Large-MIMO Receiver based on Linear Regression of MMSE Residual

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***Abstract*— Multiple input multiple output (MIMO) systems with large number of antennas have been gaining wide attention as they enable very high throughputs. A major impediment is the complexity at the receiver needed to detect the transmitted data. To this end we propose a new receiver, called LRR (Linear Regression of MMSE Residual), which improves the MMSE receiver by learning a linear regression model for the error of the MMSE receiver. The LRR receiver uses pilot data to estimate the channel, and then uses locally generated training data (not transmitted over the channel), to find the linear regression parameters. The proposed receiver is suitable for applications where the channel remains constant for a long period (slow-fading channels) and performs quite well: at a bit error rate (BER) of 10^{-3}, the SNR gain over MMSE receiver is about 7 dB for a 16×16 system; for a 64×64 system the gain is about 8.5 dB. For large coherence time, the complexity order of the LRR receiver is the same as that of the MMSE receiver, and in simulations we find that it needs about 4 times as many floating point operations. We also show that further gain of about 4 dB is obtained by local search around the estimate given by the LRR receiver.**

Keywords: *Large-MIMO receiver, linear regression, MMSE residual, receiver-based training*

I. Introduction

Communication links employing multiple antennas at the transmitter and receiver have promised high data rates without sacrificing bandwidth, owing to the increased number of independent spatial dimensions [1], [2]. Research concerning the multiple-input multiple-output (MIMO) systems has been vigorously promoted as practical implementation of these systems is deemed crucial for the next generation wireless systems. In the last decade or so many challenges thrown up by the wireless MIMO systems such as channel estimation, interference, detection complexity have been addressed by researchers. Standards such as IEEE 802.11n/802.11ac [3] and LTE [4] already use MIMO systems. A trend toward deploying larger number of antennas can be noted in the evolution of these standards. Multiuser-MIMO is typical in several popular application scenarios like cellular and WLAN. The base station or the access point can have large number of antennas, with the users having single or multiple antennas; the uplink in such a multiuser system can be considered as a *virtual* large-MIMO system. Even point-to-point large-MIMO is relevant in some practical applications. One such interesting application of point-to-point large-MIMO is providing high-speed wireless back-haul link between base stations, where tens of antennas (as considered in this paper) can be provided.

A major impediment in deploying large number of antennas is the complexity involved in detecting the transmitted symbols. Detectors which work very efficiently for smaller systems fail to scale-up when tens of antennas are deployed. Several low-complexity receivers have been proposed in the literature which perform well in the large antenna regime, the performance in a few cases being near optimal. In [5] a local search based algorithm has been applied for large-MIMO detection; this has an interesting property that the performance gets better as the number of antennas increases. In [6] the well-known Markov chain Monte-Carlo (MCMC) method had been used for detecting BPSK symbols in a 50 transmit, 50 receive antenna MIMO system. Further, the MCMC technique has been generalized for detecting higher order modulation symbols in [7] and is shown to be near optimal. Belief Propagation (BP), employed in diverse fields, has been used for MIMO detection in [8]. Variants of Tabu Search (TS) have been shown to perform well in large-MIMO systems ([9],[10]).

In this paper, we present a novel low complexity receiver structure which is suitable for applications where the channel does not vary very fast. The structure itself is very simple consisting of two linear filters. The first filter is the conventional minimum mean squared error (MMSE) receiver which is used to get the MMSE estimate of the transmitted data vector. The second filter then acts on the *residual* of the MMSE estimate - the part of received vector which is not accounted for by the MMSE estimate - to obtain a correction vector. The final estimate is just the sum of the MMSE estimate and the correction vector. We call this receiver as LRR (Linear Regression of MMSE Residual) receiver. The second filter which acts on the residual is designed once every coherence interval using a training set which is generated entirely at the receiver itself. Thus *no* additional bandwidth is required over the traditional MMSE receiver. This receiver structure works surprisingly well; indeed, we get gains of more than 7 dB when compared to conventional MMSE receiver alone, at a bit error rate (BER) of 10^{-3} for various configurations. The detection complexity itself is very low: for large coherence period, it has the same order as that of the MMSE receiver, and in simulations, we observe that it is within a factor of 4 of the number of floating point operations needed in the MMSE receiver. In this paper, we report BER performance and complexity of the receiver for 16-QAM input constellation and 16×16, 32×32, 64×64 MIMO systems. We compare with the MMSE and the MMSE-LAS (which uses the likelihood ascent search (LAS) algorithm [5] on top of the MMSE estimate) receivers, and we also investigate additional gains obtained by combining the LRR receiver with the LAS search algorithm.

