RFI REMOVAL FROM
AIRSAR POLARIMETRIC DATA

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Abstract

To facilitate the selection of the parameters used in the least-mean-square (LMS) adaptive filter to remove radio-frequency interference (RFI) in wideband radars, this paper describes the techniques that relies on the signal's statistics such as its spectral power or higher-order correlation. In particular, the Automatic Gain Control (AGC) is incorporated into the conventional LMS algorithm to equalize for the variation in the signal's amplitude, and to remove the trade-off between the convergence speed and the final misadjustment, inherited in the conventional LMS algorithm.

1. Introduction

In a previous paper [1], the LMS adaptive filter has been applied to remove RFI in wideband radars (AirSAR, GeoSAR) with good results. However, one of the constraints that prevents the use of the software in an operational mode is the judicious choice of the values of the parameters. Also, the conventional LMS algorithm, despite of its simplicity, robustness, and ease of implementation, has some drawbacks. When a fixed step size is used in the adaptation, the algorithm has a trade-off between the convergence speed (inversely proportional to the step size) and the final misadjustment (directly proportional to the step size) [2, 3]. The higher the convergence speed the greater the misadjustment, and vice versa. Various attempts were made to improve the performance of the LMS algorithm. One popular approach is to employ a time-varying step size based on the signal's statistics, such as spectral power, second-order correlation, and higher-order statistics. The main idea is to use large values of the step size at the beginning of the adaptation process to speed up the convergence rate. As the algorithm converges toward its optimum solution, the magnitude of the step size is reduced correspondingly to ensure a low level of final misadjustment. In addition, SAR signal is usually tapered off at the far-end due to propagation. Thus, the signal appears quasi-stationary and calls for a variable step size parameter.

2. Review of the Conventional LMS Algorithm

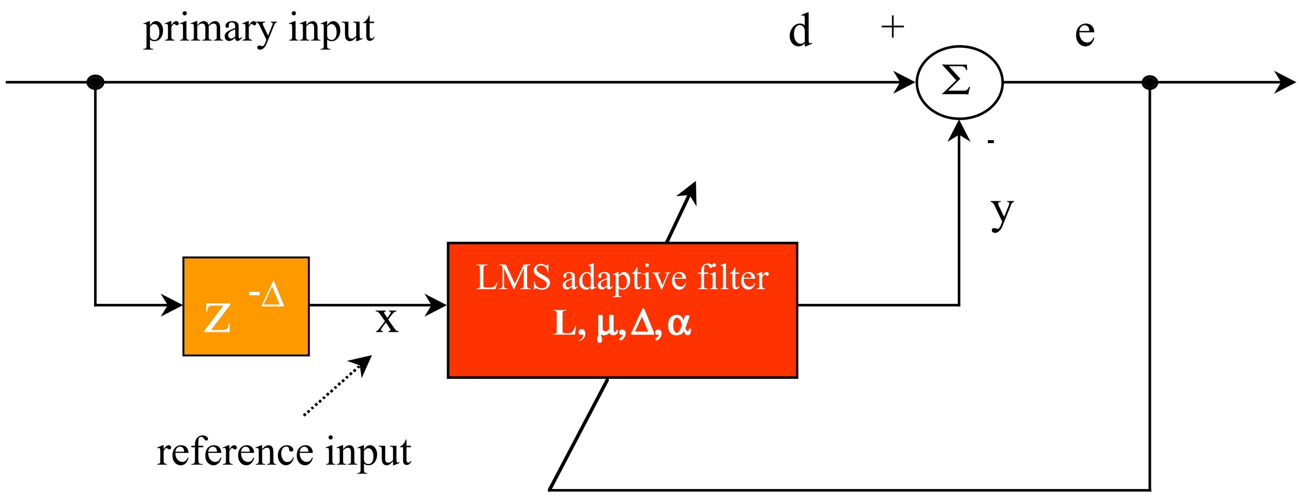

Fig. 1: The LMS adaptive algorithm.

