Received: 10 October 2018 | Revised: 12 April 2019 | Accepted: 20 May 2019

DOI: 10.4218/etrij.2018-0559

ORIGINAL ARTICLE

ETRI Journal WILEY

Blind adaptive receiver for uplink multiuser massive MIMO systems

Joonwoo Shin[1] | **Bangwon Seo**[2]

[1]Division of Navigation Science, Korea Maritime and Ocean University, Busan, Rep. of Korea

[2]Division of Electrical, Electronics and Control Engineering, The Institute of IT Convergence Technology, Kongju National University, Cheonan, Rep. of Korea

Correspondence
Bangwon Seo, Division of Electrical, Electronics and Control Engineering, the Institute of IT Convergence Technology, Kongju National University, Cheonan, Rep. of Korea.
Email: seobw@kongju.ac.kr

Funding information
This work was supported by the research grant of the Kongju National University in 2018.

Herein, we consider uplink multiuser massive multiple-input multiple-output systems when multiple users transmit information symbols to a base station (BS) by applying simple space-time block coding (STBC). At the BS receiver, two detection filters for each user are used to detect the STBC information symbols. One of these filters is for odd-indexed symbols and the other for even-indexed symbols. Using constrained output variance metric minimization, we first derive a special relation between the closed-form optimal solutions for the two detection filters. Then, using the derived special relation, we propose a new blind adaptive algorithm for implementing the minimum output variance-based optimal filters. In the proposed adaptive algorithm, filter weight vectors are updated only in the region satisfying the special relation. Through a theoretical analysis of the convergence speed and a computer simulation, we demonstrate that the proposed scheme exhibits faster convergence speed and lower steady-state bit error rate than the conventional scheme.

KEYWORDS
blind adaptive receiver, multiuser MIMO, output variance, STBC, uplink massive MIMO

1 | INTRODUCTION

The main requirements for fifth-generation (5G) cellular communications include high-peak data rate, superior spectral efficiency, ultra-low latency, and large device density [1,2]. Among these, spectral efficiency is particularly important because most of the available frequency bands have already been allocated to existing wireless communication systems. Hence, multiuser massive multiple-input multiple-output (MIMO) is considered a key technology for satisfying the spectral efficiency requirement of 5G communication networks [3–9]. In multiuser massive MIMO systems, many antennas (generally over one hundred) are deployed at a base station (BS), and many users are scheduled to use the same time-frequency resources for simultaneous multiuser communications. With these many antennas at the BS, most multiuser interference can be eliminated by the use of very high-dimensional precoding and beamforming technologies at the transmitter and receiver, respectively.

Meanwhile, space-time block coding (STBC) schemes have been developed to provide reliable transmission for MIMO systems [10–17], particularly when channel parameters vary rapidly owing to the movement of mobile stations. The simple STBC scheme proposed by Alamouti [10] has attracted substantial attention because it can achieve full-rate and full-diversity gain by a simple combining operation on the receiver side. Therefore, Alamouti's simple STBC technology has been widely utilized in 3GPP long-term evolution (LTE)-advanced systems.

In uplink multiuser massive STBC-MIMO systems, multiple users equipped with multiple transmitting antennas transmit their data to the BS using the same time-frequency resources by applying STBC technology. When the number of receiving antennas at the BS is very large, it is impractical to implement detection filters by batch-processing algorithms because such algorithms generally require inverse matrix calculation of very large matrices. Therefore, in multiuser massive MIMO systems with a very large number of antennas, it is more reasonable to implement detection filters with adaptive algorithms to reduce the computation complexity substantially.

Adaptive algorithms can be classified into two main categories: non-blind adaptive algorithms and blind adaptive algorithms [18–33]. Non-blind adaptive algorithms require the transmission of a pilot training sequence. Moreover, the optimal detection filter taps are identified by updating the filter taps with the aid of the pilot training sequence. Meanwhile, in blind adaptive algorithms, the filter taps are updated without the aid of the pilot training sequence. Therefore, blind adaptive algorithms are more efficient in terms of spectral efficiency because they do not require transmission of the redundant pilot training sequence.

To derive a blind adaptive algorithm for STBC-MIMO systems, minimization of the filter output variance was considered in [20,24,27]. If this method is directly applied to the design of receivers of uplink multiuser massive STBC-MIMO communication, two filter weight vectors will be updated independently. Here, one of the filter weight vectors is used for detecting odd-indexed symbols and the other for detecting even-indexed symbols. Because the number of filter taps is equal to the number of receiving antennas at the BS and the convergence speed of adaptive algorithms is proportional to the number of filter taps [34,35], the conventional adaptive receiver for uplink massive MIMO systems obtained from the direct application of [20,24,27] exhibits a very low convergence speed.

In this paper, we propose a blind adaptive receiver with high convergence speed for uplink multiuser massive STBC-MIMO systems when multiple users transmit information symbols applying Alamouti's simple STBC technology. By considering the minimization of the constrained output variance in the design of the detection filters, we first derive a special relation between the two filter weight vectors. Then, we propose a new blind adaptive receiver using the derived special relation. In the proposed scheme, tap weight vectors of the detection filters are updated only in the region satisfying the special relation in order to increase the convergence speed of the blind adaptive receiver. Through a theoretical analysis of the convergence speed and a computer simulation, we demonstrate that the proposed scheme exhibits higher convergence speed than the conventional blind adaptive receiver does for identical signal-to-interference-plus-noise ratio (SINR). We also demonstrate that the proposed scheme exhibits lower steady-state bit error rate (BER) performance than the conventional scheme does for identical convergence speed.

The rest of the paper is organized as follows: Section 2 describes the system model. The conventional blind adaptive receiver is explained in Section 3. The proposed blind adaptive receiver with high convergence speed is presented in Section 4, and the theoretical analysis of its convergence speed performance is described in Section 5. The simulation results are enumerated in Section 6, and conclusions are presented in Section 7.

2 | SYSTEM MODEL

Figure 1 shows a system model of the type of uplink multiuser massive MIMO communications that we consider in this paper. In the Figure 1, K users transmit data to a BS using the same time-frequency resources by means of Alamouti's simple STBC scheme. For simplicity, we assume that the BS is equipped with a large number, N, of receiving antennas and that each user is equipped with two transmit antennas. However, the extension to more than two transmit antennas at each user is straightforward when using a transmit precoding scheme for each user.

For Alamouti's simple STBC processing, at the odd-indexed symbol time $(2n-1)$, user k sends two information symbols $s_k(2n-1)$ and $s_k(2n)$ using transmit antennas 1 and 2, respectively. Then, the received signal vector $\mathbf{r}(2n-1)$ of length N at the BS during the odd-indexed symbol time $(2n-1)$ is expressed as follows:

$$\mathbf{r}(2n-1)=\sum_{k=1}^{K}\left\{\mathbf{h}_{k,1}s_k(2n-1)+\mathbf{h}_{k,2}s_k(2n)\right\}+\mathbf{v}(2n-1), \quad (1)$$

where $\mathbf{h}_{k,m}$, $m=1,2$, denotes the channel vector of length N from the transmit antenna m of user k to the receiving antennas of the BS. Moreover, the vector $\mathbf{v}(2n-1)$ is a complex additive white Gaussian noise (AWGN) vector with mean $\mathbf{0}_{N\times 1}$ and covariance matrix $\sigma_v^2\mathbf{I}_N$. Here, $\mathbf{0}_{N\times 1}$ is a zero vector of length N, and $\mathbf{I}_N$ is an identity matrix of size $N\times N$. The information symbols, $s_k(n)$, satisfy $\mathrm{E}[s_k(n)s_{k'}^*(n')]=\sigma_s^2\delta(n-n')\delta(k-k')$. Here, $\delta(n)$ is the Kronecker delta function, and $\sigma_s^2=1$ is assumed for simplicity.

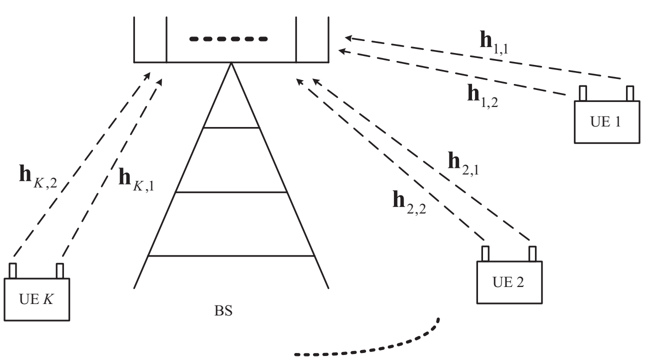

FIGURE 1 System model for uplink multiuser massive MIMO communications

Meanwhile, at the odd-indexed symbol time $2n$, user k sends information symbols $-s_k^*(2n)$ and $s_k^*(2n-1)$ using transmit antennas 1 and 2, respectively. Here, $(\cdot)^*$ represents complex conjugate operation. Then, the received signal vector $\mathbf{r}(2n)$ of length N at the BS during the even-indexed symbol time $2n$ is expressed as follows:

$$\mathbf{r}(2n)=\sum_{k=1}^{K}\left\{\mathbf{h}_{k,2}s_k^*(2n-1)-\mathbf{h}_{k,1}s_k^*(2n)\right\}+\mathbf{v}(2n), \quad (2)$$

where $\mathbf{v}(2n)$ is a complex AWGN vector.

