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Energy Efficient Power Control & Bayesian Channel Estimation for Massive MIMO

A. Suban[1], V. Karthick[1], I. Alan[2], I. Milan[2], S. V. Jeya Murugan[2]
1- Assistant Professor, 2- UG Final year Students
Deparment of Electronics and Communication Engineering
Velammal College of Engineering and Technology, Madurai.

Abstract **- Pilot contamination posts a fundamental limit on the performance of massive multiple-input–multiple-output (MIMO) antenna systems due to failure in accurate channel estimation. To address this problem, we propose estimation of channel parameters of the desired links in a target cell. In this paper, we show that if the propagation properties of massive MIMO systems can be exploited, it is possible to obtain an accurate estimate of the channel parameters. The signals are observed in the beam domain (using Fourier transform), the channel is approximately sparse, i.e., the channel matrix contains only a small fraction of large components, and other components are close to zero. This observation then enables channel estimation based on sparse Bayesian learning methods, where sparse channel components can be reconstructed using a small number of observations.**

Results illustrate that compared to conventional estimators, the proposed approach achieves much better performance in terms of the channel estimation accuracy and achievable rates in the presence of pilot contamination. In addition to channel estimation, efficient energy control technique for massive MIMO is adopted in this work.

***Index Terms*——Bayesian learning, channel estimation, massive MIMO, pilot contamination.**

I. INTRODUCTION

VERY large multiple-input–multiple-output (MIMO) or "massive MIMO" systems [1] are widely considered as a future cellular network architecture, which are anticipated to be energy-efficient, spectrum-efficient, secure, and robust; see, e.g., [2] and [3] for a survey. Such systems employ a few hundred or more base station (BS) antennas to simultaneously serve many tens of user equipments (UEs) in the same radio channel. As such, the array gain is expected to grow unboundedly with the number of antennas at the BSs so that both multiuser interference and thermal noise for any given number of users and any given powers of the interfering users can be eliminated.

The reports on the great benefits of massive MIMO systems, however, were based on the assumption that the BSs have an acceptable quality of channel knowledge, which in practice has to be estimated via finite-length pilot sequences. However, in cellular networks, pilot interference from neighboring cells limits the ability to obtain sufficiently accurate channel estimates, giving rise to the problem of "pilot contamination" [1]. It was noted that pilot contamination incurs an ultimate limit on the interference rejection performance on massive MIMO, even if the number of antennas grows without bound [1], [4]. In this paper, our focus is on the channel estimation problems with pilot contamination in the uplink, although there are other related issues in the downlink that also greatly limit the performance of massive MIMO systems. For the issues in the downlink, we refer the readers to [5]–[9]. Several approaches have emerged to deal with pilot contamination in the uplink recently [10]–[15]. By exploiting the covariance information of user channels and applying a covariance-aware pilot assignment strategy among the cells, [10] revealed that pilot contamination could disappear. Alternatively, using an eigenvalue decomposition of the sample covariance matrix of the received signals, [11]–[13] claimed that pilot contamination can be effectively mitigated by projecting the received signal onto an interference-free subspace without the need of coordination amongst the cells. Nevertheless, [10]– [13] rely heavily on the estimation of the channel or signal covariance matrices. Though the covariance matrices change slowly over time, the estimation problem under massive MIMO ystems is far from trivial [5].

The reason is that a covariance matrix is typically estimated through the sample covariance matrix, and that the sample size should be increased proportionally to the dimension of the covariance matrices.1 In massive MIMO systems, the dimension of the covariance matrices may be comparable to the number of available samples within a coherence time. The sample covariance estimation method is thus no longer sufficient and more sophisticated techniques must be used, see, e.g., [16] or [17] for more recent progress. Different from the approaches based on covariance matrices, e.g., [10]–[13], in this paper, we address the pilot contamination problem directly from a channel estimation perspective.

