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Alternating-Projection-Based Channel Estimation for Multicell Massive MIMO Systems

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Abstract

In massive multiple-input multiple-output (MIMO) systems, linear channel estimation algorithms are widely applied owing to their simple structures. However, they may cause pilot contamination, which affects the subsequent data detection performance. Therefore, herein, for an uplink multicell massive multiuser MIMO system, we consider using an alternating projection (AP) for channel estimation to eliminate the effect of pilot contamination and improve the performance of data detection in terms of the bit error rates as well. Even though the AP is nonlinear, it iteratively searches the best solution in only one dimension, and the computational complexity is thus modest. We have analyzed the mean square error with respect to the signal-to-interference ratios for both the cooperative and non-cooperative multicell scenarios. From the simulation results, we observed that the channel estimation results via the AP benefit the following signal detection more than that via the least squares for both the cooperative and non-cooperative multicell scenarios.

Index Terms: Alternating projection, Channel estimation, Least squares, Multicell massive MIMO

I. INTRODUCTION

Massive multiple-input multiple-output (MIMO) via dense antenna arrays is one of the key technologies of 5G mobile communication systems, which promises high channel capacity, low energy consumption, etc. and has recently attracted particular attention [1-3]. However, the performance of massive MIMO systems is sensitive to the quality of the channel state information (CSI). Therefore, obtaining the CSI is particularly important in massive MIMO systems, as they rely on simple CSI-dependent detection techniques at a base station (BS) to eliminate the interference between users (UEs). Pilot sequences are widely utilized in acquiring the CSI in state-of-the-art channel estimations. However, employing orthogonal pilot sequences in multicell scenarios is challenging. This is because the length of pilot sequences depends on the number of cells, and is severely limited by the channel coherence time. Consequently, UEs who are located in different cells but have to exploit the same pilot sequence simultaneously are always present, which results in the pollution of channel estimation, known as pilot contamination [4-7]. A precoding method based on the minimum mean-squared error (MMSE) is proposed to mitigate the pilot contamination problem in [4]. In [5], the pilot sequence is shifted and reused in the neighboring cells, resulting in a more accurate channel estimation. Multicell cooperation is also considered for reducing the effect of pilot contamination in [6]. However, [7] indicated that pilot contamination is not a critical problem of large antenna array systems, but merely a shortcoming caused by some linear channel estimation

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algorithms such as least squares (LS) [8] and MMSE [4]. The shortcoming can be easily overcome by using a nonlinear channel estimation algorithm, e.g., blind pilot decontamination [9]. However, most nonlinear channel estimation algorithms suffer from a curse of computational complexity due to the greedy iterative searching manner.

Therefore, herein, we consider the alternative projection (AP) algorithm, which was originally proposed for localizing multiple sources [10]. We employed the AP to estimate the channel information as it can provide near-optimum performance with an acceptable computational complexity. Furthermore, we analyzed the mean square errors with respect to the signal-to-interference ratio (SIR) for both the non-cooperative and cooperative multicell scenarios.

The paper is organized as follows: in Section II, we briefly introduce a generic multicell massive MIMO system. In Section III, we state the process of channel estimation via the AP, and analyze the mean square error (MSE) in terms of the SIR for both the cooperative and non-cooperative multicell scenarios. Finally, the simulation results are shown in Section IV, and the conclusions are presented in Section V.

