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Medium Valuation Method for Massive MIMO Using Gaussian Mixture Bayesian Learning

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ABSTRACT

Pilot contamination posts a elementary limit on the performance of huge multiple-input–multiple-output (MIMO) antenna systems owing to failure in correct channel estimation. To address this drawback, we tend to propose estimation of solely the channel parameters of the specified links during a target cell, however those of the interference links from adjacent cells. The desired estimation is, nonetheless, AN underdetermined system. During this paper, we show that if the propagation properties of huge MIMO systems will be exploited, it's potential to get a correct estimate of the channel parameters. Our strategy is impressed by the observation that for a cellular network, the channel from user instrumentality to a base station consists of solely a number of clustered methods in space. With an awfully massive antenna array, signals may be discovered under extraordinarily sharp regions in space. As a result, if the signals are discovered within the beam domain (using Fourier transform), the channel is around thin, i.e., the channel matrix contains only a little fraction of huge elements, and different elements are near zero. This observation then permits channel estimation based on thin Bayesian learning strategies, wherever thin channel components may be reconstructed employing a little variety of observations. Results illustrate that compared to traditional estimators; the planned approach achieves far better performance in terms of the channel estimation accuracy and doable rates in the presence of pilot contamination.

Index Terms -channel estimation, Gaussian mixture, massive MIMO, pilot contamination.

I.INTRODUCTION

Very giant multiple-input–multiple-output (MIMO) or “massive MIMO” systems [1] arewidethought of as a future cellular specification, thatare anticipated to be energy-efficient, spectrum-efficient, secure, and robust; see, e.g., [2] and [3] for a survey. Such systems usesome hundred or additional base station (BS) antennas to at the same time serve several tens of user equipments (UEs) within the same radio channel. As such, the array gain is predicted to grow unboundedly with range the amount of antennas at the BSs soeach multiuser interference and thermal noise for any given number of users and any given powers of the intrusive users are often eliminated. The reports on the niceedges of huge MIMO systems, however, were supportedthe belief that the BS have an appropriate quality of channel information, that in observeshould be calculable via finite-length pilot sequences .

However, in cellular networks, pilot interference from neigh boring cells limits the powerto get sufficiently correct channel estimates, giving rise to the matter of “pilot contamination” [1]. it had been noted that pilot contamination incursion final limit on the interference rejection performance on huge MIMO, thoughthe amount of antennas grows while notsure [1], [4].In this paper, our focus is on the channel estimation issues with pilot contamination within thetransmission, though there aredifferentconnectedproblemswithin the downlink that conjointly greatly limit the performance of huge MIMO systems. For the problemswithin the downlink, we have a tendency to refer the readers to [5]–[9].Several approaches have emerged to take care of pilot contamination within thetransmission recently [10]–[15]. By exploiting the varianceinfo of user channels and applying a covariance-aware pilot assignment strategy among the cells,[10] discovered that pilot contamination might disappear. Alter-natively, mistreatmentAssociate in Nursingchemistprice decomposition of the sample co-variance matrix of the received signals, [11]–[13] claimed that pilot contamination

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are often effectively relieved by sticking the received signal onto Associate in Nursing interference-free mathematical spacewhile notthe necessity of coordination amongst the cells. Still, [10]–[13] swear heavily on the estimation of the channel or signal variance matrices.

Although the variance matrices modification slowly over time, the estimation drawbackbelowhuge MIMO systems is much from trivial [5]. the rationale is that a variance matrix is usuallycalculable through the sample variance matrix, which the sample size ought to be raisedproportionately to the dimension of the variance matrices.1 In giant MIMO systems, the dimension of the variance matrices is additionallyakin tothe number of procurable samples within a coherence time. The sample variance estimation methodology is sonow not adequate and extrarefined techniques ought to be used, see, e.g., [16] or [17] for additionaltrendy progress. Totally different from the approaches supported variance matrices, e.g., [10]–[13], throughout this paper, we've gota bentto deal with the pilot contamination draw back directly from a channel estimation perspective. From [1], we've gota bentto know that pilot contamination results from acting channel estimation ignoring pilot interference from the neighboring cells therefore thecomputable channel contains channels of the interference.

To beat this, we've gota bent to therefore propose to estimate not entirely the channel parameters of the specified links among the target cell butjointly those of the interference links from adjacent cells. Although this strategy appearance natural, the challenge remains that the required estimation draw back forms Associate in nursing underdetermined linear system that usually has infinitely many solutions. To urge Associate in Nursing correct resolution, we have a tendency torelyon a key observation– The channels with most of the multi path energy tend to be centered in relativelyvery little regions within the channel angular unfold due to restricted native scatters at the BSs [18]–[22].

Associate in nursing approximate scantiness of a channel are going to be obtained by transforming the received signal into a beam domain. Exploiting the channel scantiness, we have a tendency toaready to get abundant additional correct channel estimates by investment on additionaltrendy techniques in compressive sensing.