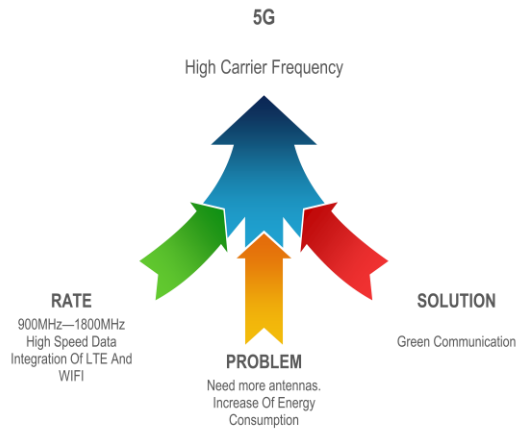
From [1], we realize that pilot contamination results from performing channel estimation ignoring pilot interference from the neighboring cells so that the estimated channel contains channels of the interference. To overcome this, we therefore propose to estimate not only the channel parameters of the desired links in the target cell but also those of the interference links from adjacent cells. Although this strategy seems natural, the challenge remains that the required estimation problem forms an underdetermined linear system which generally has infinitely many solutions. To get an accurate solution, we rely on a key observation–The channels with most of the multipath energy tend to be concentrated in relatively small regions within the channel angular spread due to limited local scatterers at the BSs [18]–[22]. An approximate sparsity of a channel can be obtained by transforming the received signal into a beam domain. Exploiting the channel sparsity, we can obtain much more accurate channel estimates by leveraging on more recent techniques in compressive sensing (CS) [23]–[26]. MIMO channel estimation based on CS techniques has been investigated in, [8], [9], [14], [15], [27], and [28]. Most of the earlier works, e.g., [27] (and references therein), exploited sparse channel estimation methods mainly to improve the performance of single-user MIMO systems. Under multiuser massive MIMO systems, CS techniques were used in [8], [9], and [28] in order to reduce the feedback overhead of the channel state information (CSI) at the transmitter side. In [14], [15], the authors also advocated to estimate the channel parameters of the desired links in the target cell and those of the interference links from adjacent cells. Nonetheless, they used a CS technique to estimate the MIMO channel based on low-rank approximation, which is completely different from that of our interest. Other popular solvers in the CS literature, e.g., the 1 optimization (L1) solver [29] and the orthogonal matching pursuit (OMP) solver [30], also appear to be not so useful in the concerned channel estimation problem. For the L1 solver, the regularization parameter has to be chosen carefully to control the channel estimation errors while determining the best regularization parameter is difficult in practice.

Meanwhile, the OMP solver greedily selects the best channel vectors for channel representation, and the best support number for channel representation is also difficult to obtain in practice. Whether channel estimation in massive MIMO systems, suffered from pilot contamination, could be effectively addressed via CS techniques is not understood.

Our contributions include the formulation of massive MIMO channel estimation with pilot contamination as a CS problem. Based on an observation of the received signals in the beam domain, we model the channel component in the beam domain as a Gaussian mixture, i.e., a weighted summation of Gaussian distributions with different variances. This model enables us to reconstruct the channel components based on the probabilistic Bayesian inference with the best mean-squared error (MSE) performance [31]. For the optimal Bayesian inference, the computational complexity is not tractable and the statistical properties of the channel component are required.

Hence, we employ the approximate message passing (AMP) algorithm in [23]–[25] to obtain the Bayesian inference and an expectation–maximization (EM) algorithm [26] to learn the statistical properties. Unlike [10], our Bayesian estimator does not require the availability of the channel covariance matrices and the background noise level. All the required channel knowledge will be learned as part of the estimation procedure. By a proper design on pilot sequences, the proposed estimator leads to a much reduced complexity without compromising performance.

Numerical results will show that the developed approach provides a huge gain in reducing the channel estimation errors. In addition, the achievable rates based on the developed channel estimator are comparable to those with perfect CSI



II. SYSTEM MODEL

In this section, we first present the massive MIMO system model and then discuss the pilot contamination problem. The discussions will be useful for aligning the requirement of CS techniques to address the pilot contamination problem.

Massive MIMO

Consider a wireless communication system with B cells, in which each cell contains a BS and K UEs. Each BS has N antennas, whereas each UE is equipped with a single antenna. In the considered uplink training phase, all UEs in the B cells simultaneously transmit pilot sequences of length T symbols. For ease of exposition, we let the first cell be our target cell. The pilot sequences used in the bth cell can be represented by a $T \, x \, K$ matrix, S_b, and the corresponding channel vector between the UEs in the bth cell and the target BS is denoted by $\mathbf{H}_b = [\mathbf{h}_{b1}...\mathbf{h}_{bK}]^T \in \mathrm{C}^{K\times N}$, where $\mathbf{h}_{bK} \in \mathrm{C}^{K\times N}$ is the channel from UE$_k$ in cell b to the target BS. The received signals during uplink training at the target BS is written as