The paper is organized as follows: in Section II, we give the system model and motivate the use of receivers designed by training. In Section III we present the description of the proposed receiver structure along with the pseudo-code. In Section IV we present the simulation results for BER performance and complexity. The conclusions are presented in Section V.

II. System Model

Let $\boldsymbol{x} \in \mathsf{Q}^{N_t}$ be the vector to be transmitted, where Q is the modulation alphabet and N_t is the number of transmit antennas. At the receiver with N_r receive antennas, the received vector is $\boldsymbol{y} \in \mathbb{C}^{N_r}$. The linear vector channel model gives the relation between $\boldsymbol{x}$ and $\boldsymbol{y}$ as

$$\boldsymbol{y} \quad = \quad \mathbf{H}\boldsymbol{x} + \boldsymbol{w}, \qquad (1)$$

where the entries of the $N_r \times N_t$ channel gain matrix $\mathbf{H}$ are modeled as i.i.d. with distribution $\mathbb{C}\mathcal{N}(0,1)$. The entries of the noise vector $\boldsymbol{w}$ are assumed to be i.i.d. $\mathbb{C}\mathcal{N}(0,\sigma^2)$.

The channel matrix $\mathbf{H}$ can be estimated using N_t pilot vectors. For example, an $N_t \times N_t$ *orthonormal* pilot matrix $\mathbf{X}_{pilot}$ can be sent over the channel with power P and the corresponding output $\mathbf{Y}_{pilot}$ observed. The corresponding MMSE channel estimate is

$$\hat{\mathbf{H}} = \frac{P}{P+\sigma^2}\mathbf{Y}_{pilot}\mathbf{X}_{pilot}^H. \qquad (2)$$

If $\mathbf{H}$ is known perfectly, the optimum detector would be the Maximum-Likelihood (ML) detector:

$$\widehat{\boldsymbol{x}}_{ML} = \arg\min_{\boldsymbol{x}\in\mathsf{Q}^{N_t}} \|\boldsymbol{y} - \hat{\mathbf{H}}\boldsymbol{x}\|^2$$

The ML detector has an exponential complexity in N_t. Further since $\mathbf{H}$ is not known perfectly, its estimate has to be used which leads to a mismatched detection [11], [12]. This is true for any detector which uses the estimate of $\mathbf{H}$; however, the loss in performance can be reduced by using a higher pilot power P.

Several low-complexity detectors have been proposed, ranging from linear detectors such as MMSE to detectors which employ complex search algorithms such as sphere decoder [13], [14]. Though the linear detectors have the least complexity, the performance is generally bad. On the other hand, the search algorithms obtain good performance with a high complexity cost. Another drawback of the search algorithms is that the search procedure has to be employed to detect each transmitted vector even if the channel has not changed. The fact that several vectors to be detected are in the same coherence interval will not lead to a significant reduction in the complexity of the search. In contrast, the linear receivers need to be designed once for each coherence interval; the complexity of applying the linear receive filters to detect data in the same coherence interval is very minimal. This motivates us to ask the question: is it possible to design a receiver (linear or otherwise) wherein the design is done only once in each coherence interval, and applying the receiver for detection will encumber minimal complexity, at the same time giving good performance? If yes, this kind of receiver will be very beneficial in low-mobility environments where the coherence period is very large such as WLANs. In the next section, we design such a receiver.