If we define the extended received signal vector of length $2N$ by $\mathbf{y}(n)=[\mathbf{r}^{\mathrm{T}}(2n-1) \quad \mathbf{r}^{\mathrm{H}}(2n)]^{\mathrm{T}}$ (where $(\cdot)^{\mathrm{T}}$ and $(\cdot)^{\mathrm{H}}$ represent transpose and Hermitian transpose operations, respectively), $\mathbf{y}(n)$ can be expressed as follows:

$$\begin{aligned}\mathbf{y}(n) &=[\mathbf{r}^{\mathrm{T}}(2n-1)\ \mathbf{r}^{\mathrm{H}}(2n)]^{\mathrm{T}}\\ &=\sum_{k=1}^{K}\left\{\mathbf{g}_{k,1}s_k(2n-1)+\mathbf{g}_{k,2}s_k(2n)\right\}+\mathbf{z}(n),\end{aligned} \quad (3)$$

where $\mathbf{g}_{k,1}$, $\mathbf{g}_{k,2}$, and $\mathbf{z}(n)$ are expressed as $\mathbf{g}_{k,1}=[\mathbf{h}_{k,1}^{\mathrm{T}} \quad \mathbf{h}_{k,2}^{\mathrm{H}}]^{\mathrm{T}}$, $\mathbf{g}_{k,2}=[\mathbf{h}_{k,2}^{\mathrm{T}} \quad -\mathbf{h}_{k,1}^{H}]^{\mathrm{T}}$, and $\mathbf{z}(n)=[\mathbf{v}^{\mathrm{T}}(2n-1) \quad \mathbf{v}^{\mathrm{H}}(2n)]^{\mathrm{T}}$, respectively.

Here, we consider the detection of the information symbols of user 1: $s_1(2n-1)$ and $s_1(2n)$. We assume that the detection filters $\mathbf{w}_1$ and $\mathbf{w}_2$ of length $2N$ each are used to detect the odd-indexed symbols $s_1(2n-1)$ and even-indexed symbols $s_1(2n)$, respectively. Then, the estimate of $s_1(2n-1)$ is obtained from the output signal of the detection filter $\mathbf{w}_1$ and is expressed as follows:

$$\begin{aligned}\hat{s}_1(2n-1) &=\mathbf{w}_1^{\mathrm{H}}\mathbf{y}(n)\\ &=\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1}s_1(2n-1)+\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,2}s_1(2n)\\ &\quad+\sum_{k=2}^{K}\left\{\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{k,1}s_k(2n-1)+\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{k,2}s_k(2n)\right\}+\mathbf{w}_1^{\mathrm{H}}\mathbf{z}(n).\end{aligned} \quad (4)$$

Similarly, the estimate of $s_1(2n)$ is obtained from the output signal of $\mathbf{w}_2$ and is expressed as follows:

$$\begin{aligned}\hat{s}_1(2n) &=\mathbf{w}_2^{\mathrm{H}}\mathbf{y}(n)\\ &=\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2}s_1(2n)+\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,1}s_1(2n-1)\\ &\quad+\sum_{k=2}^{K}\left\{\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{k,1}s_k(2n-1)+\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{k,2}s_k(2n)\right\}+\mathbf{w}_2^{\mathrm{H}}\mathbf{z}(n).\end{aligned} \quad (5)$$

3 | MOV-BASED OPTIMAL RECEIVER AND CONVENTIONAL BLIND ADAPTIVE ALGORITHM

3.1 | MOV-based optimal receiver

We define the output variances for $\mathbf{w}_1$ and $\mathbf{w}_2$ as $J_1=\mathrm{E}[|\mathbf{w}_1^{\mathrm{H}}\mathbf{y}(n)|^2]$ and $J_2=\mathrm{E}[|\mathbf{w}_2^{\mathrm{H}}\mathbf{y}(n)|^2]$, respectively. Then, J_1 and J_2 are expressed as follows:

$$\begin{aligned}J_1=\mathbf{w}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_1&=|\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1}|^2+|\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,2}|^2\\ &+\sum_{k=2}^{K}\left\{|\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{k,1}|^2+|\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{k,2}|^2\right\}+\sigma_v^2\mathbf{w}_1^{\mathrm{H}}\mathbf{w}_1,\end{aligned} \quad (6)$$

$$\begin{aligned}J_2=\mathbf{w}_2^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_2&=|\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2}|^2+|\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,1}|^2\\ &+\sum_{k=2}^{K}\left\{|\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{k,1}|^2+|\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{k,2}|^2\right\}+\sigma_v^2\mathbf{w}_2^{\mathrm{H}}\mathbf{w}_2,\end{aligned} \quad (7)$$

respectively. Here, the matrix $\mathbf{R}_y$ of size $2N\times 2N$ is a covariance matrix of $\mathbf{y}(n)$ and is expressed as follows:

$$\mathbf{R}_y=\mathrm{E}[\mathbf{y}(n)\mathbf{y}^{\mathrm{H}}(n)]=\sum_{k=1}^{K}\left\{\mathbf{g}_{k,1}\mathbf{g}_{k,1}^{\mathrm{H}}+\mathbf{g}_{k,2}\mathbf{g}_{k,2}^{\mathrm{H}}\right\}+\sigma_v^2\mathbf{I}_{2N}. \quad (8)$$

In the expressions of the output variances J_1 and J_2, the components $|\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1}|^2$ and $|\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2}|^2$ are the output variances of the desired signals, whereas the other components represent those of interference plus AWGN. Therefore, the detection filters should be designed to eliminate the interference and AWGN components in J_1 and J_2.

The optimization problem for determining $\mathbf{w}_1$ and $\mathbf{w}_2$ based on the minimization of a constrained output variance (MOV) can be expressed as follows:

$$\begin{aligned}\{\mathbf{w}_{1,\mathrm{opt}},\mathbf{w}_{2,\mathrm{opt}}\}&=\arg\min_{\mathbf{w}_1,\mathbf{w}_2} J(\mathbf{w}_1,\mathbf{w}_2)\\ &\text{s.t. } \mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1}=1, \mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2}=1,\end{aligned} \quad (9)$$

where $J(\mathbf{w}_1,\mathbf{w}_2)=\mathbf{w}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_1+\mathbf{w}_2^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_2$ is the total output variance.

The Lagrange function for the optimization problem is expressed as follows:

$$\begin{aligned}&L(\mathbf{w}_1,\mathbf{w}_2,\lambda_1,\lambda_2)\\ &=\mathbf{w}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_1+\mathbf{w}_2^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_2+\lambda_1(\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1}-1)+\lambda_2(\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2}-1),\end{aligned} \quad (10)$$

where λ_1 and λ_2 are Lagrange multipliers.

The partial derivatives of $L(\mathbf{w}_1,\mathbf{w}_2,\lambda_1,\lambda_2)$ with respect to each of $\mathbf{w}_1$, $\mathbf{w}_2$, λ_1, and λ_2 are expressed as follows:

$$\frac{\partial L}{\partial \mathbf{w}_m^*}=\mathbf{R}_y\mathbf{w}_m+\lambda_m\mathbf{g}_{1,m}=0, \quad m=1,2, \quad (11)$$

$$\frac{\partial L}{\partial \lambda_m}=\mathbf{w}_m^{\mathrm{H}}\mathbf{g}_{1,m}-1=0, \quad m=1,2. \quad (12)$$

From (11) and (12), the MOV-based optimal solution is expressed as follows:

$$\mathbf{w}_{m,\mathrm{opt}}=\frac{1}{\mathbf{g}_{1,m}^{\mathrm{H}}\mathbf{R}_y^{-1}\mathbf{g}_{1,m}}\mathbf{R}_y^{-1}\mathbf{g}_{1,m}, \quad m=1,2. \quad (13)$$

Because the size of $\mathbf{R}_y$ is $2N\times 2N$ and N is a very large number for massive MIMO systems, it is impractical to calculate the inverse matrix of $\mathbf{R}_y$ by batch processing. Therefore, it is more reasonable to implement the detection filters for massive MIMO systems using adaptive algorithms because adaptive algorithms do not require the calculation of inverse matrices.

