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A Review paper on different channel estimation techniques for MIMO-OFDM systems

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ABSTRACT

In this paper we have studied and proposed some channel estimation methods for MIMO-ofdm systems. These methods have better performance as compared to others .we have considered sparse frequency selective channel. These channels are independently sparse and share a common support. The methods estimate the impulse response for each channel observed by the antennas at the receiver. At receiver arrays of antennas have been used, antennas coordinate with each others. Estimation is performed in a coordinated manner by sharing minimal information among neighboring antennas to achieve results better than many contemporary methods.

Index Terms- massive MIMO, OFDM, MATLAB, sparse channel

1. INTRODUCTION

All wireless channels can be modeled as discrete multipath channels with large delay spread and few significant paths. This implies sparsity of channel impulse response (CIR) [1-3]. This leads from the fact that scatterers are sparsely distributed in space. Thus, it is essentially beneficial to account for such a sparse channel model when performing channel estimation. We aim to use this property in the context of MIMO-OFDM systems. The deployment of multiple antennas, offers key advantages to wireless systems performance in terms of power gains, channel robustness, diversity etc. [4]. Specifically, the use of very large antenna arrays has very recently emerged. Such systems, known as massive MIMO.

In large-scale MIMO the major performance bottleneck is the availability of CIR. Several algorithms exist that take advantage of the sparsity and the assumption that channel support does not vary as we move across the antenna grid, however with some drawbacks. For example, the algorithms assume common support throughout antenna array which is not true for large arrays. The readers are directed to [7-14] for some work on MIMO and massive MIMO channel estimation. In this work, we utilize the property of loosely space-invariant channel support along with the sparsity property to propose an efficient pilot-aided Bayesian approach estimate sparse CIR in the massive-MIMO setup. In this approach each receiving antenna collaborates with its direct neighbors to estimate its unknown sparse channel. The neighboring antennas share their knowledge of most significant taps (MST) to reach a consensus about the CIR support.

This paper is organized as follows. In Section II, we present the system model and formulate the problem. In Section III we introduce a simple Bayesian approach for channel estimation which leads us to present the proposed coordinated channel recovery algorithm in Section IV. Simulation results are discussed in Section V and Section VI concludes the paper. A detailed version of this paper is also available [15].[1]

2. SYSTEM MODEL AND PROBLEM FORMULATION

2.1 Preliminaries

We consider a MIMO-OFDM system. in which the base station (BS) is equipped with a large two-dimensional antenna array consisting of $R = M \times G$ antennas distributed across M rows and G columns.[2] OFDM is adopted as the signaling mechanism. In an OFDM system, serially incoming bits are divided into N parallel streams and mapped to a Q-ary QAM alphabet $\{A_1, A_2, \dots, A_Q\}$. This results in an N-dimensional data vector denoted by $X = [X(1), X(2), \dots, X(N)]^T$. The equivalent time-domain signal $x = F^H X$ is transmitted. Here F is an N × N unitary DFT matrix whose (c, d)th entry is $f_{c,d} = \frac{1}{\sqrt{N}} \exp\left(-j\frac{2\pi}{N}cd\right)$, and N is the number of subcarriers.

2.2 Channel Model

The channel through which the transmitted signal x is received at the receive antenna r = (m, g) (where $m \in \{1, 2, \ldots, M\}$and $g \in \{1, 2, \ldots, G\}$) as shown in Fig. 1 is denoted by $h_r \in C^L$. we shall assume that h_r has a sparse structure and is modeled as $h_r = h_A \circ h_B$ where ∘ indicates element-by-element multiplication. The vector h_A consists of element that are drawn from some unknown distribution and h_B is a Bernoulli random vector where its ith element has an active probability of $p(h_B(i) = 1) = \lambda_i$.