II.SYSTEM MODEL

In this section, we tend to 1st gift the huge MIMO system model then discuss the pilot contamination drawback. The discussions are going to be helpful for positioning the need of CS techniques to handle the pilot contamination drawback.

A.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 both cell can be represented

$$Y = \sum_{b=1}^{B} S_{ь} H_{ь} + Z \triangleq SH + Z$$

B.PILOT CONTAMINATION

In large MIMO, the applied mathematics information of the channel matrix would be much unknown as a result of the scale of the channel matrix would mean that associate intolerably sizable amount of samples would be needed. During this case, the quality method of estimating H is to use the smallest amount sq. (LS) approach. If orthogonal pilot sequences are adopted within the both cell,

$$\hat{H}^1 = (S^{1H}S^1)^{-1}S^1 Y = H^1 + \sum_{b\neq 1}^{B} H_{ь}(S_1{}^{H}S_1)^{-1}S_1 Z$$

Sparsity Characteristics we talk over with hTbk. The ordinal part of hTofhT response determined at the ordinal beam. The foremost crucial property bk is that the weather of hTofhTi.e., the channel vector contains solely a tiny low fraction of enormous components, and therefore the different parts are near zero. The meagreness property declared higher than are often simply completed by the argument as follows: take into account that the BSs are equipped with a standardized linear array (ULA) of [*fr1] wavelength spacing. With AN infinite variety of antennas at the BSs, the DFT matrix is verified to be the eigenvector matrix of the bachelor's degree correlation bk because the beam domain channel illustration bk corresponds to the channel Though during a sensible setting, the numbers of antennas at the BSs ar finite however giant, F still is associate degree approximate eigenvector matrix of Rbk. Following Fig. 1(a) however N = 256,the corresponding channel magnitude within the beam domain |hTis portrayed in Fig. 1(b). As is predicted, the channel vector is not dead distributed however close to distributed. Specifically, over ninety nine of the channel total power is found solely at intervals about 16 PF of the beam indices. The channel magnitude of the close to distributed parts extremely depends on the number of antennas. The larger the quantity

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of antennas the better a(θ) matching to the DFT basis. Moreover, its exiguity property is said to the PAS of the channel model. Despite the fact that Laplacian distribution is that the most well-liked model for the PAS, there are different categories of distributions that serve as higher models beneath bound circumstances From many experimental measurements of MIMO channels [1 it's believed that because the variety of antenna increases, the channel responses within the beam domain tend to be sparse owing to the restricted variety of native scatters at the SB. Taking the DFT of Y, we are able to so get the received signal within the beam domain given by We aim to estimate HN supported yn given the complete information of the pilot matrix S. Note that to urge S, we must always acquire the pilot sequence of the specified links and people of the interference links from the adjacent cells. within the underdetermined system of interest, the pilot sequences aren't any longer orthogonal and so are haphazardly generated. To proceed with the estimation method for each n, we tend to set the element-wise variance of Zn as Δn even though we tend to could have Δn = Δ, ∀ n. Before continuing, we discover it helpful to check an image on HN. Note that the row index of H corresponds to the UE indexing the B cells and therefore the column index of H corresponds to the beam index discovered at the bachelor's degree. Thus, the ordinal column of H represents the channel responses of the complete UEs discovered at the ordinal beam. A realization of the $64000 elements of HN at n = one hundred forty is pictured in Fig. 1(d). As will be seen from the figure, the elements of HN = [hk,n] contain solely a little fraction of huge components and therefore the different elements area unit near zero. In addition, they appear to be statistically freelance.

III.BAYESIAN CHANNEL

ESTIMATION

Among varied Cs approaches, probabilistic theorem inference has recently attracted abundant attention for its outstanding recovery performance [23]–[25], [37]. So as to use probabilistic theorem abstract thought to (8), one needs to grasp the distribution of azoimide. To the present finish, the subsequent 2 observations are useful. First, it will infer from (7) that every component of azoimide consists of a mathematician variant, though one ought to particularly notice that azoimide and hT different perspective. Second, from Fig. 1(d), we tend to observe that the elements of azoimide have considerably completely different variances, i.e., some of them square measure terribly little however some square measure giant. Inspired by the 2 observations, we tend to model the weather ofhn = [hk,n] by a Gaussian-mixture (GM) distribution: bk in (7) square measure determined from where NC(hk,n; 0, σ2function (pdf) with zero mean and variance σ2mixing chance of the lth metric weight unit element. The parameterσ2n,1 will be set to a awfully little price so ρn,1 denotes the density of the parts near zero. The remaining GM parts of huge parts. The worth of L reflectsthe number of various variances in azoimide. We are going to discuss the setting of L in Section IV-B. Note that actuality distributions ofhn couldn't be the metric weight unit distribution. However, our numerical results can demonstrate that the selection of the metric weight unit distribution is utterly fine. Finally, we tend to assume that the BK-dimensionalhn contains freelance and identically distributed (i.i.d.)components, so we haven,l) denotes a mathematician chance densityn,l, and ρn,l is theLn,l}l=2 will be accustomed model the