3.2 | Conventional blind adaptive receiver

To remove the constraints in (9) and then obtain an unconstrained optimization problem, we rewrite $\mathbf{w}_1$ and $\mathbf{w}_2$ in its canonical forms (that is, $\mathbf{w}_m = \bar{\mathbf{g}}_{1,m} + \mathbf{Q}_m \mathbf{x}_m, \quad m = 1, 2$). Here, $\bar{\mathbf{g}}_{1,m} = \mathbf{g}_{1,m} / \| \mathbf{g}_{1,m} \|^2$ is a normalized channel vector, $\mathbf{Q}_m, m = 1, 2$, is the $2N \times (2N-1)$ matrix whose columns form an orthonormal basis of the null space of $\bar{\mathbf{g}}_{1,1}$ (that is, $\mathbf{Q}_m^{\mathrm{H}} \bar{\mathbf{g}}_{1,m} = \mathbf{0}$ and $\mathbf{Q}_m^{\mathrm{H}} \mathbf{Q}_m = \mathbf{I}_{2N-1}, m = 1, 2$), and the vector $\mathbf{x}_m$ of length $(2N-1)$ is an adjustable component. Then, the constrained optimization problem (9) can be reexpressed without the constraints as follows:

$$\begin{aligned}\{\mathbf{x}_{1,\mathrm{opt}}, \mathbf{x}_{2,\mathrm{opt}}\} = \arg \min_{\mathbf{x}_1, \mathbf{x}_2} \{ & (\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1 \mathbf{x}_1)^{\mathrm{H}} \mathbf{R}_y (\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1 \mathbf{x}_1) \\ & + (\bar{\mathbf{g}}_{1,2} + \mathbf{Q}_2 \mathbf{x}_2)^{\mathrm{H}} \mathbf{R}_y (\bar{\mathbf{g}}_{1,2} + \mathbf{Q}_2 \mathbf{x}_2) \}.\end{aligned} \tag{14}$$

If we define

$$\begin{aligned}J(\mathbf{x}_1, \mathbf{x}_2) = & (\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1 \mathbf{x}_1)^{\mathrm{H}} \mathbf{R}_y (\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1 \mathbf{x}_1) \\ & + (\bar{\mathbf{g}}_{1,2} + \mathbf{Q}_2 \mathbf{x}_2)^{\mathrm{H}} \mathbf{R}_y (\bar{\mathbf{g}}_{1,2} + \mathbf{Q}_2 \mathbf{x}_2),\end{aligned} \tag{15}$$

the partial derivatives of $J(\mathbf{x}_1, \mathbf{x}_2)$ with respect to $\mathbf{x}_1$ and $\mathbf{x}_2$ are expressed as [36]

$$\begin{aligned}\frac{\partial}{\partial \mathbf{x}_m^*} J(\mathbf{x}_1, \mathbf{x}_2) &= \mathbf{Q}_m^{\mathrm{H}} \mathbf{R}_y (\bar{\mathbf{g}}_{1,m} + \mathbf{Q}_m x_m) \\ &= \mathbf{Q}_m^{\mathrm{H}} \mathbf{R}_y w_m, \quad m = 1, 2.\end{aligned} \tag{16}$$

To develop a blind adaptive algorithm for the optimization problem (14), the covariance matrix $\mathbf{R}_y$ is replaced with its one-sample mean (that is, $\mathbf{R}_y \approx \mathbf{y}(n)\mathbf{y}(n)^{\mathrm{H}}$). Therefore, a conventional MOV-based blind adaptive algorithm is expressed as follows:

$$\mathbf{x}_m(n+1) = \mathbf{x}_m(n) - \mu_{\mathrm{c}} \mathbf{Q}_m^{\mathrm{H}} \mathbf{y}(n) \{ \mathbf{y}(n)^{\mathrm{H}} \mathbf{w}_m(n) \}, \quad m = 1, 2, \tag{17}$$

where μ_{c} is the step-size of the conventional scheme. Finally, the update equation for the detection filter is expressed as

$$\mathbf{w}_m(n+1) = \bar{\mathbf{g}}_{1,m} + \mathbf{x}_m(n+1), \quad m = 1, 2. \tag{18}$$

Because the tap length of each filter in the update (17) of the conventional adaptive scheme is $2N$ and the convergence speed of adaptive algorithms is proportional to the filter tap length [34,35], the convergence speed of the conventional scheme is very low when the number of receiving antennas N is very large.

4 | PROPOSED MOV-BASED BLIND ADAPTIVE RECEIVER

To improve the convergence speed of the conventional scheme, we propose a new blind adaptive receiver with high convergence speed. First, we derive a special relation between the two MOV-based optimal detection filters expressed in (13). Then, using the special relation, we present the proposed blind adaptive receiver.

4.1 | Relation between two MOV-based optimal detection filters

Because $\mathbf{y}(n) = [\mathbf{r}^{\mathrm{T}}(2n-1) \quad \mathbf{r}^{\mathrm{H}}(2n)]^{\mathrm{T}}$, the covariance matrix of $\mathbf{y}(n)$ can be expressed as its partitioned matrices as follows:

$$\begin{aligned}\mathbf{R}_y &= \mathrm{E}[\mathbf{y}(n)\mathbf{y}(n)^{\mathrm{H}}] \\ &= \begin{bmatrix} \mathrm{E}[\mathbf{r}(2n-1)\mathbf{r}^{\mathrm{H}}(2n-1)] & \mathrm{E}[\mathbf{r}(2n-1)\mathbf{r}^{\mathrm{T}}(2n)] \\ \mathrm{E}[\mathbf{r}^*(2n)\mathbf{r}^{\mathrm{H}}(2n-1)] & \mathrm{E}[\mathbf{r}^*(2n)\mathbf{r}^{\mathrm{T}}(2n)] \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{R}_{1,1} & \mathbf{R}_{1,2} \\ \mathbf{R}_{2,1} & \mathbf{R}_{2,2} \end{bmatrix}.\end{aligned} \tag{19}$$

Moreover, by using (1) and (2), the covariance matrix can be reexpressed as follows:

$$\mathbf{R}_y = \begin{bmatrix} \sum_{k=1}^{K} \{ \mathbf{h}_{k,1}\mathbf{h}_{k,1}^{\mathrm{H}} + \mathbf{h}_{k,2}\mathbf{h}_{k,2}^{\mathrm{H}} \} + \sigma_v^2 \mathbf{I}_N & \sum_{k=1}^{K} \{ \mathbf{h}_{k,1}\mathbf{h}_{k,2}^{\mathrm{T}} - \mathbf{h}_{k,2}\mathbf{h}_{k,1}^{\mathrm{T}} \} \\ \sum_{k=1}^{K} \{ \mathbf{h}_{k,2}^*\mathbf{h}_{k,1}^{\mathrm{H}} - \mathbf{h}_{k,1}^*\mathbf{h}_{k,2}^{\mathrm{H}} \} & \sum_{k=1}^{K} \{ \mathbf{h}_{k,2}^*\mathbf{h}_{k,2}^{\mathrm{T}} + \mathbf{h}_{k,1}^*\mathbf{h}_{k,1}^{\mathrm{T}} \} + \sigma_v^2 \mathbf{I}_N \end{bmatrix}. \tag{20}$$

By comparing (19) and (20), we observe the following relation among the submatrices of $\mathbf{R}_y$:

$$\mathbf{R}_{1,1} = \mathbf{R}_{2,2}^*, \quad \mathbf{R}_{1,2} = -\mathbf{R}_{2,1}^*. \tag{21}$$

To derive a relation between $\mathbf{w}_{1,\mathrm{opt}}$ and $\mathbf{w}_{2,\mathrm{opt}}$, we define $\mathbf{w}_m$, $m = 1, 2$, by its subvectors (that is, $\mathbf{w}_m = [\mathbf{w}_{m,1}^{\mathrm{T}} \quad \mathbf{w}_{m,2}^{\mathrm{T}}]^{\mathrm{T}}$) and introduce a vector $\mathbf{v}_1 = [\mathbf{v}_{1,1}^{\mathrm{T}} \quad \mathbf{v}_{1,2}^{\mathrm{T}}]^{\mathrm{T}}$ of length $2N$ and whose subvectors $\mathbf{v}_{1,1}$ and $\mathbf{v}_{1,2}$ are each of length N.

Proposition 1 *Let the subvectors* $\mathbf{v}_{1,1}$ *and* $\mathbf{v}_{1,2}$ *be*

$$\mathbf{v}_{1,1} = -\mathbf{w}_{2,2}^*, \quad \mathbf{v}_{1,2} = \mathbf{w}_{2,1}^*. \tag{22}$$

Then, the following relation can be obtained:

$$\mathbf{w}_2^{\mathrm{H}} \mathbf{R}_y \mathbf{w}_2 = \mathbf{v}_1^{\mathrm{H}} \mathbf{R}_y \mathbf{v}_1. \tag{23}$$

Proof. Because $\mathbf{R}_y$ is a Hermitian matrix and $\mathbf{w}_2^{\mathrm{H}} \mathbf{R}_y \mathbf{w}_2$ is scalar, we obtain

$$\begin{aligned}\mathbf{w}_2^{\mathrm{H}} \mathbf{R}_y \mathbf{w}_2 &= (\mathbf{w}_2^{\mathrm{H}} \mathbf{R}_y \mathbf{w}_2)^* = \mathbf{w}_2^{\mathrm{T}} \mathbf{R}_y^* \mathbf{w}_2^* \\ &= \begin{bmatrix} \mathbf{w}_{2,1}^{\mathrm{T}} & \mathbf{w}_{2,2}^{\mathrm{T}} \end{bmatrix} \begin{bmatrix} \mathbf{R}_{1,1}^* & \mathbf{R}_{1,2}^* \\ \mathbf{R}_{2,1}^* & \mathbf{R}_{2,2}^* \end{bmatrix} \begin{bmatrix} \mathbf{w}_{2,1}^* \\ \mathbf{w}_{2,2}^* \end{bmatrix}.\end{aligned} \tag{24}$$

