Blind Channel Estimation for Massive MIMO

Ture Peken, Garrett Vanhoy and Tamal Bose
Electrical and Computer Engineering
University of Arizona
Tucson, Arizona 85719
Email: {turepeken, gvanhoy, tbose}@email.arizona.edu

Abstract*—In order to scale with the demand of higher data rates and improved spectral efficiency in next generation wireless communication systems, a large-scale multiple-input multiple-output (MIMO) technology called massive MIMO has been proposed. In massive MIMO, appropriate signal to noise ratios can be achieved by the addition of base station antennas in place of increasing transmit power. Pilot-based channel estimation is widely used in conventional MIMO systems where pilot symbols are sent from the user terminals to the base station to estimate the channel. In massive MIMO-based cellular networks, channel estimation in a given cell will be impaired by the pilot symbols transmitted by users in other cells – rendering the addition of antennas or transmit power ineffective. This effect is called pilot contamination. Therefore, pilot-based channel estimation limits the performance of massive MIMO systems. Semi-blind and blind methods are alternatives to pilot-based channel estimation that perform channel estimation with short pilot symbols and without pilot symbols, respectively. Blind channel estimation is one of the promising solutions to the pilot contamination problem in massive MIMO. This paper compares using MATLAB simulations of a cluster-based COST 2100 channel model the performance of pilot-based, semi-blind, blind, and adaptive-blind channel estimation methods. The pilot contamination effect on different channel estimation methods and how channel estimation methods can be used to overcome pilot contamination are shown. Finally, an adaptive ICA-based channel estimation method which outperforms conventional ICA in terms of computational complexity is proposed.

***Keywords* - Massive MIMO, Blind Channel Estimation, Adaptive-Blind Channel Estimation**

I. Introduction

MIMO is the key technology in next generation wireless communication systems such as IEEE 802.16M and 3GPP LTE/LTEAdvanced [1]. In cellular systems, MIMO technology has been adapted as Multi User-MIMO (MU-MIMO), where multiple antennas are used for more than one user terminal simultaneously. MU-MIMO provides important advantages for next generation wireless systems, including enhanced reliability, data rate, and energy efficiency [2]. A fifth generation (5G) of mobile networks is expected to be deployed by 2020. In these future mobile networks there will be an even greater demand for higher spectral efficiency. Massive MIMO is one very promising technology that can be leveraged to meet this demand. The key aspect of this technology is that it uses significantly more base station antennas to achieve high spectral efficiency [3]. As the number of base station antennas increases, the radiated energy from the base station becomes increasingly narrow. As beams get smaller, more user terminals can be served and less energy is required to achieve the same throughput as traditional MIMO. With such a massive amount of antennas, signal quality can theoretically be improved without bound while decreasing transmit power by adding more antennas [4]. It can be built with inexpensive, low-power components. Achieving these gains in practical cellular systems becomes a difficult task because the channel gain between each base station antenna and user terminal is unknown. The matrix of these gains is generally referred to as channel state information (CSI). In traditional MIMO systems, to estimate the CSI, a set of training signals called pilots are sent from the user terminals. To maximize the effectiveness of estimating the CSI, the pilot signals must be orthogonal. This constraint is what causes the main limitation of throughput for massive MIMO in cellular systems. Pilot signals must have a minimum duration to serve the users in each cell. If pilot signals are shared among the cells, it is possible for two users to interfere while sending long pilot signals to the base station. As the number of users in each cell increases, this becomes an inevitable event. This interference is referred to as pilot contamination which is pictured in Figure 1. This is a fundamental problem in massive MIMO systems because the length of the pilot signals is limited by the coherence time [2]. Several solutions to this problem have been proposed. Blind channel estimation, angle-of-arrival (AoA) based, precoding-based and protocol-based methods are the different techniques to solve the pilot contamination problem. Blind channel estimation methods use statistics from the incoming data to estimate the channel without the need for pilot symbols. Since the success of these algorithms does not depend on the presence of pilot symbols, this method is a good candidate for mitigating the pilot contamination problem. However, the difficulty with using blind channel estimation methods is that they have much higher computational complexity than pilot-based methods. This becomes even more exaggerated in massive MIMO systems because the number of transmitted symbols is more than traditional MIMO systems. Semi-blind channel estimation methods are also proposed for the pilot contamination problem. These methods use shorter pilot symbols to estimate the CSI with lower computational complexity than blind methods. The most common techniques

