Abstract- In this paper, an efficient and simple adaptive beam steering technique is presented. The proposed method is based on Least Mean Square (LMS) algorithm, provides a comprehensive and detailed treatment of the signal model used for beam forming. In order to improve the convergence rate of LMS algorithm in smart antenna system, this paper proposes the Block Based Normalized LMS (BBNLMS) algorithm. The performance of the BNLMS algorithm in the presence of multipath effects and multiple users is analyzed using MATLAB simulations. Simulation results confirm that the convergence rate and error reduction of BBNLMS is superior to conventional LMS algorithm.

Keywords- Smart antenna, LMS, BBNLMS, Convergence Rate

I. INTRODUCTION

Smart antenna is the critical technique of the third mobile communication, while the core of smart antenna is adaptive algorithm research. Smart antennas can be used to achieve different benefits. Among those the most important is higher network capacity [1], [2] by precise control of signal nulls quality and mitigation of interference combine to frequency reuse reduction distance improving capacity. Assume that the interference is not stationary but moving slowly. For adaptive arrays, the conventional antenna pattern concepts of beam width, side lobes and main beams are not used, as the antenna weights are designed to achieve a set performance criterion such as maximization of the output SNR. On the other hand, in conventional phased array design these characteristics are specified at the time of design [3]. In order to increase the convergence rate, LMS algorithm is modified by normalization, which is known as normalized LMS (NLMS) [4]. Generally here we are comparing the LMS algorithm, NLMS algorithm and BBNLMS algorithms electronically. In this paper, we adapt BBNLMS algorithm to increase the convergence rate [5]. In Literature several smart antenna processing techniques were presented [6]-[13], to the best of author’s knowledge such an approach is not addressed in the array processing. In finally in our simulations we considered two received signals and three directions of arrivals (DOAs). Simulation results confirm that the proposed BBNLMS based beam steering is superior to conventional LMS algorithm in terms less error level and convergence rate.

II. ADAPTIVE BEAM FORMING

Most of the algorithms are concerned with the maximization of the SNR. A functional diagram of an adaptive array system is shown in Fig. 1 Adaptive arrays utilize sophisticated signal-processing algorithms to continuously distinguish between desired signals, multipath, and interfering signals, as well as calculate their DOA. This updates the changes in both the desired and interfering signal locations.

![Functional block diagram of an adaptive array system.](image)

The known signal is then compared with what is received, and the weights are then adjusted to minimize the Mean Square Error (MSE) between the known and the received signals. System capacity increases through lower inter-cell frequency reuse patterns as well as intra-cell frequency reuse.

III. ADAPTIVE ALGORITHMS

An adaptive filter is a transversal filter trained by an adaptive algorithm. The algorithm updates the weights at each iteration by estimating the gradient of the quadratic MSE surface and then moving the weights in the negative direction of the gradient

\[
\mu(n) = \min (\eta(n-1) \frac{\delta^2(n)}{\delta e(n)}, 1)
\]
by a minute amount. The constant that determines this amount is referred to as the step size ($\mu$). When this step size is small enough, the process leads these estimated weights to the optimal weights.

A. The Least Mean Square (LMS) Algorithm

Consider a L length LMS based adaptive filter in which ‘$W$’ is the weight vector updated in accordance with the statistical nature of the input signal $x(n)$ arriving from the antenna array.

An adaptive processor will minimize the error $e(n)$ between a desired signal $d(n)$ and the array output $y(n)$. The knowledge of the received signal eliminates the need for beam forming, but the reference can also be a vector which is somewhat correlated with the received signal. As shown in Fig. 1. The output response of the uniform linear array is given by:

$$y(n) = \hat{h}^H(n)x(n)$$ (1)

We consider the adaptive filter where the input signal $x(n)$ is convolved by an unknown $h(n)$ filter (to produce $y(n)$) which has an additive interference signal $v(n)$ before being observed as $d(n)$. The value of error signal estimation is $e(n)=d(n)-y(n)$. The estimated convolved signal $\hat{y}(n)$ we arrive at the recursion for the LMS adaptive algorithm for updating the step size:

$$h(n) = h(n-1) + 2\mu e(n)x(n)$$ (2)

where $\mu$ is constant step and the filter taps can be adaptively updated by using above recursive relation.