Now, using (21) and (22), $\mathbf{w}_2^{\mathrm{H}} \mathbf{R}_y \mathbf{w}_2$ can be reexpressed as follows:

$$\mathbf{w}_2^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_2 = \begin{bmatrix} \mathbf{v}_{1,2}^{\mathrm{H}} & -\mathbf{v}_{1,1}^{\mathrm{H}} \end{bmatrix} \begin{bmatrix} \mathbf{R}_{2,2} & -\mathbf{R}_{2,1} \\ -\mathbf{R}_{1,2} & \mathbf{R}_{1,1} \end{bmatrix} \begin{bmatrix} \mathbf{v}_{1,2} \\ -\mathbf{v}_{1,2} \end{bmatrix}$$
$$= \mathbf{v}_{1,2}^{\mathrm{H}}\mathbf{R}_{2,2}\mathbf{v}_{1,2} + \mathbf{v}_{1,1}^{\mathrm{H}}\mathbf{R}_{1,2}\mathbf{v}_{1,2} + \mathbf{v}_{1,2}^{\mathrm{H}}\mathbf{R}_{2,1}\mathbf{v}_{1,1} + \mathbf{v}_{1,1}^{\mathrm{H}}\mathbf{R}_{1,1}\mathbf{v}_{1,1} = \mathbf{v}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{v}_1. \quad (25)$$

■

Moreover, the constraint on $\mathbf{w}_2$ in (9), $\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2} = 1$, is equivalent to $(\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2})^* = 1$. Furthermore, by using (22), $(\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2})^* = 1$ can be reexpressed as follows:

$$(\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2})^* = \begin{bmatrix} \mathbf{w}_{2,1}^{\mathrm{T}} & \mathbf{w}_{2,2}^{\mathrm{T}} \end{bmatrix} \begin{bmatrix} \mathbf{h}_{1,2}^* \\ -\mathbf{h}_{1,1} \end{bmatrix} = \begin{bmatrix} \mathbf{v}_{1,2}^{\mathrm{H}} & -\mathbf{v}_{1,1}^{\mathrm{H}} \end{bmatrix} \begin{bmatrix} \mathbf{h}_{1,2}^* \\ -\mathbf{h}_{1,1} \end{bmatrix} = \mathbf{v}_{1,2}^{\mathrm{H}}\mathbf{h}_{1,2}^* + \mathbf{v}_{1,1}^{\mathrm{H}}\mathbf{h}_{1,1} = \mathbf{v}_1^{\mathrm{H}}\mathbf{g}_{1,1}. \quad (26)$$

Therefore, the constraint $\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2} = 1$ can be reexpressed as $\mathbf{v}_1^{\mathrm{H}}\mathbf{g}_{1,1} = 1$. Now, by using $\mathbf{v}_1$ rather than $\mathbf{w}_2$, the optimization problem (9) can be reexpressed as follows:

$$\{\mathbf{w}_{1,\mathrm{opt}}, \mathbf{v}_{1,\mathrm{opt}}\} = \arg\min_{\mathbf{w}_1, \mathbf{v}_1} \mathbf{w}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_1 + \mathbf{v}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{v}_1 \quad \text{s.t.} \quad \mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1} = 1, \quad \mathbf{v}_1^{\mathrm{H}}\mathbf{g}_{1,1} = 1. \quad (27)$$

By comparing (9) and (27), we observe that $\mathbf{w}_{1,\mathrm{opt}} = \mathbf{v}_{1,\mathrm{opt}}$. From (22), we can obtain the following special relation between the two MOV optimal detection filters:

$$\mathbf{w}_{1,1,\mathrm{opt}} = -\mathbf{w}_{2,2,\mathrm{opt}}^*, \quad \mathbf{w}_{1,2,\mathrm{opt}} = \mathbf{w}_{2,1,\mathrm{opt}}^*. \quad (28)$$

4.2 | Proposed blind adaptive receiver

Because the optimal detection filters satisfy the special relation (28), it is reasonable to consider that the convergence speed of a blind adaptive algorithm will be improved if adaptive detection filters are updated only in the region satisfying the relation in (28).

Therefore, by substituting $\mathbf{w}_{2,1}$ and $\mathbf{w}_{2,2}$ with $\mathbf{w}_{1,2}^*$ and $-\mathbf{w}_{1,1}^*$, respectively, $\mathbf{w}_2$ can be expressed as follows:

$$\mathbf{w}_2 = \begin{bmatrix} \mathbf{w}_{2,1} \\ \mathbf{w}_{2,2} \end{bmatrix} = \begin{bmatrix} \mathbf{w}_{1,2}^* \\ -\mathbf{w}_{1,1}^* \end{bmatrix} = \begin{bmatrix} 0 & \mathbf{I}_N \\ -\mathbf{I}_N & 0 \end{bmatrix} \begin{bmatrix} \mathbf{w}_{1,1}^* \\ \mathbf{w}_{1,2}^* \end{bmatrix} = \mathbf{D}\mathbf{w}_1^*, \quad (29)$$

where $\mathbf{D} = \begin{bmatrix} 0 & \mathbf{I}_N \\ -\mathbf{I}_N & 0 \end{bmatrix}$.

Using (29) rather than $\mathbf{w}_2$, the total output variance in (9) can be modified as a function of $\mathbf{w}_1$ only and expressed as follows:

$$J_M(\mathbf{w}_1) = \mathbf{w}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{w}_1 + \mathbf{w}_1^{\mathrm{H}}\mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}\mathbf{w}_1 = \mathbf{w}_1^{\mathrm{H}}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})\mathbf{w}_1. \quad (30)$$

Furthermore, the constraint $\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2} = 1$ in (9) is equivalent to $(\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2})^* = 1$. If we use (29) rather than $\mathbf{w}_2$ and apply certain linear manipulation, it is convenient to demonstrate that the constraint $(\mathbf{w}_2^{\mathrm{H}}\mathbf{g}_{1,2})^* = 1$ is equivalent to $\mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1} = 1$.

Then, the original constrained output variance minimization problem in (9) can be modified as follows:

$$\mathbf{w}_{1,\mathrm{opt}} = \arg\min_{\mathbf{w}_1} J_M(\mathbf{w}_1) \quad \text{s.t.} \quad \mathbf{w}_1^{\mathrm{H}}\mathbf{g}_{1,1} = 1. \quad (31)$$

To eliminate the constraint in (31) and then to obtain an unconstrained optimization problem, we reexpress $\mathbf{w}_1$ in its canonical form (that is, $\mathbf{w}_1 = \bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1\mathbf{x}_1$).

Now, the modified output variance can be reexpressed as follows:

$$J_M(\mathbf{x}_1) = (\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1\mathbf{x}_1)^{\mathrm{H}}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})(\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1\mathbf{x}_1). \quad (32)$$

The partial derivative of $J_M(\mathbf{x}_1)$ with respect to $\mathbf{x}_1$ is expressed as [36]

$$\frac{\partial J_M}{\partial \mathbf{x}_1^*} = \mathbf{Q}_1^{\mathrm{H}}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})(\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1\mathbf{x}_1). \quad (33)$$

The optimal weight vectors $\mathbf{x}_{1,\mathrm{opt}}$ and $\mathbf{w}_{1,\mathrm{opt}}$ are obtained by setting $\partial J_M / \partial \mathbf{x}_1^* = \mathbf{0}$. Hence, we obtain

$$\mathbf{Q}_1^{\mathrm{H}}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})(\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1\mathbf{x}_{1,\mathrm{opt}}) = \mathbf{Q}_1^{\mathrm{H}}(\mathbf{R}_y + \mathbf{D}^T\mathbf{R}_y\mathbf{D})\mathbf{w}_{1,\mathrm{opt}} = \mathbf{0}. \quad (34)$$

To derive the proposed blind adaptive algorithm, the covariance matrix $\mathbf{R}_y$ is approximated by its one-sample mean $\mathbf{R}_y \approx \mathbf{y}(n)\mathbf{y}^{\mathrm{H}}(n)$. Then, the blind adaptive algorithm for $\mathbf{x}_1$ is expressed as follows:

$$\mathbf{x}_1(n+1) = \mathbf{x}_1(n) - \mu_{\mathrm{p}}\mathbf{Q}_1^{\mathrm{H}}\{\mathbf{y}(n)\mathbf{y}^{\mathrm{H}}(n) + \mathbf{D}^{\mathrm{T}}\mathbf{y}(n)\mathbf{y}^{\mathrm{H}}(n)\mathbf{D}\}\{\bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1\mathbf{x}_1(n)\}, \quad (35)$$

where μ_{p} is the step-size of the proposed scheme.

Now, the detection filter $\mathbf{w}_1(n+1)$ is expressed as follows:

$$\mathbf{w}_1(n+1) = \bar{\mathbf{g}}_{1,1} + \mathbf{Q}_1\mathbf{x}_1(n+1). \quad (36)$$

In addition, the submatrices of $\mathbf{w}_2(n+1)$ are directly obtained from $\mathbf{w}_1(n+1)$ without applying another independent adaptive algorithm for $\mathbf{w}_2(n+1)$; that is, $\mathbf{w}_{2,1}(n+1) = \mathbf{w}_{1,2}^*(n+1)$, and $\mathbf{w}_{2,2}(n+1) = -\mathbf{w}_{1,1}^*(n+1)$.