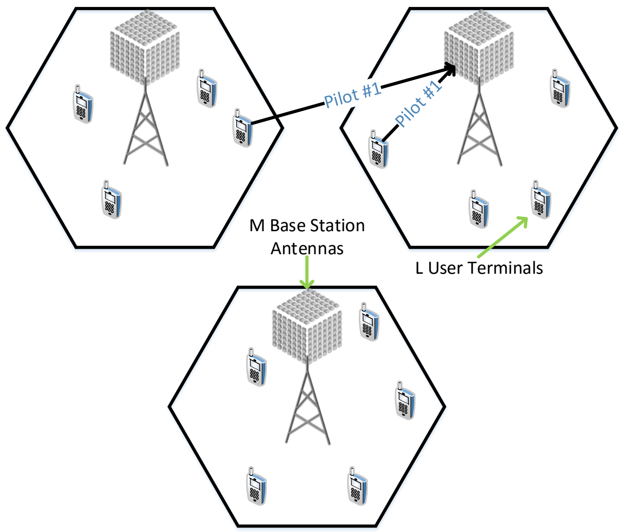

Fig. 1: Pilot Contamination

are based on singular value decomposition (SVD) and eigenvalue decomposition (EVD) that are used to estimate the CSI up to a phase and an amplitude ambiguity. In this paper, we analyze the relative computational complexity and accuracy between pilot-based, semi-blind, and blind channel estimation methods in a massive MIMO system. Additionally, we propose a novel blind adaptive channel estimation method based on the Independent Component Analysis (ICA) algorithm. The proposed method has a reduced computational complexity over an unmodified version of the ICA-based blind channel estimation [5].

The paper is organized as follows. In Section II, we summarize the related work on pilot-based, blind, and semi-blind channel estimation methods. In Section III, we explain our system model for massive MIMO communication systems. In Section IV, we discuss different channel estimation methods for massive MIMO. In Section V, we propose an ICA-based adaptive-blind channel estimation. In Section VI, we review our simulation results. We conclude our work in Section VII.

II. Related Work

There have been many proposed solutions to mitigating or eliminating pilot contamination in massive MIMO systems. Protocol-based methods try to eliminate pilot contamination by forcing users in adjacent cells to transmit pilot signals at separate times. These methods effectively increase the signal-to-interference-plus-noise ratio (SINR) for individual users, but ultimately less users can be served. Another solution to this problem is to design a precoding matrix at the base station to decrease the interference to users in neighboring cells. Pilot contamination can be mitigated by using this type of a precoding-based method, but there is a need for the base stations to cooperate and thus also a need for a backhaul between the base stations. AoA-based methods aim to assign pilots to the users in adjacent cells whose AoA with the base station do not overlap. Finally, blind channel estimation methods have been proposed to potentially eliminate pilot contamination [3].

Channel estimation for MIMO systems have been studied extensively and have recently been studied in the context of massive MIMO systems. The most common approach to channel estimation in these systems is pilot-based channel estimation. In this scheme predetermined pilot symbols selected along some periodic pattern are sent before the transmission of actual data. The base station receives these pilot symbols after having been transformed by the channel and uses one of several proposed estimation methods to estimate the channel. The more common channel estimators include maximum likelihood (ML), least squares (LS), and minimum mean squared error (MMSE) [6].

Blind channel estimations have also been proposed to cope with the disadvantages of pilot-based channel estimation methods. Blind channel estimation methods estimate the channel by using statistics of the received symbols after having been transformed by the channel. Most of the blind channel estimation methods are based on second or higher order statistics. Pilot Symbol Assisted Modulation (PSAM), Space Alternating Generalized Expectation (SAGE), Multiple Signal Classification (MUSIC), Estimation of Signal Parameters via Rotational Invariance Techniques (ESPIRIT), A Posteriori Probability (APP), Viterbi algorithm, ICA, game theory and many other parameter estimation techniques have been proposed as blind channel estimation methods [7]. Blind channel estimation methods can be used to mitigate pilot contamination, but the computational complexity of these algorithms is much higher than pilot-based methods. This computational complexity can be significantly decreased by using iterative blind channel estimation methods [8]. Semi-blind channel estimation methods have also been proposed as a compromise between the computational complexities of pilot-based and blind methods. A semi-blind channel estimation which employs EVD on the received signals and resolves a phase ambiguity matrix using short pilots is proposed in [9]. In [10], another semi-blind approach is proposed using SVD to exploit the asymptotic orthogonality of the channel vectors and resolve the ambiguity matrix which can be estimated by the means of pilot signals. The SVD-based estimation achieves better performance than the EVD-based estimation. However, both SVD-based and EVD-based estimation have relatively high computational complexity when compared to pilot-based channel estimation.