II. SYSTEM MODEL

We consider an uplink multicell massive MIMO system in which a target cell exists with L number of interfering cells. For each cell, the BS employs M number of receiver antennas, and each UE employs K number of transmit antennas. For simplicity, we consider only one UE for each cell, and the received signal at the BS of the target cell is given as

$$Y = \sqrt{P}HX + \Sigma_{i=1}^{L}\sqrt{I}H_iX_i + N, \quad (1)$$

where $Y \in \mathbb{C}^{M\times K}$ denotes the received signal matrix, P is the power used by the target UE for transmitting the information signal (or pilot signal) $Y \in \mathbb{C}^{M\times K}$, where T denotes the transmission duration (or the length of pilot sequences), and $X_i \in \mathbb{C}^{M\times K}$ is the information signal (or pilot signal) transmitted by one UE located at the i^{th} interfering cell using the power I. $N \in \mathbb{C}^{M\times K}$ describes the noise matrix in which each entry is a Gaussian distribution with a zero mean and variance of σ^2. $H \in \mathbb{C}^{M\times K}$ and $H_i \in \mathbb{C}^{M\times K}$ are the channel matrices from the UE of the target cell and the UE of the i^{th} interfering cell to the BS of the target cell, respectively.

If X and X_i are different and orthogonal pilot signals, the channel matrix H can be easily estimated via a linear process as

$$\tilde{H} = YX^H(X^HX)^{-1} = \sqrt{P}H + X^H(X^HX)^{-1}N. \quad (2)$$

The estimated channel $\tilde{H}$ will be employed for the following information signal detection. If the UEs of the target and interfering cells are using the same pilot sequence because of the lack of orthogonal pilot sequences, i.e., $X = X_i$, the estimated channel $\tilde{H}$ is populated by L number of interfering channel matrices, i.e.,

$$\tilde{H} = \sqrt{P}H + \Sigma_{i=1}^{L}\sqrt{I}H_i + \tilde{N} \quad (3)$$

where $\tilde{N} = X^H(X^HX)^{-1}N$ and X^H represents the Hermitian of X. This kind of phenomenon is known as pilot contamination [4]. However, we noticed that this problem merely results from the orthogonality constraint required by the linear channel estimation algorithm. If nonlinear algorithms that do not require pilot sequences are employed for channel estimation, the problem will no longer be the primary one.

III. BLIND CHANNEL ESTIMATION VIA ALTERNATIVE PROJECTION

A. Alternative Projection Algorithm

AP was first proposed in [10] for locating multiple sources. It can provide similar performance as maximum likelihood (ML). Moreover, since it converts a nonlinear multivariate optimization problem into a single-variate optimization problem, it requires only an acceptable computational complexity. Therefore, it can be an alternative for channel estimation to achieve an elegant tradeoff between performance and complexity. The AP algorithm for channel estimation is primarily summarized as follows:

1. Calculate the covariance matrix $\tilde{R} = (1/T)\Sigma_{t=1}^{T}y_ty_t^H$ where y_t is the t^{th} column vector of Y given in (1);
2. Use singular value decomposition (SVD) for the covariance matrix to achieve its eigenvalues λ_i and eigenvectors μ_i;
3. Initialize $\tilde{H} = \tilde{H}^{(0)}$;
4. **For** the i^{th} iteration **do**

$$P_{\tilde{H}} = \tilde{H}^{(i-1)}(\tilde{H}^{(i-1)H}\tilde{H}^{(i-1)})^{-1}H^{(i-1)H}$$

$$\tilde{H}^{(i)} = argmax\sum\lambda_i\|P_{\tilde{H}}\mu_i\|^2$$

5. **End**

The resulting channel matrix $\tilde{H}$ will be presented in the following signal detection. Further details of the AP algorithm can be found in [10].

Compared to ML, which is optimal but computationally expensive owing to its exhaustive multidimensional searching, the AP-based algorithm significantly reduces computational complexity as it is a simple one-dimensional searching problem. Unlike [11], which only focused on cooperative multicell massive MIMO systems, we herein analyze the MSE with respect to the SIR for both the cooperative and non-cooperative multicell massive MIMO systems.