Therefore, the entries of h_B form a collection of iid Bernoulli random variables. Thus, h_r is an L-tap discrete-time sparse channel where no assumption whatsoever is made about the distribution of its non-zero complex-valued coefficients.[3] Moreover, depending upon factors such as antenna separation and transmission bandwidth, the MST locations of h_r's have common support are termed space-invariant arrays (SIA) while the arrays for which this is not true are called space-varying arrays (SVA).

The received signal at the rth antenna is best described in the frequency domain and is given by

$$Y_r = \text{diag}(X)\, H_r + W_r, \quad (1)$$

where γ_r is the Fourier transform of the received vector, $W_r \sim CN(0, \sigma_w^2 I)$ is the frequency-domain noise vector and diag is an operator that produces a diagonal matrix by spreading the elements of X along the diagonal. Moreover, $H^r = F\left[h_r^T\, 0_{1\times N-L}\right]^T = \underline{F}h_r$ is the N × 1 channel frequency response vector where $\underline{F}$ is the truncated Fourier matrix of size N × L formed by selecting the first L columns of F. Finally, we can rewrite (1) as $\gamma_r = Ah_r + W_r$, where $A \overset{\Delta}{=} \text{diag}(X)\,\underline{F}$ is an N × L matrix.

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2.3 Problem Formulation

Let the transmit antenna sends pilots in K subcarriers and the remaining N - K subcarriers are used for data transmission. Let P represents the set of indices of the K subcarriers over which pilots are transmitted. Thus,

$$Y_r(P) = A(P)\, h_r + W_r(P) \quad (2)$$

where $Y_r(P)$ and $W_r(P)$ are formed, respectively, by selecting entries of Y_r and W_r indexed by P. Similarly, A (P) is a K × L matrix formed by selecting the rows of A indexed by P. We aim to solve for h_r in equation (2). This obviously requires that $K \geq L$. Since the channel delay spread (equivalently L) is usually large, this requires a large number of subcarriers to be reserved for pilots, severely affecting the spectral efficiency of the system. However, by virtue of channels being sparse with large delay spread, we could actually solve for h_r if $K < L$ as suggested by the compressed sensing theory [16, 17]. We consider a random placement of pilot tones P over the OFDM subcarriers as it has been found to be optimal for sparse channel estimation [18, 19]. The aforementioned system model will be used in subsequent sections to develop our coordinated approach for estimation of all R channels h_r.

3. SPARSITY-AWARE DISTRIBUTIONAGNOSTIC BAYESIAN CHANNEL ESTIMATION

Consider the model showed in (2). For simplicity, we will drop the symbols r and P unless required for clarity. Hence,

$$Y = Ah + W, \quad (3)$$

here we are interested in performing Bayesian estimation of the wireless CIR h.

we have to characterize(mean and variance for Gaussian) the distribution but as the nature of the wireless channel is dynamic it is quite difficult. Even if the distribution is known it is very difficult or even impossible to estimate the distribution parameters (e.g., mean and variance for Gaussian) especially when the channel statistics are not i.i.d. In that respect, the use of distribution agnostic Bayesian sparse signal recovery method (SABMP) [20] will be most suitable which provides Bayesian estimates even when the prior is non-Gaussian or unknown.

Another way could be to use SABMP to perform sparse channel recovery at each antenna element in the array. It is easy fewer complexes but increase the time. The channels would be estimated independently and the receivers will not take advantages of the additional information of common support. We have proposed a coordinated channel estimation method in Sec. 4 which utilizes the common support information this method would be different. Now we introduce in the following some necessary modifications to the SABMP algorithm presented in [16].