III. System Model

A massive MIMO uplink system in which the base station has M antennas and each terminal user has one antenna is considered here. In this system, there are N terminal users where $M \geq N$. The L received symbols at M antennas of the base station can be represented as:

$$Y = HS + W, \tag{1}$$

where $Y \in \mathbb{C}^{M \times L}$ is a matrix of the L received symbols at the M receive antennas of the base station. $S \in \mathbb{C}^{N \times L}$ is a matrix of the transmitted symbols that can generally be split up into pilot and data sub-matrices as $S = \begin{bmatrix} S_p & S_d \end{bmatrix}$. $H \in \mathbb{C}^{M \times N}$ is the CSI between the base station and N users, and $W \in \mathbb{C}^{M \times L}$ is the additive white Gaussian noise (AWGN) matrix. The propagation channel is assumed to be wide-sense stationary (WSS) in conventional MIMO systems. However, massive MIMO systems have a large number of antennas which span tens to hundreds of wavelengths in space. Therefore, the propagation channel is resolved into scatterers [11]. The propagation channel model which is characterized through scatterers is shown in Figure 2. The COST 2100 MIMO channel model, which is a geometry based stochastic channel model (GSCM), models the radio channel with geometric distribution of scatterers that contribute scattering to the radio channels. Therefore, we model the radio channel between the base station and user terminals through COST 2100 MIMO channel model. In this model, radio channels are constructed by superposition of multipath components (MPCs). These MPCs are clustered, as shown in Figure 2. Here, local clusters have omnidirectional spread in the azimuth plane. On the other hand, single bounce clusters have independent delay and azimuth spreads. The large-scale properties of the channel can be defined by clustering the MPCs [12].

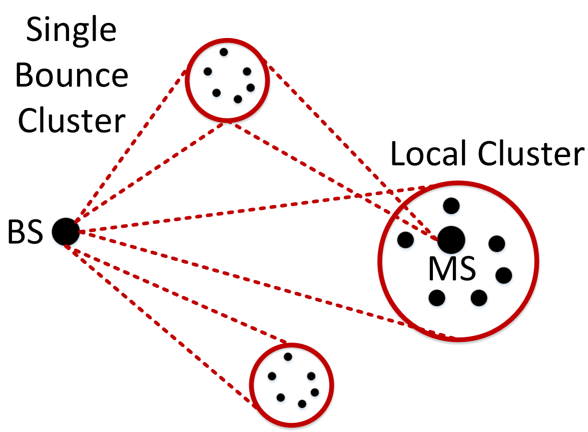

Fig. 2: Channel Model

IV. Channel Estimation Methods for Massive MIMO

A. Pilot Based Channel Estimation

In the pilot-based channel estimation, known pilot signals are transmitted from each user terminal to the base station. By using these pilot signals, channel coefficients between the base station and user terminals can be estimated. MIMO systems that use pilot-based channel estimation methods send pilot signals periodically so that channel estimates can be updated continuously as the CSI changes. LS channel estimation method is one of the most common pilot-based channel estimation methods. It minimizes the squared distance between the received symbols vector and the transmitted symbols vector [13].

LS estimate of the channel is given as in the following:

$$\hat{H}_{LS} = Y(S_p^T S_p)^{-1} S_p^T. \tag{2}$$

B. Blind Channel Estimation

In blind channel estimation, channel coefficients between the base station and the terminal users can be evaluated by using the statistical information of the channel and the particular properties of the received symbols. Since blind channel estimation methods estimate the channel coefficients without pilot symbols, the pilot contamination problem can be mitigated. Several blind channel estimation methods have been proposed in the literature, and ICA is one of the most common.