B. Cooperative Multicell Scenarios

In a multicell BS cooperation mode such as coordinated multiple points (CoMP) in LTE-A systems [12], all BSs can exchange their information about channel states and data such that the interfering BSs do not exist. In this case, we can rewrite the system model in (1) as

$$Y = [H \quad H_1 \quad \dots \quad H_L][\sqrt{P}X \quad \sqrt{I}X_1 \quad \dots \quad \sqrt{I}X_L]^T + N \quad (4)$$

by defining

$$\tilde{H} = [H \quad H_1 \quad \dots \quad H_L]$$

and

$$\tilde{X} = [\sqrt{P}X \; \sqrt{I}X_1 \; \dots \sqrt{I}X_L]^T.$$

The analysis of the AP performance is not straightforward. However, assuming that the noise N satisfies the Gaussian distribution, the performance of the AP algorithm approaches ML [10]. Therefore, we can analyze the ML instead of the AP itself to obtain some insight. For simplicity, we consider only a single interfering cell; therefore, we achieved our first lemma for the cooperative multicell massive MIMO systems.

LEMMA 1. The MSE of the cooperative system model in (4) is approximated as

$$MSE = MK\sigma^2\left(SIR + \frac{1}{SIR} + 2\right), \quad (5)$$

where $SIR = P/I$ refers to the SIR.

Proof: According to [8], with a known pilot sequence, the performance of ML is identical to that of the LS. Therefore, the channel estimation results can be described as

$$\hat{H} = Y\tilde{X}^H(\tilde{X}\tilde{X}^H)^{-1} = H + N\tilde{X}^H(\tilde{X}\tilde{X}^H)^{-1}. \quad (6)$$

MSE is thus given by

$$MSE = \boldsymbol{E}\{\|\tilde{H} - H\|_F^2\} = \boldsymbol{E}\{\|N\tilde{X}^H(\tilde{X}\tilde{X}^H)^{-I}\|_F^2\}, \quad (7)$$

where $\boldsymbol{E}(A)$ denotes the expectation of A. Let $N_1 = N\tilde{X}^H$ and $N_2 = (\tilde{X}\tilde{X}^H)^{-1}$; therefore, we have the following approximation:

$$MSE = \boldsymbol{E}\{\|N_1N_2\|_F^2\} \approx E\{\|N_1\|_F^2\ \|N_2\|_F^2\}. \quad (8)$$

If T is sufficiently large, we can use the approximation given as

$$\boldsymbol{E}\{\tilde{X}\tilde{X}^H\} \approx \begin{bmatrix} PTI_k & 0 \\ 0 & ITI_k \end{bmatrix},$$

where I_K is a $K \times K$ identity matrix, which results in another two approximations:

$$\boldsymbol{E}\{\|N_2\|_F^2\} = \frac{K}{T}\left(\frac{1}{P} + \frac{1}{I}\right)$$

and

$$\boldsymbol{E}\{\|N_1\|_F^2\} = (P + I)TM\sigma^2.$$

Substituting the results above into (8), we can conclude Lemma 1.

We noticed that the MSE in (5) is a non-decreasing function when the SIR is larger than one, but a non-increasing function when the SIR is less than one. This implies that the AP algorithm can benefit from an interfering user closed to the targeted BS with a relatively large interfering power in a cooperative multicell scenario.

C. Non-cooperative Multicell Scenarios

In this scenario, the interference embodied in the second term of (1) is treated as additional noise. We can then rewrite (1) as

$$Y = \sqrt{P}HX + \sqrt{I}H_1X_I + N = \sqrt{P}HX + \tilde{N}, \quad (9)$$

where $\tilde{N} = \sqrt{I}H_1X_I + N$.

We can still employ the AP algorithm in estimating the channel information and derive the second lemma for a non-cooperative multicell scenario.