$$\mathbf{Y} = \sum_{b=1}^{B} \mathbf{S}_b \mathbf{H}_b + \mathbf{Z} \cong \mathbf{SH} + \mathbf{Z} \quad (1)$$

where $\mathbf{Z} \in C^{T\times N}$ denotes the temporally and spatially white Gaussian noise with zero mean and element-wise variance Δ. Also, in (1), we have defined $\mathbf{S} \equiv [\mathbf{S}_1 \ldots \mathbf{S}_B] \in \mathbf{C}^{T\times N}$ and $\mathbf{H} \cong [\mathbf{H}_1^H \ldots \mathbf{H}_B^H]^H \in \mathbf{C}^{BK\times N}$ for conciseness.

Pilot Contamination

In massive MIMO, the statistical knowledge of the channel matrix would be practically unknown because the size of the channel matrix would mean that an unacceptably large number of samples would be required. In this case, the standard way of estimating H is to employ the least square (LS) approach. If orthogonal pilot sequences are adopted in the bth cell, i.e., $\mathbf{S}_b^H \mathbf{S}_b = \mathbf{I}_K$, and the same pilot sequences are reused in all B cells, i.e., $\mathbf{S}_1 = \cdots = \mathbf{S}_B$, the outputs of the LS estimator at the targeted BS can be written as

H^ 1 = SH 1 S1

−1 b S1Y=H1+ B

=1 Hb+ SH 1 S1

−1 S1Z. (2)

From the perspective of the LS estimator, the assumption of using the same set of pilot sequences makes no fundamental difference in terms of estimation performance compared with using different pilots in different cells [1]. Clearly, in (2), the interfering channels will leak directly to the desired channel estimate, which gives rise to “pilot contamination” [1], [4], [10]. The fundamental effect of pilot contamination can also be understood from other perspective through linear estimation theory. First, we note that if the BK × N channel matrix H can be estimated from the T × N measurement matrix Y with sufficient accuracy, then the pilot contamination effect can be mitigated or eliminated. A straightforward requirement for an accurate channel estimation is T ≥ BK; otherwise, unknown variables will outnumber measurements and in this case accurate channel estimation is clearly impossible. Unfortunately, the requirement for accurate channel estimation usually cannot be satisfied in the massive MIMO system because most scenarios of our interests have T ≈ K and B > 1. 2 The estimation of H from the noisy underdetermined measurement has infinitely many solutions. For this reason, many speculate that the pilot contamination problem will exist regardless of which channel estimation method is used [1], [4]. Clearly, to get a correct solution, one must impose extra constraints in choosing the solution.

Cognitive Radio System with OFDM

*O*FDM is Orthogonal Frequency Division Multiplexing. It is used to trim down the interference among the number of users. In this the single broadband frequency is divided into a large number of parallel narrow band of frequencies. By this we can transmit the in order with less bandwidth. This makes the channel to be frequency flat and also it eliminates reverberation. The block diagram is shown in Fig

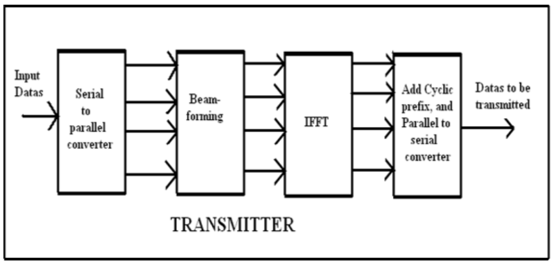


Fig 2: Cognitive radio transmitter with OFDM

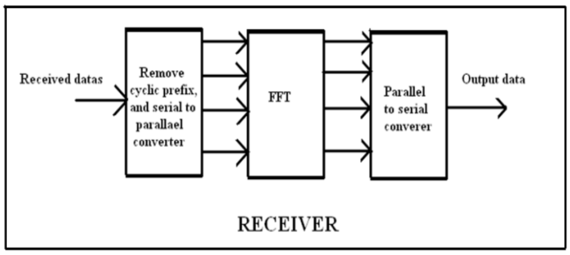


Fig 3: Cognitive radio receiver with OFDM

Thus from this block diagram we can infer that the OFDM intrinsic systemproduce orthogonal carriers by using the Inverse Fast Fourier Transform (IFFT). In addition to that IFFT is also used to lift up the frequency used in the baseband to that of transmittable high frequency. Thus this mitigate the interference among the carriers of nearer frequencies. Moreover the cyclic prefix addition makes us to reduce the most significant problem of the digital contact that is the Inter Symbol Interference (ISI).

