CHAPTER 8

A COMBINATION OF TWO ADAPTIVE ALGORITHMS

8.1 Introduction

A combination of two adaptive algorithms LMS and SMI is presented in this chapter. The simulation results are also provided to analyze the performance of the new combined algorithm. The previous discussions on LMS and SMI have provided us with an understanding of their advantages and disadvantages. In the combined algorithm the individual good aspects of both the algorithms are used.

LMS is a simple algorithm and is well suited for continuous transmission systems since it is a continuously adaptive algorithm. However, it is not known for its convergence speed, which has prompted people to use other complicated algorithms such as the *Recursive least square* (RLS) algorithm. SMI on the other hand has a very fast convergence speed as discussed in the earlier chapter. The speedy convergence is achieved because they use inversion of matrices, which makes it very computationally intensive. Also, the SMI algorithm has a block adaptive approach for which it is required that the signal environment does not undergo significant change during the course of block acquisition. Therefore there is a need for an algorithm, which is simple to implement yet has a fast convergence rate and is not computationally intensive. The algorithm featured in this chapter is an attempt in achieving this goal and we will be referred to as the SMI/LMS algorithm.

8.2 Formulation and characteristics

The SMI/LMS approach discussed here uses the merits of both the LMS and the SMI algorithm. In order to speed up convergence the initial weights are calculated by using the SMI algorithm. The SMI algorithm achieves this by directly calculating the inversion of the covariance matrix as illustrated by the following equation:

$$w_{opt} = R^{-1}r \tag{8.1}$$

where the covariance matrix R and the correlation matrix r is given $R = E[x(t)x^H(t)]$ and $r = E[d(t)x(t)]$.

The weights calculated here are only for the first few samples or for a small block of incoming data. Therefore the initial weight estimate equation can be re-written as

$$\hat{w}_{in} = \hat{R}^{-1}\hat{r} \tag{8.2}$$

The covariance matrix estimate $\hat{R}$ is given

$$\hat{R} = \sum_{i=1}^{b} x(i)x^H(i) \qquad \text{where } i \text{ is the time sample index.} \tag{8.3}$$

and the correlation matrix estimate $\hat{r}$ is given by

$$\hat{r} = \sum_{i=1}^{b} d^*(i)x^H(i) \tag{8.4}$$

where b is the block size and is taken to be small just to ensure that the effect due to the change in the signal environment during the block acquisition does not affect the performance of the algorithm. Also, a large block will only mean more matrix inversions making it computationally intensive.

In a regular LMS algorithm as described previously, weights are initialized arbitrarily and then updated using the LMS equation given here in equation 8.5. Since the weight initialization is arbitrary in regular LMS algorithm, it can take longer to converge because the initial weights may not be similar to the final solution.

$$w(n+1) = w(n) + \mu x(n)[d^*(n) - x^h(n)w(n)] \tag{8.5}$$

In the SMI/LMS algorithm $w(0)$, the initial weight for the above LMS update equation is equal to w_{in} obtained from the SMI algorithm. Therefore the weight initialization for LMS is not any arbitrary value but an estimate of the optimum value computed by the SMI algorithm. Before the LMS adaptation begins, depending on the initial weight estimate based on SMI algorithm, the antenna beam is already steered to an approximate direction of the desired signal. Henceforth LMS part of the SMI/LMS algorithm takes little time to converge. Also, after the estimation of the initial weight the SMI/LMS algorithm uses a continuous adaptive approach by updating the weights for every incoming sample and adapts itself to the changing signal environment. Since the initial convergence is faster SMI/LMS should take much less time than conventional LMS to adapt to the signal environment changes. Therefore SMI/LMS is better suited for continuous transmission systems. The basic SMI algorithm alone uses a block adaptive approach which makes it unsuitable for continuous transmission system.

8.3 Simulation setup

In order to compare the performance of the SMI/LMS algorithm with LMS and SMI algorithms individually, all the required simulation parameters and conditions in this algorithm are taken to be identical to those used for LMS and SMI simulations previously. For convenience they are re-iterated here.

For simulation purposes a 4-element linear array is used with its individual elements spaced at half-wavelength distance. The desired signal $s(t)$ arriving at θ_0 is a simple complex sinusoidal-phase modulated signal of the following form,

$$s(t) = e^{j\sin(\omega t)} \tag{8.6}$$

The interfering signals $u_i(t)$ arriving at angles are also of the above form. By doing so it can be shown in the simulations how interfering signals of the same frequency as the desired signal can be separated to achieve rejection of co-channel interference. However, Rayleigh fading is added to the incoming interfering signals. For simplicity the reference signal $d(t)$ is considered to be the same as the desired signal $s(t)$.

