A new blind adaptive method using RLS algorithm with Decision direction method

Tae-song Kwon[1], Sung-kyun Yoo and Kyung-sup Kwak[2]
[1] Department of Electronics Engineering, Inha University,
YongHyun Dong, Nam Gu, Incheon, Korea
e-mail : signal37@hanmail.net
[2] The Graduate School of Information Technology&Telecommunication,
Inha University,
YongHyun Dong, Nam Gu, Incheon, Korea
Tel. +82-32-864-8935, Fax.: +82-32-876-1212

Abstract: RLS algorithm is a kind of the adaptive algorithms in smart antennas and adapts the weight vector using the difference between the output signal of array antennas and the known training sequence. In this paper, we propose a new algorithm based on the RLS algorithm. It calculates the error signal with reference signal derived from blind scheme. Simulation results show that the proposed algorithm yields more user capacity by 67~74% than other blind adaptive algorithms(LS-DRMTA, LS-DRMTCMA) at the same BER and the beamformer forms null beams toward interference signals and the main beam toward desired signal.

1. Introduction

The increasing demand for mobile communication capacity in limited RF spectrum motivates the need for new techniques to improve spectrum utilization. One approach for increasing spectrum efficiency is a kind of adaptive array antennas. By using the adaptive antenna array in a CDMA system, the amount of co-channel interference from users within the same cell as well as neighboring cells can be reduced, and therefore the system capacity can be increased. There exist many adaptive algorithms that can be used to adapt the weight of the adaptive antennas array[1][2][3]. Adaptive algorithms renew the weight vector with the error signal from the difference between the output signal of array antennas and the training sequence transmitted from transmitter, but the blind adaptive algorithm calculates the error signal from the reference signal produced by output signal instead of training sequence. If the average probability of symbol error is small(less than 10 percent), the decisions made by the receiver are correct enough for the estimates of the error signal(used in the adaptive process)to be accurate most of the time[4]. In this paper, we propose a new blind adaptive algorithm based on RLS algorithm with decision direction. The algorithm, called the despread respread recursive least squares(DR-RLS), utilizes the information of the spreading signals of difference users in a CDMA system to adapt the weight vectors. In Section 2, we describe the system model used in this work. In Section 3, we explain the previous blind adaptive algorithms[5] and the new blind algorithm based on the RLS algorithm with decision direction. In Section 4, we present the simulation results of the different adaptive array algorithms and the proposed algorithm about BER and the type of beamforming of the desired user. Finally, Section 5 presents the conclusion of this work.

2. System Model

A block diagram of a multitarget adaptive beamformer with M antenna elements and P output ports is showen in Fig 1. The M antenna elements are assumed to be equally spaced along a line with interelement spacing Δx ,i.e., the array is a uniform linear array. Suppose there are q signals $s_1(t),...,s_q(t)$. The complex envelope representation of the $M\times 1$ array input data vector $\boldsymbol{x}(t)=[x_1(t),...,x_M(t)]^T$ may be modeled as

$$\boldsymbol{x}(t)=A(\Theta)\boldsymbol{s}(t)+\boldsymbol{n}(t) \quad (1)$$

where $\boldsymbol{s}(t)=[s_1(t),...,s_q(t)]^T$ is the complex envelope representation of the $q\times 1$ source vector, $\boldsymbol{n}(t)=[n_1(t),...,n_M(t)]^T$ is an $M\times 1$ additive noise vector, and $A(\Theta)=[\boldsymbol{a}(\theta_1),...,\boldsymbol{a}(\theta_q)]$ is the array response matrix with the steering vector $\boldsymbol{a}(\theta_i)$ as its *ith* column. If the data vector $\boldsymbol{x}(t)$ is sampled K times, the sampled data may be expressed as

$$X=A(\Theta)S+N \quad (2)$$

where $X=[\boldsymbol{x}(1),...,\boldsymbol{x}(K)]$ and $N=[\boldsymbol{n}(1),...,\boldsymbol{n}(K)]$ are $M\times K$ matrix containing K snapshots of the input data vector and noise vector, respectively, and $S=[\boldsymbol{s}(1),...,\boldsymbol{s}(K)]$ is the $q\times K$ matrix containing K snapshots of the source signals.

