2011 3rd International Conference on Signal Processing Systems (ICSPS 2011)
IPCSIT vol. 48 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.V48.3

Design of an Adaptive Line Enhancer Using a RGR-RLS Algorithm

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Abstract. This paper presents design of an adaptive line enhancer (ALE) for improving weak signal detection using a new relaxed Givens rotation RGR-RLS algorithm. ALE is an adaptive technique that may be used to detect a periodic signal buried in a broadband noise background such as in weak signal detection. However, most of the conventional methods for ALE system are based primarily on an adaptive filter with the least-mean-square (LMS) error algorithm. Unfortunately, convergence speed is limited when a filtering plant is varied, because the learning process of the adaptive algorithm fails to respond quickly enough to the changing operational conditions. The convergence of the RLS algorithm is faster, but its computation complexity higher. This study proposed a RGR-RLS for improving the convergence speed and reducing the computation burden. While the algorithm has good robustness forλ. The application was used for reducing the background broadband noise during detecting weak signal. The experimental results indicated that the ALE with RGR-RLS has an effective performance for this application.

Keywords: component; Adaptive line enhancer; RGR-RLS; convergence; robustness; signal detection

1. Introduction

The ALE is an adaptive filtering technique that can be used to detect a sinusoidal signal buried in a broadband noise background [1, 2]. Research interest in ALE algorithm has developed since Widrow in 1975 [3]. However, most of the conventional methods for ALE system are based primarily on an adaptive filter with the least-mean-square (LMS) error algorithm. The LMS algorithm is a well-known adaptive algorithm due to the significant feature of its adaptive property, which is important in many practical applications. Unfortunately, convergence speed is often limited when a sound source or a filtering plant is varied, because the learning process of the adaptive algorithm fails to respond quickly enough to the changing operational conditions.

The convergence of the RLS algorithm is faster than that of the LMS algorithm, but its computation complexity higher. The QR decomposition (QR)-RLS algorithm using triangularization process is the most promising RLS algorithm since it is known to have good numerical properties, but the critical period of the QRD-RLS algorithm is limited by the operation time in the recursive loop of the individual cells. In many applications, very high throughput would be desired, and the QRD-RLS algorithm may not be capable of operating at such high throughput [4, 5].

Based on these unsolved problems, we are motivated to provide a new algorithm. This paper is organized as follows. We propose the RGR-RLS algorithm. We focus on developing a new relaxed Givens rotation (RGR)-RLS algorithm, nearly the same convergence as the QRD-RLS, good robustness for λ .

In order to verify the proposed algorithm in the ALE system, the denoising application is conducted in the present study. The proposed ALE system is used to reduce the background noise during detecting weak

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signal. The signals including basic frequency and harmonics are generally buried in broadband background noise. In the present study, the ALE system is used to evaluate background noise reduction by using the proposed filtering algorithm.

This paper is organized as follows. The principle of ALE with RGR-RLS adaptive filtering algorithm is described in Section Ⅱ. In sections Ⅲ and Ⅳ, comparisons and simulation results are discussed. Conclusion is given in the last section.

2. Principle of ALE with RGR-RLS Algorihm

Adaptive line enhancer (ALE) is used in many signal processing fields for its capability of tracking a signal of interest. The ALE is in fact a degenerate form of the adaptive noise canceller in that its reference signal, instead of being derived separately, consists of a delayed version of the input signal [6, 7]. The main advantage of it is that it does not require any reference signal to eliminate the noise signal. The reference signal is the delayed version of the primary signal. The delay △ is the prediction depth of the ALE, measured in units of the sampling period. The reference input u(n-△) is processed by a transversal filter to produce an error signal e(n), defined as the difference between the actual input u(n) and the ALE's output. The error signal is used to accurate the adaptive algorithm through adjusting the weighs of the transversal filter. A general block diagram of ALE system is depicted in Fig.1(TABLE Ⅰ) [8, 9].