5 | PERFORMANCE ANALYSIS

In this section, we theoretically analyze the convergence speed of the proposed blind adaptive algorithm by following an approach similar to the one in [34].

Let the weight-error vector in the blind adaptation of $\mathbf{x}_1(n)$ be defined as

$$\boldsymbol{\varepsilon}_1(n) = \mathbf{x}_1(n) - \mathbf{x}_{1,\mathrm{opt}}, \quad (37)$$

where the optimal weight vector $\mathbf{x}_{1,\mathrm{opt}}$ is expressed as (34).

By subtracting $\mathbf{x}_{1,\text{opt}}$ from each side of (35) and through certain linear manipulation, we can obtain

$$\boldsymbol{\varepsilon}_1(n+1)=\{\mathbf{I}_{2N-1}-\mu_\text{p}\mathbf{Q}_1^\text{H}[\mathbf{y}(n)\mathbf{y}^\text{H}(n)+\mathbf{D}^\text{T}\mathbf{y}(n)\mathbf{y}^\text{H}(n)\mathbf{D}]\mathbf{Q}_1\}\boldsymbol{\varepsilon}_1(n) -\mu_\text{p}\mathbf{Q}_1^\text{H}\{\mathbf{y}(n)\mathbf{y}^\text{H}(n)+\mathbf{D}^\text{T}\mathbf{y}(n)\mathbf{y}^\text{H}(n)\mathbf{D}\}\mathbf{w}_{1,\text{opt}}. \tag{38}$$

If we apply the expectation operation to each side of (38) and use the relation for $\mathbf{w}_{1,\text{opt}}$ expressed as (34), we obtain

$$\text{E}[\boldsymbol{\varepsilon}_1(n+1)]=\{\mathbf{I}_{2N-1}-\mu_\text{p}\mathbf{Q}_1^\text{H}(\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D})\mathbf{Q}_1\}\text{E}[\boldsymbol{\varepsilon}_1(n)]. \tag{39}$$

Let the l-th eigenvalue of any $L\times L$ matrix $\mathbf{A}$ be denoted by $\lambda_l(\mathbf{A})$, and let the eigenvalues be arranged in increasing order such as $\lambda_1(\mathbf{A})\le\lambda_2(\mathbf{A})\le\cdots\le\lambda_L(\mathbf{A})$.

Now, following a procedure for the convergence speed analysis of the adaptive receiver similar to that in [34], we observe from (39) that the convergence speed of the proposed adaptive scheme depends on the eigenvalue spread χ of the $(2N-1)\times(2N-1)$ matrix $\mathbf{Q}_1^\text{H}(\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D})\mathbf{Q}_1$ defined by

$$\chi(\mathbf{Q}_1^\text{H}[\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1)=\frac{\lambda_{2N-1}(\mathbf{Q}_1^\text{H}[\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1)}{\lambda_1(\mathbf{Q}_1^\text{H}[\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1)}. \tag{40}$$

Moreover, using an approach for the conventional scheme similar to that in (17), we observe that the convergence speed of the conventional scheme depends on the eigenvalue spread χ of the matrix $\mathbf{Q}_1^\text{H}\mathbf{R}_y\mathbf{Q}_1$ defined by

$$\chi(\mathbf{Q}_1^\text{H}\mathbf{R}_y\mathbf{Q}_1)=\frac{\lambda_{2N-1}(\mathbf{Q}_1^\text{H}\mathbf{R}_y\mathbf{Q}_1)}{\lambda_1(\mathbf{Q}_1^\text{H}\mathbf{R}_y\mathbf{Q}_1)}. \tag{41}$$

To compare the convergence speeds of the proposed and conventional adaptive schemes, we need to compare (40) and (41). To do that, we first analyze the properties of the eigenvalues of $\mathbf{R}_y$ and $\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}$, and then $\mathbf{Q}_1^\text{H}\mathbf{R}_y\mathbf{Q}_1$ and $\mathbf{Q}_1^\text{H}[\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1$.

Proposition 2 *All the eigenvalues of* $\mathbf{R}_y$ *are repeated eigenvalues expressed as follows:*

$$\lambda_1(\mathbf{R}_y)=\lambda_2(\mathbf{R}_y)\le\lambda_3(\mathbf{R}_y)=\lambda_4(\mathbf{R}_y)\le\cdots\le\lambda_{2N-1}(\mathbf{R}_y)=\lambda_{2N}(\mathbf{R}_y). \tag{42}$$

Proof. Any eigenvalue $\lambda_l(\mathbf{R}_y)$ and its corresponding eigenvector $\mathbf{c}=[\mathbf{c}_1^\text{T}\quad\mathbf{c}_2^\text{T}]^\text{T}$ for $\mathbf{R}_y$ are obtained by solving the following simultaneous equations:

$$\mathbf{R}_y\mathbf{c}=\lambda_l(\mathbf{R}_y)\mathbf{c}\Rightarrow\begin{bmatrix}\mathbf{R}_{11} & \mathbf{R}_{12}\\ \mathbf{R}_{21} & \mathbf{R}_{22}\end{bmatrix}\begin{bmatrix}\mathbf{c}_1\\ \mathbf{c}_2\end{bmatrix}=\lambda_l(\mathbf{R}_y)\begin{bmatrix}\mathbf{c}_1\\ \mathbf{c}_2\end{bmatrix}. \tag{43}$$

Using the relation among the submatrices of $\mathbf{R}_y$ given by (21), the (43) can be reexpressed as follows:

$$\begin{aligned}\mathbf{R}_{11}\mathbf{c}_1+\mathbf{R}_{12}\mathbf{c}_2&=\lambda_l(\mathbf{R}_y)\mathbf{c}_1\\ \mathbf{R}_{11}\mathbf{c}_2^*+\mathbf{R}_{12}\left(-\mathbf{c}_1^*\right)&=\lambda_l(\mathbf{R}_y)\mathbf{c}_2^*.\end{aligned} \tag{44}$$

For a specified eigenvalue $\lambda_l(\mathbf{R}_y)$, it is conveniently demonstrated that $\bar{\mathbf{c}}=[-\mathbf{c}_2^\text{H}\quad\mathbf{c}_1^\text{H}]^\text{T}$ is also the solution of (44). Because $\mathbf{c}$ and $\bar{\mathbf{c}}$ are orthogonal (that is, $\mathbf{c}^\text{H}\bar{\mathbf{c}}=\mathbf{0}$), $\bar{\mathbf{c}}$ is another eigenvector corresponding to the eigenvalue $\lambda_l(\mathbf{R}_y)$. Therefore, any eigenvalue $\lambda_l(\mathbf{R}_y)$ is a repeated eigenvalue. ■

Moreover, applying a similar approach for $\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}$ and using the relation of the submatrices of $\mathbf{R}_y$, we can conveniently demonstrate that all the eigenvalues of $\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}$ are repeated eigenvalues. That is,

$$\lambda_{2l-1}(\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D})=\lambda_{2l}(\mathbf{R}_y+\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}),\quad l=1,\ldots,N. \tag{45}$$

Proposition 3 *The eigenvalues of* $\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}$ *are identical to those of* $\mathbf{R}_y$. *That is,*

$$\lambda_l(\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D})=\lambda_l(\mathbf{R}_y),\quad l=1,2,\ldots,2N. \tag{46}$$

Proof. Let $\lambda_l(\mathbf{R}_y)$ and $\mathbf{c}=[\mathbf{c}_1^\text{T}\quad\mathbf{c}_2^\text{T}]^\text{T}$ be the eigenvalue and its corresponding eigenvector for $\mathbf{R}_y$ satisfying $\mathbf{R}_y\mathbf{c}=\lambda_l(\mathbf{R}_y)\,\mathbf{c}$. Because $\mathbf{R}_y$ is a Hermitian matrix, $\lambda_l(\mathbf{R}_y)$ is a real number and therefore, can be reexpressed as $\mathbf{R}_y^*\mathbf{c}^*=\lambda_l(\mathbf{R}_y)\,\mathbf{c}^*$. Using the submatrices of $\mathbf{R}_y$, it can be reexpressed as follows:

$$\begin{bmatrix}\mathbf{R}_{11}^*\mathbf{c}_1^*+\mathbf{R}_{12}^*\mathbf{c}_2^*\\ \mathbf{R}_{21}^*\mathbf{c}_1^*+\mathbf{R}_{22}^*\mathbf{c}_2^*\end{bmatrix}=\lambda_l(\mathbf{R}_y)\begin{bmatrix}\mathbf{c}_1^*\\ \mathbf{c}_2^*\end{bmatrix}. \tag{47}$$

To obtain the relation of the eigenvalues and eigenvectors between $\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}$ and $\mathbf{R}_y$, we calculate

$$(\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D})\mathbf{c}^*-\lambda_l(\mathbf{R}_y)\mathbf{c}^* =\begin{bmatrix}\mathbf{R}_{22}\mathbf{c}_1^*-\mathbf{R}_{21}\mathbf{c}_2^*\\ -\mathbf{R}_{12}\mathbf{c}_1^*+\mathbf{R}_{11}\mathbf{c}_2^*\end{bmatrix}-\lambda_l(\mathbf{R}_y)\begin{bmatrix}\mathbf{c}_1^*\\ \mathbf{c}_2^*\end{bmatrix}. \tag{48}$$

