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Investigation of Blind Multi-User Detection Technology

Investigation of Blind Multi-User Detection Technology

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Abstract. Blind multi-user detection algorithm is an effective method to overcome multi-access interference and influence of near-far effect. This paper briefly describes commonly used algorithms of blind multi-user detection technology, introduces the application of the least mean square algorithm (LMS) and compares the performance with other algorithms. Aiming at the shortcomings of the LMS algorithm, the variable step size LMS algorithm and the relatively low complexity LMK algorithm based on the change of the input signal vector are studied.

1. Introduction

Blind multi-user detection is a technology developed in the processing of communication signals in recent years. The Least Mean Square (LMS) algorithm is widely adopted in blind adaptive multi-user detection and it is mainly simulated and analyzed in this paper. The LMS algorithm is easier to implement and can automatically track the changes of system. However, the convergence step of the fixed step-size adaptive algorithm is related to the matrix eigenvalue of the input signal.

To this regard, a variable step-size LMS algorithm is proposed in this paper, which overcomes the defect that the convergence step of the fixed step-size adaptive algorithm is related to the matrix eigenvalue of the input signal, so that the step size of the new algorithm can change with the change of the input signal vector. Based on simulation and analysis, it is demonstrated that the improved algorithm has better convergence performance.

Another improved algorithm is LMK algorithm, the convergence performance of which is better than that of LMS algorithm, but has little computation requirement[1]. It is an adaptive multi-user detection algorithm based on high-order statistics that can be adopted in reality. Besides, by means of LMK structure, a blind adaptive detection algorithm that can be used in multichannel is put forward. Through the analysis of the algorithm, it is proved that the algorithm conforms to decorrelation, and has a relatively low complexity for implementation[2].

2. Blind Multi-user Detection Algorithm Based on LMS

The Least Mean Square (LMS) algorithm[3] is an iterative algorithm which takes the minimum mean square error between the filtered output signal and the expected response as the criterion, and updates the weight coefficient according to the estimated gradient vector of the input signal in the iterative process, so as to achieve the best adaptive value.

The cost function is taken as

$$J(i) = \min_{c_k} \arg E\left\{< \boldsymbol{r}, \boldsymbol{c}_k >^2\right\} \tag{1}$$

In order to ensure the convergence of the algorithm, the step-size μ should meet the following conditions

$$\mu < \frac{2}{\sum_{n=1}^{N} A_n^2 + M\sigma^2} \tag{2}$$

M is spread spectrum gain and σ^2 is background noise.

The learning curve is defined as the relationship between the mean square error and the number of iterations. If the step size is smaller, the fluctuation amplitude on the attenuation curve will decrease, that is, the smoothness of the learning curve will be better.

3. Two Improved Algorithms Based on LMS

3.1. Blind adaptive LMK algorithm

The detector model in figure 1 is adopted. x and s_1 is perpendicular to each other so $x \cdot s_1^T = 0$ and the judgment amount is $z = r \cdot (s_1 + x)^T$. The cost function based on LMK criterion[4]is used to adjust the orthogonal components x

$$J(w) = 3[E(e^2)]^2 - E(e^4) \tag{3}$$

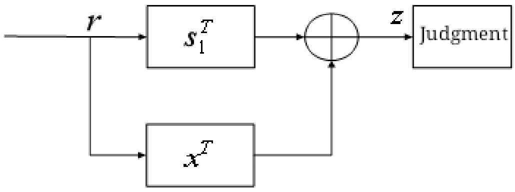

Figure 1. Detector model

Mean square error $e = wr^T - A_1 b_1$, $w = s_1 + x$ .Based on $e = wr^T - A_1 b_1$, $w = s_1 + x$,through b_k , $k = 1,2,\cdots,$,the mutual independence between K and n,and the constraint condition $ws_1^T = 1$, consider $E[(wr^T)b_1] = A_1$,it can be obtained that:

$$J(w) = 3[E(wr^T)^2]^2 - E(wr^T)^4 - 2A_1^4 = J_B(w) - 2A_1^4 \tag{4}$$

It can be seen from the formula mentioned above that if $J_B(w)$ is used as the cost function, blind adaptive detection is achieved without the need to know the power information of user 1 and to train it in advance.

$$J_B(w) = 3[E(wr^T)^2]^2 - E(wr^T)^4 \tag{5}$$

The LMK algorithms mentioned above are all based on AWGN channel. Considering the asynchronous and multipath conditions of DS / CDMA system in reality, the LMK algorithm is adopted to the multipath channel[5-6].