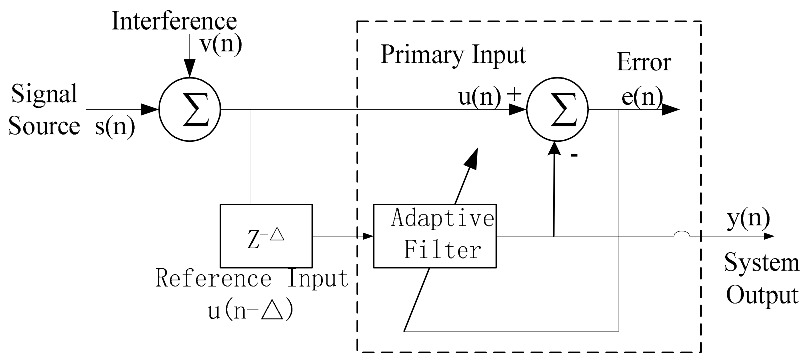

Figure 1. Block diagram of adaptive line enhancer

TABLE I. NOTATION LIST OF FIGURE

Variable	Definition
△	The delay of ALE system
n	Discrete-time or number iterations
u(n)	The input signal of ALE at time n
v(n)	Broadband interference noise
e(n)	The estimation error
y(n)	The output of ALE system

The error signal is the difference between the desired and the output signals, and is used to accurate the adaptive algorithm through updating the filter coefficient.

The convergence of the RLS algorithm is faster than that of the LMS algorithms, but its computational complexity higher than the latter is an order of magnitude. The QR decomposition (QRD)-RLS algorithm using triangularization process is the most promising RLS algorithm since it is known to have good numerical properties. The critical period of the QRD-RLS algorithm is limited by the operation time in the recursive loop of the individual cells. An example of such a low-complexity algorithm is the RGR-RLS. We are given a time series of inputs x(1) , x(2), ..., x(n), and we want to estimate some desired signal d(i) based on a weighted sum of present sample and a few of the past samples. In order to efficiently approach the optimal solution based on least square criterion, the QRD-RLS algorithm using the Givens rotations can be applied, where a Givens rotation is defined as

$$G(n) = \begin{bmatrix} c(n) & s(n) \\ -s(n) & c(n) \end{bmatrix} \tag{1}$$

The QRD-RLS algorithm at each boundary cell in has the following equation

$$\begin{aligned} r(n) &= c(n)\lambda^{1/2}r(n-1) + s(n)x(n) \\ &= \sqrt{\lambda r^2(n-1) + x^2(n)} \end{aligned} \tag{2}$$

Where c(n) is to represent cos θ that is a function of iteration number n in the triangularization process and s(n) has a similar definition. At the internal cell, in addition to Eq. (2), another equation can be easily obtained as

$$b(n) = -s(n)\lambda^{1/2}r(n-1) + c(n)x(n) \tag{3}$$

Where b(n) denotes the output of the internal cell. In order to bypass square root and achieve fine-grain pipelining, we take some approaches to relax the Givens rotation. Therefore, the resulting RGR is assumed in the form:

$$\mathrm{G_R}(n)=\begin{bmatrix} c_1(n) & s_1(n) \\ -s_2(n) & c_2(n) \end{bmatrix} \tag{4}$$

Note that GR(n) is very close to G(n) after the verification of the adaptive equalization experiment. In Eq. (2), there are two cases to be investigated. Both cases including the $\lambda^{1/2}\left|r(n-1)\right| \geq \left|x(n)\right|$ and the $\lambda^{1/2}\left|r(n-1)\right| < \left|x(n)\right|$ correspond to two different GR(n), respectively.

According to the above discussion, our proposed RGR-RLS algorithm is presented in TABLE Ⅱ.

TABLE II. RGR-RLS ALGORITHM

Initiation: $r_{ii}(0) = 0, i = 1,2,\cdots,M$; $u_i(0) = 0$ $r_{ij}(0) = 0, i = 1,2,\cdots,M; j = i, i+1,\cdots,M$

When $n = 0,1,\cdots$
$d^{(1)}(n) = d(n)$ $x_j^{(1)} = x_i(n), i = 1,2,\cdots,M$
For i=1 to M do
If $\lambda^{1/2}\left\|r(n-1)\right\| \geq \left\|x(n)\right\|$, then
$G_R(n) = \begin{bmatrix} 1 & \frac{x(n)}{2\lambda^{1/2}r(n-1)} \\ -\frac{x(n)}{\lambda^{1/2}r(n-1)} & 1-\frac{x^2(n)}{2\lambda r^2(n-1)} \end{bmatrix}$
Else
$G_R(n) = \begin{bmatrix} \frac{\lambda^{1/2}r(n-1)}{2\left\|x(n)\right\|} & sign(x(n)) \\ sign(x(n))(1-\frac{\lambda r^2(n-1)}{2x^2(n)}) & \frac{\lambda^{1/2}r(n-1)}{\left\|x(n)\right\|} \end{bmatrix}$
For j = i + 1 to M do
$x_j^{(i+1)} = \mathrm{c}_i x_j^{(i)}(n) - s_i^* r_{ij}(n-1), r_{ij}(n)$
$= \mathrm{c}_i r_{ij}(n-1) + s_i x_j^{(i)}(n)$
End of loop j
$d^{(i+1)}(n) = \mathrm{c}_i d^{(i)}(n) - s_i^* u_i(n-1), u_i(n)$
$= \mathrm{c}_i u_i(n-1) + s_i d^{(i)}(n)$
End of loop i