For a direct sequence CDMA(DS-CDMA) system with P co-channel users, the *ith* user may be expressed as

$$s_i(t)=\sqrt{2P_i}b_i(t-\tau_i)c_i(t-\tau_i)\exp\{-j\phi_i\},\ i=1,...,P \quad (3)$$

where P_i, $b_i(t)$, $c_i(t)$, τ_i, ϕ_i are the power, the data signal, the spreading signal(PN sequence), the time delay, and the random phase, respectively. The data signal $b_i(t)$ is given by

$$b_i(t)=\sum_{n=-\infty}^{\infty}b_{in}P_{T_b}(t-nT_b) \quad (4)$$

where $b_{in}\in\{-1,+1\}$ is the *nth* data bit of *ith* user, and P_{T_b} is a unit rectangular pulse of duration T_b, which is the bit period of the CDMA signal. The spreading signal $c_i(t)$ is given by

$$c_i(t)=\sum_{m=-\infty}^{\infty}c_{im}P_{Tc}(t-mT_c) \quad (5)$$

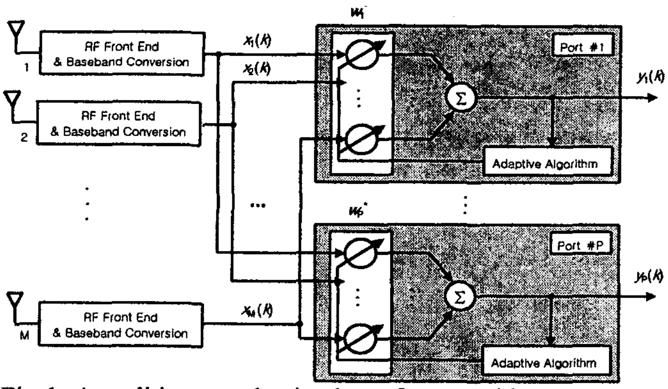

Fig 1. A mulititarget adaptive beamformer with M antenna elements and P output port.

where $c_{im} \in \{-1,+1\}$ is the *mth* data bit of *ith* user, and P_{T_c} is a unit rectangular pulse of duration T_c, which is the chip period of the CDMA signal.

In Fig 1, the output signal of the *ith* port is $y_i(k) = w_i^H(k)x(k)$, where $w_i(k) = [w_{i1}(k),...,w_{iM}(k)]^T$ is the adaptive weight vector adjusted by the adaptive control processor using a multitarget-type algorithm

3. Despread-Respread RLS

3.1 Least-Squares Despread Respread Multitarget Array(LS-DRMTA)

In the base station of a CDMA system, if the *nth* data bit of the *ith* user is detected correctly by the detector, $\hat{b}_{in} = b_{in}$, where $\hat{b}_{in}$ is the detector output. This respreaded signal can then be used in the beamformer to adapt the weight vector for *ith* user.

The LS-DRMTA tries to adapt the weight vector w_i to minimize a cost function.

$$F(w_i) = \sum_{k=1}^{K} | y_i(k) - r_i(k) |^2 = \sum_{k=1}^{K} | w_i^H x(k) - r_i(k) |^2 \quad (6)$$

Using the extension of Gauss's method, we obtain the LS-DRMTA for the *ith* user

$$y_i(l) = [w_i^H(l)X(l)]^T = [y_i(1+lK), y_i(2+lK), ..., y_i(K+lK)]^T \quad (7)$$

$$\hat{b}_{il} = \mathrm{sgn}\{\mathrm{Re}(\sum_{k=1+lK}^{K+lK} y_i(k)c_i(k-k_{\tau_i}))\} \quad (8)$$

$$r_i(l) = \hat{b}_{il}[c_i(1+lK-k_{\tau_i}), c_i(2+lK-k_{\tau_i}), ..., c_i(K+lK-k_{\tau_i})]^T \quad (9)$$

$$w_i(l+1) = [X(l)X^H(l)]^{-1} X(l) r_i^*(l) \quad (10)$$

where $c_i(k)$ is the *kth* sample of the spreading signal of *ith* user, k_{τ_i} is the number of samples corresponding to the delay of *ith* user, τ_i , $\hat{b}_{il}$ is the estimate of *lth* bit for *ith* user, and $r_i(l)$ is the estimate of the signal waveform of *ith* user over the *lth* bit interval. The LS-DRMTA algorithm has several advantages. First, no GSO(Gram Schmit Orthogonalization) procedure is needed[6]. Second, no sorting procedure is needed[6]. Third, the number of output ports of the beamformer is not limited by the number of antenna elements of the array.

