Recursive Joint Channel Estimation and Signal Detection for Massive MIMO Systems

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***Abstract*—In this paper, a low-complexity recursive joint channel estimation and signal detection method is proposed for massive multiple-input multiple-output (MIMO) systems to improve both estimation and detection performance. Specifically, by approximating the autocorrelation matrix of the input data signal as a diagonal matrix, the complexity of the recursive least squares (RLS) channel estimation algorithm can be reduced. Then, based on RLS channel estimation, the complexity of signal detection can also be reduced by a two-stage Sherman formula. After that, the results of signal detection are then fed back to channel estimation and a weighting matrix is applyed for further performance improvement, which leads to the proposed weighted diagonalized recursive channel estimation and detection (WDRCED). Simulation results demonstrate that WDRCED improves the performance of both estimation and detection with reduced computational complexity.**

***Index Terms*—Joint channel estimation and signal detection, weighted diagonalized RLS, iterative method, massive MIMO.**

I. Introduction

Due to the increasing demands for system capacity, spectrum, and energy efficiency, massive multiple-input multiple-output (MIMO) technology is pivotal in B5G and 6G communication systems [1]–[4]. Typically, the performance of massive MIMO systems chiefly depends on the accuracy of channel state information (CSI). In time division duplexing (TDD) systems, accurate channel estimation enhances uplink detection and enables precise precoding for the downlink. Among the existing methods, semi-blind estimation is much more preferred by taking advantages of both the pilot symbols and the unknown data symbols [6]–[13] .

In particular, a two-level maximum likelihood (ML) method is proposed for joint channel estimation and detection in [6], which iteratively minimizes the cost function but also incurs high complexity unfortunately. In [9], the channel matrix is treated as a hidden variable, where an expectation-maximization (EM) algorithm is used to alternate between channel estimation and signal detection. Along this direction, authors in [10], [11] explored two EM-based estimation methods utilizing linear detection techniques by adding different assumptions on the data symbols. Similar alternating method have also been given in [12], [13]. However, these methods commence to work when all signals including pilots and data are received. Different from them, the recursive least squares (RLS) filter is proposed in [14]–[16], which dynamically updates the channel estimates promptly with the incoming data.

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In this paper, based on RLS channel estimation, a low-complexity weighted diagonalized recursive channel estimation and detection (WDRCED) method is proposed for improving both estimation and detection performance. Specifically, WDRCED consists of three aspects. First of all, it diagonalizes the autocorrelation matrix of the input signal to simplify the traditional RLS channel estimation. Secondly, based on RLS channel estimation, the complexity of signal detection is significantly reduced by circumventing the matrix multiplexing and inversion in an efficient way. Finally, the detection outcomes are integrated back into the channel estimation for extra performance gains, thus establishing a loop between channel estimation and signal detection.

II. Traditional framework for joint channel estimation and data detection

Consider a TDD protocol scenario, the base station is equipped with N_r antennas, and receives transmissions from N_t single-antenna users. Each user sends $T = N_p + N_d$ symbols during the uplink transmission, with N_p known pilot symbols followed by N_d data symbols. This transmission occurs in a block-fading scenario, where the channel remains constant over the block. As shown in Fig. 1, after receiving T symbol vectors, the traditional joint channel estimation and detection method begins to work by exchanging information iteratively.

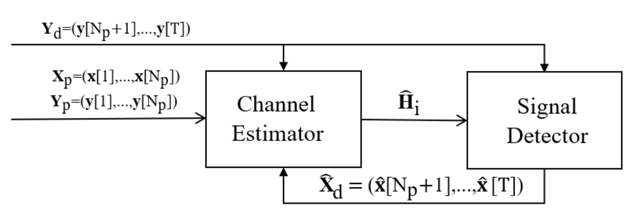

Fig. 1. Traditional joint channel estimation and signal detection.

