An Iterative Widely Linear Interference Suppression Algorithm based on Auxiliary Vector Filtering

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Abstract—We introduce a new Widely Linearly (WL) framework that combines the WL filter with the Auxiliary Vector Filtering (AVF) technique for non-circular signals. Moreover, an adaptive interference suppression algorithm is developed for a high data rate Direct Sequence Ultra Wideband (DS-UWB) system. The proposed algorithm exploits the second-order behavior of the received signal and takes full advantage of the improper nature of the non-circular data. It utilizes an iterative procedure to update the WL weight vector. The key properties of the proposed algorithm corresponding to the WL processor are analyzed. Simulation results are provided to show the superior performance of the proposed algorithm over its linear counterpart and conventional linear/WL Minimum Mean Square Error (MMSE) adaptive algorithms.

I. INTRODUCTION

In wireless communication systems, most interference suppression or parameter estimation techniques are based on linear signal processing [1], [2]. However, when a non-circular modulation is applied, e.g., Binary Phase Shift Keying (BPSK), the strict linear estimation of an improper real signal from complex data appears complex, which, in some sense, is not optimal. It has been shown in [3], [4] that by exploiting the improper nature of the received signal the estimation performance can be significantly improved. Therefore, the resulting Widely Linear (WL) estimation has gained great popularity for systems using non-circular modulation schemes [4]-[6]. The WL Minimum Mean Square Error (MMSE) filter based on the Recursive Least Squares (RLS) algorithm has been introduced in [5]. The corresponding low-complexity Least Mean Square (LMS) adaptation has been proposed in [6]. These adaptive WL algorithms exhibit a superior steady-state performance compared to the linear counterparts. One of the most important properties is that the WL estimate of a real signal from complex data is still real.

In many communication systems, the data to be processed have a large dimension due to a high processing gain, a large number of antennas, or numerous multipath components, which considerably restricts the convergence performance of the adaptive estimation algorithms. Furthermore, for the WL processing, both the original received vector and its complex conjugate must be considered. Under this condition, the conventional LMS and RLS algorithms require an even larger number of symbols to reach the steady-state and thus the convergence is deteriorated. Auxiliary Vector Filtering (AVF) is an effective technique that utilizes an iterative procedure to update the weight vector for improving the convergence and enhancing the output performance [7]. Its weight solution converges to the Minimum Variance Distortion-less Response (MVDR) filter [8]. However, the existing AVF-based algorithms only consider linear processing.

In this paper, we propose an adaptive WL-AVF interference suppression algorithm in the application of a high data rate Direct Sequence Ultra Wideband (DS-UWB) system. Due to the broadband nature of the UWB signal, a large number of resolvable multipath components are collected at the receiver, resulting in severe Inter-/Intra-Symbol Interference (ISI). In a multi-user scenario, the multiple access performance of the DS-UWB system is also significantly degraded by the Multi-User Interference (MUI). The large bandwidth requires a high sampling rate and leads to the observation data of a large dimension. We introduce a new WL-AVF receiver for DS-UWB systems exploiting the non-circular properties of the BPSK modulation, where the WL filter is combined with the AVF technique in order to achieve a fast convergence and a superior performance over the linear one. The new receiver includes a bijective transformation block and a WL-AVF filter that is adjusted by an adaptive algorithm. The bijective transformation block uses the received signal and its complex conjugate to formulate an augmented vector for the WL processing. The WL-AVF filter processes the augmented received vector to generate the WL output. In the proposed algorithm, the linear AVF concept is applied to the WL processor for the weight adaptation. The proposed algorithm takes full advantage of the second-order information of the complex received vector, i.e., the covariance matrix and the complementary covariance matrix, and thus improves the performance. The key properties are analyzed. Simulation results are provided and discussed to show the enhanced performance of the proposed algorithm over its linear counterpart as well as the conventional L/WL adaptive MMSE algorithms.
The rest of this paper is organized as follows: we outline the system model in Section II. The proposed WL-AVF filtering design is introduced and the adaptive algorithm is developed in Section III. The properties of the proposed algorithm are also analyzed in this section. Simulation results are provided and discussed in Section IV, and conclusions are drawn in Section V.