LEMMA 2. The MSE of the non-cooperative system model in (9), considering one interfering cell, is approximated as

$$MSE \approx MK\left(\sigma^2 + \frac{1}{SIR}\right). \quad (10)$$

Proof: Similarly, the MSE is computed via

$$MSE = \boldsymbol{E}\left\{\frac{1}{P}\|\tilde{N}X^H(XX^H)^{-1}\|_F^2\right\}$$

$$\approx^{(a)} \frac{1}{P}\boldsymbol{E}\{\|\sqrt{I}H_1\|_F^1\} + \frac{1}{P}\boldsymbol{E}\{\|NX^H(XX^H)^{-1}\|_F^2\}$$

$$\approx^{(b)} \frac{I}{P}MK + KM\sigma^2$$

where (a) is because the channel matrix H_1, the signal matrix X, and the noise matrix N are independent, and (b) is because of the assumption that all entries of the channel matrix H_1 are i.i.d Gaussian distribution with zero mean and unit variance. Clearly, (10) is a non-increasing function with respect to the SIR. Therefore, we argue that the AP algorithm can perform well since the interfering cell, in general, is far away from the target cell, resulting in a relatively small interference power.

IV. SIMULATION RESULTS AND DISCUSSIONS

In this section, we consider a two-cell massive MIMO system for simplicity, and a zero-forcing (ZF) detector is employed for the following information signal detection. The conventional LS algorithm is applied to provide a baseline for performance comparison.

Fig. 1 provides a performance comparison in terms of the bit error rates (BER) between ZF incorporated with CSI achieved via the AP, and ZF with perfect CSI for the massive MIMO system, in which M = 16 and K = 4. With the condition that M > 2K, ZF with perfect CSI can approach an optimal performance [8]. In Fig. 1, we observe that ZF incorporated with CSI achieved via the AP performs as well as ZF incorporated with perfect CSI, which confirms again that with the Gaussian noise assumption, the AP can approach the optimal channel estimation.

In Fig. 2, we compare the performances of ZF incorporated with AP-based CSI and that incorporated with LS-based CSI for a cooperative multicell scenario. We observe that both the AP-based ZF and the LS-based ZF suffer from low interfering power. This is because, in cooperation scenarios, the interfering power contributes to channel estimation and signal detection as well as the transmitting power used by the user of the target cell. Therefore, the higher the interfering power, the better is the performance, which is also consistent with Lemma 1. Furthermore, we conclude that the AP-based channel estimation outperforms the LS-based channel estimation since the data detection is very sensitive to the channel information, while ZF with the AP-based channel estimation achieves better performance compared to that with the LS-based channel estimation, as illustrated in Fig. 2.

In Figs. 3 and 4, we compare the BER performances between ZF incorporated with the AP-based channel estimation, and ZF incorporated with the LS-based channel estimation in a non-cooperative multicell scenario for M = 16 and M = 20, respectively. In the non-cooperative multicell sce-

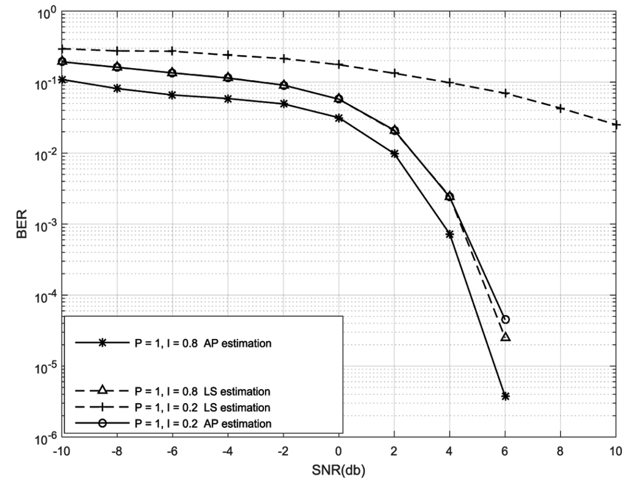

Fig. 2. Performance comparison between ZF with CSI via AP and ZF with CSI via LS for different interfering power levels in a cooperative scenario.