3.1 SABMP for non-iid Bernoulli random vector

The development of the SABMP algorithm assumes that elements of h are activated with equal probability λ (iid Bernoulli). However, if some elements are more probable than others, it is desirable to assign those elements a higher probability. This requires us to assume a non-iid Bernoulli behavior for h. Thus if S contains the indices of the elements of h (i.e. the support of h), the probability of that support is given by, $p(S) = \prod_{i\in S} \lambda_i \prod_{j\in \{1,\dots,L\}\setminus S}(1-\lambda_j)$ where λ_i is the active probability of index i. Using this p (S) results in a modified version of the dominant support selection metric of [20] (see eq. (13) therein). The new metric is,

$$v(S) \overset{\Delta}{=} -\frac{1}{2\sigma_n^2}\left\|P_S^{\perp}Y\right\|_2^2 + \sum_{i\in S}\ln\lambda_i + \sum_{j\notin S}\ln(1-\lambda j) \quad (4)$$

For future reference, let us call the algorithm taking advantage of this new dominant support selection metric RS1.

4. ITERATIVE COORDINATED CHANNEL RECOVERY

Following section will describe the proposed channel estimation methods. The method is based on coordination among the all antennas they coordinate and find the MST and consequently the channel.all the antennas coordinate and communicate in an effective manner(stagewise) so as to reduce the overhead. Basically, each receiver element r and only its immediate 4-neighbors $N = \{r_N, r_S, r_E, r_W\}$ as shown in Fig. 1 communicate with each other. This process is repeated which effectively share the information present at each antenna to all distant antennas. In this manner the collaboration is performed to estimate channels accurately. Following sections will describe in detail three algorithms for CIR estimation that take advantage of collaboration.

4.1 Algorithm 1: Channel Estimation pilots

Problem seen in (2) can be solved by using observation of the pilots. This algorithm starts by estimating the sparse channels h_r at each antenna element r using the RS2 algorithm. Algorithm is initialized by considering that all taps of h_r have equal active probability λ_{init} throughout the array. Therefore, $p(h_B(l) = 1) = \lambda_l = \lambda_{init}, \forall l \in \{1, 2, \dots, L\}$.

Let $T^r = \{\alpha_1^r, \alpha_2^r, \dots, \alpha_{Tmax}^r\}$ be the set of active taps of channel h_r as detected by RS2. Note that since λ_{init} is same throughout the array, the number of detected active taps T_{max} will also be equal for all the receivers i.e., the cardinality $|T^r| = T_{max}, \forall r$. The RS2 algorithm will also find the marginal probabilities $p\left(\alpha_t^r\right)$, $t \in \{1, 2, \dots, T_{max}\}$. Each antenna r, which is acting as central antenna collects these probabilities from its 4-neighors and computes the average for each tap α_i, $i \in \{1, 2, \dots, L\}$ as follows

$$p(\alpha_i) = \sum_{\substack{j\in N^+ \\ psmall}} p\left(\alpha_i^j\right) \Big/ \left|N^+\right|, \text{ if } \alpha_i \in \bigcup_{j\in N^+} T^j, s \quad (5)$$

Taps that are not detected by any of the antenna or the central antenna are reprented by, where

$N^+ = N \cup r$ and psmall is an arbitrarily small value assigned to the taps. For effective estimation this process must be repeated so This averaging step is repeated D times by each antenna where the value of D depends on whether the array under consideration is SIA or SVA. In the SIA case, since the MST locations do not vary across the array, contribution from as many antennas as possible will strong our belief in these locations. Therefore, we may select D = max (M, G) which equals to the largest dimension of the antenna array which ensures that each antenna receives information from every other antenna in the array while in SVA we have to consider array configuration and other parameters for deciding the value of D.Specially, according to lemma 1 in |23| if observations from q antennas are used to recover n-sparse channel vectors using K pilots then for a unique solution n ≤ $\lceil (K+q)/2 \rceil$ - 1 holds which simplifies to the condition on D as D > $\sqrt{n - \frac{K}{2} - \frac{1}{4}} - \frac{1}{2}$. Here [·] denotes the ceiling operation. now, each antenna uses the newly computed probabilities as new initial probabilities with the RS1 algorithm to find new sparse channel estimates. The algorithm is described in Algorithm 1.