Fig. 1 shows the LMS adaptive filter while Eqs. 1a, 1b, 1c, and 1d describe the conventional LMS algorithm

$$x[n] = d[n - \Delta] \tag{1a}$$

$$y[n] = \mathbf{w}[n] \bullet \mathbf{x}[n] \tag{1b}$$

$$e[n] = d[n] - y[n] \tag{1c}$$

$$w[n+1] = w[n] + \mu\, e[n]\, \mathbf{x}[n] \tag{1d}$$

where d is the received radar signal, x the reference function obtained by delaying the received signal by a time delay Δ(Eq. 1a)_, y the estimated RFI signal (Eq. 1b), $\boldsymbol{w}$ the adaptive weight vector of length L, e the prediction error which is the radar signal of interest (Eq. 1c), μ the step size parameter, and α the forgetting factor used in estimating the signal power. The weight update according to the LMS algorithm is given in Eq. 1d. Note that in the conventional LMS algorithm, the step size parameter μ is a constant.

The behavior of the LMS adaptive filter has been extensively studied and well published in the literature (see [2, 3, 4] and the references therein). Here, we only give a summary of the main features and important results. Let λ_n be the eigenvalues associated with the input correlation matrix $\boldsymbol{R}_{dd} = <\boldsymbol{d}[n]\boldsymbol{d}^H[n]>$, where d is an L-element input vector defined as d[n] = (d[n], d[n-1], … , d[n-L+1])^T with the superscript H and T denoting the complex conjugate and matrix transposes, respectively. Then, the learning time (convergence time) of the adaptive filter for each mode is

$$\tau_n = \frac{1}{4\mu\lambda_n} \tag{2}$$

With one sinusoid in white Gaussian noise, the convergence time can be expressed as

$$\tau = \frac{1}{2\mu\sigma_n^2\left(1 + \frac{L}{2} SNR\right)} \tag{3}$$

where σ_n is the average noise power and SNR is the signal-to-noise ratio. We note that in our RFI problem σ_n is the power of the radar signal, that is, the radar signal is treated as noise as far as the adaptive filter concerns. The SNR will then be the interference-to-signal-to-noise ratio (ISNR). Another important parameter is the final misadjustment error (after convergence). It is defined to be the ratio of the mean-squared error produced by the LMS algorithm to the minimum mean-squared error produced by the optimum Wiener filter. Its expression can be approximated as

$$M = \frac{\mu L \lambda_{av}}{2} \tag{4}$$

where λ_{av} is defined as the average eigenvalue of the input correlation matrix $\boldsymbol{R}_{dd}$.

3. The Variable Step-Size (VSS) Algorithm

We recall that in the weight update equation (Eq. 1d) of the conventional LMS algorithm, the step size parameter μ is a constant. In the VSS algorithm, the step size is a function of time $\mu = \mu[n]$ according to different measures. It can be updated using the power of the error signal [5]

$$\begin{aligned} &\mu[n] = \alpha\mu[n-1] + \gamma e^2[n] \\ &\alpha \approx 0.97, \quad \gamma \approx 10^{-4} \\ &\mu_{\min}(\approx 0.01) \le \mu[n] \le \mu_{\max}(\approx 1), \end{aligned} \tag{5}$$

or using the auto-correlation of the error signal [6]

$$\begin{aligned} &\mu[n] = \alpha\mu[n-1] + \gamma\rho^2[n] \\ &\rho[n] = \beta\rho[n-1] + (1-\beta)e[n]e[n-1] \\ &\alpha \approx 0.97, \quad \gamma \approx 10^{-4}, \quad \beta \approx 0.99 \\ &\mu_{\min}(\approx 0.01) \le \mu[n] \le \mu_{\max}(\approx 1), \end{aligned} \tag{6}$$

or using the cross-correlation between the input and the error signals [7]

$$
\begin{aligned}
\mathbf{w}[n+1] &= \mathbf{w}[n] + g[n]\frac{e[n]\mathbf{x}[n]}{x[n]\bullet x^T[n]} \\
g[n-1] &= \alpha\rho[n] \\
\rho[n] &= \beta\rho[n-1] + (1-\beta)e[n]x_{avg}[n] \\
x_{avg}[n] &= \tfrac{1}{L}\sum_{i=1}^{L} x_i[n]
\end{aligned}
\tag{7}
$$