Specifically, given the MIMO channel matrix $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$, the received signals can be expressed by

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{N}, \tag{1}$$

where $\mathbf{Y} = [\mathbf{Y}_p \, \mathbf{Y}_d] \in \mathbb{C}^{N_r \times T}$, $\mathbf{X} = [\mathbf{X}_p \, \mathbf{X}_d] \in \mathbb{C}^{N_t \times T}$ and $\mathbf{N} = [\mathbf{N}_p \, \mathbf{N}_d] \in \mathbb{C}^{N_r \times T}$ are the received signal matrix, transmit signal matrix and zero-mean additive noise matrix respectively. Meanwhile, the subscripts p and d represent the pilot and the data transmission phase respectively.

In the traditional joint channel estimation and signal detection, an initial estimated channel is normally obtained based on the pilot signals via least squares (LS) or minimum mean square error (MMSE) estimation, i.e.,

$$\mathbf{H}_{\text{LS}} = \mathbf{Y}_p \mathbf{X}_p^H (\mathbf{X}_p \mathbf{X}_p^H)^{-1}, \tag{2}$$

$$\mathbf{H}_{\text{MMSE}} = \mathbf{Y}_p (\mathbf{X}_p^H \mathbf{R}_H \mathbf{X}_p + \sigma_n^2 N_r \mathbf{I})^{-1} \mathbf{X}_p^H \mathbf{R}_H, \tag{3}$$

where $\mathbf{R}_H = \mathbb{E}[\mathbf{H}^H \mathbf{H}]$ is channel correlation matrix and σ_n^2 is the noise variance. Then the estimated channel $\hat{\mathbf{H}}$ is used to detect signals $\hat{\mathbf{X}}_d \in \mathbb{C}^{N_t \times N_d}$. Let $\mathbf{y}(t)$, $\mathbf{x}(t)$ and $\mathbf{n}(t)$ denote the t-th column vectors of $\mathbf{Y}$, $\mathbf{X}$ and $\mathbf{N}$ (t correspond to the index of time instance). Then we have

$$\mathbf{y}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{n}(t), t = 1, 2, ..., T, \tag{4}$$

where the optimal ML detection computes

$$\hat{\mathbf{x}}(t) = \underset{\mathbf{x}(t) \in \mathcal{O}^{N_t}}{\arg\min} \|\mathbf{y}(t) - \hat{\mathbf{H}}\mathbf{x}(t)\|^2, t = N_p + 1, ..., T. \tag{5}$$

In general, the classic linear detectors like zero forcing (ZF) and MMSE are normally applied for detection. Specifically, the linear detector firstly performs the following detections

$$\tilde{\mathbf{x}}_{\text{ZF}} = (\hat{\mathbf{H}}^H \hat{\mathbf{H}})^{-1} \hat{\mathbf{H}}^H \mathbf{y}(t), \tag{6}$$

$$\tilde{\mathbf{x}}_{\text{MMSE}} = (\hat{\mathbf{H}}^H \hat{\mathbf{H}} + \sigma_n^2 \mathbf{I})^{-1} \hat{\mathbf{H}}^H \mathbf{y}(t), \tag{7}$$

then the detection output is obtained by quantizing $\hat{\mathbf{x}}_{\text{ZF}} = \lceil \tilde{\mathbf{x}}_{\text{ZF}} \rfloor_{\mathcal{Q}} \in \mathcal{O}^{N_t}$ or $\hat{\mathbf{x}}_{\text{MMSE}} = \lceil \tilde{\mathbf{x}}_{\text{MMSE}} \rfloor_{\mathcal{Q}} \in \mathcal{O}^{N_t}$.

After signal detection, the detected signal matrix $\hat{\mathbf{X}}_d = [\hat{\mathbf{x}}(N_p+1) \ldots \hat{\mathbf{x}}(T)]$ is fed back to channel estimator, which uses $\mathbf{X}_p$ and $\hat{\mathbf{X}}_d$ to update the channel estimates through LS in (2) or MMSE in (3). Then, the refined channel estimates are used to enhance signal detection performance by providing a better channel estimates for (5), thus forming a feedback loop between channel estimation and detection. However, this conventional approach requires complete sets of received data, i.e., $t = 1, ..., T$ for each iteration. To this end, RLS based joint channel estimation and signal detection is proposed [15].

III. Algorithm Description

As shown in Fig. 2, different from the traditional joint channel estimation and signal detection, RLS joint method updates the channel estimation at every time instance.