ICA separates signals blindly by first calculating the SVD of the covariance matrix $C = \mathbb{E}\left\{YY^T\right\}$. The SVD of C can be represented as $C = UDU^T$ where $U \in \mathbb{C}^{M \times M}$ is an orthogonal matrix and $D = diag\left\{\lambda_1, \lambda_2, ..., \lambda_M\right\}$ is a singular matrix. U and D matrices can be used to divide the signal subspace and noise subspace as $U = \begin{bmatrix} U_S & U_N \end{bmatrix}$ and $D = \begin{bmatrix} D_S & 0 \\ 0 & D_N \end{bmatrix}$ respectively [5]. The received symbols vector is then whitened by projecting the received symbols into the signal subspace in order to decrease the computation complexity. The whitening operation of received symbols can be represented as:

$$Y_W = {D_S}^{-1/2} {U_S}^T Y, \tag{3}$$

where Y_W is the whitened data. The channel estimate $\hat{H}_{ICA}$ is obtained by finding an orthogonal matrix such that $W = [w_1, \ldots, w_L]$ by applying fastICA algorithm which is given in [5]. The fastICA algorithm iteratively finds orthogonal vectors which construct W. The estimation of w_p or p^{th} column vector of the orthogonal matrix W starts by taking a random unit-norm initial vector $w_p(1)$. After that, $w_p(1)$ is updated by:

$$\begin{aligned} w_p(k) = \mathbb{E}\left\{Y_{W_p} g(w_p(k-1)^T Y_{W_p})\right\} - \\ \mathbb{E}\left\{g^{'}(w_p(k-1)^T Y_{W_p})\right\} w_p(k-1) \end{aligned} \tag{4}$$

$$w_p(k) = w_p(k)/\|w_p(k)\| \tag{5}$$

where $w_p(k-1)$ and $w_p(k)$ are estimates of w_p at $k-1^{th}$ and k^{th} iterations respectively. Y_{W_p} is p^{th} column vector of Y_W. $g(.)$ and $g^{'}(.)$ are the derivatives of $G(.)$ and $g(.)$ respectively. $G(.)$ can be any nonquadratic function. In fastICA algorithm $G(.)$ is chosen as:

$$G(u) = log(f_p(u)) \tag{6}$$

where $f_p(.)$ is the density function of $s_p = {w_p}^T Y_{W_p}$. Then, Gram-Schmidt like decorrelation algorithm is applied to prevent outputs to converge to the same maxima [5]. This decorrelation algorithm can be given as in the following:

$$w_p(k) = w_p(k)[1 - \sum_{j=1}^{p} w_j(k)^T w_j(k)] \tag{7}$$

$$w_p(k) = w_p(k)/\sqrt{(w_p(k)^T w_p(k))} \tag{8}$$

If $|w_p(k) - w_p(k-1)|$ is greater than a tolerance value, the algorithm goes to next iteration. Otherwise, the estimation of w_p is found as $w_p = w_p(k)$. After p orthogonal vectors $w_1, \ldots, w_p$ have been estimated, the fastICA algorithm is run for w_{p+1}. Once the orthogonal matrix W is obtained, the ICA-based channel estimation can be applied. The estimated channel $\hat{H}_{ICA}$ can be expressed as:

$$\hat{H}_{ICA} = WY_W{}^{-1}. \tag{9}$$

C. Semi-blind Channel Estimation

Even though blind channel estimation mitigates pilot contamination in massive MIMO, the computational complexity is much greater in blind methods. Semi-blind channel estimation methods have also been proposed to cope with pilot contamination by instead using shorter pilot symbols than pilot-based methods. Using shorter pilots effectively reduces the chance for pilot contamination while making use of pilot symbols which can be used for purposes other than channel estimation. One of the most efficient semi-blind channel estimation method in terms of error rate and computational complexity uses SVD. K left singular vectors are spanned by the channel vectors $[h_1, \ldots, h_M]$ or columns of the channel matrix H, where K is the number of user terminals that are in the subspace. The matrix of K left singular vectors can be approximately defined as the product of the normalized channel matrix and an ambiguity matrix. The ambiguity matrix, which is estimated by means of pilot symbols, can be resolved completely by this method [10].