Fig. 2 illustrates the effectiveness of the VSS algorithms in removing the RFI energy from the received signal. Data were obtained from the AIRSAR polarimetric system [8]. Note that this particular site presents a heavily RFI-contaminated environment to the wideband system. The conventional algorithm would have a hard time in cleaning the *dense* RFI spikes in the signal spectrum. However, the VSS algorithms not only effectively removed the RFI energy, but also faithfully preserved the spectral shape. Another example is shown in Fig. 3 where there appears to be a relatively *wideband* RFI source on the right side of the spectrum. A third example, with data taken from the GeoSAR system [9], compares the performances of the conventional and the VSS algorithms. Note some residual RFI remained from using the conventional algorithm, which was removed with the VSS algorithm.

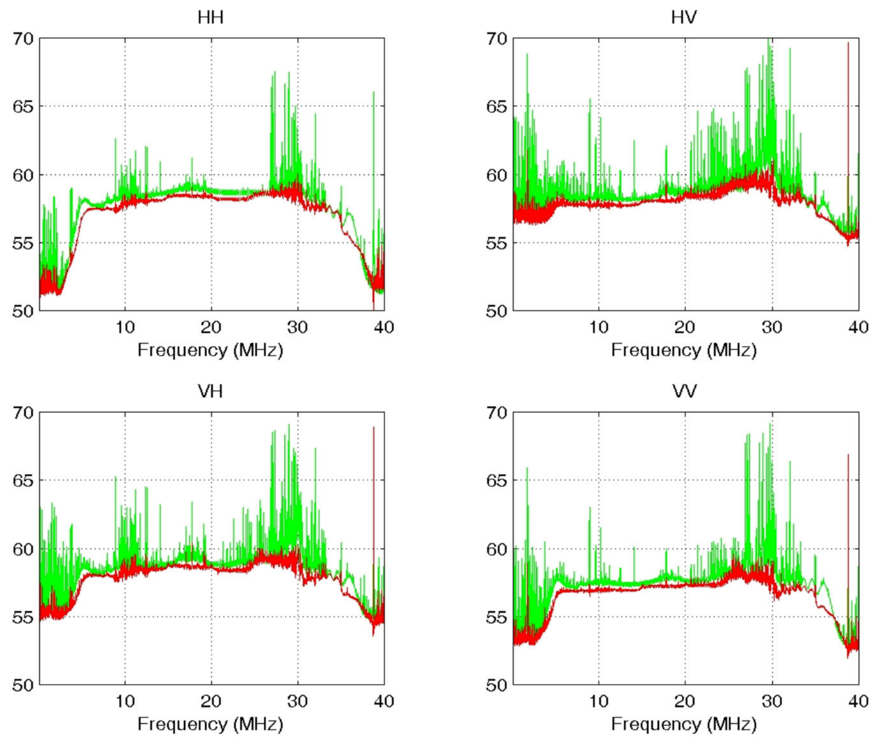

Fig. 2: Contaminated (green) and cleaned (red) signals in dense RFI environment.