III. Receiver Structure

Consider a traditional MIMO system given by (1). A standard low complexity receiver structure is to apply a linear transformation $\mathbf{G}$ to the received vector $\boldsymbol{y}$ and then form an estimate $\hat{\boldsymbol{x}} = \mathcal{Q}(\mathbf{G}\boldsymbol{y})$, where $\mathcal{Q}(\cdot)$ is the nearest neighbor quantizer for the input modulation. The minimum mean square error (MMSE) receiver is given by

$$\mathbf{G}_{mmse} = \arg\min_{\mathbf{G}} E[\|\boldsymbol{x} - \mathbf{G}\boldsymbol{y}\|^2],$$

where it is common to assume that the entries of $\boldsymbol{x}$ are chosen i.i.d. uniform over the input constellation. The MMSE estimate is given by

$$\hat{\boldsymbol{x}} = \mathcal{Q}(\mathbf{G}_{mmse}\boldsymbol{y}).$$

While the MMSE receiver yields decent performance, it is not optimal, and the error vector $\tilde{\boldsymbol{x}} = \boldsymbol{x} - \hat{\boldsymbol{x}}$ is *not* independent of $\boldsymbol{y}$. Thus further processing of $\boldsymbol{y}$ can lead to an improvement over the MMSE receiver, and several previous works, such as LAS [5] etc., provide techniques to do so. In this paper, we offer an additional technique with computational and performance advantages over previous methods, particularly in the large-MIMO case with large alphabet constellations. We notice that if the channel matrix $\mathbf{H}$ is known at the receiver, then we can form the residual $\tilde{\boldsymbol{y}} = \boldsymbol{y} - \mathbf{H}\hat{\boldsymbol{x}}$, which satisfies

$$\tilde{\boldsymbol{y}} = \mathbf{H}\tilde{\boldsymbol{x}} + \boldsymbol{w}.$$

This relationship between the residuals $\tilde{\boldsymbol{y}}$, $\tilde{\boldsymbol{x}}$ suggests that we could use linear regression again: we can form an estimate $\hat{\tilde{\boldsymbol{x}}} = \mathbf{G}_{res}\tilde{\boldsymbol{y}}$, where $\mathbf{G}_{res}$ could again be chosen as per the MMSE criterion. To implement such a receiver, we have to address two practical constraints.

- First, the channel matrix $\mathbf{H}$ is not known and we use its estimate $\hat{\mathbf{H}}$ given in (2). Let $\hat{\boldsymbol{x}}$ denote the estimated vector in the first stage. Then we use the residuals

  $$\tilde{\boldsymbol{y}} = \boldsymbol{y} - \hat{\mathbf{H}}\hat{\boldsymbol{x}}, \quad \tilde{\boldsymbol{x}} = \boldsymbol{x} - \hat{\boldsymbol{x}},$$

  that is, we use the estimated channel matrix instead of the true matrix to form the residual.
- Second, the second-order statistics of $\tilde{\boldsymbol{x}}, \tilde{\boldsymbol{y}}$ are not analytically tractable due to the quantizer non-linearity. Hence,

the MMSE linear transformation in the second stage of the receiver is difficult to find. To get around this problem, we use the estimated channel matrix to *simulate* input-output pairs, which are used to fit a linear regression model.

We call our receiver the LRR (Linear Regression of (MMSE) Residual) receiver and its pseudo-code is given in Algorithm 1.