By using the frequency response of sub-carrier used for broadcast, the amount of information for each sub-band can be altered. Conversely these narrow bands have a smaller amount frequency selective fading. So the OFDM also conserves the bandwidth along with improved data rate to the highest degree which is the main intention. These character made OFDM to be more suitable for MIMO. In addition to that the OFDM technique provides very less BER even for negative SNR that makes the system to be more consistent.

Approximate message passing (AMP) for Massive MIMO detection

In this exposition, we want to highlight that the approximate message passing (AMP) has superior complexity when serving the Massive MIMO uplink detection, although AMP was initially proposed for solving a LASSO problem [DMM09]. Regarding expository detail about why AMP works, please see [BM11].

Regarding the problem of Massive MIMO uplink detection [HBD13], the architecture serves tens of users by employing hundreds of antennas,

y=Hx+w

y=Hx+w

where the channel HϵCm×nHϵCm×n has its elements sampled from NC(0,1/m)NC(0,1/m) , m≫nm≫n , yϵCmyϵCm is the received signal, AWGN noise components wiwi are i.i.d with NC(0,σ2)NC(0,σ2) ; regarding the transmitted xx , we only assume that it's zero mean and finite variance σ2sσs2 .

Before incorporating the AMP algorithm, we should be well aware of two facts: 1. directly using maximum a priori (MAP) argmaxp(x|y)arg maxp(x|y) or MMSE estimation Ep(x|y)(X)Ep(x|y)(X) to work with the exact prior degrade the necessity of employing AMP, because achieving a full diversity requires an extremely large set of constellation points, in which AMP works slowly while doing the moment matching process, not to mention problems about its inability to converge to the lowest fixed point. 2. In the CDMA multiuser detection theory [Verdu98, etc.], their "MMSE" detector does not mean the one working with exact prior , but rather the one assuming a Gaussian prior.

So we use a proxy prior for detecting xx , i.e., assuming that xi∼NC(0,σ2s)xi∼NC(0,σs2) , even though it may be inexact. In this occurrence, we have the signal power σ2s=2σs2=2 in QPSK, σ2s=10σs2=10 in 16QAM, etc. So the target function becomes:

min‖ y−Hx‖ 2,s.t.xi∼NC(0,σ2s)

min‖y−Hx‖2,s.t.xi∼NC(0,σs2)

The AMP algorithm to solve the above problem only requires three lines

$$\min\|y-Hs\|^2, s_i \cong N(0,\sigma^2)$$

AMP Iterations

$$r_t = (y - Hs^{t-1}) + (n \div m * \sigma^2 \div [\sigma^2 + \alpha^{t-1}] * r^{t-1})$$

Where,

$$\alpha^t = \sigma^2 + (n \div m * [\alpha^{t-1} * \sigma^2] \div \alpha^{t-1} + \sigma^2)$$

$$s^t = (\sigma^2 \div [\alpha^t + \sigma^2]) * (H * r^t + s^{t-1})$$

where the initialization is to let r0=0r0=0 , x0=0x0=0 , α0=σ2sα0=σs2 . In terms of complexity, it only costs 2mn×(#Iteration)2mn×(#Iteration) . Also, according to the second equation of the algorithm, it is converging extremely fast. On the contrary, MMSE has complexity O(mn2)O(mn2) . It is noteworthy that known approximation methods to MMSE, such as Richardson's method or Newman series approximation, both fall behind the complexity-performance trade-off of AMP according to our simulations.

A. *Channel Stipulation*

Based on the estimated channel stipulation, Beamforming cognitive transmitter is premeditated and is shown to be able of directing Cognitive Users (CU's) transmit signals through the channel and thus removing the interference. When the PUs channel is free, it will be owed among the number of secondary users. If there are a number of users in cognitive radio scheme, the interference among the CUs will enhance. These interferences among the CUs will be reduced by Beamforming technique. Beamforming is a technique that is done for the transmission or reception of data. This technique is done by concentrating a particular user at an instance. The Beamforming will be done during the transmission of data on the transmission side of the CUs.