3.2 Least-Squares Despread Respread Multitarget Constant Modulus Algorithm (LS-DRMTCMA)

The LS-DRMTCMA utilizes the sum of the weighted respreaded signal and complex-limited output. In LS-DRMTCMA, the cost function that the algorithm minimizes has the same form as shown in Eq(1). However, $r_i(k)$ now becomes the sum of the weighted respread signal and complex-limited output. a_{PN} and a_{CM} are the real positive weight coefficients for the respreaded signal and the complex-limited output of *ith* user, respectively. The coefficients a_{PN} and a_{CM} should satisfy the condition:

$$a_{PN} + a_{CM} = 1, \qquad a_{PN}, a_{CM} > 0. \quad (11)$$

Using the extension of Gauss's method, we obtain the following equations for LS-DRMTCMA:

$$y_i(l) = [w_i^H(l)X(l)]^T = [y_i(1+lK), y_i(2+lK), ..., y_i(K+lK)]^T \quad (12)$$

$$\hat{b}_{il} = \mathrm{sgn}\{\mathrm{Re}(\sum_{k=1+lK}^{K+lK} y_i(k)c_i(k-k_{\tau_i}))\} \quad (13)$$

$$r_{iPN}(l) = \hat{b}_{il}[c_i(1+lK-k_{\tau_i}), c_i(2+lK-k_{\tau_i}), ..., c_i(K+lK-k_{\tau_i})]^T \quad (14)$$

$$r_{iCM}(l) = \left[\frac{y_i(1+lK)}{|y_i(1+lK)|}, \frac{y_i(2+lK)}{|y_i(2+lK)|}, ..., \frac{y_i(K+lK)}{|y_i(K+lK)|}\right]^T \quad (15)$$

$$r_i(l) = a_{PN} r_{iPN}(l) + a_{CM} r_{iCM}(l) \quad (16)$$

$$w_i(l+1) = [X(l)X^H(l)]^{-1} X(l) r_i^*(l) \quad (17)$$

From Eqs (12)-(17), we see that if a_{CM} is set to zero, the LS-DRMTCMA becomes the LS-DRMTA, therefore the LS-DRMTA can be viewed as a special case of the LS-DRMTA. The LS-DRMTCMA has many advantages which possess all the advantages of LS-DRMTA. It also provides other advantages that the LS-DRMTA does not possess. The most important advantage is that it can achieve a much lower BER than the LS-DRMTA.

3.3 Recursive Least Squares (RLS)

Given the estimate of the weight vector at iteration $l-1$, we may compute the updated estimate of this vector at iteration l upon the arrival of new data. We refer to the resulting algorithm as the recursive least squares(RLS) algorithm. An important feature of the RLS algorithm is that it utilizes information contained in the input data, and can achieve much faster convergence than both the SMI and the LMS in higher SINR. It has better performance than both the SMI(Sample Matrix Inversion) and the LMS(Least Mean Square) in flat fading channel. But disadvantage of the RLS algorithm is more complex than the others. The following equations constitute the RLS algorithm.

$$K(l) = \eta^{-1} P(l-1) X(l) \{I + \eta^{-1} X^H(l) P(l-1) X(l)\}^{-1} \quad (18)$$

$$\xi(l) = d_i(l) - w_i^H(l-1)X(l) \qquad (19)$$

$$w_i(l) = w_i(l-1) + K(l)\xi^H(l) \qquad (20)$$

$$P(l) = \eta^{-1}P(l-1) - \eta^{-1}K(l)X^H(l)P(l-1) \qquad (21)$$

where K is a gain matrix, ξ is a priori estimation error, I is a identity matrix, P is an inverse correlation matrix., d is desired signal, η is a real scalar smaller than but close to one, which is used for exponential weighting of the past data and is referred to as the forgetting factor, as the update equation tends to deemphasize the old samples. The RLS method initializes the algorithm by setting $P(0) = \delta I$ and $w(0) = 0$, where δ is a small positive constant. The RLS algorithm renews the weight vector with the reference signal transmitted from the transmitter.

3.4 The new algorithm (DR-RLS)

A new algorithm(despread-respread recursive least squares: DR-RLS) is based on the RLS algorithm. It utilizes the reference signal produced by array antennas output which can be obtained by respreading the detected data bit $\hat{b}_{il}$, with the PN sequence of the *ith* user $c_i(k)$, instead of training sequence transmitted from the transmitter. It is the new blind algorithm and illustrated in Fig 2.

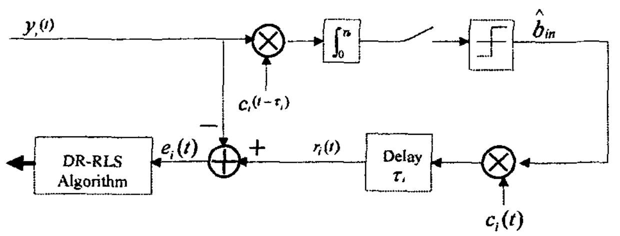

Fig 2. DR-RLS block diagram for user *i*.