Training Phase:

$$\mathbf{X}_T \leftarrow [\boldsymbol{x}_1 \boldsymbol{x}_2 \cdots \boldsymbol{x}_t \cdots \boldsymbol{x}_T]$$
$$\mathbf{W}_T \leftarrow [\boldsymbol{w}_1 \boldsymbol{w}_2 \cdots \boldsymbol{w}_t \cdots \boldsymbol{w}_T]$$
$$\mathbf{Y}_T \leftarrow \hat{\mathbf{H}}\mathbf{X}_T + \mathbf{W}_T$$

Find $\mathbf{G}_{mmse}$:

$$\mathbf{G}_{mmse} \leftarrow \left(\hat{\mathbf{H}}^H\hat{\mathbf{H}} + \frac{\sigma^2}{E_s}\mathbf{I}\right)^{-1}\hat{\mathbf{H}}^H$$

$$\widehat{\mathbf{X}}_T \leftarrow \mathcal{Q}(\mathbf{G}_{mmse}\mathbf{Y}_T)$$
$$\widetilde{\mathbf{Y}}_T \leftarrow \mathbf{Y}_T - \widehat{\mathbf{H}}\widehat{\mathbf{X}}_T \qquad \widetilde{\mathbf{X}}_T \leftarrow \mathbf{X}_T - \widehat{\mathbf{X}}_T$$

Find $\mathbf{G}_{res}$:

$$\mathbf{G}_{res} \leftarrow \widetilde{\mathbf{X}}_T\widetilde{\mathbf{Y}}_T^H\left(\widetilde{\mathbf{Y}}_T\widetilde{\mathbf{Y}}_T^H\right)^{-1}$$

Detection Phase:

$$\widehat{\boldsymbol{x}}_{mmse} \leftarrow \mathcal{Q}(\mathbf{G}_{mmse}\boldsymbol{y})$$

$$\widetilde{\boldsymbol{y}} \leftarrow \boldsymbol{y} - \widehat{\mathbf{H}}\widehat{\boldsymbol{x}}_{mmse}$$
$$\widehat{\boldsymbol{x}} \leftarrow \mathcal{Q}(\widehat{\boldsymbol{x}}_{mmse} + \mathbf{G}_{res}\widetilde{\boldsymbol{y}})$$

Algorithm 1: Linear Regression of MMSE Residual

The training data $\{\mathbf{X}_T, \mathbf{Y}_T\} \in \{\mathbb{Q}^{N_t \times T} \times \mathbb{C}^{N_r \times T}\}$ are generated at the receiver using the relation

$$\mathbf{Y}_T = \hat{\mathbf{H}}\mathbf{X}_T + \mathbf{W}_T$$

where T is the length of the training data, $\hat{\mathbf{H}}$ is the estimate of the channel matrix and $\mathbf{W}_T$ is the noise matrix artificially generated at the receiver, whose entries are i.i.d. with zero mean and variance σ^2 corresponding to the SNR at the receiver. The receiver essentially simulates transmit and receive data over the channel; this is purely done at the receiver and does not require any bandwidth over the channel. In particular, $\mathbf{X}_T$ and $\mathbf{W}_T$ can be pre-generated and stored at the receiver. The receiver then computes the MMSE estimate of $\mathbf{X}_T$:

$$\hat{\mathbf{X}}_T = \mathcal{Q}\left(\mathbf{G}_{mmse}\mathbf{Y}_T\right)$$

where

$$\mathbf{G}_{mmse} = \left(\hat{\mathbf{H}}^H\hat{\mathbf{H}} + \frac{\sigma^2}{E_s}\mathbf{I}\right)^{-1}\hat{\mathbf{H}}^H.$$

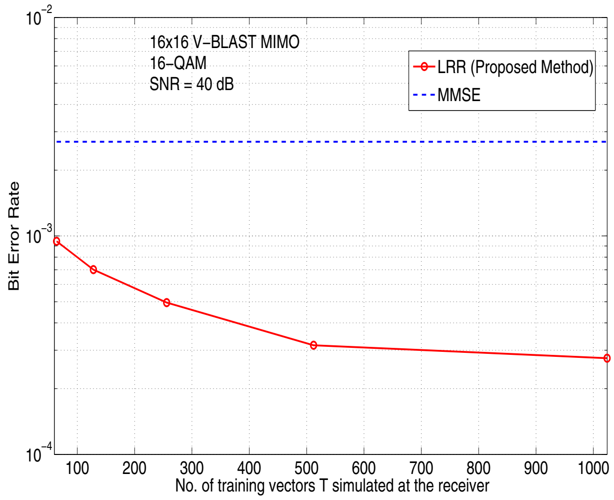

Fig. 1. BER performance of the LRR receiver in 16×16 V-BLAST MIMO with 16-QAM as T varies.