III. RESULTS AND DISCUSSION

The performance analysis of the channel is improved by using Beamforming technique that was revealed in this work. The noise added by the channel is also reputed to be Gaussian random noise. The purpose of our scrutiny is to draw attention to the concert of this system by comparing them with various interconnected systems. For an analysis of the efficiency of this system a performance measure is made between the SNR (in dB) and BER.

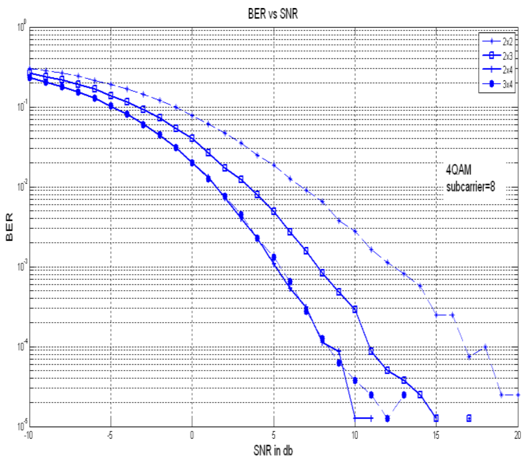


Fig.5 BER vs. SNR for 4-QAM for various dimensions of MIMO

The Fig 5 the performance analysis of a MIMO-OFDM system with 4-QAM modulation with a subcarrier of 8 for diverse dimensions of MIMO systems i.e. for 2×2,2×3,2×4,3×4. It is experiential that the probability of error is low down in the MIMO dimension of 2×4 and 3×4 due to receiver's diversity. The penalty are simulated only with MIMO's particular features of spatial diversity where identical information is transmitted in all the transmitting antennas for improved feature. This makes obtainable good adaptation of the signal all the way through one or more paths, thus tumbling the probability of error as the affable faded signals can be left alone.

If the number of subcarriers enlarges, then the amount of the error reduces. This makes OFDM more appropriate for MIMO systems. The orthogonal carriers cause a reduced amount of interference in a MIMO antenna that is narrowly positioned. MIMO-OFDM gives supplementary capacity than the conventional MIMO in existence of multipath as shown in Fig 6.

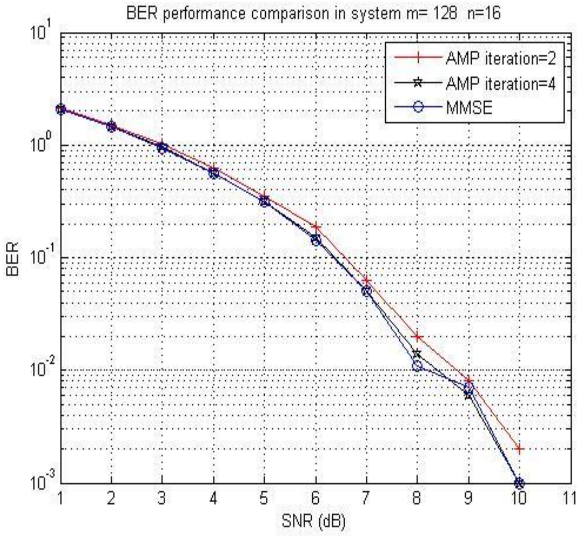


Table I

SNR (dB)	TECHNIQUE	PROBABILITY OF ERROR
2	MMSE	1.468
	AMP-2	1.468
	AMP-4	1.468
4	MMSE	0.144
	AMP-2	0.188
	AMP-4	0.144
6	MMSE	0.011
	AMP-2	0.020
	AMP-4	0.014
10	MMSE	0.001
	AMP-2	0.002
	AMP-4	0.001

The implication of Fig 6is given in the Table I. It is inferred that when the number of subcarriers increases, the probability of error decreases.

In the above proposed system including the MIMO-OFDM proposal we find PAPR to be a cause that need to be measured. So the porch of this system for a better performance will be probable by reducing this PAPR to the minimal value promising by an apt technique. Analysis can be made on the system based CDF. The preliminary analysis here is done for an untutored system concerning different subcarriers without any technique to condense PAPR.

The fig 7 is the estimation of PAPR for the system with different subcarriers.

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