II. SYSTEM DESCRIPTION

We consider the uplink of a BPSK DS-UWB system with \( N_u \) asynchronous users. In the complex baseband, the transmitted signal for the \( k \)-th user is given by

\[
s_k(t) = \sum_{i=-\infty}^{\infty} b_k(i) \sum_{n=0}^{N-1} \sqrt{E_k} c_k(n) g(t - iT_b - nT_c),
\]

where \( b_k(i) \in \{ \pm 1 \} \) is the \( i \)-th BPSK symbol for the user \( k \) with bit energy \( E_k \) and duration \( T_b \). \( c_k(n) \in \{ \pm \sqrt{N} \} \) is the multiple access code with chip interval \( T_c \), and the pulse shape \( g(t) \) is chosen as a Raised Cosine (RC) pulse with a 6-dB bandwidth \( B_0 \) and a roll-off factor \( \beta \). The processing gain \( N \) is determined by \( T_c/T_b \).

A general multipath UWB channel (considered in complex baseband) can be fully described by its samples if the sampling rate is at least \( B = (\beta + 1)B_0 \). The normalized tapped-delay line model is given by \( h_k(t) = \sum_{l=0}^{L-1} c_k(l) \delta(t-l/B), \) where \( c_k(l) \) is the \( l \)-th complex channel tap for the \( k \)-th user and \( \sum_{l=0}^{L-1} |c_k(l)|^2 = 1 \). In our case, the channel is assumed time-invariant for UWB communications.

![Data model of the signal for a synchronous user](image)

The received signal after the pulse matched filter \( g(-t) \) can be expressed as

\[
y(t) = \sum_{i=-\infty}^{\infty} \sum_{k=1}^{N_u} \sum_{l=0}^{N-1} \sum_{n=0}^{L-1} \sqrt{E_k} b_k(i) \left( i + \left\lfloor \frac{n-D_k}{N} \right\rfloor \right) c_k(n) \alpha_k(l) \hat{g} \left( t - iT_b - nT_c - \frac{l}{B} - \tau_k \right) + n(t),
\]

where \( \hat{g}(t) = g(t) \ast g(-t) \) and \( n(t) = \hat{n}(t) \ast g(-t) \) are the filtered pulse and noise, respectively. Zero-mean, complex-baseband Additive White Gaussian Noise (AWGN) \( \hat{n}(t) \) has a Power Spectral Density (PSD) \( N_0 \). Asynchronous (but chip synchronous) transmission is assumed, meaning that \( \tau_1 - \tau_k = D_kT_c \) and the random variable \( D_k \in \{ 0, 1, \ldots, N-1 \} \) with equal probability. The floor operator \( \lfloor x \rfloor \) rounds the argument \( x \) down to the closest integer that is less and equal to \( x \).

Where the bits \( b_k \in \mathbb{R}^{N_u \times 1} \) are transmitted, by sampling \( g(t) \) at chip rate \( 1/T_c \), the resulting received vector of size \( N_uN + L - 1 \) is given by

\[
y = \sum_{k=1}^{N_u} \sqrt{E_k} F_k H_k b_k + n,
\]

where \( F_k \in \mathbb{R}^{(N_uN+L-1) \times N_uL} \) as shown in Fig. 1 is the code matrix, the channel matrix is represented as \( H_k = I_{N_u} \otimes h_k \in \mathbb{C}^{N_u \times N_uL} \) (\( \otimes \) denotes the Kroneker product) containing the channel information \( h_k = [c_k(0), \ldots, c_k(L-1)]^T \), and \( n \in \mathbb{C}^{N_uN \times L} \) is the AWGN vector. Assume that the delay of the desired user \( \tau_1 \) is known and \( \tau_1 = 0 \) is chosen without loss of generality. For the \( i \)-th transmitted bit, the corresponding received vector

\[
r(i) = y(iN : iN + M - 1), \quad i = 0, 1, \ldots, N_u - 1
\]

of length \( M = N + L - 1 \) includes the desired user’s signal, the MUI part \( v(i) \), all the interference from the chips of the current symbols (intra-symbol) as well as from the previous and subsequent symbols (inter-symbol) \( \eta(i) \) and the AWGN. The code matrix for the desired user \( C_1 \in \mathbb{R}^{M \times L} \) is shown in Fig. 1 for \( k = 1 \). In the case of this BPSK-modulated system, both the desired signal and the interference (MUI and ISI) are improper.