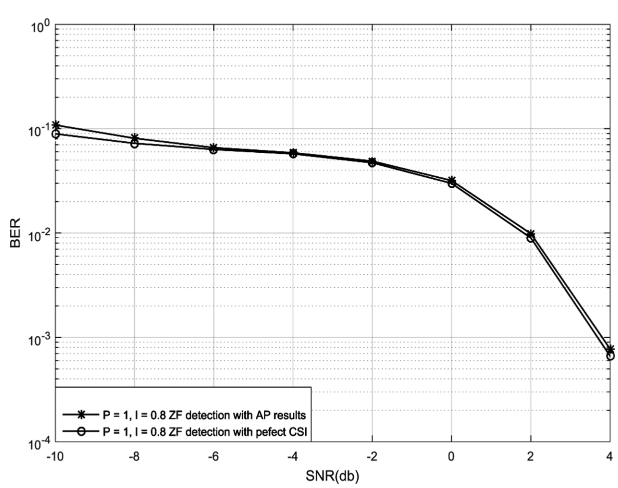

Fig. 1. Performance comparison between ZF with AP-based channel estimation and ZF with perfect CSI.

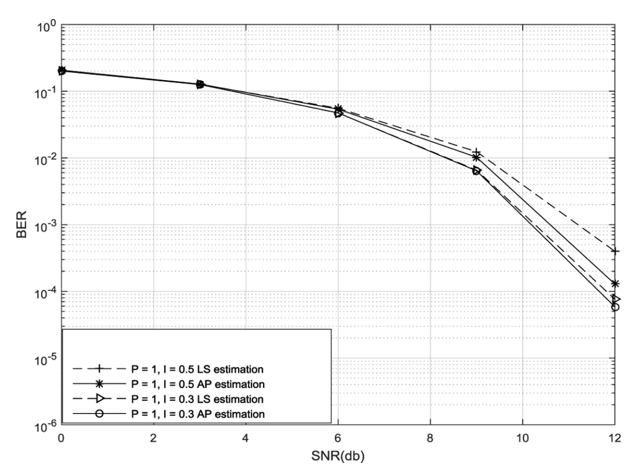

Fig. 3. BER comparison between ZF with AP and ZF with LS for different interfering power levels in a non-cooperative scenario for M=16.

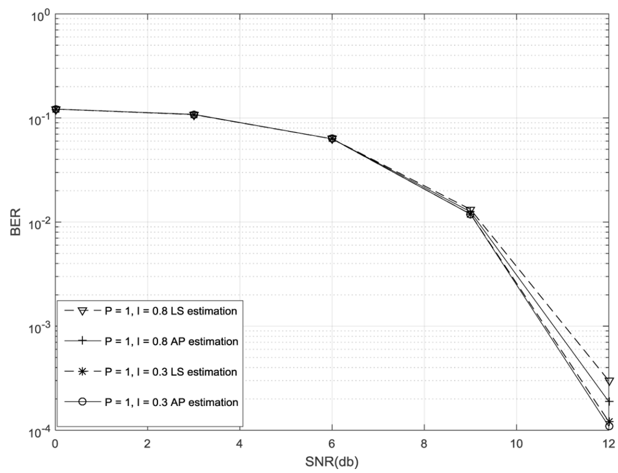

Fig. 4. BER comparison between ZF with AP and ZF with LS for different interfering power levels in a non-cooperative scenario for M=20.

nario, the signals transmitted by the interfering users are treated as additional noises. Therefore, we observed that both ZF with AP-based CSI and ZF with the LS-based CSI suffer from a larger interfering power and performance loss. The higher the interfering power, the worse is the performance, which confirms the validity of Lemma 2. From the simulation results, we still notice that the channel estimation results via the AP are more accurate than those via LS, in that the former results in a better performance in terms of the BER.