Specifically, consider (2) as a cumulative form at each time instance, i.e.,

$$\mathbf{H}_{\text{LS}}(t) = \left[\sum_{l=1}^{t} \mathbf{y}(l)\hat{\mathbf{x}}^H(l)\right] \left[\sum_{l=1}^{t} \hat{\mathbf{x}}(l)\hat{\mathbf{x}}^H(l)\right]^{-1}, \tag{8}$$

and RLS estimation serves as a recursive version of LS by

$$\hat{\mathbf{H}}(t) = \hat{\mathbf{H}}(t-1) + \mathbf{e}(t)\mathbf{k}(t). \tag{9}$$

Here $\mathbf{e}(t) = \mathbf{y}(t) - \hat{\mathbf{H}}(t-1)\hat{\mathbf{x}}(t) \in \mathbb{C}^{N_r \times 1}$ represents the prior error vector at time t, the Kalman gain vector $\mathbf{k}(t) \in \mathbb{C}^{1 \times N_t}$ is expressed as

$$\mathbf{k}(t) = \frac{\hat{\mathbf{x}}^H(t)\mathbf{P}(t-1)}{1 + \hat{\mathbf{x}}^H(t)\mathbf{P}(t-1)\hat{\mathbf{x}}(t)}, \tag{10}$$

with information matrix

$$\mathbf{P}(t) = \mathbf{P}(t-1) - \mathbf{P}(t-1)\hat{\mathbf{x}}(t)\mathbf{k}(t). \tag{11}$$

After obtaining $\hat{\mathbf{H}}(t)$, the current data $\hat{\mathbf{x}}(t)$ is detected using ZF in (6) or MMSE in (7). Then the detected data is sent back to refine channel estimates by (9). Clearly, we can see from Fig. 2, this updated channel is then used to detect data in the next instance, creating a recursive process for joint channel estimation and detection. To better utilize the information from joint channel estimation and detection, we propose a joint weighted diagonalized recursive channel estimation and detection (WDRCED) method.

A. Complexity Reduction in Channel Estimation by Diagonalizing the Information Matrix

In the RLS channel estimation algorithm, updating the information matrix $\mathbf{P}$ involves matrix-vector and vector-vector multiplications, which contribute to its computational complexity. The matrix $\mathbf{P}$, on the other hand, represents the approximation of the inverse of $\mathbf{X}_{\text{cur}}\mathbf{X}_{\text{cur}}^H$ where $\mathbf{X}_{\text{cur}} \in \mathbb{C}^{N_t \times t}$ represents the matrix of signals sent from time index 1 to the current time index t ($t_{\max} = T$).

As time index t increases, matrix $\mathbf{P}$ exhibits a dominantly diagonal characteristic when $t \gg N_t$ [17]. This situation arises because the signals transmitted from different antennas are becoming weakly correlated or approximately orthogonal to each other, so that the diagonal entries of $\mathbf{X}_{\text{cur}}\mathbf{X}_{\text{cur}}^H$ are getting larger compared to the off-diagonal entries. Motivated by this, we update only the diagonal elements of the matrix $\mathbf{P}$, i.e.,

$$\bar{\mathbf{P}}(t) = \text{diag}\left(\bar{\mathbf{P}}(t-1) - \bar{\mathbf{P}}(t-1)\hat{\mathbf{x}}(t)\mathbf{k}(t)\right) \tag{12}$$

where diag $(\cdot)$ represents retaining only the diagonal elements of a matrix. Clearly, we emphasize that such an approximation is getting more accurate as t increases.