8.3.1 A beamforming example

It is assumed that the desired angle is arriving at 30 degrees and there are three interfering signals arriving at angles –20, 0 and 60 degrees respectively. The block size for the computation of the initial weights is considered to be 5, which is enough to estimate the initial weights. For these conditions the SMI/LMS algorithm is able to iteratively update the weights to force deep nulls at the direction of the interferers and achieve maximum in the direction of the desired signal. It can be seen that nulls are up to -70dB. The nulls formed by SMI/LMS algorithm are much deeper compared to the nulls formed by the LMS and SMI algorithms for the same situation. The error plot in figure 8.2 shows that the error is quite small during the initial iterations indicating that the initial weight estimate computed by the SMI method is quite close to the optimum value.

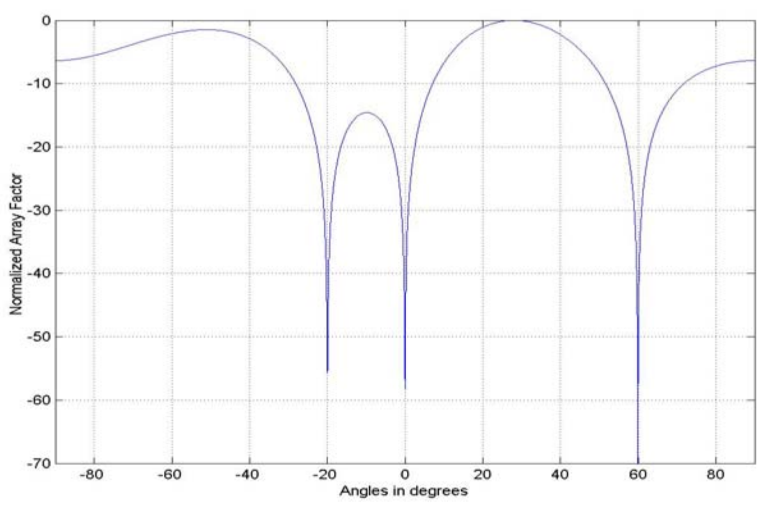

Figure 8.1 Normalized array factor Plot for SMI/LMS algorithm

The residual error is reduced by the LMS part of the algorithm which has to do very little to converge to the optimum value. Hence form the graph we observe that overall the SMI/LMS algorithm has a much faster convergence rate than the basic LMS algorithm (figure 8.3a). The inherent residual error found in the SMI algorithm (figure 8.3b) is also absent in SMI/LMS algorithm.