Suppose the first user is the demand user. In multipath channel, the cost function is taken as

$$J_{LMK}(w) = 3[E(|w^H r|^2)]^2 - E(|w^H r|^4), \quad w^H s_1 = 1 \tag{6}$$

The weight w of the filter is determined by the following optimization problem

$$w_{opt} = \min_{w^H s_1 = 1} J(w) \tag{7}$$

The convergence performance of the system without noise is considered here, that is, $\sigma = 0$. Assuming $u_i = A_i w^H s_i$, $\boldsymbol{u} = [u_1, \cdots, u_K]^T$, b_i takes a random variable with a value of ± 1 , it is obtained that:

$$J_{LMK}(\boldsymbol{u}) = 2[\sum_{i=1}^{K}(a_i^2 + b_i^2)]^2 - 4\sum_{i=1}^{K}\sum_{j=i+1}^{K}(a_i a_j + b_i b_j)^2 \tag{8}$$

Next, the steepest descent method is used to achieve the blind adaptive implementation of the algorithm, it is obtained that:

$$\nabla J_{LMK}(w_l) = 12[w_l^H E(rr^H)w]E[(w_l^T r)r] - 4E[(w_l^H r)^3 r] \tag{9}$$

Assuming $\boldsymbol{W} = [w_1, w_2, \cdots, w_L]$, and $\boldsymbol{W}$ is a $N \times L$ matrix, the constraint can be expressed as $\boldsymbol{W}^H \boldsymbol{S}_1 = \boldsymbol{I}_L$, $\boldsymbol{f}(n) = [f_1(n), f_2(n), \cdots, f_L(n)]^T$ is the weighted vector of branch output, then the weight vector of the whole multi-user detection receiver can be expressed as

$$\boldsymbol{w}(n) = \boldsymbol{W}(n)\boldsymbol{f}(n) \tag{10}$$

Based on (10) and the constraint $w^H(n)s_1 = 1$, it is known that the optimal value of $\boldsymbol{f}(n)$ should be equal to the channel parameter vector $\boldsymbol{h}_1$. Because of the unknown value of $\boldsymbol{h}_1$ in general, the maximum ratio combination method is selected to maximize the output of the receiver, and $\|f\| = 1$, that is:

$$\boldsymbol{f} = \arg\max_{\|f\|=1} \boldsymbol{f}^H E\{\boldsymbol{y}\boldsymbol{y}^H\}\boldsymbol{f} = \arg\max_{\|f\|=1} \boldsymbol{f}^H \boldsymbol{R}_{yy}\boldsymbol{f} \tag{11}$$

Where $\boldsymbol{R}_{yy} = E\{\boldsymbol{y}\boldsymbol{y}^H\}$, the optimal value is the eigenvector corresponding to the maximum eigenvalue of R_{yy}. SVD decomposition or fast subspace decomposition algorithm can be used to solve the equations. The complexity of SVD decomposition algorithm[7]is $O(L^3)$, where L dimension is the maximum path, and the computational complexity of general fast subspace eigenvalue decomposition is $O(L)$. In this algorithm, the complexity of the algorithm is $O(N)$ for each path, and the complexity of the whole algorithm is $O(NL)$. The performance of this algorithm is consistent with the decorrelation, and the implementation complexity is relatively low.

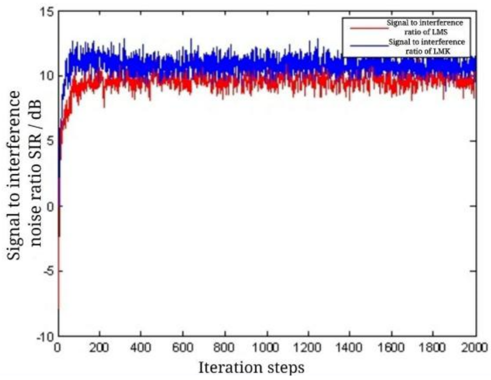

Figure 2. SIR comparison of LMS and LMK algorithm

From the SIR comparison of LMS and LMK in the figure above, it can be seen that the signal to interference ratio of LMK is higher than that of LMS, and the performance of LMK algorithm is better than that of LMS algorithm.

3.2. Variable step-size LMS algorithm and its simulation

The convergence rate of LMS algorithm is related to the step size μ selected in the algorithm. In order to achieve fast convergence, it is necessary to select the appropriate step size $\mu[i]$ by reducing the instantaneous output energy as much as possible. The variable step-size LMS algorithm is mainly introduced in the following part.

The instantaneous output energy is

$$\boldsymbol{E}_0[i] = \boldsymbol{c}^T[i]\boldsymbol{r}[i] = ((\boldsymbol{s} + \boldsymbol{x}[i] + \mu[i]z[i](\boldsymbol{r}[i] - z_{MF}[i]\boldsymbol{s}_k))^T \boldsymbol{r}[i])^2 \tag{12}$$

To increase the speed of convergence, it is necessary to select appropriate $\mu[i]$ value to minimum the output energy. And make the derivative of $\mu[i]$ equal to zero to obtain the variable step-size of LMS algorithm.

$$\mu[i] = \frac{(\boldsymbol{s}_k + \boldsymbol{x}[i])\boldsymbol{r}^T[i]}{z[i](\boldsymbol{r}[i] - z_{MF}[i]\boldsymbol{s}_k)\boldsymbol{r}^T[i]} \tag{13}$$

The essence of this variable step-size LMS algorithm is that the step size of LMS algorithm changes according to the change of input signal vector. When the input signal vector is small, the step size is large, which ensures the convergence speed of the algorithm. When the input signal vector is large, the step size is small, which ensures the stability of the algorithm convergence.