By using this diagonal approximation method, the complexity reduction in (10) and (11) can be readily achieved. Here, the computational complexity is evaluated in terms of the required number of complex multiplications. Firstly, the computation of $\mathbf{k}(t)$ in (10) mainly involves vector-matrix multiplication. According to $\bar{\mathbf{P}}(t)$ in (12), this vector-matrix multiplication is simplified, where the multiplication complxity of (10) is reduced from $N_t^2 + 2N_t$ to $3N_t$. Secondly, when computing matrix $\mathbf{P}$, the matrix-vector multiplication between $\mathbf{P}(t-1) \in \mathbb{C}^{N_t \times N_t}$ and $\hat{\mathbf{x}}(t) \in \mathbb{C}^{N_t \times 1}$ in (11) only needs to take the diagonal elements into account. Moreover, the vetcor-vector multiplication between $\mathbf{P}(t-1)\hat{\mathbf{x}}(t) \in \mathbb{C}^{N_t \times 1}$ and $\mathbf{k}(t) \in \mathbb{C}^{1 \times N_t}$ in (11) only needs to consider the the diagonal elements of the resulting matrix due to diagonalization, so that the multiplication complxity of (11) is reduced from $2N_t^2$ to $2N_t$. To summarize, the total multiplication complexity of RLS estimation is reduced from $2N_rN_t + 3N_t^2 + 2N_t$ to $2N_rN_t + 5N_t$.

B. Complexity Reduction in Signal Detection by Two-stage Sherman Formula

According to (10) and (11), the update of RLS channel estimation requires the known transmit data signal $\hat{\mathbf{x}}(t)$. To

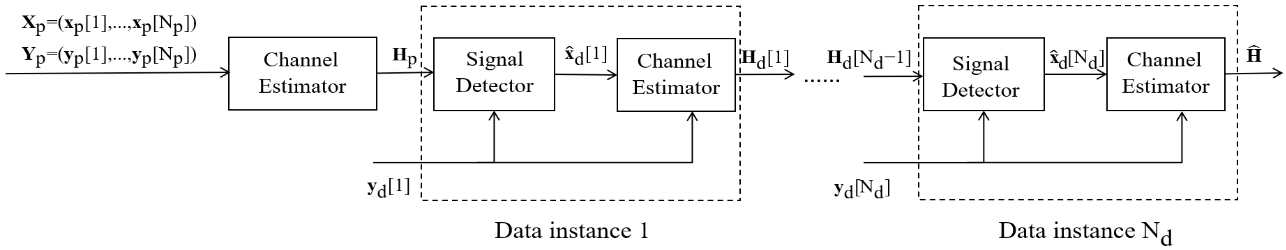

Fig. 2. System diagram of massive MIMO RLS joint channel estimation and signal detection.

obtain $\hat{\mathbf{x}}(t)$, using ZF linear detection as an example, we can observe that the computation and inversion of the Gram matrix $\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t)$ in (6) are rather computationally expensive. To this end, we now show that leveraging the iterative form of RLS channel estimation in (9) can effectively reduce the complexity required for computing (6).

Specifically, by (9), the Gram matrix $\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t)$ in (6) at time instance t can be formulated as

$$\begin{aligned}\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t) &= (\hat{\mathbf{H}}(t-1)+\Delta\hat{\mathbf{H}}(t))^H(\hat{\mathbf{H}}(t-1)+\Delta\hat{\mathbf{H}}(t)) \\ &= \hat{\mathbf{H}}^H(t-1)\hat{\mathbf{H}}(t-1)+\Delta\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t-1) \\ &\quad +\hat{\mathbf{H}}^H(t-1)\Delta\hat{\mathbf{H}}(t)+\Delta\hat{\mathbf{H}}^H(t)\Delta\hat{\mathbf{H}}(t),\end{aligned} \tag{13}$$

where $\Delta\hat{\mathbf{H}}(t)=\mathbf{e}(t)\mathbf{k}(t)$ is the update part of the new estimated channel. Given $\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t)$ in (13), to bypass the matrix inversion of it, a two-stage detection method is proposed based on the information from the previous time instance.

At the first stage, considering the first three terms of the Gram matrix update calculation in (13), we have

$$\begin{aligned}&\hat{\mathbf{H}}^H(t-1)\hat{\mathbf{H}}(t-1)+\Delta\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t-1)+\hat{\mathbf{H}}^H(t-1)\Delta\hat{\mathbf{H}}(t) \\ &= \hat{\mathbf{H}}^H(t-1)\hat{\mathbf{H}}(t-1)+\mathbf{k}^H(t)(\mathbf{e}^H(t)\hat{\mathbf{H}}(t-1)) \\ &+(\hat{\mathbf{H}}^H(t-1)\mathbf{e}(t))\mathbf{k}(t).\end{aligned} \tag{14}$$