In this method, SVD decomposition is performed on the covariance matrix $C = \mathbb{E}\left\{YY^T\right\}$ as given in Section IV-B. After a pilot-based channel estimation is applied to the received symbols as in (2), the SVD-based semi-blind channel estimation is evaluated as in the following [10]:

$$\hat{H}_{SVD} = U_S U_S{}^H \hat{H}_{LS}. \tag{10}$$

V. ICA Based Adaptive Blind Channel Estimation

In this section, we propose an adaptive-blind channel estimation method which improves on the fastICA algorithm. The ICA-based channel estimation calculates $\hat{H}_{ICA}$ by finding an orthogonal matrix such that $W = [w_1, \ldots, w_L]$ and applying fastICA algorithm which is given in [5]. As described in Section IV-B, the fastICA algorithm first iteratively finds orthogonal vectors which construct W. A random unit-norm initial vector $w_p(1)$ which corresponds to p^{th} column of W is selected at the beginning of each time frame. Then, it is updated by using the iterative algorithm, which is described in Section IV-B. Since generating random unit-norm vector $w_p(1)$ is done in each time frame, the computational complexity of this method can become much more than semi-blind and pilot-based channel estimation methods, which were described in Section IV. To reduce the computational complexity, we propose to send the orthogonal matrix W that is produced in a given frame $i-1$ to the ICA-based channel estimation algorithm as a feedback at i^{th} frame. In this case, computational complexity is reduced as compared to the ICA-based blind channel estimation algorithm, while getting the same root-mean-square error for the same signal-to-noise ratio (SNR) values. The algorithm of the proposed ICA-based adaptive-blind channel estimation is given in Algorithm (1). In the algorithm, $w_p^i(k)$ stands for p^{th} column vector of W at the k^{th} iteration of the i^{th} frame.

Algorithm 1 Algorithm for ICA-based adaptive-blind channel estimation

for $i = 1^{st}$ to n^{th} Frame **do**
  Calculate $C = \mathbb{E}\left\{YY^T\right\}$
  Calculate $Y_W = D_S{}^{-1/2} U_S{}^T Y$
  for $p = 1$ to L **do**
    $w_p^i(0) = 0$
    $k = 1$
    if $(i = 1)$ **then**
      Take a random unit-norm $w_p^i(1)$ vector
    else
      $w_p^i(1) = w_p^{i-1}(1)$
    end if
    while $(|w_p^i(k) - w_p^i(k-1)| > tol)$ **do**
      $w_p^i(k-1) = w_p^i(k)$
      Update $w_p^i(k)$ by using fastICA algorithm
      Apply Gram-Schmidt algorithm
      $w_p^i(k) = w_p^i(k)/\|w_p^i(k)\|$
      $k = k + 1$
    end while
    $w_p^i = w_p^i(k)$
  end for
  $\hat{H}_{ICA} = WY_W{}^{-1}$
end for

VI. Simulation Results

A model of a multi-cellular massive MIMO system is constructed in MATLAB to test the relative performance of pilot-based, semi-blind, blind, and proposed adaptive-blind channel estimation methods. We study the effect of pilot contamination in massive MIMO in the context of a virtually extended cellular network, as shown in Figure 3. The values chosen for the different parameters in our MATLAB simulation are summarized in Table I. In the simulation, orthogonal pilots are created with a gold sequence generator. Additionally, we assume that the cells are synchronized during the time pilots are sent for channel estimation. This is generally considered the worst-case scenario for pilot contamination. In our simulation, SNR is defined by:

$$SNR = \sqrt{P_{S_i}/P_{N_i}}, \tag{11}$$

where P_{S_i} and P_{N_i} are average signal and noise power at the i^{th} antenna of the base station respectively. Average signal power at the i^{th} antenna of the base station is defined as:

$$P_{S_i} = \frac{1}{L}\sum_{n=1}^{L} {E_n}^2, \tag{12}$$

where L is the number of transmitted symbols and E_n is the energy of the n^{th} received symbol at the i^{th} antenna of the base station.