Using the relation between the submatrices of $\mathbf{R}_y$ given in (21) and referring to (47), we obtain

$$(\mathbf{D}^T\mathbf{R}_y\mathbf{D})\mathbf{c}^*-\lambda_l(\mathbf{R}_y)\mathbf{c}^* =\begin{bmatrix}\mathbf{R}_{11}^*\mathbf{c}_1^*+\mathbf{R}_{12}^*\mathbf{c}_2^*\\ \mathbf{R}_{21}^*\mathbf{c}_1^*+\mathbf{R}_{22}^*\mathbf{c}_2^*\end{bmatrix}-\lambda_l(\mathbf{R}_y)\begin{bmatrix}\mathbf{c}_1^*\\ \mathbf{c}_2^*\end{bmatrix}=0. \tag{49}$$

Therefore, $\lambda_l(\mathbf{R}_y)$ is also an eigenvalue of $\mathbf{D}^\text{T}\mathbf{R}_y\mathbf{D}$. ■

We introduce the following two theorems to aid the convergence speed analysis of the proposed scheme:

Hermann Weyl Theorem [37] *Let* $\mathbf{A}$ *and* $\mathbf{B}$ *be* $L\times L$ *Hermitian matrices, and let the eigenvalues of* $\mathbf{A}$, $\mathbf{B}$, *and* $\mathbf{A}+\mathbf{B}$ *be* $\lambda_l(\mathbf{A})$, $\lambda_l(\mathbf{B})$, *and* $\lambda_l(\mathbf{A}+\mathbf{B})$, *respectively. Here, the eigenvalues of each matrix are arranged in increasing order. Then, we obtain*

$$\lambda_l(\mathbf{A}+\mathbf{B})\le\lambda_{l+m}(\mathbf{A})+\lambda_{L-m}(\mathbf{B}),\quad m=0,1,\ldots,L-l, \tag{50}$$

for each $l = 1, \ldots, L$, with equality for a certain pair l, m if and only if there is a nonzero vector $\mathbf{c}$ such that $\mathbf{Ac} = \lambda_{l+m}(\mathbf{A})\mathbf{c}$, $\mathbf{Bc} = \lambda_{L-m}(\mathbf{B})\mathbf{c}$, and $(\mathbf{A}+\mathbf{B})\mathbf{c} = \lambda_l(\mathbf{A}+\mathbf{B})\mathbf{c}$.

Furthermore,

$$\lambda_{l-m+1}(\mathbf{A}) + \lambda_m(\mathbf{B}) \le \lambda_l(\mathbf{A}+\mathbf{B}), \quad m = 0, 1, \ldots, l, \tag{51}$$

for each $l = 1, \ldots, L$, with equality for a certain pair l,m if and only if there is a nonzero vector $\mathbf{c}$ such that $\mathbf{Ac} = \lambda_{l-m+1}(\mathbf{A})\mathbf{c}$, $\mathbf{Bc} = \lambda_m(\mathbf{B})\mathbf{c}$, and $(\mathbf{A}+\mathbf{B})\mathbf{c} = \lambda_l(\mathbf{A}+\mathbf{B})\mathbf{c}$. If $\mathbf{A}$ and $\mathbf{B}$ have a non-common eigenvector, each inequality in (50) and (51) is a strict inequality. ■

Poincare Separation Theorem [37] *Let* $\mathbf{A}$ *be an* $L \times L$ *Hermitian matrix and* $\mathbf{U}$ *be an* $L \times m$ $(m \le L)$ *matrix whose columns are orthonormal. Let* $\mathbf{B} = \mathbf{U}^{\mathrm{H}}\mathbf{A}\mathbf{U}$ *and the eigenvalues of* $\mathbf{A}$ *and* $\mathbf{B}$ *be arranged in increasing order. Then, we obtain*

$$\lambda_l(\mathbf{A}) \le \lambda_l(\mathbf{B}) \le \lambda_{l+L-m}(\mathbf{A}), \quad l = 1, \ldots, m. \tag{52}$$

■

Using the Hermann Weyl theorem, it can be conveniently demonstrated that

$$\lambda_{2N}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}) \le \lambda_{2N}(\mathbf{R}_y) + \lambda_{2N}(\mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}), \tag{53}$$

$$\lambda_1(\mathbf{R}_y) + \lambda_1(\mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}) \le \lambda_1(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}). \tag{54}$$

Moreover, from Proposition 3, (53) and (54) can be reexpressed as follows:

$$\lambda_{2N}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}) \le 2\lambda_{2N}(\mathbf{R}_y), \tag{55}$$

$$2\lambda_1(\mathbf{R}_y) \le \lambda_1(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}). \tag{56}$$

Using the Poincare separation theorem, we can develop the following proposition:

Proposition 4 *For the eigenvalues of* $\mathbf{Q}_1^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1$ *and* $\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}$, *we obtain*

$$\lambda_1(\mathbf{Q}_1^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1) = \lambda_1(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}), \tag{57}$$

$$\lambda_{2N-1}(\mathbf{Q}_1^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1) = \lambda_{2N}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}). \tag{58}$$

Proof. Because $\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}$ is a $2N \times 2N$ Hermitian matrix and $\mathbf{Q}_1$ is a $2N \times (2N-1)$ matrix satisfying $\mathbf{Q}_1^{\mathrm{H}}\mathbf{Q}_1 = \mathbf{I}_{2N-1}$, we can derive the following from the Poincare separation theorem:

$$\begin{aligned}\lambda_1(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}) &\le \lambda_1(\mathbf{Q}^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}) \\ &\le \lambda_2(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}).\end{aligned} \tag{59}$$

Because $\lambda_1(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}) = \lambda_2(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})$ from (45), we obtain (57). Moreover, from the Poincare separation theorem, we obtain

$$\begin{aligned}\lambda_{2N-1}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}) &\le \lambda_{2N-1}(\mathbf{Q}^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}) \\ &\le \lambda_{2N}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}).\end{aligned} \tag{60}$$

Because $\lambda_{2N-1}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}) = \lambda_{2N}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})$ from (45), we obtain (58). ■

By applying a similar approach to $\lambda_1(\mathbf{R}_y)$, $\lambda_1(\mathbf{Q}^{\mathrm{H}}\mathbf{R}_y\mathbf{Q})$, $\lambda_{2N}(\mathbf{R}_y)$, and $\lambda_{2N-1}(\mathbf{Q}^{\mathrm{H}}\mathbf{R}_y\mathbf{Q})$, we can obtain

$$\lambda_1(\mathbf{Q}^{\mathrm{H}}\mathbf{R}_y\mathbf{Q}) = \lambda_1(\mathbf{R}_y), \tag{61}$$

$$\lambda_{2N-1}(\mathbf{Q}^{\mathrm{H}}\mathbf{R}_y\mathbf{Q}) = \lambda_{2N}(\mathbf{R}_y). \tag{62}$$

By using Proposition 4, we obtain the following relation:

$$\begin{aligned}\chi(\mathbf{Q}_1^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1) &= \frac{\lambda_{2N-1}(\mathbf{Q}_1^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1)}{\lambda_1(\mathbf{Q}_1^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1)} \\ &= \frac{\lambda_{2N-1}(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})}{\lambda_1(\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D})}.\end{aligned} \tag{63}$$

From (55) and (56), we can obtain the following inequality between the eigenvalue spreads of the proposed and conventional schemes:

$$\begin{aligned}\chi(\mathbf{Q}_1^{\mathrm{H}}[\mathbf{R}_y + \mathbf{D}^{\mathrm{T}}\mathbf{R}_y\mathbf{D}]\mathbf{Q}_1) &\le \frac{2\lambda_{2N-1}(\mathbf{R}_y)}{2\lambda_1(\mathbf{R}_y)} \\ &= \frac{2\lambda_{2N-1}(\mathbf{Q}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{Q}_1)}{2\lambda_1(\mathbf{Q}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{Q}_1)} = \chi(\mathbf{Q}_1^{\mathrm{H}}\mathbf{R}_y\mathbf{Q}_1).\end{aligned} \tag{64}$$

From [37], this result implies that the proposed adaptive receiver provides a higher convergence speed in the mean sense than the conventional adaptive scheme does.

6 | SIMULATION RESULTS

This section describes a computer simulation that we performed to compare the performance of the proposed and conventional blind adaptive algorithms. We compared the learning curves of the output SINR averaged for the two symbols $s_1(2n-1)$ and $s_1(2n)$, and the steady-state BER.