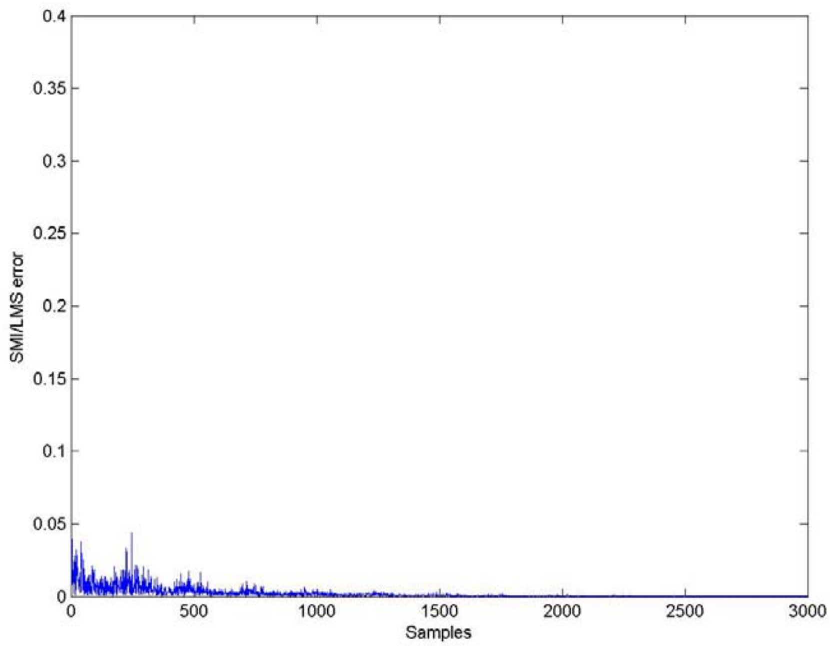

Figure 8.2 SMI/LMS error plot

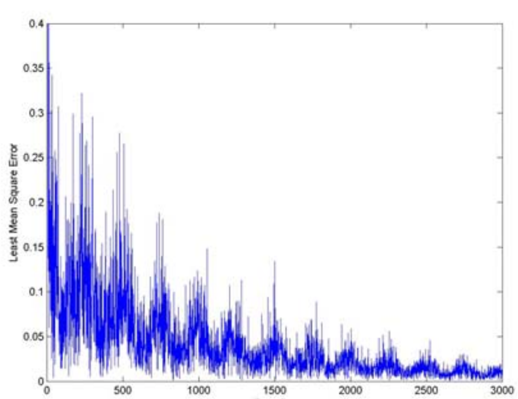

Figure 8.3a LMS error

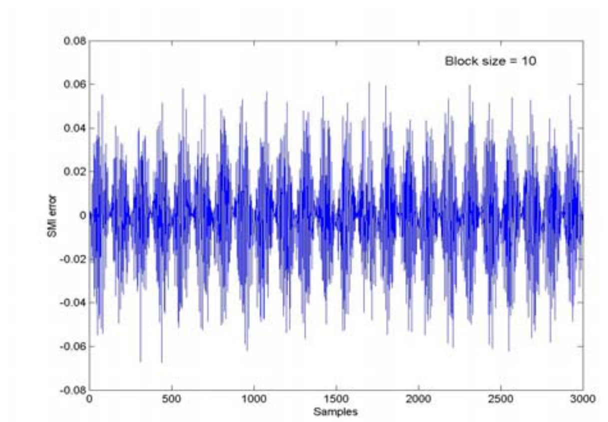

Figure 8.3b SMI error

In Figure 8.4 it is quite evident that the SMI/LMS algorithm is able to track the signal of interest quite efficiently with almost no error giving a direct indication of the performance of the algorithm.

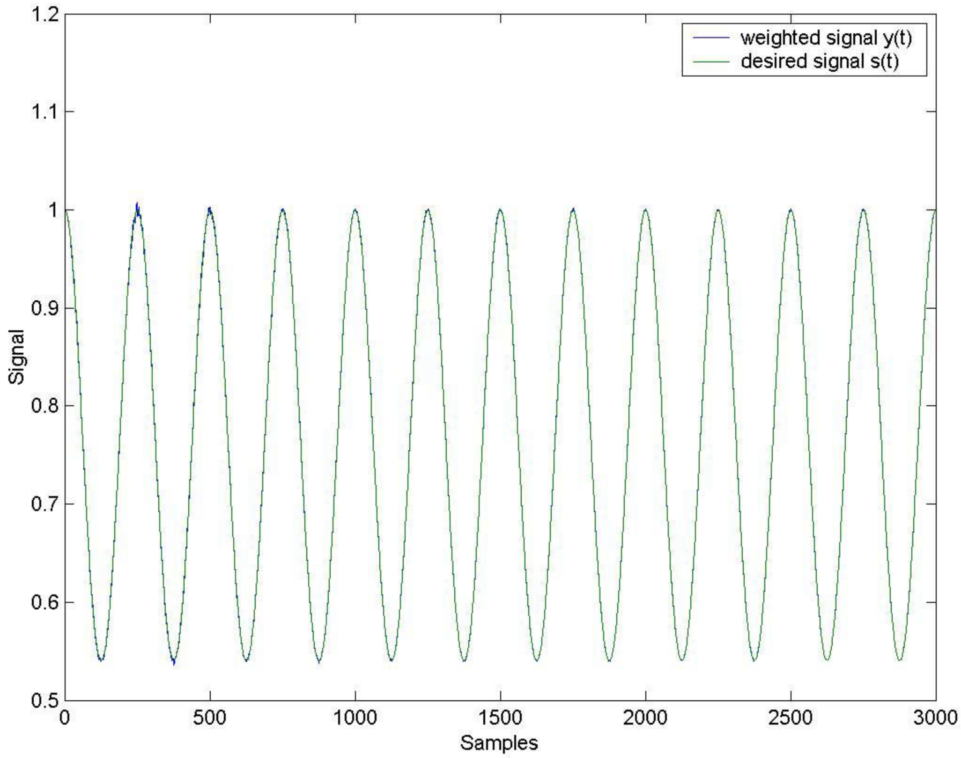

Figure 8.4 Output signal response for SMI/LMS algorithm