This approach will reduce the communication cost by simply sharing the integers. It is also less computational complex

4.2 Algorithm 2: Low Communication/Computational Cost

In this marginal probabilities are not considered, at receiving antenna channel is estimated by using original SABMP algorithm. At each receiver, as per this algorithm each tap location will have some score assigned, this score is based on detected amplitudes. Since there are T_{max} possible channel tap location with highest absolute amplitude, moves downward until a score of 1 is assigned to the tap location with the least amplitude among the top T_{max} taps. All other tap locations are assigned a score of zero. Here Each antenna is acting like a central antenna, collects the T_{max} scores from each neighbor and determine an average score $\Psi(\alpha_i)$ for each tap α_i in a fashion similar to that in (7). Finally, after repeating the process D times, a belief measure $b(\alpha_i) = \Psi(\alpha_i)/T_{max}$ is computed to be used by the RS1 algorithm. $b(\alpha_i)$ is the estimated belief that the ith tap is active. The beliefs $b(\alpha)$ are used in place of the marginal probabilities to re-estimate the channels following a strategy similar to the explained in Algorithm reduces the communicating floating point numbers, Now this algorithm will have lower computational complexity since we are not considering and computing marginal probabilities. Now there is new algorithm we are going to suggest for the posteriors/scores by selecting reliable data carriers to perform channel estimation.

4.3 Algorithm 3: Using Reliable Carriers :

The estimated channels from previous sections are used to perform equalization and recover the transmitted data. This channel estimation can be more reliable and improved if we can include user data in it. But for that we have to investigate and analyze the user data i.e to find out data carriers which are most reliable. So, we seek to assign a reliability measure $\Re(i)$, $i \in \{1, \ldots, N\}\backslash P$ to each of the N - |P| data carriers. For this purpose, we use the reliability measure suggested in [16] to compute carrier reliabilities. The reliability values are then sorted and the carriers corresponding to the top U values of $\Re$ are considered in calculations. Let R^r contains the indices of the top U reliable carriers for receiver r. Collaboration among receiver antennas could be performed to further strengthen the belief in the reliable carriers. In order to do so, each antenna r_c, acting as central antenna, collects the indices of the reliable carriers from its 4-neighbors N and selects only those which are common to all antennas under consideration $R = \bigcap_{r \in \{r_C \cup N\}} R^r$ are the indices of reliable carriers of antenna r. R is then transmitted to the neighbors which then send back the corresponding data. Further refinement is done by retaining only those carriers which carry same data. Let us represent these carriers by R⋆. The central antenna uses this final list of reliable carriers plus the pilots i.e., $R^\star \cup P$ to solve,

$$Y_r (R^\star \cup P) = A (R^\star \cup P) h_r + W_r (R^\star \cup P) \quad (6)$$

and estimate channel h_r. Thus the pilots and reliable carriers are used together to reach at better estimates of channels which is evident from the simulation results presented in Section 5. The resulting algorithm is presented in Algorithm 2. Note that the proposed algorithms are independent of the antenna grid topology as the only information required by an antenna is that of its neighbors.

4.4 MMSE estimation

The goal is to estimate the complex matrix H from the knowledge of Y and P. Assuming the training matrix is known the channel matrix can be estimated using the minimum mean square error method as described in [4][5].

$$\hat{H} = \frac{\rho}{M_t} YP^H (R_H^{-1} + \frac{\rho}{M_t} PP^H)^{-1} \quad (7)$$

with MSE estimation error given by:

$$J_{MMSE} = E\{\left\| H - \hat{H}_{MMSE} \right\|_F^2\} = tr\{(R_H^{-1} + \frac{\rho}{M_t} PP^H)^{-1}\}$$

where p is the signal to noise ratio, E{.} is a statistical 2 expectation and tr {.} denotes the trace of matrix, $\| \ \|_F^2$ stands for the Frobenius norm and $R_H = E\{H^H H\}$ is the channel correlation matrix. Using eigenvalues decomposition, RH can be expressed as

