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Joint channel estimation algorithm via weighted Homotopy for massive MIMO OFDM system

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A B S T R A C T

Massive (or large-scale) multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) system is widely acknowledged as a key technology for future communication. One main challenge to implement this system in practice is the high dimensional channel estimation, where the large number of channel matrix entries requires prohibitively high computational complexity. To solve this problem efficiently, a channel estimation approach using few number of pilots is necessary. In this paper, we propose a weighted Homotopy based channel estimation approach which utilizes the sparse nature in MIMO channels to achieve a decent channel estimation performance with much less pilot overhead. Moreover, inspired by the fact that MIMO channels are observed to have approximately common support in a neighborhood, an information exchange strategy based on the proposed approach is developed to further improve the estimation accuracy and reduce the required number of pilots through joint channel estimation. Compared with the traditional sparse channel estimation methods, the proposed approach can achieve more than 2 dB gain in terms of mean square error (MSE) with the same number of pilots, or achieve the same performance with much less pilots.

1. Introduction

The reliable high-speed broadband wireless links are expected to be on a huge development prospective due to the foreseen rapidly increases in the number of users, amount of data traffic and number of applications [1]. To meet these demands, it is expected that future communication systems, i.e., beyond 4G or 5G systems, will reach a faster data rate at gigabit-scale over the next few years. One of the recent proposed technologies for the future communication system is the massive (or large-scale) multiple-input multiple-output (MIMO) orthogonal frequency division multiplexing (OFDM) which is based on the same concepts of the classical MIMO OFDM but with much larger number of antenna arrays on each side of the link. As such, the massive MIMO techniques could provide unprecedented spectral efficiency and array gain that potentially meet the rapidly growing demand for high data rates [2]. For instance, NTT DoCoMo has performed the field experiment of a massive MIMO system with 12×12 antennas, which could reach the spectral efficiency of 50 bps/Hz and a data rate of 4.92 Gbps on the wireless channel with 100 MHz bandwidth [3], while currently a 16×16 MIMO configuration is considered by the evolution of WiFi standard called IEEE 802.11 ac [4].

However, the very large number of channel matrix entries make the traditional channel estimation strategy infeasible for frequency division duplex (FDD) protocol. Therefore, most researches on massive MIMO systems suggest the use of time division duplex (TDD), where the channel state information (CSI) can be acquired at the base station (BS) side and then utilized at both transmission directions based on the assumption of channel reciprocity [5]. However, the inaccurate CSI acquired in the uplink can lead to significant performance degradation. Thus, accurate estimation of the high-dimensional MIMO channel matrix in the uplink is critical for the deployment of massive MIMO.

Basically, there are two categories of channel estimation techniques for MIMO OFDM systems: blind estimation and pilots-based estimation. In [5], a blind channel estimation technique based on the eigenvalue decomposition (EVD) has been proposed recently. Though this method could approach the near maximum-likelihood performance in theory, it has two shortcomings. Firstly, it utilizes the sample covariance matrix as a substitution of the actual covariance matrix to estimate the channel coefficients. Secondly, it

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assumes that the number of BS antennas is infinite. For these reasons, the EVD based method suffers from severe mean square error (MSE) performance penalty in practical dimensional massive MIMO systems. Unlike the blind estimation techniques, several pilot-based channel estimation schemes such as the Bayesian MMSE estimator and minimum variance unbiased (MVU) have been adopted in MIMO system [6,7]. However, the pilot overhead of those estimation schemes increases sharply in massive MIMO system where the number of antennas is very large. To solve this problem, some recent works have exploited the sparse nature of the multi-path channel and used compressive sensing (CS) based estimators to reconstruct the channel perfectly with relatively less pilots [8,9]. Some CS algorithms, e.g., orthogonal matching pursuit (OMP) and basis pursuit (BP), have been already used in channel estimation for MIMO systems [9–12]. However, neither of these algorithms can attain accurate estimation performance and low complexity at the same time. More recently, one quadratic semidefinite programming (SDP) method has been discussed in [1], where the author demonstrated that SDP solver can be stable and provide accurate channel estimation, as long as the degree of freedom (DoF) of the channel matrix is much smaller than the size of channel matrix (i.e., total number of elements in the channel matrix). However, experimental results have shown that the convex optimization solver runs slowly in the large-scale applications since it requires explicit operations on the large matrix [13]. Therefore, scholars have abandoned the convex optimization based estimators and turned their attentions to the fast iterative methods.

The Homotopy algorithm has been originally proposed to solve noisy overdetermined ℓ_1-penalized least squares problems, which becomes popular quickly since it can achieve the estimation accuracy as good as convex optimization schemes with the estimation speed as fast as OMP [12]. Existing literature includes several improvements proposed for the standard Homotopy algorithm [14–18]. One of the latest researches is the weighted Homotopy in [15], which improves the original Homotopy by replacing its ℓ_1 term with a weighted ℓ_1 term. However, this method can only work in the real domain, which restricts its applications in the complex domain.

In this paper, we propose a set of algorithms for channel estimation in massive MIMO systems. Firstly, we extend the conventional weighted Homotopy to the complex field and adopt it to estimate the sparse channel on each BS antenna. By adjusting the weight separately according to the channel coefficients, this approach improves the channel estimation performance with faster convergence rate. In addition, inspired by the fact that neighboring BS antennas observe similar channel support (i.e., sparsity pattern) [19], we propose a simple information sharing method between the BS antennas to further improve the channel estimation performance. Compared with the conventional sparse channel estimators, the required pilots in the proposed method is significantly reduced, leading to higher spectral efficiency, while its computational complexity is proved to be much lower than the convex optimization solvers.