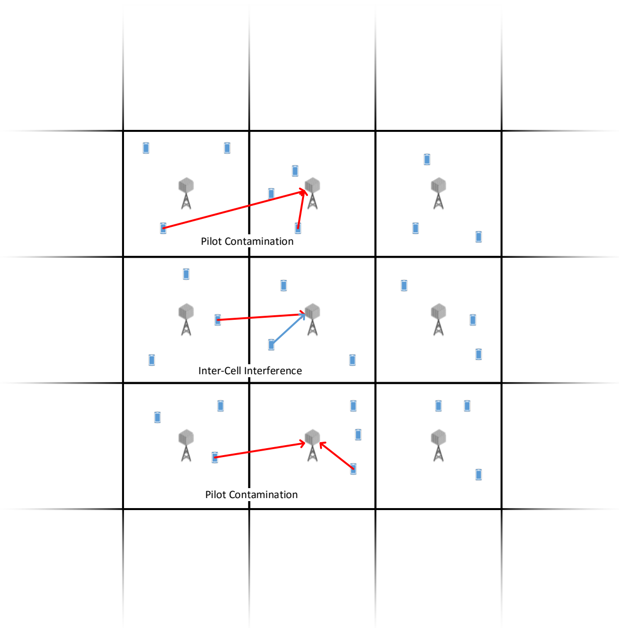

Fig. 3: Massive MIMO Simulation

Parameter	Value
Channel Model	COST 2100
Mobiles	90
Mobile Velocity	<1 m/s
Frequency	2.4 GHz
BS Antennas	1000
BS Antenna Type	Ideal Dipole
Mobile Antennas	1
Pilot Length	20 symbols
Data Length	60 symbols
Cell Area	10,000 sq. m.
Channel Type	Rayleigh (NLOS)

TABLE I: Parameter Values of MATLAB Simulation

First, LS channel estimation, SVD-based semi-blind channel estimation, ICA-based blind channel estimation and ICA-based adaptive-blind channel estimation methods are compared in terms of root-mean-square error (RMSE) for each channel element in the case with no inter-cellular interference when SNR changes from 0 dB to 20 dB. Then, pilot contamination effect on the same channel estimation methods are compared. This time RMSE of each channel estimation is observed when interference occurs. The length of pilot sequence and data sequence are kept constant at 20 and 60 symbols respectively. The results in Figure 4 show that ICA and ICA-based adaptive-blind channel estimation methods are more accurate than LS and SVD-based channel estimation methods when there is no inter-cellular interference. Since ICA and adaptive ICA methods use both pilot and data symbols to estimate the channel, they give better performance than LS and SVD methods in terms of error rate. When interference occurs the error rate increases for both LS and SVD methods because of pilot contamination. With pilot contamination, each cell uses the same set of pilot symbols. Thus even for increasing SNR, both LS and SVD methods reach a limit in accuracy. On the other hand, ICA and adaptive ICA methods overcome this issue since they are the least affected by pilot contamination. Moreover, ICA and adaptive ICA methods give same performance in terms of error rate in both scenarios (with or without interference).

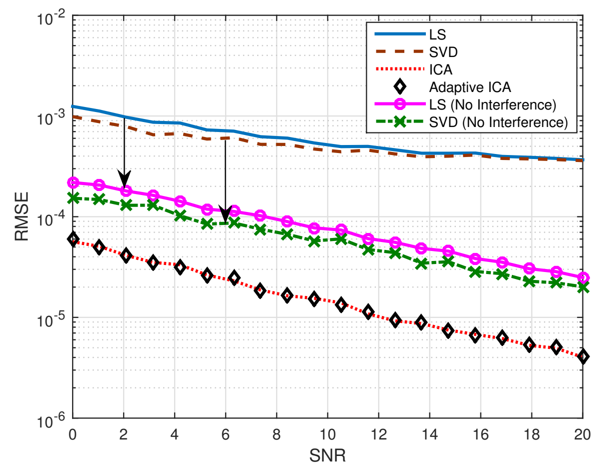

Fig. 4: RMSE vs SNR

Then, we analyze the improvement of the adaptive ICA algorithm in terms of the computational complexity. In Figure 5, the run time of LS, SVD-based semi-blind, ICA-based blind and ICA-based adaptive-blind channel estimation methods are compared while the number of transmitted symbols increases from 50 to 100 with step of ten. The number of pilot symbols increases from 5 to 10. The results show that ICA has the highest computational complexity. LS, SVD and adaptive ICA have much lower computational complexity than ICA. The change of computational complexity of LS, SVD and adaptive ICA can be seen clearly in Figure 6. LS has the least computational complexity. We also observe that the computational complexity of adaptive ICA increases linearly and starts to become greater than the computational complexity of SVD while the number of transmitted symbols increases. However, the computational complexity of adaptive ICA is still very small compared to conventional ICA. These results show that adaptive ICA has a reduced computational complexity over conventional ICA.