IV.DISCUSSIONS AND SIMULATION RESULTS

Unless expressed otherwise, the simulation parameters altogether the simulations during this section square measure the withγ = three.8. We have a tendency to normalize the cell radius such d ⁢ one for the desired users within the target cell. to manage the S/Nratio (SNR) of the system, we have a tendency to normalize the signal strength of all users in order that the typical signal strength of the required users received within the target cell becomes E outlined as SNR ΔPilot Sequences—In the underdetermined system (or with pilot contamination) of interest, the pilot matrix is not any longer orthogonal. Therefore, for the Bayesian figurer, the pilot sequences square measure arbitrarily generated from the equal probability, wherever ξ is chosen such the full information of the pilot matrix S is assumed to be available. On the opposite hand, for the LS figurer (2), the orthogonal pilot sequences, i.e., SH optimal performance. bSb = IK, square measure adopted due to their only measure the MSE of the users within the target cell. Average User Rate—In addition, we have a tendency to measure the typical user rate within the target cell doable by the quality highest ratio combining (MRC) receivers. With the MRC receiver, the linear detection vector of the k-the user within the target cell is hˆ1k.The average user rate is outlined by

$$C = \frac{1}{K}\sum_{k=1}^{K}\log_2(1+\mathsf{SINR}_k).$$

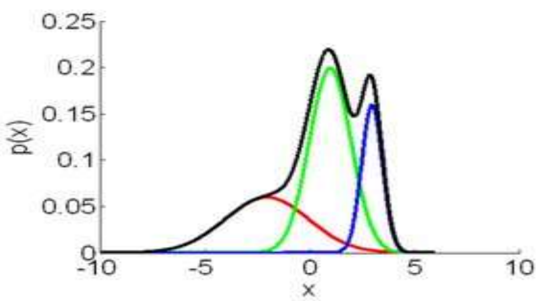

Fig 1. Modeling the pdf of {hn}

V.PROPERTIES OF BAYESIAN ESTIMATOR

Before running simulations, we provide some discussions to understand the properties of Algorithm 1 (namely the Bayesian estimator). Specifically, our aim is to show how the MSE of the Bayesian estimator can be improved over the LS estimator. We begin by investigating the simplest case of not having pilot contamination, i.e., B = 1, and adopt the orthogonal pilot sequences. In that case, combining (2) with (8), we have the following equivalent channel

$$\underline{y}_{k,n} = \underline{h}_{k,n} + \underline{z}_{k,n},$$

In the higher than analysis, we have a tendency to did not take into account the pilot interference from different users as a result of the pilot sequences area unit orthogonal. However, within the underdetermined system of interest, the pilot matrix isn't any longer orthogonal. Recent ends up in[23], [24] in contestable that once S is random and sufficiently large, near-minimum MSE (MMSE) estimation continues to be potential via the AMP algorithmic rule. For this reason, the pilot sequences are haphazardly generated for the Bayesian expert. It absolutely was illustrated in [39] that within the large-system limit,11 the output of AMPis comparable to the scalar channel (29) however with a rise inthe background level. Therefore, the MSE of the AMP algorithmic rule is identical to (32) however substitution Δn with an efficient background level Δeff. Recall that AMP is repetitious. Following [39], the effective noise level at iteration are often obtained from the state evolutioncomparable to the proper channel information and provides significant gain over the R-LS calculator. From [1], we all know that the pilot contamination leading to poor user rate is as a result of the estimated channel contains channels of robust interference from neighboring cells. Thus, the results of this figure indicate that the theorem calculator presents a considerable removal in terms of the robust interference. Note that the typical user rates conferred here are accomplishable by the MRC receivers. Scrutiny to the MRC receivers, other receivers, like the zero-forcing (ZF) and also the linear MMSE receivers, will have higher interference rejection capability. When applying the ZF and also the MMSE receivers, each the date symbols within the target cell and people from the adjacent cells willbe detected as a result of their corresponding channel parameters are available. Therefore, the typical user rates are expected to beenenhanced considerably by these receivers.

VI.CONCLUSION

To address pilot contamination in large MIMO systems, we projected to estimate not solely the channel parameters of thedesired links in a very target cell, however additionally that of the interference links from the adjacent cells. The channel estimation problem constitutes associate degree underdetermined system. By reworking the received signals into the beam domain, we tend to showed that the channel estimation drawback will be solved the exploitation thin Bayesian learning techniques. For the theorem approach, a good information regarding the applied math properties of the channels is needed. We tend to sculptured the channel part within the beam domain as a gram distribution and used EM to be told the previous parameters. Simulation results unconcealed that gram is much finer than the standard GB distribution in Cs. In addition, to create the optimum Bayes estimation tractable, we employed the AMP formula, and a major procedure saving was obtained by coming up with the pilots fittingly. The proposed channel estimation approach doesn't need the availability of the channel variance matrices, the background noise level, nor the necessity for coordination amongst the cells. Results illustrated that the developed channel expert presents a substantial improvement over the standard estimators in the presence of pilot contamination.

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