computational cost and the tracking characteristics. The computational cost is a fixed factor where the RLS algorithm has the disadvantage of having a higher computational cost, because of its necessary calculation.

A comparison between the algorithms cost function until 2500 iterations is shown in figure . It can be easily noticed that the LMS algorithm has a very slow rate of convergence comparing to the other two algorithms. Indeed, the rate of convergence of the LMS algorithm was noted to be 8 times smaller than the NLMS algorithm and 40 times smaller than the rate of convergence of the RLS algorithm. The last one presents the fastest rate of convergence, which makes it ideal for application were a fast convergence is necessary.

The figure below depicts the results obtained by applying the LMS algorithm for the given problem, containing the input signal s(n), the desired signal x(n)=s(n) + n2(n) and the error signal, which should be equal to the input signal s(n). The step-size parameter was chosen to be equal to 0.0002 and the adaptive filter has length 5. It can be seen in blue, the signal s(n), the input signal. In green color it is presented the input signal after the noise corruption s(n) + n2(n), and in red, the error signal e(n).

$L = 5$, $\mu = 0.0002$.



The application of the algorithm described above, having the small positive constant δ equal to 3.2 and the NLMS step-size parameter ¯ equal to 0.005, has resulted in the following:Figures above depict the results of the application of the ANC using the NLMS algorithm. The input signal s(n), represented by the blue color is corrupted by the noise signal n1(n) resulting in the corrupted signal x(n)=s(n)+n2(n), represented by the green color. The error signal e(n), which is supposed to imitate the input signal s(n) is represented by the red color.

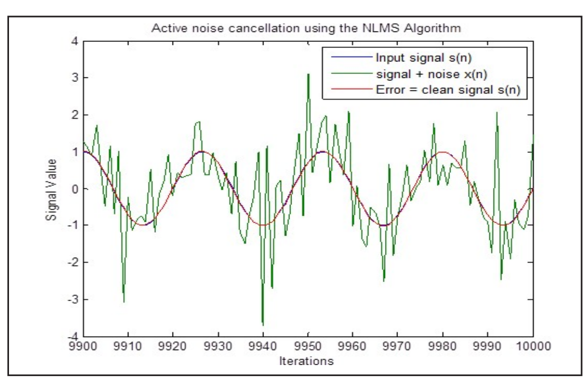
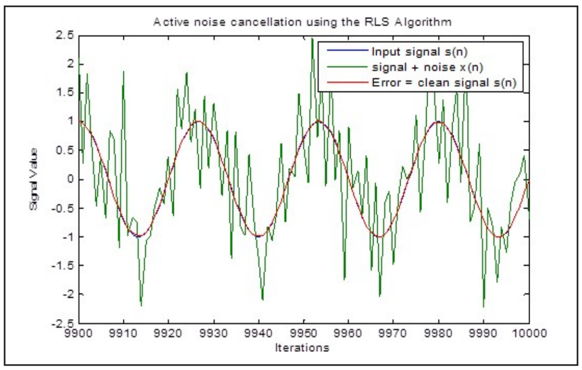


Figure below depict the results of the application of the RLS algorithm explained before in the noise cancelling problem. It can be noted that the algorithm has a good performance while working as an ANC. The blue line represents the original input signal s(n), the green line represents the same signal after the noise corruption x(n)=s(n)+n2(n) and the red line represents the error signal, which should be, and indeed it is, close to the original input signal s(n).

$L = 5, \lambda = 1$



Conclusion

Keeping in mind the factors described in sections above and the complexity of computational cost presented, the following deductions about the algorithms presented in this chapter for the ANC problem can be made. The RLS algorithm has a fixed computational cost, derived from its way of calculation, higher than the two other algorithms. It can be noticed that the LMS algorithm has a very slow convergence, compared to the convergence of the RLS algorithms, the LMS also converge to a higher error value, approximately 30dB against 20dB for the other two. In this case, if it is needed an algorithm which the convergence speed is important, the LMS is not a good choice. The RLS algorithm presents a convergence three times faster than LMS algorithm, being the fastest algorithm for the ANC problem and having a good efficiency. The study presented in this work describes the adaptive filter theory and presents solutions for the four basic classes of applications. It goes deeper in the active noise cancellation problem, presenting solutions with the three most popular algorithms for a general ANC problem. The study proves that the RLS algorithm is more robust than the LMS algorithm, having a smaller error and a faster convergence for the case of the white Gaussian noise interference. The RLS algorithm has a bigger complexity and computational cost, but depending on the quality required for the ANC device, it is the best solution to be adopted. Whereas LMS algorithm, which has proved its inefficiency in such environment, having big variations in the noise cancellation error when the colored noise presented a strong signal. Those error variations are big enough to be listened in the error output signal.