The array antennas output signal of DR- RLS algorithm can be expressed as

$$y_i(l) = w^H{}_i(l)X(l) \qquad (22)$$

The time-delayed version of the signal $r(l)$ is given by

$$\hat{b}_{il} = \mathrm{sgn}\{\mathrm{Re}(\sum_{k=1+lK}^{K+lK} y_i(k)c_i(k-k_{\tau_i}))\} \qquad (23)$$

$$r_i(l) = \hat{b}_{il}\, c_i(l) \qquad (24)$$

In the RLS algorithm, the gain matrix $K(l)$ is illustrated as the Eq (18), but the DR-RLS algorithm can be expressed as

$$K(l) = R^{-1}(l)X(l) \qquad (25)$$

The Eq(18) can be rearranged as

$$K(l) = \eta^{-1}P(l-1)X(l) - \eta^{-1}K(l)X^H(l)P(l-1)X(l)$$
$$= [\eta^{-1}P(l-1) - \eta^{-1}K(l)X^H(l)P(l-1)]X(l) \qquad (26)$$

The eq(21) is equal to the right-hand side of the Eq(26). Where P is the inverse correlation. And the RLS algorithm uses the gain matrix $K(l)$ to adapt the weight vector, but the DR-RLS algorithm only uses the gain matrix $K(l)$ to calculate a priori estimation error $\xi(l)$, where $R(l)$ is defined as the gain matrix.

First, the defined function $h(l)$ is expressed as

$$h(l) = (diag(K^H(l)X(l)))^T \qquad (27)$$

where $h(l)$ is the $1 \times K$ vector of diagonal element in $K^H(l)X(l)$, which is used to calculate a priori estimation $\xi(l)$. $e_i(l)$ is a posteriori estimation error which is the difference between the output signal of the array antennas and the reference signal derived from output signal using blind scheme.

$$e_i(l) = r_i(l) - y_i(l) \qquad (28)$$

To establish the relationship between these two errors, we substitute the update Eq(21) in Eq(28), then the priori estimation error $\xi(l)$ can be rewritten as

$$e_i(l) = r_i(l) - y_i(l)$$
$$= r_i(l) - [w_i(l-1) + K(l)\xi_i{}^H(l)]^H X(l)$$
$$= r_i(l) - w_i{}^H(l-1)X(l) - \xi_i(l)K^H(l)X(l)$$
$$= \xi_i(l)(I - K^H(l)X(l))$$

$\xi_i(l) = e_i(l)\{I - K^H(l)X(l)\}^{-1}$, I is the identity matrix (29)

As Eq(29) is modified, the priori estimation error $\xi(l)$ using function $h(l)$ is defined as

$$\xi_i(l) = \left[\frac{e_i(1+lK)}{1-h(1+lK)}, \frac{e_i(2+lK)}{1-h(2+lK)}, \ldots, \frac{e_i(K+lK)}{1-h(K+lK)}\right] \qquad (30)$$

The equation to update a gain matrix is defined as

$$R(l+1) = \eta R(l) + X(l)X^H(l) \qquad (31)$$

The equation to update the weight vector is defined as

$$w_i(l+1) = w_i(l) + R^{-1}(l+1)X(l)\xi_i^H(l) \qquad (32)$$

This method initializes the algorithm by setting the gain matrix $R(0) = \delta I$ (I is $M \times M$ identity matrix), the weight vector $w(0)$ is $M \times 1$ column vector with the first element of 1 and the other elements of 0. The method repeats until the algorithm converges. RLS algorithm needs GSO and sorting procedure, but DR-RLS needs not.

4. Simulation results

For the purpose of comparison, we consider a direct sequence CDMA(DS-CDMA) system with a processing gain, *N*, equal to 15 in the simulation. The modulation scheme used in the system is BPSK. An 8-element uniform linear array with half wavelength spacing between the element is assumed to be located at the base station of the system to perform spatial filtering in the reverse link. The sampling rate is four times the chip rate. We assume that there is no multipath and the radio channel only introduces additive white Gaussian noise(AWGN). We also assume perfect power control in the base station, so all the signals impinging on the array have the same power. All the algorithms converge within 1000 bits and the BER is computed using the converged weight vector. In the simulations, to estimate the BER, a total number of 1 million bits were used. All the DOAs of the signals are equally spaced between -70 and 90 degree. We note the LS-DRMTCMA with $a_{PN} : a_{CM}$ = 2 : 1, the DR-RLS with forgetting factor η = 0.99 and δ = 0.004 in the initial gain matrix. Fig 3 shows the BER performance of different algorithms. In this case, E_b/N_0 for all users is set to 8dB.