III. WIDELY-LINEAR AUXILIARY VECTOR FILTERING DESIGN

In this section, we introduce a WL-AVF structure for interference suppression in DS-UWB systems and develop a training-based adaptive algorithm. The improper properties of the proposed algorithm for non-circular modulation schemes are provided to show the advantages of the WL based receiver over its linear counterpart.

A. WL-AVF Structure

In [5], [6], it has been shown that for some non-circular or improper modulation schemes (e.g., BPSK), the performance of the linear receiver can be further improved if not only the received signal itself, but also its complex conjugate are processed. This is because, for improper signals, the covariance matrix \( R_o = \mathbb{E}[rr^H] \) cannot completely describe the information of the second-order statistics of the received vector \( r \), and the complementary covariance matrix \( R_o = \mathbb{E}[rr^T] \) needs to be taken into account. The resulting receiver is referred to as a WL receiver.

In order to exploit the second-order information, we perform the WL processing that utilizes the received vector \( r \) and its
complex conjugate $r^*$ to form an augmented vector, which yields,

$$r^T \rightarrow \tilde{r} : \tilde{r} = \begin{bmatrix} r^T, r^H \end{bmatrix}^T \in \mathbb{C}^{2M \times 1},$$  \hspace{1cm} (5)$$

where $T\{ \cdot \}$ denotes the bijective transformation for the WL processor, $T$, $H$, and $*$ in the superscript denote transpose, conjugate transpose, and complex conjugation, respectively. In what follows, all WL based quantities are denoted by an over tilde. An important property of $T\{ \cdot \}$ is that, for complex vectors $r$ and $u$, where $\tilde{u}^H \tilde{r} = \tilde{r}^H \tilde{u} = 2\Re\{u^H r\}$. As shown in Fig. 2, the augmented vector $\tilde{r}$ is viewed as a new received vector to the WL filter.

Compared with the linear filter, the WL filter has to deal with the augmented vector with a larger dimension $\tilde{r}$ due to the bijective transformation. This leads to a slow convergence. An effective way is to employ the AVF technique, which utilizes an iterative procedure to update the weight vector and achieves a relatively fast convergence rate. The existing AVF based approaches are based on linear receivers [7], [8]. In this paper, we extend them to WL receivers, which is termed WL-AVF design. In Fig. 2, the augmented vector $\tilde{r}$ is processed by the WL-AVF filter that is adjusted by the AVF based algorithm to generate the output $z = \tilde{w}^H \tilde{r}$. It is clear that the WL-AVF receiver will take full advantage of the improper signals if $\tilde{w}$ is a bijective transformation of a certain linear weight vector $\tilde{w}$. We will show this derivation in the following subsection. The bijective transformation, the WL-AVF filter, and the adaptive algorithm constitute the proposed WL-AVF structure.

**B. Proposed WL-AVF Algorithm**

In contrast to the conventional adaptive WL MMSE receiver, we employ the AVF technique for the WL processing and develop a new adaptive algorithm for interference suppression in DS-UWB systems. In Fig. 3, we show a block diagram that illustrates the iterative procedure of the proposed WL-AVF algorithm. Specifically, we initialize the WL-based weight vector $\tilde{w}_0$ with the normalized conventional matched filter

$$\tilde{w}_0 = \gamma \frac{\tilde{p}}{\| \tilde{p} \|^2},$$  \hspace{1cm} (6)$$

where $\gamma$ is the desired response and $\tilde{p} = \mathbb{E}[b_1^H \tilde{r}]$ is the augmented cross-correlation vector of the desired signal $b_1$ and the augmented received vector $\tilde{r}$.

After that, the WL weight vector is iteratively computed by subtracting a scaled auxiliary vector from $\tilde{w}_0$, that is

$$\tilde{w}_d = \tilde{w}_0 - \sum_{l=1}^{d} \mu_l \tilde{g}_l = \tilde{w}_{d-1} - \tilde{\mu}_d \tilde{g}_d,$$  \hspace{1cm} (7)$$

where $\tilde{g}_d$ is a WL auxiliary vector with $\tilde{g}^H_d \tilde{p} = 0$ and $\tilde{\mu}_d$ is a scalar factor to control the weight of $\tilde{g}_d$. The aim of (7) is to suppress interference and noise step by step while maintaining the contribution of the desired user.