References

[1]System identification using adaptive filter algorithms ,S.d.shinde,A.p.patil, P.p.belagali IOSR Journal of Electronics and Communication Engineering (IOSR-JECE) ISSN: 2278-2834-, ISBN: 2278-8735, PP: 54-59.

[2] Efficient Implementation of the Affine Projection Sign Algorithm, Jingen Ni; Feng Li Signal Processing Letters, IEEE Volume: 19, Issue: 1 Digital Object Identifier: 0.1109/LSP.2011.2174784 Publication Year: 2012 , Page(s): 24 – 26

[3] Low-Complexity Implementation of the Affine Projection Algorithm Zakharov, Y.V.Signal Processing Letters, IEEE Volume: 15 Digital Object Identifier: 10.1109/LSP.2008.2001111 Publication Year: 2008 , Page(s): 557 – 560

[4] A new sign algorithm for interference suppression in DS-CDMA systems Liping Sun; Guangrui Hu Communications Letters, IEEE Volume: 7 , Issue: 5 Digital Object Identifier: 10.1109/LCOMM.2003.811194 Publication Year: 2003 , Page(s): 233 – 235

[5] A robust mixed-norm adaptive filter algorithm Chambers, J.; Avlonitis, A.Signal Processing Letters, IEEE Volume: 4 , Issue: 2 Digital Object Identifier: 10.1109/97.554469 Publication Year: 1997 , Page(s): 46 – 48

[6] An Affine Projection Sign Algorithm Robust Against Impulsive Interferences Tiange Shao; Zheng, Y.R.; Benesty, J. Signal Processing Letters, IEEE Volume: 17, Issue: 4 Digital Object Identifier: 10.1109/LSP.2010.2040203 Publication Year: 2010, Page(s): 327 – 330

[7] Proportionate Affine Projection Sign Algorithms for Network Echo Cancellation Zengli Yang; Zheng, Y.R.; Grant, S.L. Audio,

Speech, and Language Processing, IEEE Transactions on Volume: 19 , Issue: 8 Digital Object Identifier: 10.1109/ TASL. 2011. 2125955 Publication Year: 2011 , Page(s): 2273 – 2284

[8] Low-complexity constrained affine-projection algorithms Werner, S.; Apolinario, J.A., Jr.; de Campos, M.L.R.; Diniz, P.S.R. Signal Processing, IEEE Transactions on Volume: 53 , Issue: 12 Digital Object Identifier: 10.1109/TSP.2005.859348 Publication Year: 2005 , Page(s): 4545 – 4555

[9] A New Robust Variable Step-Size NLMS Algorithm Vega, L.R.; Rey, H.; Benesty, J.; Tressens, S. Signal Processing, IEEE Transactions on Volume: 56 Issue: 5 Digital Object Identifier: 10.1109/TSP.2007.913142 Publication Year: 2008 , Page(s): 1878 – 1893

[10]Mohammad Zia Ur Rahman, Rafi Ahamed Shaik and D V Rama Koti Reddy, “Noise Cancellation in ECG Signals using computationally Simplified Adaptive Filtering Techniques: Application to Biotelemetry”, Signal Processing: An International Journal 3(5), November 2009.

[11] Allan Kardec Barros and Noboru Ohnishi, “MSE Behavior of Biomedical Event-Related Filters” IEEE Transactions on Biomedical Engineering, 44(9), September 1997. 12) Ahmed I. Sulyman, Azzedine Zerguine, “Convergence and Steady-State Analysis of a Variable Step- Size Normalized LMS Algorithm”, IEEE 2003.

[12] S.C.Chan, Z.G.Zhang, Y.Zhou, and Y.Hu, “A New Noise-Constrained Normalized Least Mean Squares Adaptive Filtering Algorithm”, IEEE 2008.

[13] Syed Zahurul Islam, Syed Zahidul Islam, Razali J idin, Mohd. Alauddin Mohd. Ali,“Performance Study of Adaptive Filtering Algorithms for Noise Cancellation of ECG Signal”,IEEE 2009.