When the detection filters $\mathbf{w}_1(n)$ and $\mathbf{w}_2(n)$ are used, the output SINR averaged for the two symbols is defined by

$$\mathrm{SINR}(n) = \frac{1}{2}\sum_{m=1}^{2}\frac{|\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{g}_{1,m}|^2}{I_m}, \tag{65}$$

where I_m is an interference plus noise expressed as follows:

$$\begin{aligned}I_m = &\sum_{k=1}^{K}\left\{|\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{g}_{k,1}|^2 + |\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{g}_{k,2}|^2\right\} \\ &+ \sigma_v^2\,\|\,\mathbf{w}_m(n)\,\|^2 - |\mathbf{w}_m^{\mathrm{H}}(n)\mathbf{g}_{1,m}|^2.\end{aligned} \tag{66}$$

Each user is equipped with two transmit antennas, and the BS is equipped with N = 128 receiving antennas. Each

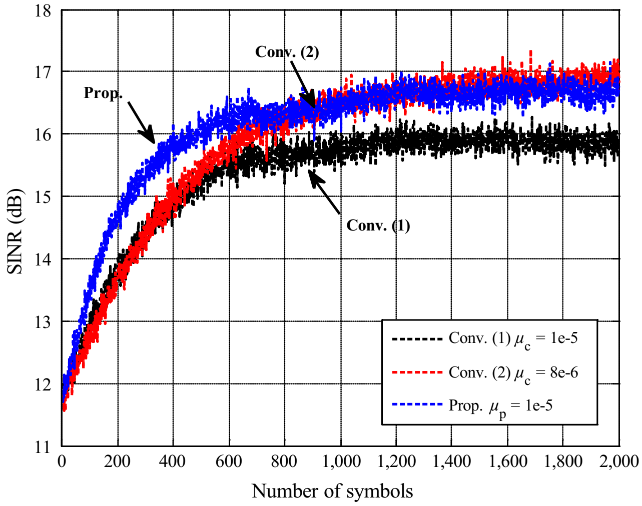

FIGURE 2 SINR comparison of proposed and conventional schemes for uplink massive MIMO systems when $N = 128$, $K = 10$, and SNR = 20 dB

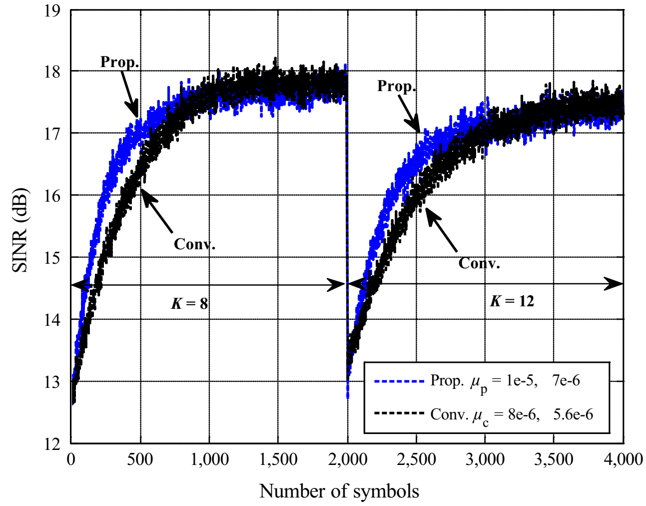

FIGURE 4 SINR comparison of proposed and conventional schemes for uplink massive MIMO systems when different step-sizes are used for both schemes

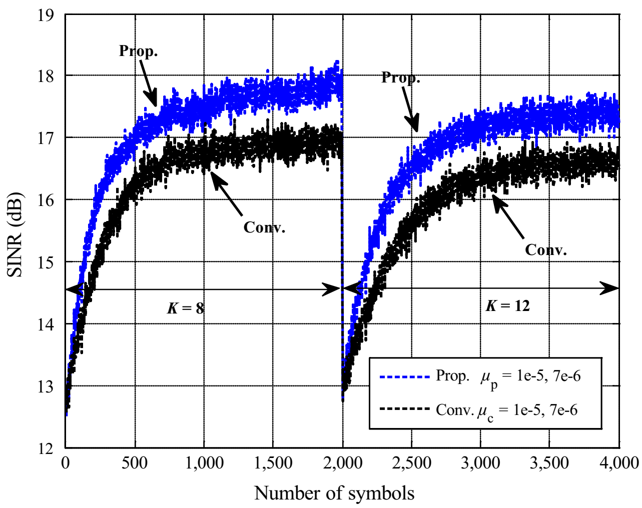

FIGURE 3 SINR comparison of proposed and conventional schemes for uplink massive MIMO systems when number of users varies at symbol time $n = 2000$

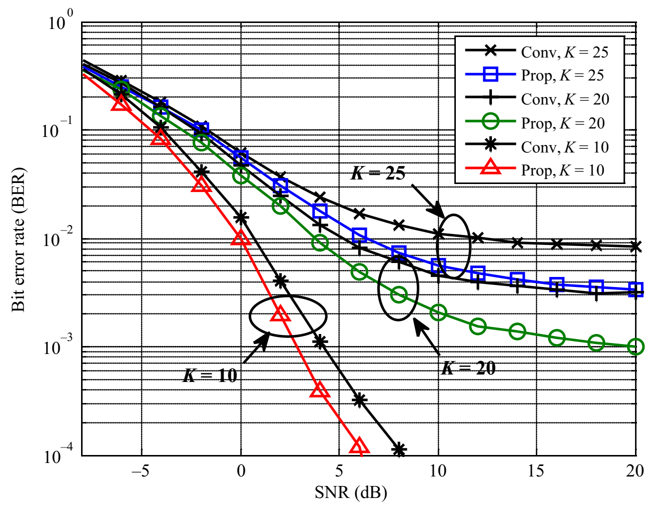

FIGURE 5 Steady-state BER comparison of proposed and conventional schemes for uplink massive MIMO systems when number of users is $K = 10$, 20, and 25

element of the channel vectors $\mathbf{h}_{k,m}, k = 1, 2, \ldots, K, m = 1, 2,$ is generated by independent and identically distributed (*i.i.d.*) Rayleigh fading with zero mean and unit variance.

Figure 2 shows the learning curves of the averaged output SINR for the proposed and conventional blind adaptive algorithms when the number of receiving antennas at the BS is $N = 128$ and the number of users is $K = 10$. The simulation results were averaged by 500 independent channel generations. In the figure, the black and red curves represent the performance of the conventional scheme for the step-sizes $\mu_c = 1 \times 10^{-5}$ and $\mu_c = 8 \times 10^{-6}$, respectively. The blue curve illustrates the performance of the proposed scheme for the step-size $\mu_p = 1 \times 10^{-5}$. The figure shows that the proposed scheme exhibits higher steady-state SINR than the conventional scheme does for identical step size. Moreover, by comparing the red and blue curves, we observe that the proposed scheme exhibits a higher convergence speed than the conventional scheme has for an identical steady-state SINR.

Figure 3 shows the learning curves of the averaged output SINR when the number of users varies at the symbol time $n = 2000$ and equal step-sizes are used for the proposed and conventional schemes. The number of users starts with $K = 8$ and then varies to $K = 12$ at the symbol time $n = 2000$. The step-size is $\mu_c = \mu_p = 1 \times 10^{-5}$ until the symbol time $n = 2000$. Thereafter, it is varied to $\mu_c = \mu_p = 7 \times 10^{-6}$. When the number of users varies, the SINR performance of the proposed and conventional schemes deteriorates instantaneously. Then, both the schemes recover their SINR performance. We also observe that the proposed scheme exhibits higher steady-state SINR performance than the conventional scheme does for an identical step-size even when the number of users varies.

Figure 4 shows the learning curves of the averaged output SINR when different step-sizes are used for the proposed and conventional schemes, and when the number of users varies at the symbol time $n = 2000$. Until the symbol time $n = 2000$, the step-sizes for the proposed and conventional schemes are $\mu_c = 8\times10^{-6}$ and $\mu_p = 1\times10^{-5}$, respectively. Thereafter, they are altered to $\mu_c = 5.6\times10^{-6}$ and $\mu_p = 7\times10^{-6}$, respectively. When the step-size of the conventional scheme is smaller than that of the proposed scheme, the steady-state SINR for the proposed and conventional schemes is almost identical. However, the proposed scheme exhibits a higher convergence speed than the conventional scheme does. Therefore, even when the number of users varies, the proposed scheme exhibits a higher convergence speed than the conventional scheme does.

Figure 5 shows the steady-state BER curves for the proposed and conventional schemes when the number of users is k = 10, 20, and 25. In the figure, we have adjusted the step-sizes of the proposed and conventional schemes to equalize the convergence speed. The steady-state BERs have been calculated after adequate convergence of the filter weighting vectors. The figure shows that the proposed scheme exhibits a lower steady-state BER performance than the conventional scheme for all the different numbers of users and that the performance difference increases as the received SNR increases. We also observe that the BER performances of both the proposed and conventional schemes deteriorate when the number of users increases. This is because the interchannel interference increases in proportion to the number of users.

7 | CONCLUSIONS

In this paper, we propose a blind adaptive receiver design for uplink multiuser massive MIMO systems when each user employs Alamouti's simple STBC to transmit its information symbols. Because the number of receiving antennas of the BS is very large, it is impractical to implement the receiving filters with a batch-processing algorithm owing to the complexity of the inverse matrix calculation.