B. The Normalized Least Mean Square (NLMS) Algorithm

The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm which by passes this issue by selecting a different step size value, $\mu(n)$, for each iteration of the algorithm. This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector $x(n)$.

The standard (NLMS) algorithm is given by

$$e(n) = d(n) - h(n)x(n)$$ (3)

$$h(n) = h(n-1) + \frac{\mu}{\|x(n)\|^2} e^*(n)x(n)$$ (4)

Comparing (2) and (4), it is observed that update is a scaled version of regression vector $x(n)$, namely $\mu x(n)$. This increases the convergence rate. In (4) $\mu(n)$ is the variable stepsize.

The NLMS algorithm has a convergence rate and a steady state error better than LMS algorithm.

C. The Block Based Normalized Least Mean Square (BBNLMS) Algorithm

The additional computations required to compute $\mu(n)$ in (5) can be further reduced by using BBNLMS in which the input data is portioned in to blocks and maximum magnitude within each block is used to compute $\mu(n)$. Which this the weight update relation in (5) for $x_m \neq 0$ and $p = 0$ takes the following form

$$h(n) = h(n-1) + \frac{\mu}{x_m^*x_m} e^*(n)x(n)$$ (6)

Where $x_m$ is the maximum of $x(n)$ in the block. Using such an approach the number of multiplications reduces in the computation on $\mu(n)$. In addition to this, BBNLMS enjoys fast convergence rate as the normalization factor is maximum data sample of the block. Where as in NLMS normalization factor varies from sample to sample.

IV SIMULATIONS

To prove the ability of BBNLMS algorithm in adaptive beam forming we consider two transmitting training signals, each with three multipath components. The second and third multipath of both signals is set to arrive at the base station. This is the case with two white signals and three DOAs. The convergence characteristics of the various algorithms are shown in Figure 2. From this figure it is clear that BBNLMS and NLMS algorithms converge faster than the conventional LMS algorithm.

The mean square error for various algorithms is shown in Fig. 3. From the figure it is clear that the error amplitude decreases as we are moving from LMS to BBNLMS algorithm. We can say that convergence starts for LMS approximately after 300th sample, where as for NLMS algorithm it is approximately after 200th sample, superiorly for BBNLMS convergence starts approximately after 45th sample. More ever among all algorithms BBNLMS has minimum error level.
In our simulations we have considered the case of two received signals with three DOAs. The transmission of two different signals with one DOA each is in effect the same as sending one signal with two multipath separated by at least one sample period. This is because in both situations the two signals are uncorrelated with each other. The 1st signal is exposed to gain with amplitude 0.5 and the 2nd signal 1.0. These results vary to a certain degree, when compared to the BBNLMS algorithm shown in Fig. 9. The 3rd multipath of signal 1, is made weak in order to limit the interference caused by the 1st and 2nd multipath of signal 2. The result of which is the increased signal power in the direction of 30°. Similarly, the reason for the 3rd multipath of signal 2 being weak is due to presence of nearby DOAs.

V. CONCLUSIONS

In this paper several beam forming algorithms are presented with some simulations and results. Using NLMS and BBNLMS algorithms, compared to LMS algorithm, a 100% and 1455% increase in overall convergence rate is achieved in a multi user multipath environment. With regards to beam patterns, NLMS and BBNLMS algorithms are able to steer beams in the direction of the desired signal and place nulls elsewhere.
Fig. 6. Received signal error with 2 signals and 3 DOA’s each for NLMS algorithm.

Fig. 7. NLMS: polar plot for 2 signals and 4 DOA’s each.

Fig. 8. Received signal error with 2 signals and 3 DOA’s each for BB-NLMS algorithm.

Fig. 9. BB-NLMS: polar plot for 2 signals and 3 DOA’s each.

REFERENCES