Then, for notational simplicity, the following definitions are made:

$$\begin{gathered}\mathbf{G}\triangleq\hat{\mathbf{H}}^H(t-1)\hat{\mathbf{H}}(t-1)\in\mathbb{C}^{N_t\times N_t}, \\ \mathbf{u}\triangleq\mathbf{k}^H(t)\in\mathbb{C}^{N_t}, \mathbf{B}=\mathbf{I}\in\mathbb{C}^{2\times 2} \\ \mathbf{v}\triangleq\hat{\mathbf{H}}^H(t-1)\mathbf{e}(t)\in\mathbb{C}^{N_t}, \\ \mathbf{U}\triangleq[\mathbf{u},\mathbf{v}]\in\mathbb{C}^{N_t\times 2}, \mathbf{V}\triangleq[\mathbf{v},\mathbf{u}]^H\in\mathbb{C}^{2\times N_t},\end{gathered}$$

and we then introduce Sherman-Woodbury formula to compute the first stage filter matrix $\mathbf{F}_{\text{first}}\in\mathbb{C}^{N_t\times N_t}$, i.e.

$$\begin{aligned}\mathbf{F}_{\text{first}} &= (\mathbf{G}+\mathbf{UBV})^{-1} \\ &= \mathbf{G}^{-1}-\mathbf{G}^{-1}\mathbf{U}(\mathbf{B}^{-1}+\mathbf{V}\mathbf{G}^{-1}\mathbf{U})^{-1}\mathbf{V}\mathbf{G}^{-1}.\end{aligned} \tag{15}$$

Next, at the second stage, we add the last term $\Delta\hat{\mathbf{H}}^H(t)\Delta\hat{\mathbf{H}}(t)$, i.e.,

$$\Delta\hat{\mathbf{H}}^H(t)\Delta\hat{\mathbf{H}}(t)=(\mathbf{e}(t)\mathbf{k}(t))^H\mathbf{e}(t)\mathbf{k}(t)=\mathbf{k}^H(t)\|\mathbf{e}(t)\|^2\mathbf{k}(t) \tag{16}$$

to the results of the first stage. Then, by letting $\mathbf{d}=\mathbf{k}^H(t)\|\mathbf{e}(t)\|\in\mathbb{C}^{N_t}$ and introducing Sherman-Morrison-Woodbury formula, the target matrix inversion $(\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t))^{-1}$ can be computed by the following formation:

$$\begin{aligned}(\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t))^{-1} &= \mathbf{F}_{\text{second}} \\ &= (\mathbf{F}_{\text{first}}^{-1}+\mathbf{d}\mathbf{d}^H)^{-1} \\ &= \mathbf{F}_{\text{first}}-\frac{\mathbf{F}_{\text{first}}\mathbf{d}\mathbf{d}^H\mathbf{F}_{\text{first}}}{1+\mathbf{d}^H\mathbf{F}_{\text{first}}\mathbf{d}}.\end{aligned} \tag{17}$$

More importantly, according to (17), calculation of the matrix inversion $(\hat{\mathbf{H}}^H(t+1)\hat{\mathbf{H}}(t+1))^{-1}$ can be calculated directedly based on the results of $(\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t))^{-1}$ without the traditional matrix multiplication and inversion. By doing this, the matrix multiplication and inversion are only required at the first time instance. To be precise, the calculation flow chart is shown in Fig. 3, where 'Mul' and 'Inv' represent multiplication and inversion respectively.

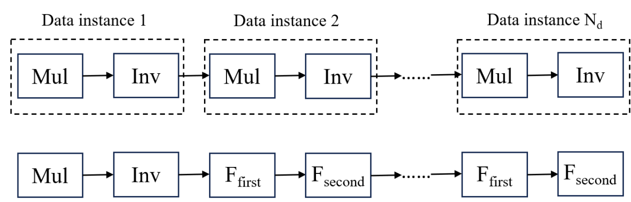

Fig. 3. Comparison of linear detection and two-stage detection.