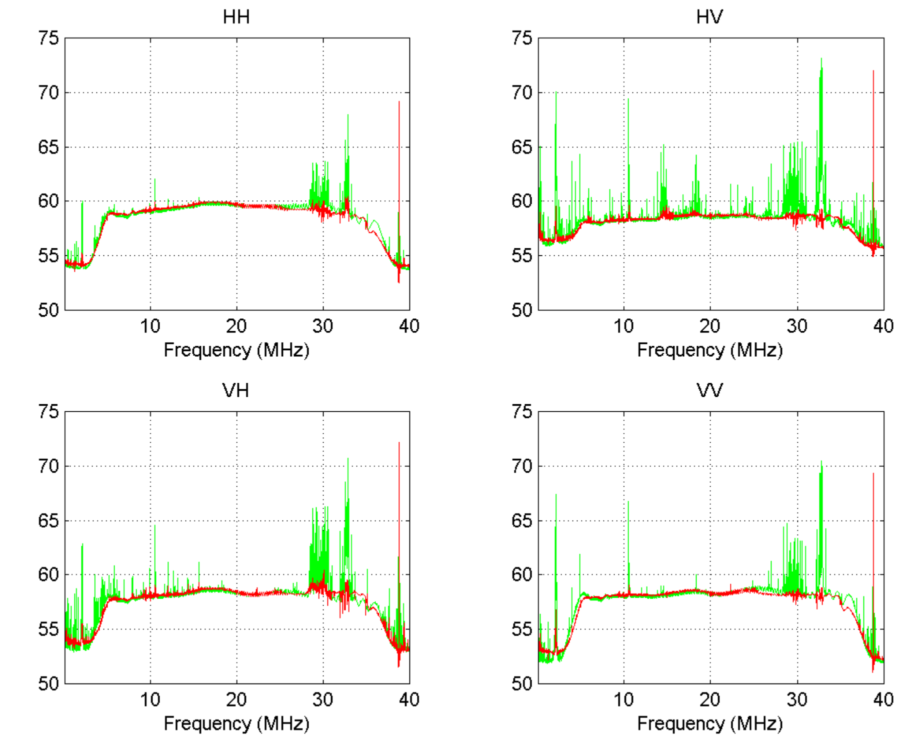

Fig. 3: Contaminated (green) and cleaned (red) signals in wideband RFI environment.

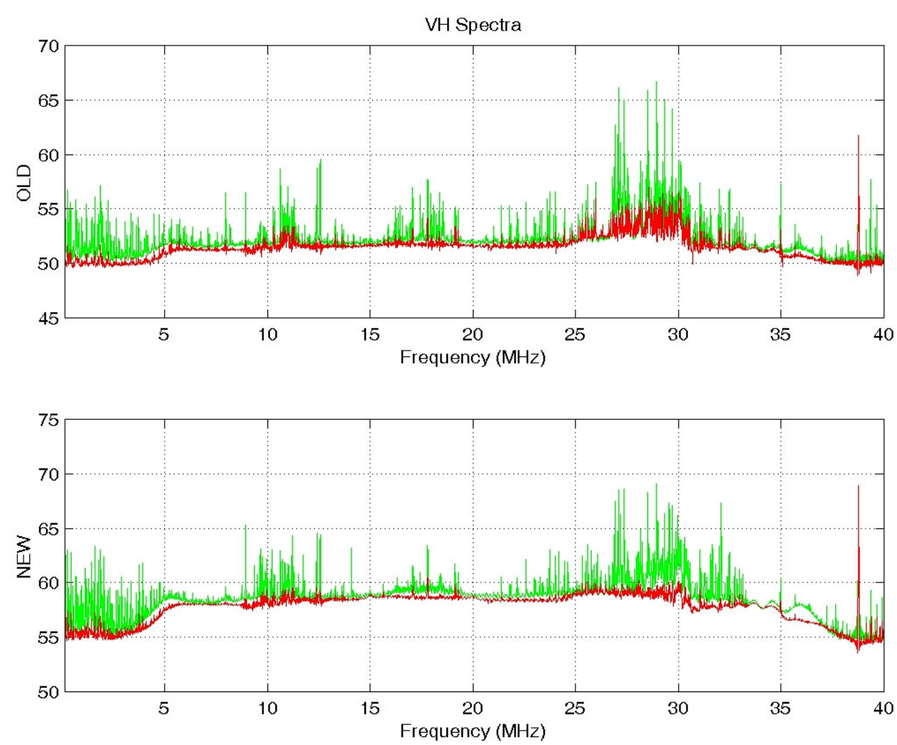

Fig. 4: Comparisons between the conventional (top) and VSS (bottom) algorithms.

4. Summary

Three techniques have been applied in this paper to remove the drawbacks inherited in the conventional LMS algorithm. The main idea is to use a time-varying adaptation step size, which takes large values at the beginning of the adaptation process to speed up the convergence, and switches to small values near the optimum solution to ensure a small final misadjustment. The techniques have been tested with AIRSAR and GeoSAR data with excellent results.

References

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