From (7), it is necessary to determine the WL auxiliary vector $\tilde{g}_d$ and the scalar factor $\tilde{\mu}_d$ for the calculation of $\tilde{w}_d$. Given $\tilde{g}_d$, $\tilde{\mu}_d$ can be obtained by minimizing the variance at the output of $\tilde{w}_d$

$$\tilde{\mu}_d = \arg \min_{\tilde{\mu}} \mathbb{E}[\tilde{w}^H_d \tilde{r} \tilde{r}^H \tilde{w}_d].$$  \hspace{1cm} (8)$$

Substituting the second expression of $\tilde{w}_d$ in (7) into (8), computing the gradient with respect to $\tilde{\mu}_d$ and equating it to zero, we have

$$\tilde{\mu}_d = \frac{\tilde{g}^H_d \tilde{R} \tilde{w}_{d-1}}{\tilde{g}^H_d \tilde{R} \tilde{g}_d}.$$  \hspace{1cm} (9)$$

where $\tilde{R} = \mathbb{E}[\tilde{r} \tilde{r}^H]$ denotes the augmented covariance matrix.

The calculation of $\tilde{g}_d$ is determined by maximizing a constrained cost function:

$$\tilde{g}_d = \arg \max_{\tilde{g}} \mathbb{E}[\tilde{w}^H_{d-1} \tilde{r} \tilde{r}^H \tilde{g}_d]$$

subject to $\tilde{g}^H_d \tilde{p} = 0$ and $\tilde{g}^H_d \tilde{g}_d = 1$,\hspace{1cm} (10)

where the maximization of the cross-correlation between $\tilde{w}^H_{d-1} \tilde{r}$ and $\tilde{r}^H \tilde{g}_d$ strives to determine the auxiliary vector that can capture most of the interference present in $\tilde{w}^H_{d-1} \tilde{r}$.

According to (7), computing the gradient of (10) with respect to $\tilde{g}_d$, we have

$$\tilde{g}_d = \frac{\tilde{g}^H_d \tilde{R} \tilde{w}_{d-1}}{\| (I_{2M} - \tilde{p} \tilde{p}^H) \tilde{R} \tilde{w}_{d-1} \|},$$  \hspace{1cm} (11)$$

where $I_{2M}$ denotes the corresponding identity matrix.

The expressions $\tilde{w}_0$, $\tilde{w}_d$, $\tilde{\mu}_d$, and $\tilde{g}_d$ compose the iteration of the proposed WL-AVF algorithm which is summarized in Table I. We drop the normalization of the WL auxiliary vector [8]. The estimation of $\tilde{R}$ and $\tilde{p}$ is calculated by their recursive forms:
TABLE I
PROPOSED WL-A VF ALGORITHM

For the time index \(i = 1, 2, \ldots, N_s\),

**Initialization:**
\[
\mathbf{w}_0(i) = \gamma^* \mathbf{p}(i)/\|\mathbf{p}(i)\|^2.
\]

**Iterative procedure:**
For \(d = 1, 2, \ldots, D\)
\[
\mathbf{g}_d(i) = (I - \frac{\mu_d}{\mu_d + \mu_b}) \mathbf{R}(i) \mathbf{w}_{d-1}(i)
\]
if \(\|\mathbf{g}_d(i) - \mathbf{w}_{d-1}(i)\| < \epsilon\) then EXIT.
\[
\mathbf{\hat{w}}_d(i) = \left[ \begin{array}{c} \mathbf{R}_{ss} \mathbf{w}_d(i) \\ \mathbf{R}_{in} \mathbf{w}_d(i) \end{array} \right],
\]
\[
\mathbf{\hat{R}}(i) = \lambda \mathbf{R}(i) - \mathbf{r}(i) \mathbf{r}(i)^H,
\]
\[
\mathbf{p}(i) = (1 - \lambda) \mathbf{b}_1(i) \mathbf{r}(i),
\]
\[
\mathbf{\hat{w}}_{d-1}(i) = \mathbf{w}_{d-1}(i) - \mu_d(i) \mathbf{g}_d(i)
\]
End

**Weight expression:**
\[
\mathbf{w}(i) = \mathbf{w}_D(i)
\]

**Output:**
\[
\hat{z}(i) = \mathbf{w}^H(i) \mathbf{r}(i)
\]

where \(\lambda\) is a forgetting factor that is close to but less than 1. It should be noticed that, for the proposed algorithm, the WL weight vector should be adapted at each time instant. Thus, the iteration procedure is performed for each time instant and \(i\) is included in the quantities. Generally, there exists a maximum number of iterations \(D\), which is obtained if \(\|\mathbf{g}_d(i) - \mathbf{w}_{d-1}(i)\| < \epsilon\) with \(\epsilon\) being a small positive value. Alternative termination rules can be found in [9].