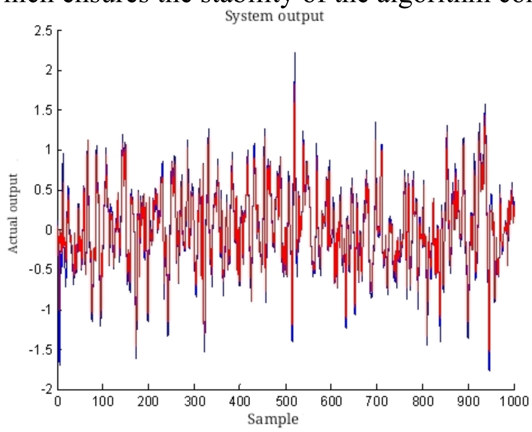

Figure 3.The fluctuation figure of actual signal output and the system output

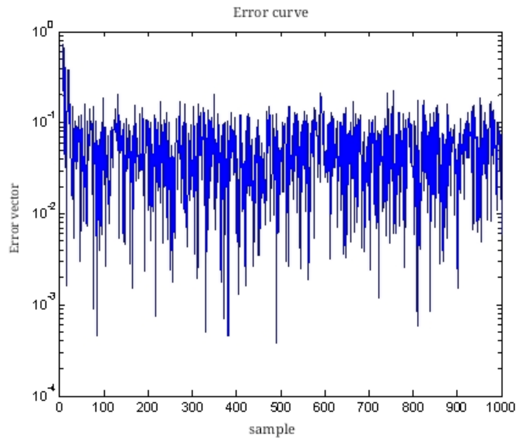

Figure 4. The error curve convergence with the number of sampling

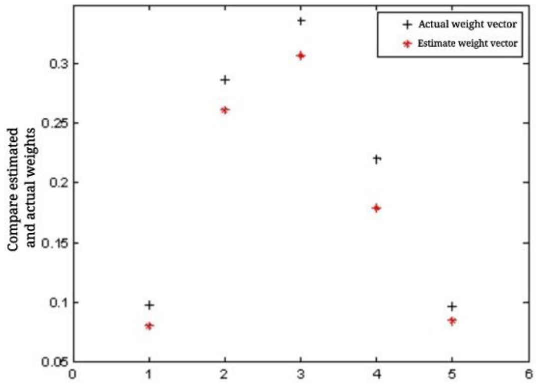

Figure 5. The error of actual right vector and estimate the right vector

The figure above is the MATLAB simulation of NLMS algorithm. It can be seen from figure 6 that the output of the actual signal fluctuates within the range of 0 point of the coordinate, and most of the output of the system fluctuate within (- 0.5, 0.5), a small number of signal fluctuate outside, and the fluctuation range decreases with the increase of sampling times of N. It can be seen from figure 7 that with the decrease of step size parameter, the convergence rate of LMS also decreases, which affects the change of learning curve. At the same time, the component of error curve converges to 10^{-1} with the change of iteration times of n, and it becomes more obvious with the increase of N Therefore, compared with the learning curve of LMS, LMS algorithm has better performance. From figure 8, it can be seen that there is a great error between the actual weight vector and the error weight vector, and the error vector always fluctuates around the actual weight vector. With the increase of N, there is a smaller error between them, and the the error change is much smaller than that of LMS.

The convergence condition of NLMS has nothing to do with the eigenvalue of the input signal, meanwhile, when the input signal is speech, the convergence rate of NLMS algorithm is faster than that of LMS algorithm, and the robustness is better. In terms of computation, NLMS algorithm has the same amount of computation as LMS. Therefore, NLMS algorithm is more widely used than LMS algorithm[8].

4. Conclusion

This paper mainly introduces the blind adaptive multiuser detection algorithm for multiple access interference and near far effect. In the research of blind adaptive multi-user detection technology, LMS algorithm has low complexity and is easy to implement, besides, it can automatically track the changes of the system[9].However, the convergence rate of the algorithm is related to the step size μ selected in the algorithm. The improved LMK algorithm has low computational complexity and is based on high-order statistics. In this paper, LMK algorithm is applied to multi-user signal detection in Synchronous DS / CDMA system[10], which achieves relatively low complexity. For the LMS algorithm with fixed step size, a time-varying convergence coefficient is set to make the step size larger at the initial stage of convergence[11], and the convergence speed is fast, and then it decreases rapidly to reduce the error. The improved variable step size LMS algorithm can reduce step size and improve system performance when strong interference occurs. The improved LMK algorithm and fixed step size LMS algorithm have better performance than LMS algorithm.

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