3G

Analysis of the Wavelet Adaptive Algorithm in Smart Antenna System for 3G
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Abstract—This article is based on the analysis of traditional LMS algorithm, replacing the previous moment gradient with the current one is to be modified LMS (MLMS) algorithm. In order to improve its convergence rate, we proposed the algorithm based on wavelet transform. Processed by the wavelet transform, the correlation of the signal will decline, the convergence speed will improve, and also to the signal de-noising. The simulation results show that the algorithm has good stability, fast convergence rate. Under the big step factor it can also be diminished, and also meets the real-time requirements. At the same time, we do the simulation of the algorithm applied in the smart antenna system, the results show that the system has a smaller and stable bit error rate.

Keywords—wavelet transform; MLMS; array signal processing; bit error rate; Antenna Array

I. INTRODUCTION

Adaptive technology has been applied in the areas such as aerospace, aviation, radar and communications. Adaptive beam-forming technology changes the direction of the array pattern by adjusting the weight amplitude and phase to make the main lobe of the antenna array aligned desired users, null lobe and side lobe aligned interference signals, thereby improving signal to noise ratio to achieve the best reception under certain criteria [1,2]. Researchers has done a lot of works to get different applications [3,4]. LMS algorithm has the advantage of simple structure, low complexity, easy to implement, and good stability, but slow convergence comes its biggest drawback, this is because the convergence speed depends on the input signal autocorrelation matrix eigenvalue divergence, the greater the divergence, the slower it converges. In addition, In addition, the step length factor has a great influence on the convergence speed. Small can reduce the gradient noise, but the slow convergence speed; large can speed up the convergence rate, but it will increase the gradient noise and steady-state offset. In order to improve convergence speed, the frequency-domain approach has been promote to the transform domain, and has been widely used. The emergence of the theory of wavelet has been a new method for transform domain algorithms with its good time-frequency characteristics. Signals by the wavelet transform was a special zonal distribution, thus can improve the convergence speed, and effectively remove Gaussian white noise [5]. In smart antenna system, different direction of arrival (DOA) corresponds to a different airspace resolution at a fixed spacing of the array, so the signal with a multi-resolution feature, which is the basis for this paper to use wavelet theory.

Smart antenna is one of the main techniques for 3G, it has been applied in TD-SCDMA, WCDMA and CDMA2000 systems. This article will propose a new adaptive algorithm and apply it to the smart antenna array. The auxiliary pilot signals have been used for getting the weight vector. By simulation we find that the algorithm yields a good performance.

II. SMART ANTENNA ALGORITHM

A. The traditional MLMS

LMS algorithm is based on the mean square error criteria, the gradient vector of \( J(n) = E[e^2(n)] \) is replaced with the instantaneous estimates, that is:

\[
\nabla = \frac{\partial J(n)}{\partial \omega} = 2R\omega - 2r
\]

Where \( R = E[x(n)x^T(n)] \), \( r = E[d(n)x(n)] \), according to the LMS, we can get the best weight vector is \( \omega_0 = R^{-1}r \), and further we get \( \omega_0 = \omega - \frac{1}{2}R^{-1}\nabla \), so the iterative form can be written as:

\[
\omega(n+1) = \omega(n) - \frac{1}{2}R^{-1}\nabla(n)
\]

In practice, we replace \( \nabla(n) \) with gradient estimate \( \hat{\nabla}(n) \), we use the current estimated value of the gradient to replace the one of previous moments [6], and get a new form as:

\[
\omega(n+1) = \omega(n) + \mu R^{-1} e(n+1) x(n+1)
\]

Where \( \mu \) is gradient step size that controls the convergence characteristic of the algorithm, \( e(n+1) = d(n+1) - \omega^T(n+1)x(n+1) \), so (3) can be written as:

\[
\omega(n+1) = \omega(n) + \frac{\mu R^{-1} x(n+1)e(n+1)}{I + \mu x^T(n+1)R^{-1}x(n+1)}
\]

B. MLMS algorithm in Wavelet domain

Wavelet domain beamforming algorithm structure is shown in Fig. 1. According to wavelet theory: The function \( f(x) \) can
be expressed in $L^2(R)$ with a series of wavelet functions $\psi_{j,k}(n)$ and Scaling functions $\phi_{j,k}(n)$. Signals obtained after the wavelet transform is a sparse matrix. Therefore, its convergence speed is much quicker, and because the maximum modulus of the signal and noise is completely different at different scales of wavelet transform, so it also can signal de-noising.

$X(n) \xrightarrow{\text{Wavelet transform}} r(n) \xrightarrow{\text{MLMS}} Y(n)$

Figure 1. Wavelet domain beamforming algorithm structure

When the BS uses a smart antenna to receive the signals, the signal that arrives at the BS can be written as:

$$x(n) = \sum_{l=1}^{L} \sum_{j=1}^{J} \sum_{k=1}^{M} \beta_{l,j,k} \alpha(\theta_{l,j,k}) S_l(t - \tau_{l,j,k}) + \sum_{l=1}^{L} \sum_{j=1}^{J} \sum_{k=1}^{M} \beta_{l,j,k} \alpha(\theta_{l,j,k}) S_l(t - \tau_{l,j,k}) + n(t)$$

(6)