**C. Key Properties**

The proposed WL-AVF algorithm has the following key properties:

1) The initial WL weight vector \(\mathbf{w}_0\) is a bijective transformation of the original (linear) weight vector \(\mathbf{w}_0\), which is
\[
\mathbf{w}_0 \xrightarrow{T} \mathbf{w}_0^0: \mathbf{w}_0 = \left[ \begin{array}{c} \mathbf{w}_0^T \\ \mathbf{w}_0^H \end{array} \right]^T,
\]
where \(\mathbf{w}_0 = \gamma^* \mathbf{p}/\|\mathbf{p}\|^2\) with \(\mathbf{p} = \mathbb{E}[\mathbf{b}_1 \mathbf{r}]\).

2) The \(d\)-th WL auxiliary vector \(\mathbf{g}_d\) can be constructed by a bijective transformation of a linear auxiliary vector \(\mathbf{g}_d\), i.e.,
\[
\mathbf{g}_d = \left[ \begin{array}{c} \mathbf{R}_{ss} \mathbf{R}_{in} \mathbf{w}_{d-1}(i) \\ \mathbf{R}_{ss} \mathbf{R}_{in} \mathbf{w}_{d-1}(i) \end{array} \right]
\]
where \(\mathbf{P}_d = \mathbf{P}_d^H/\|\mathbf{p}\|^2\) and \(\mathbf{P}_b = \mathbf{P}_b^T/\|\mathbf{p}\|^2\). For BPSK modulated signals, \(\mathbf{R}_a = \mathbb{E}[\mathbf{r}\mathbf{r}^T]\) is non-zero and thus the improper property of the received vector can be exploited by means of WL processing. Both \(\mathbf{R}_a\) and \(\mathbf{R}_b\) can completely describe the second-order information of \(\mathbf{r}\). The vectors \(\mathbf{g}_d\) and \(\mathbf{w}_{d-1}\) are not necessary for implementation of the proposed WL-AVF algorithm but are given here to show the improper property of the WL-based filter.

3) The scalar factor \(\mu_d\) can be written as
\[
\mu_d = \mu_a + \mu_b^*, \quad \mu_b = \mu_b^*\]
\[
\mu_a = \mathbf{g}_a^H \mathbf{R}_a \mathbf{g}_a + \mathbf{g}_b^H \mathbf{R}_b \mathbf{g}_b, \quad \text{and} \quad \mu_b = \mathbf{g}_a^H \mathbf{R}_a \mathbf{g}_a + \mathbf{g}_b^H \mathbf{R}_b \mathbf{g}_b.
\]
It is clear that \(\mu_d\) is a real value.

From the properties 1)-3), we conclude that \(\mathbf{w}_d = [\mathbf{w}^T_d, \mathbf{w}^H_d]^T\). Thus, after \(D\) iterations, the output can be expressed as
\[
\hat{z} = \mathbf{w}^H \mathbf{r} + \mathbf{w}^T \mathbf{r}^* = \hat{z} + \hat{z}^*,
\]
which is a real value. For the non-circular signals (e.g., BPSK), the estimation error of the WL receiver is \(\epsilon_{WL} = b_1 - 2\Re\{\hat{z}^H \mathbf{r}\}\) and that of the linear one is \(\epsilon_L = b_1 - \mathbf{w}^H \mathbf{r}\). The WL processing takes advantage of the fact that \(b_1\) is real-valued, whereas linear processing treats \(b_1\) as if it was complex-valued. As the close relationship between the WL MVDR filter \(\mathbf{w}_{mvdr} = \gamma^* \mathbf{p}^H \mathbf{P}_a^{-1} \mathbf{p}\) and the WL MMSE filter \(\mathbf{w}_{mmse} = \mathbf{R}^{-1} \mathbf{p}\) (the desired response \(\gamma\) can be adjusted to yield a scaled version of \(\mathbf{p}\)), the WL estimation error \(\epsilon_{WL}\) leads to a “conventional” MMSE problem [6]. The computational complexity of the proposed WL-AVF algorithm with \(O(DM^2)\) is even slightly lower than the corresponding L-AV method. The reason is that the estimated parameters \(\mathbf{w}_d\), \(\mathbf{g}_d \subset \mathbb{C}^{2M}\) can be associated with a bijective transformation of the complex vectors of size \(M\), and thus the computation is only determined by \(M\). The real-valued quantities \(\mu_d\) and \(\hat{z}\) restrict the processing to the real data.