The proposed algorithm shows a lower BER than the different algorithms, and its BER is much lower than RLS when users are over 8. Fig 4 shows the BER performance comparison of DR-RLS for the varying η value(8dB, 14users). As η value increases a real scalar smaller than but close to 1, BER is minimized. Fig 5 is the average SINR of output $y(l)$ for each blind adaptive algorithm(E_b/N_0 =8dB, 14users). It shows that DR-RLS improves SINR and converges faster than other algorithms. Fig 6 shows the beampattern of DR-RLS and RLS. It shows that DR-RLS forms better beampattern which removes MAI(Multiple Access Interference).

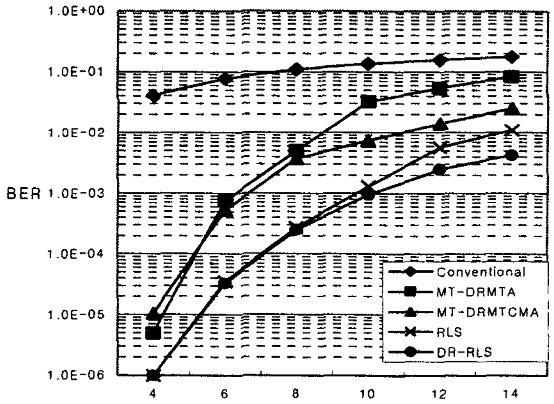

Fig 3. BER performance comparison for the varying users in AWGN (8dB).

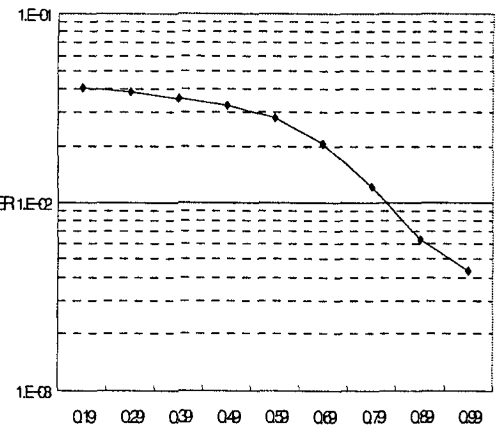

Fig 4. BER performance comparison of DR-RLS for the varying η value(8dB, 14 users).

5. Conclusion

In this paper, we propose a new algorithm based on the RLS algorithm. It calculates the error signal with reference signal derived from blind scheme. The BER performance of all these algorithms is compared. And It is shown from simulation that the proposed algorithm yields more user capacity by 67~74% than other blind adaptive algorithms at the same BER and converges faster than other blind adaptive algorithms. Also it has more advantages(no GSO, no sorting procedure) than RLS.

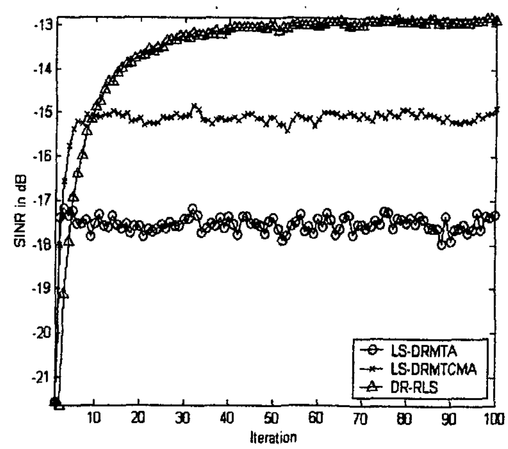

Fig 5. Average SINR of output $y(l)$ for each blind adaptive algorithm(E_b/N_0 =8dB, 14 users).

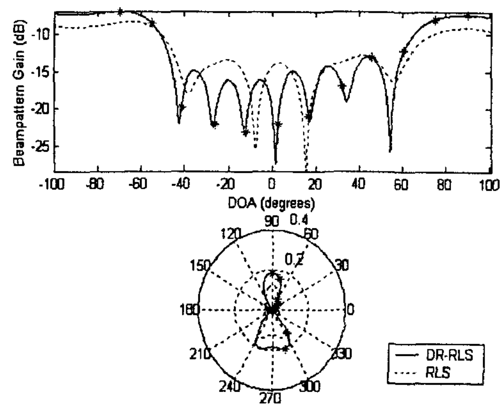

Fig 6. beampattern comparison between DR-RLS and RLS. (E_b/N_0 is 4dB, the input angle of desired user is -70degree, all the DOAs of the signals(*) are equally spaced between -70 degree and 90degree and the number of users is 12).

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