Specifically, at each time instance, the traditional computational complexity of directly calculating $(\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t))^{-1}$ is $N_rN_t^2+0.5N_t^3$. Note that at the first stage, the matrix inversion involved has a dimension of only 2, where the multiplication complexity is $N_rN_t+8N_t^2+4N_t+4$. At the second stage, all computations only involve matrix-vector or vector-vector multiplications and the multiplication complexity is $2N_t^2+3N_t+N_r$. In RLS joint method, to detect the current data $\mathbf{x}(t)$, both linear detector and the proposed two-stage detector also require the computation of $\hat{\mathbf{H}}^H(t)\mathbf{y}(t)$ and multiplexing between $(\hat{\mathbf{H}}^H(t)\hat{\mathbf{H}}(t))^{-1}$ and $\hat{\mathbf{H}}^H(t-1)\mathbf{y}(t)$, where the multiplication complexity is $N_rN_t+N_t^2$. Therefore, the total complexity reduction is achieved from the direct detection $N_rN_t^2+0.5N_t^3+N_rN_t+N_t^2$ to the proposed one $2N_rN_t+11N_t^2+7N_t+N_r+4$.

C. Performance Improvement in Both Channel Estimation and Signal Detection by Weighted RLS

According to (10), the update of RLS channel estimation also involves updating the Kalman vector $\mathbf{k}(t)$, which is crucial for incorporating new detection results into the current channel estimates. Therefore, we consider modifying $\mathbf{k}(t)$ by applying a weight matrix $\mathbf{W}$ to obtain further performance improvement.

TABLE I
THE COMPUTATIONAL COMPLEXITIES OF WDRCED AND OTHER ALGORITHMS PER UPDATE

Channel Estimation	Multiplication	Summation
RLS	$2N_rN_t + 3N_t^2 + 2N_t$	$2N_rN_t + 3N_t^2 - N_t$
estimation in WDRCED	$2N_rN_t + 5N_t$	$2N_rN_t + 3N_t$

Signal Detection	Multiplication	Summation
Linear method	$N_rN_t^2 + 0.5N_t^3 + N_rN_t + N_t^2$	$N_rN_t^2 + 0.5N_t^3 + N_rN_t - 2N_t$
detection in WDRCED	$2N_rN_t + 11N_t^2 + 7N_t + N_r + 4$	$2N_rN_t + 11N_t^2 - 2N_t + 1$

Specifically, the weight matrix $\mathbf{W}$ is a diagonal matrix, where its i-th diagonal element w_{ii} reflects the reliability of transmit antenna i. This reliability refers to the confidence level in the data transmitted from antenna i, which is assessed based on how accurately the signal from this antenna is detected at the receiver. Moreover, such a reliability can be measured based on the distance between the signal $\tilde{\mathbf{x}}$ processed in (6) or (7) and its nearest constellation point $\hat{\mathbf{x}}$. This distance quantifies the deviation of the received signal from its expected constellation point. For instance, the distance for detected signals at transmit antenna i is given as:

$$r_i^2 = |\mathbf{J}_{\text{linear}}(i,:)\mathbf{y}(t) - x_{\text{nearest}}|^2. \tag{18}$$

Here, $\mathbf{J}_{\text{linear}}$ is the equalization matrix for linear detection, which maps the received signals back to the transmitted signal space through a linear transformation and can obtain via (17) and $\hat{\mathbf{H}}$. Furthermore, we update the weight coefficient w_{ii} as:

$$w_{ii} = \frac{1}{2}\tanh\{\frac{1}{r_i^2}\}. \tag{19}$$

The update rule in (19) is a heuristic approach designed to provide a smooth and bounded adjustment for the weight coefficient. After getting the weight matrix $\mathbf{W}$, the improved weighted $\mathbf{k}(t)$ is then given by:

$$\bar{\mathbf{k}}(t) = \mathbf{k}(t)\mathbf{W}, \tag{20}$$

and the following RLS channel estimation is reformulated as:

$$\hat{\mathbf{H}}(t) = \hat{\mathbf{H}}(t-1) + \mathbf{e}(t)\bar{\mathbf{k}}(t), \tag{21}$$

$$\bar{\mathbf{P}}(t) = \bar{\mathbf{P}}(t-1) - \bar{\mathbf{P}}(t-1)\hat{\mathbf{x}}(t)\bar{\mathbf{k}}(t). \tag{22}$$

By using this weighted RLS method, the performance of both channel estimation and signal detection can be improved. To summarize, the proposed WDRCED algorithm for uplink massive MIMO systems is shown in Algorithm 1. As for the convergence of RLS, the results of WDRCED method will gradually converge to the MMSE solution with the initial setup $\hat{\mathbf{H}}(0) = \mathbf{0}$ and $\delta = \frac{1}{\sigma_n^2}$.