3. Algorithm Comparison Results

In this section, first, we compare the convergence speed characteristics of various adaptive filters; a numerical simulation is indicated in Fig. 3. In the figures, the convergence speeds and mean square error of

LMS, RLS, QR-RLS and RGR-RLS are compared. From the results, we verify that the convergence of our proposed RGR-RLS algorithm is close to that of the QRD-RLS algorithm for radar weak signal detection application. The simulation environment of the adaptive equalization is set to the same as described in [1]. Obviously, the RGR-RLS demonstrated a satisfactory convergence speed in the simulation.

Second, we simulate the algorithm's robustness for λ including two cases: λ =0.6, λ =0.3. A numerical simulation is indicated in Fig. 4. From Fig. 4, it can be seen that our proposed RGR-RLS algorithm has similar convergence performance to the QRD-RLS algorithm for different values of λ . So, the proposed RGR-RLS algorithm has good robustness for λ .

In TABLE III, it can be seen that our proposed algorithm nearly orthogonality, good robustness, and square-root free reduced the algorithm computation complexity. Therefore, the RGR-RLS is an efficient algorithm architecture.

TABLE III. COMPARISION RESULTS WITH DIFFERENT ALGORITHM

	QRD-RLS	Our algorithm
Orthogonality	Exact	Approximate
Robustness for λ	Good	Good
Square Root	Not free	Free

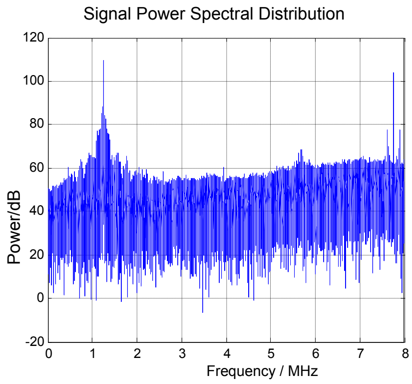

Figure 2. TV Signal power spectral

4. Applicaation of RGR-RLS Algorithm

In this section, we verify the effect of RGR-RLS, a performance evaluation of an ALE system under different SNR conditions. First, we acquired the TV signal during data acquisition system in Lab, then analyzed power spectral using MATLAB shown in Fig. 2. These signals normally consist of a combination of two basic frequency and harmonics, located at 1.25 MHz and 7.75 MHz obviously.

With the lower SNR, the harmonics were buried in the background broadband noise, even covering the basic frequency spectral line in the worst case. In the present application, the proposed RGR-RLS ALE system is used to reduce the background noise from space environment. The results of ALE system using RGR-RLS algorithm under different lower SNR are shown in Fig. 5, and then calculated and found to improve the SNR to 12 dB, averagely. Therefore, it can greatly improve the detection of signals in low SNR application. The experimental results demonstrated that the proposed ALE system with the RGR-RLS filtering algorithm effectively suppresses the background broadband noise under both conditions.

5. Conclusion

An experimental investigation was used to evaluate a novel ALE system with RGR-RLS adaptive filtering algorithms in weak signal detection application. The proposed RGR-RLS incorporates the advantages of the QR-RLS in convergence speed, good robustness for λ , and square-root free computation. The ALE application was conducted in different low SNR conditions detecting effective signal. The experimental results indicated that the ALE system with RGR-RLS algorithm performed more effectively performance in denoising the background broadband noise.