V. CONCLUSION

Herein, we employed an AP algorithm to estimate the channel state information for a multicell massive MIMO system and studied the mean square error (MSE) with respect to the SIRs following the LS approach for both the cooperative and noncooperative multicell scenarios, according to the argument that the AP performs almost as well as ML, which is identical to the LS with the Gaussian noise assumption. Our simulation results show that the AP-based channel estimation is biased for high SIRs in a cooperative scenario, but unbiased for high SIRs in a non-cooperative scenario. Compared to the LS-based channel estimation, the channel estimation results via the AP are more accurate compared to that via LS, in that a better performance of the following signal detection is achieved.

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REFERENCES

[1] E. G. Larsson, O. Edfors, F. Tufvesson, and T. Marzetta, “Massive MIMO for next generation wireless systems,” *IEEE Communications Magazine*, vol. 52, no. 2, pp. 186–195, 2014. DOI: 10.1109/MCOM.2014.6736761.

[2] F. Rusek, D. Persson, B. K. Lau, E. G. Larsson, T. L. Marzetta, O. Edfors, and F. Tufvesson, “Scaling up MIMO: opportunities and challenges with very large arrays,” *IEEE Signal Processing Magazine*, vol. 30, no. 1, pp. 40–46, 2014. DOI: 10.1109/MSP.2011.2178495.

[3] H. Q. Ngo, E. G. Larsson, and T. L. Marzetta, “Energy and spectral efficiency of very large multiuser MIMO systems,” *IEEE Transactions on Communications*, vol. 61, no. 4, pp. 1436–1449, 2012. DOI: 10.1109/TCOMM.2013.020413.110848.

[4] K. Appaiah, A. Ashikhmin, and T. L. Marzetta, “Pilot contamination reduction in multi-user TDD systems,” in *Proceedings of IEEE International Conference on Communications*, Cape Town, South Africa, pp. 1–5, 2010. DOI: 10.1109/ICC.2010.5502810.

[5] J. Jose, A. Ashikhmin, and T. L. Marzetta, “Pilot contamination and precoding in multi-cell TDD systems,” *IEEE Transactions on Wireless Communications*, vol. 10, no. 8, pp. 2640–2651, 2011. DOI: 10.1109/TWC.2011.060711.101155.

[6] A. Ashiknmin and T. L. Marzetta “Pilot contamination precoding in multi-cell large scale antenna systems,” in *Proceedings of IEEE International Conference on Information Theory Proceedings, Cambridge*, MA, pp. 1137–1141, 2012. DOI: 10.1109/ISIT.2012.6283031.

[7] L. Cottatellucci, R. R. Muller, and M. Vehkapera, “Analysis of pilot decontamination based on power control,” in *Proceedings of IEEE 77th Vehicular Technology Conference (VTC Spring)*, Dresden, Germany, pp. 1–5, 2013. DOI: 10.1109/VTCSpring.2013.6691891.

[8] A. Khlifi and R. Bouallegue, “Performance analysis of LS and LMMSE channel estimation techniques for LTE downlink systems,” *International Journal of Wireless & Mobile Networks*, vol. 3, no. 5, pp. 141–149, 2011. DOI: 10.5121/ijwmn.2011.3511.

[9] R. R. Muller, L. Cottatellucci, and M. Vehkapera, “Blind pilot decontamination,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 773–786, 2014. DOI: 10.1109/JSTSP.2014.2310053.

[10] I. Ziskind and M. Wax, “Maximum likelihood localization of multiple sources by alternating projection,” *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 36, no. 10, pp. 1553–1560, 1988. DOI: 10.1109/29.7543.

[11] Y. Chen, R. Ran, and S. Oh, “Performance analysis for pilot decontamination of massive MIMO using alternative projection,” in *Proceedings of IEEE International Conference on Ubiquitous and Future Networks*, Vienna, Austria, pp. 297–300, 2016. DOI: 10.1109/ICUFN.2016.7537036.

[12] A. Roessler, J. Schlienz, S. Merkel, and M. Kottkamp, “LTE-Advanced (3GPP Rel. 11) technology introduction,” Rohde & Schwarz GmbH, White Paper, 2013.

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