Where $S_l(t - \tau_{l,j,k})$ denotes the desired signal form of the $l$ th path, $S_l(t - \tau_{l,j,k})$ denotes the interfering signals of $k$ th user from the $l$ th path, and $n(t)$ is the noise vector. The parameter $K$ in (6) represents the number of users, $\beta_{l,j,k}$. $\theta_{l,j,k}$, $\tau_{l,j,k}$ denote the channel fading Amplitude of $k$ th user in the $l$ th path, and the direct arrived angle (DOA), time delay, respectively. The notation $\alpha(\theta_{l,j,k})$ is an array response vector, which can be written as:

$$\alpha(\theta_{l,j,k}) = \left[1, e^{-j2\pi \mu_{\min}(\theta_{l,j,k})}, \ldots, e^{-j2\pi \mu_{\min}(\theta_{l,j,k})} \right]^T$$

The output of the antenna array is

$$y(n) = \sum_{k=0}^{M-1} \alpha_k x(n-k)$$

(7)

We define

$$a_i(n) = \sum_{j=1}^{J} \sum_{k=1}^{M} d_{j,k} \psi_{j,k}(n) + \sum_{j=1}^{J} \sum_{k=1}^{M} c_{j,k} \phi_{j,k}(n), i=0,1,...,M-1$$

(8)

where $M$ is the antenna number, $J$ is the maximum scaling function, $k = M/2$ the largest transfer of wavelet function under $J$, $d_{j,k}$ and $c_{j,k}$ can reflect the characteristic of $W(n)$.

According to the theory above, we can get a former as follows:

$$y(n) = W^T(n)v(n)$$

(9)

Where $y(n) = PX(n), W(n) = [\phi_{0,n}(n), \phi_{1,n}(n), \ldots, \phi_{M-1,n}(n)]^T$, $X(n)$ is the input signals, $P$ is a matrix composed of Wavelet functions and scaling functions, usually we use a pair of filters $g$ and $h$ to present the orthogonal waves, so $P = \{g_{0}, g_{1}, g_{2}, \ldots, h_{0}, h_{1}, h_{2}, \ldots\}$ is a orthogonal matrix.

So the algorithm can be described as: the output of the wavelet transform is $v(n) = PX(n)$, the output of the antenna array is $y(n) = W^T(n)v(n)$, $W^T(n)$ is the weight vector $e(n+1) = \alpha(n+1) - y(n+1)$, and $\alpha(n+1) = \alpha(n) + \frac{\mu R_0^{-1}}{1 + \mu x^T(n+1)R_0^{-1}x(n+1)} x(n+1)$.

In the algorithm above, the convergence rate depends on the autocorrelation matrix of $v(n)$, that is $\hat{\lambda}_{\max} / \hat{\lambda}_{\min}$, the smaller it is, the faster it converges. We Suppose that $R_v$ and $R_s$ is different, so we can get:

$$R_v = Q_v \Lambda_v Q_v^T = R_s Q_s \Lambda_s Q_s^T = B \Lambda_s B^T$$

(10)

where $Q_v, Q_s, \Lambda_v, \Lambda_s$ denote the eigenvector and Eigenvalue diagonal matrix of $R_v$ and $R_s$, respectively. As $0 \leq \lambda_{\min} \sum_i b_{k,i}^2 \leq \lambda_{\max} \leq \lambda_{\max} \sum_i b_{k,i} + b_{k,i}$ is the $(k,j)$ number of $B$. So $\hat{\lambda}_{\max} / \hat{\lambda}_{\min}$, which means the convergence rate has been improved.

III. SIMULATION

To verify the performance of the wavelet domain adaptive LMS algorithm, we conducted an experimental simulation and performance comparisons. In the simulation, we take 4 ULA SA system, array space is set to be $\lambda/2$, SNR is 20dB, we also assume there are 64 auxiliary pilot symbols in one slot, and the total number of data $N=26$, Fig. 2 shows the Mean square error curve of the two algorithms when $\mu = 0.005$. From the figure, we can find that both the two algorithm converge when the data number goes beyond 1200, but though the wavelet transform, the convergence rate is greatly improved.

Figure 2. The Learning Curve of the LMS and wavelet LMS

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Fig. 3 and Fig. 4 show the advantages of the new algorithm. From the figure below, we conclude that the wavelet modified LMS can converge quickly under big gradient step size.

In the simulation, we assumed there were only one path. Fig. 5 and Fig. 6 show the performance of the algorithm proposed above. Fig. 5 shows the BER rise by the interfering users increased, and Fig. 6 describes the BER degradation by SNR changed. Both of the two figure prove that the BER is much lower than one element omni-antenna communication system, which means the performance of the system is improved by using SA.

IV. CONCLUSION AND FUTURE WORK

The paper puts forward the wavelet domain LMS, using wavelet transform pre-processing the input signals, then achieving smart antenna algorithms. It takes the advantage of the declination of the signal autocorrelation by wavelet transform to improve the convergence speed. In addition, the wavelet transform can also signal de-noising. Theoretical analysis and simulation results show that the algorithm has a faster convergence rate. The algorithm is applied in the four array elements smart antenna systems. Though simulation results, we found that the output bit error rate of SA system with adaptive algorithm is smaller and more stable than the single-antenna one. As the space-time codes is popular, next, we are going to introduce the decode method to the system, and study the performance improvement. Further research will be done along the live.

This paper proposes a 3D reconstruction using projection of virtual height line based on dynamic programming. The simulation and experimental results are given to show the proposed method is feasible and effective. In our future work, we will focus on real-time implementation and error analysis.

REFERENCES