6. References

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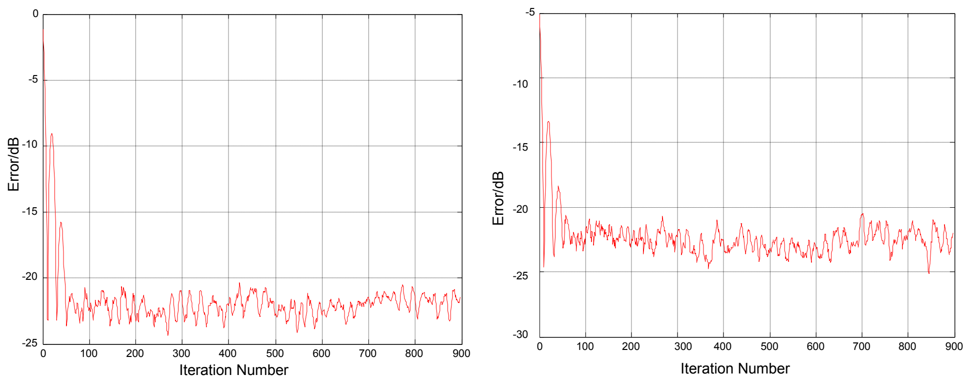
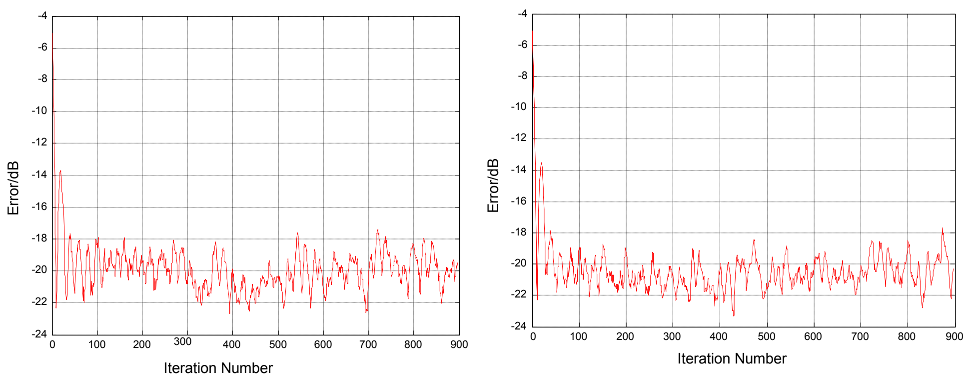


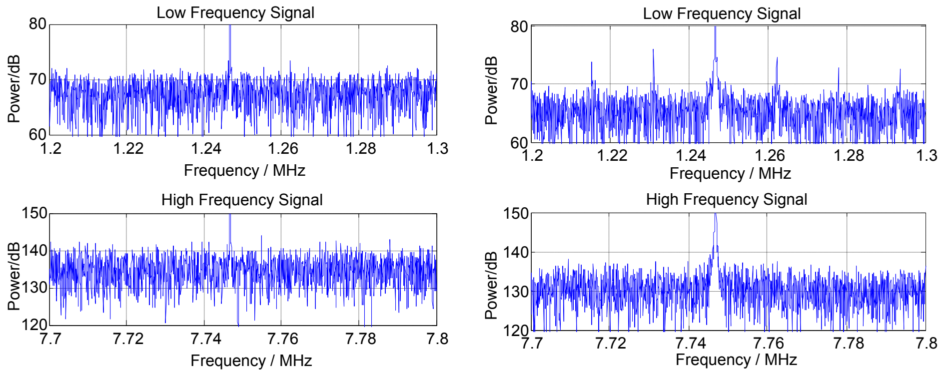
(a) (b)

Figure 3. Comparison of convergence speed and estimation error in various adaptive filters.(a) QR-RLS;(b)RGR-RLS

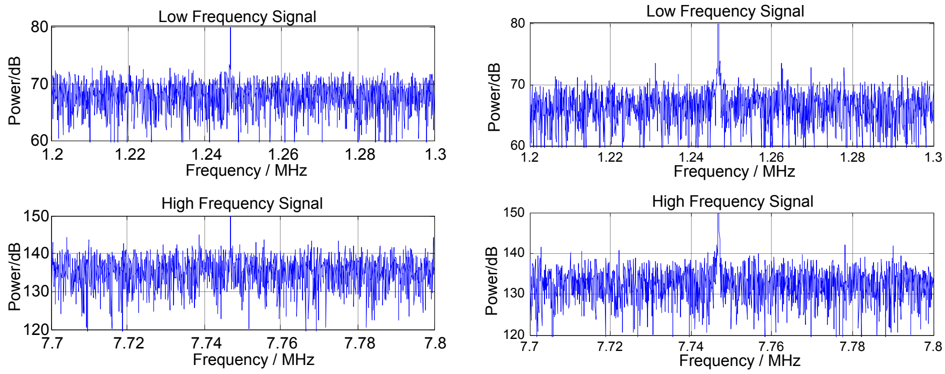


(a) (b)

Figure 4. RGR-RLS algorithm for different λ .(a) λ =0.6;(b) λ =0.3



(a)



(b)

Figure 5. ALE with RGR-RLS algorithm for different SNR.(a)-20dB;(b)-30dB