Therefore, we present a fast-converging blind adaptive algorithm for uplink multiuser massive MIMO systems. First, we derive a special relation between the optimal filter weighting vectors for odd-indexed symbols and even-indexed symbols. Then, we propose a new blind adaptive algorithm using the special relation. In the proposed scheme, detection-filter weighting vectors are updated only in the region satisfying the special relation. Through a theoretical analysis of the convergence speed and a computer simulation, we demonstrate that the proposed scheme exhibits a higher convergence speed than the conventional scheme for an identical steady-state SINR. We also demonstrate that the former exhibits a higher steady-state SINR than the conventional scheme for an identical convergence speed. We further illustrate that the proposed scheme exhibits a lower steady-state BER performance than the conventional scheme does for an identical convergence speed.

ORCID

Bangwon Seo https://orcid.org/0000-0002-7152-1941

REFERENCES

1. J.G. Andrews et al., What will 5G be? IEEE J. Sel. Areas Commun. **32** (2014), no. 6, 1065–1082.
2. A. Gupta and R.K. Jha, A survey of 5G network: Architecture and emerging technologies, IEEE Access **3** (2015), 1206–1232.
3. T.L. Marzetta, Noncooperative cellular wireless with unlimited numbers of base station antennas, IEEE Trans. Wireless Commun. **9** (2010), no. 11, 3590–3600.
4. F. Rusek et al., *Scaling up MIMO: Opportunities and challenges with very large array*, IEEE Signal Process. Mag. **30** (2013), no. 1, 40–60.
5. Y.-H. Nam et al., *Full-dimension MIMO (FD-MIMO) for next generation cellular technology*, IEEE Commun. Mag. **51** (2013), no. 6, 172–179.
6. E.G. Larsson et al., Massive MIMO for next generation wireless systems, IEEE Commun. Mag. **52** (2014), no. 2, 186–195.
7. L. Lu et al., *An overview of massive MIMO: Benefits and challenges*, IEEE J. Select. Topics Signal Process. **8** (2014), no. 5, 742–758.
8. E. Bjornson, E.G. Larsson, and T.L. Marzetta, Massive MIMO: Ten myths and one critical question, IEEE Commun. Mag. **54** (2016), no. 2, 114–123.
9. D.C. Araujo et al., Massive MIMO: Survey and future research topics, IET Commun. **10** (2016), no. 15, 1938–1946.
10. S.M. Alamouti, A simple transmit diversity technique for wireless communications, IEEE J. Sel. Areas Commun. **16** (1998), no. 8, 1451–1458.
11. V. Tarokh, H. Jafarkhani, and A.R. Calderbank, Space-time block codes from orthogonal designs, IEEE Trans. Inf. Theory **45** (1999), no. 5, 1456–1467.
12. E. Basar and U. Aygolu, *Full-rate full-diversity STBCs for three and four transmit t antennas*, Electron. Lett. **44** (2008), no. 18, 1076–1077.
13. E. Biglieri, Y. Hong, and E. Viterbo, *On fast-decodable space-time block codes*, IEEE Trans. Inf. Theory **55** (2009), no. 2, 524–530.
14. E. Basar and Ü. Aygölü, *High-rate full-diversity space-time block codes for three and four transmit antennas*, IET Commun. **3** (2009), no. 8, 1371–1378.
15. N. Varshney and A.K. Jagannatham, MIMO-STBC based multiple relay cooperative communication over time-selective Rayleigh fading links with imperfect channel estimates, IEEE Trans. Vehic. Technol. **66** (2017), no. 7, 6009–6025.

16. X. Meng, X.-G. Xia, and X. Gao, *Omnidirectional space-time block coding for common information broadcasting in massive MIMO systems*, IEEE Trans. Wireless Commun. **17** (2018), no. 3, 1407–1417.
17. D. Lee, *Symbol error rate analysis of scheduled STBC with power allocation in CR-MIMO systems*, IEEE Trans. Veh. Technol. **67** (2018), no. 7, 6218–6228.
18. P.B. Rapajic and B.S. Vucetic, *Adaptive receiver structures for asynchronous CDMA systems*, IEEE J. Select. Areas Commun. **12** (1994), no. 4, 685–697.
19. S.L. Miller, *An adaptive direct-sequence code-division multiple-access receiver for multiuser interference rejection*, IEEE Trans. Commun. **43** (1995), no. 2/3/4, 1746–1755.
20. M. Honig, U. Madhow, and S. Verdu, *Blind adaptive multiuser detection*, IEEE Trans. Inform. Theory **41** (1995), no. 4, 944–960.
21. X. Wang and H.V. Poor, *Blind equalization and multiuser detection in dispersive CDMA channels*, IEEE Trans. Commun. **46** (1998), no. 1, 91–103.
22. U. Madhow, *Blind adaptive interference suppression for direct-sequence CDMA*, Proc. IEEE **86** (1998), no. 10, 2049–2069.
23. M. Honig and M.K. Tsatsanis, *Adaptive techniques for multiuser CDMA receivers*, IEEE Signal Process. Mag. **17** (2000), no. 3, 49–61.
24. Z. Xu and M.K. Tsatsanis, *Blind adaptive algorithms for minimum variance CDMA receivers*, IEEE Trans. Commun. **49** (2001), no. 1, 180–194.
25. D. Reynolds, X. Wang, and H.V. Poor, *Blind adaptive space-time multiuser detection with multiple transmitter and receiver antennas*, IEEE Trans. Signal Process. **50** (2002), no. 6, 1261–1276.
26. X. Liu, K.C. The, and E. Gunawan, *A blind adaptive MMSE multiuser detector over multipath CDMA channels and its analysis*, IEEE Trans. Wireless Commun. **7** (2008), no. 1, 90–97.
27. A. Elnashar, S. Elnoubi, and H.A. El-Mikati, *Performance analysis of blind adaptive MOE multiuser receivers using inverse QRD-RLS algorithm*, IEEE Trans. Circuits Syst. **55** (2008), no. 1, 398–411.
28. R.C. de Lamare and R. Sampaio-Neto, *Blind adaptive MIMO receivers for space-time block-coded DS-CDMA systems in multipath channels using the constant modulus criterion*, IEEE Trans. Commun. **58** (2010), no. 1, 21–27.
29. R.C. de Lamare, R. Sampaio-Neto, and M. Haardt, *Blind adaptive constrained constant-modulus reduced-rank interference suppression algorithms based on interpolation and switched decimation*, IEEE Trans. Signal Process. **59** (2011), no. 2, 681–695.
30. R.C. de Lamare and P.S.R. Diniz, *Blind adaptive interference suppression based on set-membership constrained constant-modulus algorithms with dynamic bounds*, IEEE Trans. Signal Process. **61** (2013), no. 5, 1288–1301.
31. M.Z.A. Bhotto and I.V. Bajic, *Constant modulus blind adaptive beamforming based on unscented Kalman filtering*, IEEE Signal Process. **22** (2015), no. 4, 474–478.
32. S.S. Khalid and S. Abrar, *Blind adaptive algorithm for sparse channel equalisation using projections onto ℓ-ball*, Electr. Lett. **51** (2015), no. 18, 1422–1424.
33. G. Yang et al., *A Kalman filter-based blind adaptive multi-user detection algorithm for underwater acoustic networks*, IEEE Sensors J. **16** (2016), no. 11, 4023–4033.
34. S. Haykin, *Adaptive filter theory*, 3rd ed., Prentice-Hall, Englewood Cliffs, NJ, 1996.
35. Y. Gu et al., *Convergence analysis of a deficient length LMS filter and optimal-length sequence to model exponential decay impulse response*, IEEE Signal Process. Lett. **10** (2003), no. 1, 4–7.
36. A. Hjorungnes and D. Gesbert, *Complex-valued matrix differentiation: Techniques and key results*, IEEE Trans. Signal Process. **55** (2007), no. 6, 2740–2746.
37. R.A. Horn and C.R. Johnson, *Matrix analysis*, ch. 4, Cambridge University Press, Cambridge, UK, 1993.

AUTHOR BIOGRAPHIES

Joonwoo Shin received his BS degree in electronic, electronic communication, and radio engineering from Hanyang University, Seoul, Rep. of Korea, in 2000 and his MS and PhD degrees in electrical engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Rep. of Korea, in 2002 and 2013, respectively. From January 2002 to August 2014, he was with the Electronics Telecommunications Research Institute, Daejeon, Rep. of Korea. In September 2014, he joined the Division of Navigation Science, Korea Maritime and Ocean University, Rep. of Korea, where he is currently an associate professor. His research interests include statistical signal processing, and mathematical and numerical optimization of wireless communication systems. (joonoos@kmou.ac.kr)

Bangwon Seo received his BS, MS, and PhD degrees in electrical engineering from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Rep. of Korea, in 1997, 1999, and 2010, respectively. From November 2004 to February 2013, he was with the Electronics Telecommunications Research Institute, Daejeon, Rep. of Korea. In March 2013, he joined the Division of Electrical, Electronic and Control Engineering, Kongju National University, Rep. of Korea, where he is currently an associate professor. His research interests include massive MIMO, hybrid transceiver, device-to-device (D2D) direct communications, MIMO systems, and OFDM systems. (seobw@kongju.ac.kr)