The rest of the paper proceeds as follows. We first describe the system model and analyze the channel properties in Section 2. Then we propose the improved Homotopy-based channel estimator in Section 3. A simple joint channel estimation method is presented in Section 4 while the performance analysis is provided in Section 5. Numerical experiments are presented in Section 6. Finally, Section 7 concludes the paper.

Notations: Throughout this paper, matrices and vectors are denoted in bold letters while the signals in frequency and time domains are represented by upper and lowercase characters, respectively. $diag\{x\}$ is the diagonal matrix with x on its main diagonal and $\min(\cdot)_+$ means that the minimum is taken over only positive arguments. Operators ^{T} and * represent transpose and complex conjugate transpose. $|\cdot|$, $\|\cdot\|_p$ and $sgn(\cdot)$ denote absolute value, ℓ_p-norm and sign function respectively. $\boldsymbol{F}_N$, $\mathbb{C}$, $\mathbb{R}$, $\boldsymbol{I}_L$, $\Re$, $\Im$ represent the $N \times N$ normalized discrete Fourier transform (DFT) matrix, the set of complex number, the set of real number, the identity matrix with dimension L, the real part and the imaginary part, respectively.

2. System model and problem formulation

2.1. System model

Considering the uplink of a massive MIMO OFDM system where the BS (receiver) is equipped with a large antenna array consisting of $N_r = M_r \times M_c$ antennas distributed across M_r rows and M_c columns[2] [19]. The BS simultaneously serves several UTs. Accordingly, for a certain UT the ith OFDM symbol is composed of N_{CP}-length cyclic prefix (CP) and N-length data block $\boldsymbol{x}_i = [x_{i,0}, \ldots, x_{i,1}, \ldots, x_{i,N-1}]^T$ among which N_p positions are randomly collected to transmit the pilots [20]. Let $\boldsymbol{p} = [P_1, \cdots, P_j, \cdots, P_{N_p}]$ $(1 \le P_1 < \cdots < P_j < \cdots < P_{N_p} \le N)$ where P_j denotes the index of the jth pilot. Thus the pilots of the ith OFDM symbol can be expressed as $\bar{\boldsymbol{x}}_i = [x_{i,P_1}, x_{i,P_2}, \cdots, x_{i,P_{N_p}}]$.

For the kth receiving antenna at the BS side, the channel impulse response (CIR) $\boldsymbol{h}_i^k (1 \le k \le N_r)$ of the ith OFDM symbol can be represented as

$$\boldsymbol{h}_i^k = [h_{i,0}^k, \ldots, h_{i,l}^k, \ldots, h_{i,L-1}^k]^T$$

where $h_{i,l}^k$ is the path gain of the lth path with the path delay $\tau_{i,l}^k$, L is the maximum channel spread. Therefore, the received pilots $\boldsymbol{y}_i^k = [y_{i,P_1}^k, y_{i,P_2}^k, \ldots, y_{i,P_{N_p}}^k]$ at the kth antenna can be denoted in the frequency domain as [20]

$$\begin{aligned} \boldsymbol{y}_i^k &= diag\{\bar{\boldsymbol{x}}_i\}\boldsymbol{F}_{p,L}\boldsymbol{h}_i^k + \boldsymbol{v}_i^k \\ &= \boldsymbol{P}_i^k\boldsymbol{h}_i^k + \boldsymbol{v}_i^k, \end{aligned} \tag{1}$$

where $diag\{\bar{\boldsymbol{x}}_i^k\}$ is a $N_p \times N_p$ diagonal matrix with $\bar{\boldsymbol{x}}_i^k$ on its diagonal, $\boldsymbol{F}_{p,L}$ is a partial discrete Fourier transform (DFT) matrix indexed by $\boldsymbol{p} = [P_1, P_2, \cdots, P_{N_p}]$ in row and $[1, 2, \cdots, L]$ in column from a standard $N \times N$ DFT matrix, $\boldsymbol{P}_i^k = diag\{\bar{\boldsymbol{x}}_i^k\}\boldsymbol{F}_{p,L}$, $\boldsymbol{v}_i^k$ denotes the additive white Gaussian noise (AWGN). For the sake of brevity, without loss of generality we hereafter omit the script of i and k unless these are required. Hence (1) becomes

$$\boldsymbol{y} = \boldsymbol{P}\boldsymbol{h} + \boldsymbol{v}. \tag{2}$$

2.2. Channel properties

Note that extensive literature has demonstrated that the wireless channels are sparse in nature. This indicates that there are only few entries of the channel matrix containing the significant fraction of the channel information while most of the other entries are ignorable [21,22] (e.g., the ITU Vehicular B channel with 200 samples has only 6 resolvable paths [23]). As such we can draw a conclusion that the number of resolvable propagation paths (or most significant taps) S is much smaller than the maximum channel spread L $(S \ll L)$.

Moreover, it is suggested in [24] that two channel taps are resolvable if the time interval of arrival is larger than $\frac{1}{10B}$ where B is the bandwidth of signal. Therefore, it is reasonable to assume that the CIRs measured at different BS antennas share almost the same locations of the significant taps from a certain transmitter if

[2] Note that although we focus on the rectangular array configuration in this paper, there is no limitations for our approach to be applied to any other array configurations.