Here E_s is the average transmit symbol energy.

The residual is computed as

$$\tilde{\mathbf{Y}}_T = \mathbf{Y}_T - \hat{\mathbf{H}}\hat{\mathbf{X}}_T.$$

The error between the actual and estimated training data is $\tilde{\mathbf{X}}_T = \mathbf{X}_T - \hat{\mathbf{X}}_T$. The linear filter $\mathbf{G}$ which minimizes $E[\|\tilde{\boldsymbol{X}}_T - \mathbf{G}\tilde{\boldsymbol{Y}}_T\|^2]$ is given by

$$\mathbf{G}_{res} = \widetilde{\mathbf{X}}_T\widetilde{\mathbf{Y}}_T^H\left(\widetilde{\mathbf{Y}}_T\widetilde{\mathbf{Y}}_T^H\right)^{-1}$$

This completes the training phase which needs to be carried out once for each coherence interval.

In the actual detection phase, the MMSE estimate $\hat{\boldsymbol{x}}_{mmse}$ is found first, followed by the residual $\tilde{\boldsymbol{y}}$. The final estimate is given by $\widehat{\boldsymbol{x}} = \mathcal{Q}(\widehat{\boldsymbol{x}}_{mmse} + \mathbf{G}_{res}\widetilde{\boldsymbol{y}})$.

IV. BER Performance and Complexity of the LRR Receiver

In this section, we compare the BER performance and complexity of the following receivers:

- the MMSE receiver;
- the MMSE-LAS receiver, which employs the local search technique LAS [5] around the MMSE estimate;
- the proposed LRR receiver;
- and the LRR-LAS receiver, which employs LAS for local search around the LRR estimate.

In all the simulations, we have used the MMSE estimate of the channel matrix $\mathbf{H}$.

A. BER Performance

In Figure 1, we show the improvement of the BER performance with increase in the number of training vectors T for a 16×16 system with 16-QAM modulation. Though the performance does improve with T, the complexity also increases and therefore we have to choose a trade-off value

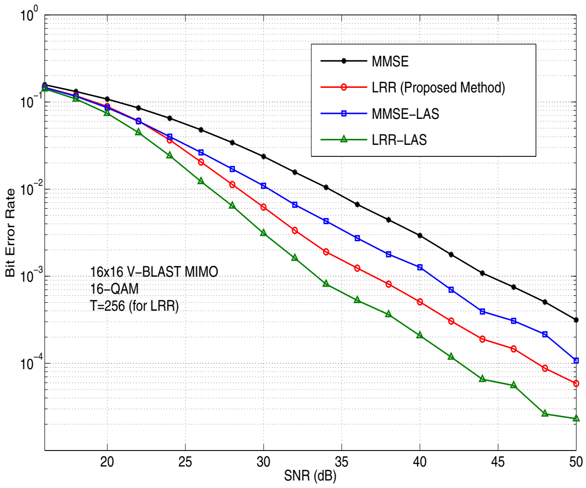

Fig. 2. BER performance of the LRR receiver in 16×16 V-BLAST MIMO with 16-QAM.