**IV. SIMULATION RESULTS**

The multipath channel impulse responses are obtained by UWB measurements (including antennas) in a line-of-sight office of size 5 m \(\times\) 5 m \(\times\) 2.6 m [10]. The transfer function of a certain channel realization is firstly transformed from the band-pass to the low-pass range at a center frequency \(f_c = 4\) GHz, and then converted into a tapped-delay line model with equally spaced taps. The RRC pulse is chosen with \(\beta = 500\) MHz and \(\beta = 0.3\). At the receiver, the sampling rate is 1 GHz. The maximum channel delay is 64 ns with a resolution of 1 ns. We assume that the UWB channel is time-invariant during the estimation procedure. The DS code of length \(N = 24\) is generated pseudo-randomly for the DS-UWB system, where \(N_u = 16\) users operate with perfect power control in the system. The size of the received vector \(\mathbf{r}\) is \(M = 87\).

We evaluate the Signal-to-Interference plus Noise Ratio (SINR) performance for the proposed algorithm. The instantaneous output SINR of the WL filtering algorithm with the estimated weights \(\mathbf{w}(i)\) can be calculated by
\[
\text{SINR}(i) = \frac{\mathbb{E}[\hat{z}^H(i) \mathbf{r}(i)b_1(i)]}{\mathbb{V}[\mathbf{w}^H(i) \mathbf{r}(i)b_1(i)]} = \frac{\mathbf{w}^H(i) \mathbf{R}_a \mathbf{w}(i)}{\mathbf{w}^H(i) \mathbf{R}_a \mathbf{w}(i)}
\]
where the signal part \( \hat{R}_{ss} \) is written as
\[
\hat{R}_{ss} = E_1 \left[ C_1 h_1 h_1^H \right] (C_1 h_1 h_1^H)^* (C_1 h_1 h_1^H) \] * ,
\]
and the interference plus noise part \( \hat{R}_{in} \) is
\[
\hat{R}_{in} = \left[ \mathbb{E} \{ vv^T + \eta \eta^T \} + N_0 I \right] \mathbb{E} \{ vv^T + \eta \eta^T \}^* \mathbb{E} \{ vv^T + \eta \eta^T \} + N_0 I \] * .

Fig. 4 shows the SINR performance of the WL-AVF using \( D = 8 \) iterations and compare it to the L/WL-RLS as well as the L/WL-LMS methods at \( E_b/N_0 = 15 \) dB, where the corresponding optimal L/WL MMSE solutions act as the reference. The forgetting factor is \( \lambda = 0.998 \). It can be observed that the WL methods outperform the linear counterparts and the proposed WL-AVF converges faster than all the other tested adaptive algorithms.

In Fig. 5, we check the impact of the number of iterations \( D \) on the proposed algorithm and show the Bit Error Rate (BER) performance. The scenario is the same as that in Fig. 4. We find that the most adequate number of iterations for the proposed WL-AVF algorithm is \( D = 8 \) since after this number, the BER values are relatively on the same level. Note that \( D \) is different with respect to different \( E_b/N_0 \). Besides, a smaller \( D \) may provide a faster convergence during the initial stages of the estimation and a slightly larger \( D \) tends to yield a better steady-state performance.

V. CONCLUSION

To suppress the MUI and ISI in a high-data-rate DS-UWB system based on non-circular modulation, we introduce a new WL receiver with the AVF technique and develop a training-based adaptive algorithm. This new framework employs the bijective transformation to combine the received vector and its complex conjugate into an augmented vector, which is processed by the WL-AVF filter to estimate the decision variable. The proposed algorithm utilizes an iterative way to update the WL weight vector. Since the WL processor takes full advantage of the second-order information of the received vector, the proposed algorithm exhibits a superior performance over its linear counterpart and the conventional L/WL-MMSE adaptive algorithms.

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