Algorithm 1 Weighted Diagonalized Recursive Channel Estimation and Detection (WDRCED) algorithm

Input: $\mathbf{y}(t), \mathbf{x}_p(t), N_p, N_d$
Output: $\hat{\mathbf{H}}, \hat{\mathbf{X}}_d$

Phase I: Pilot based estimation
Initialize: $\hat{\mathbf{H}}(0) = \mathbf{0}, \mathbf{P}(0) = \delta\mathbf{I}$
for $t = 1, 2, \ldots, N_p$ **do**
  $\mathbf{e}(t) = \mathbf{y}(t) - \hat{\mathbf{H}}(t-1)\mathbf{x}_p(t)$
  $\mathbf{k}(t) = \frac{\mathbf{x}_p^H(t)\mathbf{P}(t-1)}{1+\mathbf{x}_p^H(t)\mathbf{P}(t-1)\mathbf{x}_p(t)}$
  $\hat{\mathbf{H}}(t) = \hat{\mathbf{H}}(t-1) + \mathbf{e}(t)\mathbf{k}(t)$
  $\mathbf{P}(t) = \mathbf{P}(t-1) - \mathbf{P}(t-1)\mathbf{x}_p(t)\mathbf{k}(t)$
end for
Phase II: Joint channel estimation and detection
Initialize: $\mathbf{G}^{-1}(N_p+1) = (\hat{\mathbf{H}}^H(N_p)\hat{\mathbf{H}}(N_p) + \sigma_n^2\mathbf{I})^{-1}$, $\bar{\mathbf{P}}(N_p+1) = \text{diag}(\mathbf{P}(N_p))$
for $t = N_p+1, N_p+2, \ldots, N_p+N_d$ **do**
  Signal detection using $\mathbf{G}^{-1}(t)$:
  Calculate $\mathbf{F}_{\text{first}}$ by (15)
  Calculate $\mathbf{F}_{\text{second}}$ by (17)
  $\hat{\mathbf{x}}(t) = \lceil \mathbf{F}_{\text{second}}\hat{\mathbf{H}}^H(t-1)\mathbf{y}(t) \rfloor_{\mathcal{Q}} \in \mathcal{O}^{N_t}$
  Channel estimation update:
  Calculate r_i by (18)
  Construct the weight matrix $\mathbf{W}(t)$
  $\mathbf{e}(t) = \mathbf{y}(t) - \hat{\mathbf{H}}(t-1)\hat{\mathbf{x}}(t)$
  $\bar{\mathbf{k}}(t) = \frac{\hat{\mathbf{x}}^H(t)\bar{\mathbf{P}}(t-1)}{1+\hat{\mathbf{x}}^H(t)\bar{\mathbf{P}}(t-1)\hat{\mathbf{x}}(t)}\mathbf{W}(t)$
  $\hat{\mathbf{H}}(t) = \hat{\mathbf{H}}(t-1) + \mathbf{e}(t)\bar{\mathbf{k}}(t)$
  $\bar{\mathbf{P}}(t) = \text{diag}\left(\bar{\mathbf{P}}(t-1) - \bar{\mathbf{P}}(t-1)\hat{\mathbf{x}}(t)\bar{\mathbf{k}}(t)\right)$
  Update $\mathbf{G}^{-1}(t+1) = \mathbf{F}_{\text{second}}$ for next time instance
end for