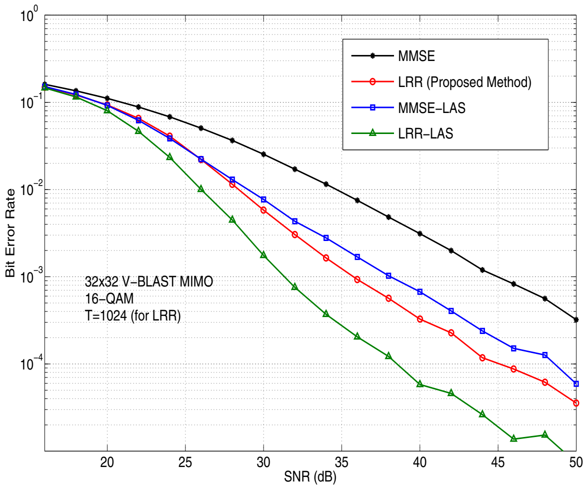

Fig. 3. BER performance of the LRR receiver in 32×32 V-BLAST MIMO with 16-QAM.

for T. In all our simulations, we have chosen $T = N_t^2$ so that the overall complexity of the receiver does not exceed $O(N_t^4)$.

In Figure 2, we show the BER performance of the receivers for a 16×16 system with 16-QAM. At a BER of 10^{-3}, the LRR receiver has a gain of about 7 dB when compared to MMSE and about 4 dB compared to MMSE-LAS receiver. Also shown is the BER performance of LRR-LAS detector, which further improves the performance by about 4 dB and the overall gain of LRR-LAS detector when compared to plain MMSE receiver is about 11 dB.

Figure 3 shows the performance of the receivers for a 32×32 system. The LRR receiver still performs better than MMSE and MMSE-LAS detectors. At 10^{-3} BER, the LRR receiver has a gain of about 9 dB over MMSE and about 2 dB over MMSE-LAS. The LRR-LAS detector performs even better with a gain of 13 dB over MMSE at 10^{-3} BER.

In a 64×64 system, MMSE-LAS performs slightly better than the proposed LRR receiver as shown in Figure 4. However, the LRR receiver still has a gain of about 10 dB over the MMSE receiver at 10^{-3} BER. The LRR-LAS detector has a gain of approximately 4 dB over MMSE-LAS at the same BER and about 16 dB over the MMSE receiver.

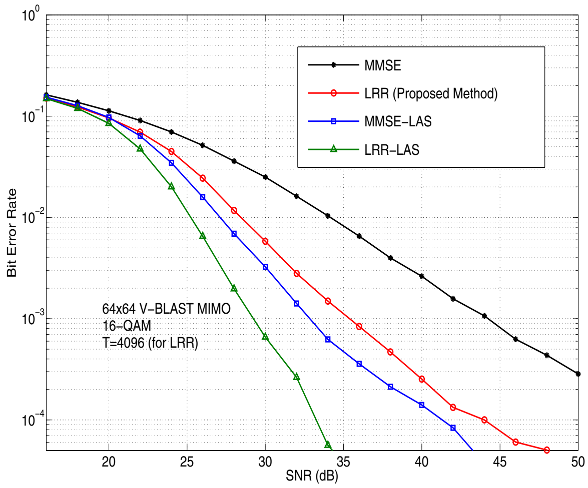

Fig. 4. BER performance of the LRR receiver in 64×64 V-BLAST MIMO with 16-QAM.

B. *Complexity*

The complexity of the LRR receiver consists of two parts: the complexity of training (or simulation) phase and the actual detection phase. (We recall that the training phase is entirely done at the receiver and requires no extra bandwidth; it is different from the channel training.) We do not consider the complexity of channel estimation since it is the same for all the receivers. For simplicity, consider $N_r = N_t$ and $T = N_t^2$. Below we discuss how the complexity scales with N_t and also report the number of real operations needed in our simulation.

The complexity of the training phase is $O(N_t^3 + TN_t^2)$ for $N_r = N_t$. We have chosen T to be of $O(N_t^2)$, which makes the overall complexity $O(N_t^4)$. However, this complexity is incurred only once in every coherence interval, so if the length of the coherence period is large, say of $O(N_t^2)$ or more, the effective complexity of the training phase becomes $O(N_t^2)$ per channel use. The total complexity of the detection phase is only $O(N_t^2)$ per channel use. For the MMSE receiver, the complexity of forming the matrix $\mathbf{G}_{mmse}$ is $O(N_t^3)$, and the detection complexity is $O(N_t^2)$ per channel use. Thus for a coherence period of $O(N_t^2)$ or more, the complexity of the LRR receiver scales similar to that of the MMSE receiver.