$$R_H = Q \Lambda Q^H \quad (8)$$

In (10) Q is the unitary eigenvector matrix and A is the diagonal matrix with nonnegative eigenvalues. By substituting (8) into (7), one can get

$$J_{MMSE} = tr\{(\Lambda^{-1} + \frac{\rho}{M_t} Q^H PP^H Q)^{-1}\}$$

5. CONCLUSION

We have studied various channel estimation methods for massive MIMO such as least square ,mean square error MMSE and sparse channel estimation methods. We have used modified version of SABMP to exploit the sparse common support property and share information in a step by step manner to perform channel recovery. We have also analyzed and compare them. We have compared them on the basis of BER performance and complexity.

REFERENCES

[1] S.-S. Sadough, M. Ichir, P. Duhamel, and E. affrot, “Waveletbased semiblind channel estimation for ultrawideband OFDM systems,” IEEE Trans.Veh. Technol., pp.1302–1314, 2009.

[2] W. Bajwa, A. Sayeed, and R. Nowak, “Sparse multipath channels: Modeling and estimation,” in Proc. Digital Signal Processing Workshop and IEEESignalProcessing Education Workshop (DSP/SPE),2009, pp. 320–325.

[3] H. Minn and V. Bhargava, “An investigation into time-domain approach for OFDM channel estimation,” IEEE Trans. Broadcast., pp. 240–248, 2000.

[4] H. Holma and A. Toskala, LTE Advanced: 3GPP Solution for IMT-Advanced. Wiley, 2012.

[5] G. J. Foschini, “Layered space-time architecture for wireless communication in a fading environment when using multiple antennas,” *Bell Labs Technical Journal*, vol. 1, no. 2, pp. 41–59, 1996.

[6] P.W.Wolniansky, G. J. Foschini, G. D. Golden, and R. A. Valenzuela, “V-BLAST: an architecture for realizing very high data rates over the rich-scattering wireless channel,” in *URSI ISSSE’98*, Pisa, Italy, Oct. 1998, pp. 295–300.

[7] V. Tarokh, N. Seshadri, and A. R. Calderbank, “Space-time codes for high data rate wireless communication: performance criterion and code construction,” *IEEE Trans. Inf. Theory*, vol. 44, no. 2, pp. 744–765, Mar. 1998.

[8] H. Schoeneich and P. A. Hoeher, “Iterative pilot-layer aided channel estimation with emphasis on interleave-division multiple access systems,” *EURASIP Journal on Applied Signal Processing*, vol. 2006, pp. 1–15, 2006.

[9] T. Zemen, C. Mecklenbrauker, J.Wehinger, and R. Muller, “Iterative joint time-variant channel estimation and multi-user detection for MC-CDMA,” *IEEE Transactions on Wireless Communications*, vol. 5, pp. 1469–1478, Jun. 2006.

[10] P. Salvo Rossi and R. M¨uller, “Joint iterative time-variant channel estimation and multi-user detection for MIMO-OFDM systems,” in *Proc. IEEEGlobal Communications Conference*, pp. 4263–4268, Nov. 2007.

[11] S. Suyama, L. Zhang, H. Suzuki, and K. Fukawa, “Performance of iterative multiuser detection with channel estimation for MC-IDMA and comparison with chip-interleaved MC-CDMA,” in *Proc. IEEE Global Communications Conference*, pp. 1–5, 2008.

[12] A. Mukherjee and H. Kwon, “Multicarrier interleave-division multipleaccess systems with adaptive pilot-based user interleavers,” in *Proc. IEEE Vehicular Technology Conference*, pp. 1–5, 2009.

[13] Q. Guo, L. Ping, and D. Huang, “A low-complexity iterative channel estimation and detection technique for doubly selective channels,” *IEEE Transactions on Wireless Communications*, vol. 8, pp. 4340 –4349, Aug. 2009.

[14] Y. Li, N. Seshadri, and S. Ariyavisitakul, “Channel estimation for OFDM systems with transmitter diversity in mobile wireless channels.