IV. SIMULATION RESULTS

In this section, we evaluate the performance achieved by the proposed WDRCED method. The performance is estimated under i.i.d Rayleigh MIMO channels i.e., all elements in $\mathbf{H}$ follow a circularly symmetric complex-valued Gaussian distribution with zero-mean and unit variance. We consider using the transpose of random N_t columns of $N_p \times N_p$ DFT matrix as the orthogonal pilots matrix and each user send signals independently. In the first set of experiments, we investigate the channel estimation performance MSE, which can be computed as:

$$\text{MSE} = \frac{\|\mathbf{H} - \hat{\mathbf{H}}\|^2}{N_rN_t}. \tag{23}$$

We set $N_r = 32$, $N_t = 4$, $N_p = N_t$, $N_d = 80N_p$, 64-QAM modulation and compare the MSE performance of three types training based channel estimator, SVD subspace estimator [8], EM with Gaussian Data estimator [10], heuristic EM estimator [11] and data-aided RLS estimator [15]. MMSE Genie assumes the channel estimator has the perfect knowledge of data symbols and serves as a limit band. The proposed WDRCED uses weighted diagonalized RLS channel estimator combined with MMSE initial based two-stage detector.

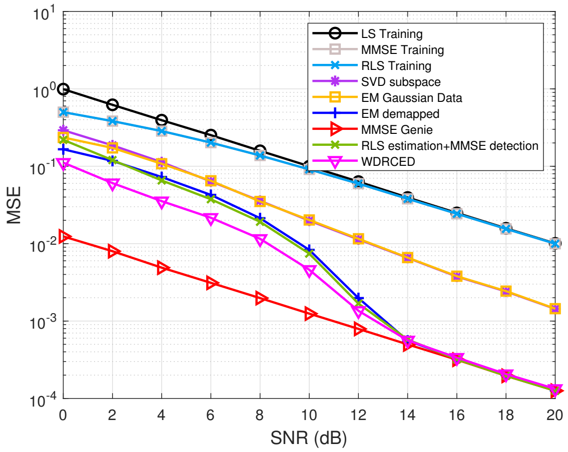

Fig. 4. MSE versus SNR under 64-QAM scheme with $N_r = 32$, $N_t = 4$, $N_p = N_t$, $N_d = 80N_p$.

As shown in Fig. 4, compared with pilot based method, data-aided methods achieve better estimation performance. It also proves that with a proper initial value, RLS can achieve MMSE performance. The proposed WDRCED method outperforms other methods and operates as an online method without requiring a full dataset. Under high SNR conditions, WDRCED achieves estimation performance comparable to scenarios with perfectly known transmitted signals, as the high accuracy of signal detection minimizes errors in the estimation process.

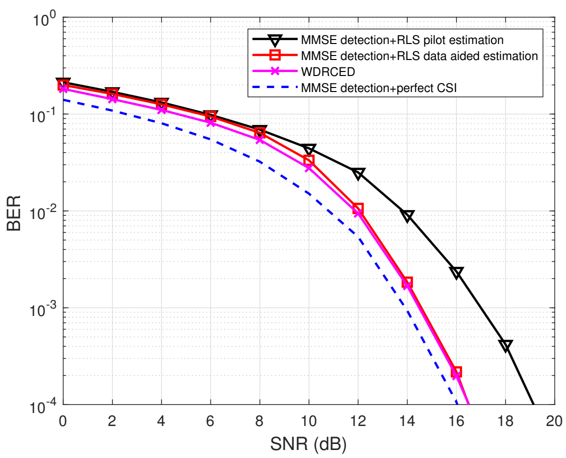

Fig. 5. BER versus SNR under 64-QAM scheme with $N_r = 32$, $N_t = 4$, $N_p = N_t$, $N_d = 80N_p$.

The detection performance is evaluated in terms of the bit error rates (BERs) under MMSE detection. Fig. 5 demonstrates that data-aided methods are superior to pilot-based methods. It can be seen that the performance become better as SNR increases. The proposed method can achieve better performance compared with traditional approach that combine linear detection with a simple RLS estimator by providing a more accurate channel estimates while maintaining lower complexity.

V. Conclusion

In this paper, we propose a weighted diagonalized recursive channel estimation and detection method named as WDRCED for massive MIMO systems. The autocorrelation matrix of the input signal is diagonalized to simplify the RLS channel estimation, and the complexity of signal detection is significantly reduced by a two-stage method. Moreover, a weight coefficient is updated for extra performance gains. Then the complexity analysis of the proposed algorithm is also provided. Simulation results confirm that the proposed method attains better performance than other algorithms.

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