Another point to be noted is that the proposed LRR receiver is of *fixed complexity*, which is crucial in the design of communication systems. Most of the search algorithms have variable complexity during different channel uses and hence estimating the worst case latency becomes difficult. Some approaches limit the search for certain number of iterations or on a particular subset of the search space, compromising

MIMO system	Training Complexity ($\times 10^6$ FLOPs)	Detection Complexity ($\times 10^6$ FLOPs) per channel use	p_* (channel uses)
16×16	2.24	0.006	368
32×32	34.75	0.024	1418
64×64	546.46	0.098	5567

TABLE I

COMPLEXITY (IN FLOPS) FOR THE PROPOSED LRR RECEIVER. p_* IS THE MINIMUM COHERENCE PERIOD FOR WHICH DETECTION COMPLEXITY EXCEEDS TRAINING COMPLEXITY.

MIMO system	Receiver	SNR req. for BER 10^{-3}	Complexity ($\times 10^6$ FLOPs)
16×16	MMSE	44 dB	2.30
	MMSE-LAS	41 dB	7.79
	LRR ($T = 256$)	37 dB	8.97
	LRR-LAS	33 dB	14.46
32×32	MMSE	45 dB	35.24
	MMSE-LAS	38 dB	115.60
	LRR ($T = 1024$)	36 dB	138.92
	LRR-LAS	31 dB	218.51
64×64	MMSE	44 dB	550.67
	MMSE-LAS	33 dB	1879.42
	LRR ($T = 4096$)	35 dB	2186.00
	LRR-LAS	29 dB	3443.66

TABLE II

COMPLEXITY (IN NUMBER OF FLOPS REQUIRED) FOR DIFFERENT RECEIVERS. COHERENCE PERIOD $p = 3p_*$ IS THE NUMBER OF CHANNEL USES FOR WHICH CHANNEL IS CONSTANT.

on performance. This problem does not arise for the LRR receiver, as the detection does not depend on the channel condition or the noise.

To get a sense of the constants involved in the $O(\cdot)$ terms above, we measured the total number of floating point operations (FLOPs) in our simulations. For the LRR receiver, the total number of floating point operations for the training phase and for the detection phase is reported in Table I. In the last column in Table I, we show the number of channel uses p_* for which the detection complexity equals the training phase complexity. Whenever the coherence time $p \gg p_*$, we see that the training complexity is small compared to the detection complexity. Specifically, if $p = 3p_*$, then the training phase complexity is 1/3 that of the detection phase (and 1/4 the total complexity). This roughly corresponds to a coherence period of 1100, 4250, 16700 for $N_t = 16, 32, 64$ respectively. For these values of coherence period, in Table II, we report the total number of real operations needed for the different receivers. We see that the LRR receiver needs about a factor of 4 more operations than the MMSE receiver. For the LRR-LAS receiver the complexity includes forming the LRR solution and the LAS search part. In all cases, the total complexity of the LRR-LAS receiver is slightly more than 6 times that of the MMSE receiver for the coherence periods considered.

V. CONCLUSION

We have proposed a new receiver structure based on using simulated data and linear regression. The receiver designs a filter based on the training data during each coherence interval. Once the filter is designed, the actual detection part is very simple, with the complexity being almost the same as a linear receiver with only a minimal increase. The BER performance of the receiver, obtained through simulations, was found to be significantly better than that of plain MMSE receiver. The performance is also comparable to that of LAS, a local search based low-complexity algorithm, in very high dimensions. We believe this receiver structure has the potential to be deployed in practical systems which have a large coherence interval. Future work on improving the receiver can involve reducing the number of training vectors required in the training phase without compromising on the performance.

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