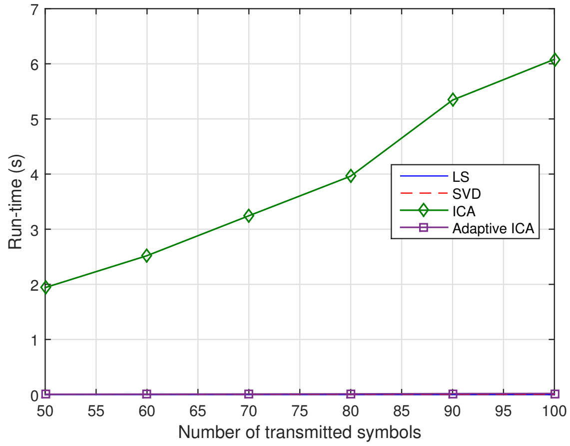

Fig. 5: The computational complexity of LS, SVD-based semi-blind, ICA-based blind and ICA-based adaptive-blind channel estimation methods

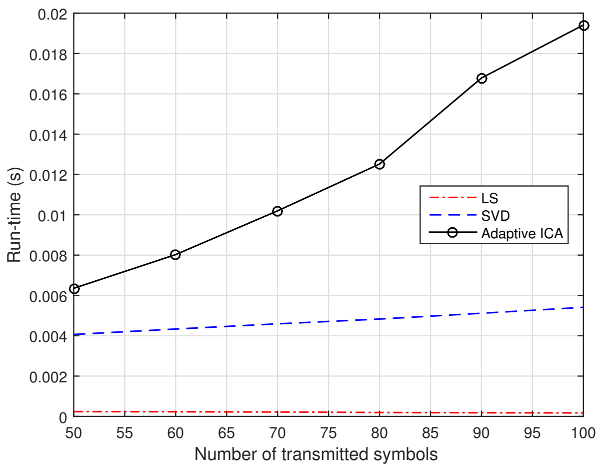

Fig. 6: The computational complexity of LS, SVD-based semi-blind and ICA-based blind channel estimation methods

We show the average run-time of one frame for LS, SVD-based semi-blind, ICA-based blind and ICA-based adaptive-blind channel estimation methods in Table II. LS has the least average run-time. SVD-based semi-blind channel estimation has a higher average run-time than LS due to the SVD operation. ICA-based blind channel estimation has the highest average run-time because of the SVD operation and iterative calculation. It is worth mentioning that adaptive ICA outperforms the conventional ICA by having a lower average run-time.

VII. Conclusion

Massive MIMO is expected to be one of the key technologies in 5G wireless systems. Massive MIMO systems, in which significantly more base station antennas are used, have been proposed to improve the spectral efficiency and data rates. Effective channel estimation for massive MIMO systems is one of the most important challenges in addressing pilot contamination. In this paper, pilot contamination effect on LS channel estimation, SVD-based semi-blind channel estimation, ICA-based blind channel estimation and ICA-based adaptive-blind channel estimation methods are compared for massive MIMO systems. Simulation results show that ICA and adaptive ICA give better performance than LS and SVD in terms of error rate when there is no inter-cellular interference. ICA and adaptive ICA also achieve better error rates than LS and SVD in the case with interference. Moreover, both LS and SVD reach a limit in accuracy when there is interference due to pilot contamination. Therefore, blind channel estimation methods provide a more promising solution to the pilot contamination problem than pilot-based and semi-blind channel estimation methods. Computational complexity of these channel estimation methods are also compared using MATLAB simulations. It is observed that adaptive ICA outperforms conventional ICA in terms of computational complexity.

Channel Estimation	Run Time
LS	0.0002 s
SVD	0.005 sec
ICA	3.8 s sec
Adaptive ICA	0.01 s sec

TABLE II: Average run-time

References

[1] Q. Li, G. Li, W. Lee, M. il Lee, D. Mazzarese, B. Clerckx, and Z. Li, "MIMO Techniques in WiMAX and LTE: A Feature Overview," *Communications Magazine, IEEE*, vol. 48, no. 5, pp. 86–92, May 2010.

[2] E. Larsson, O. Edfors, F. Tufvesson, and T. Marzetta, "Massive MIMO for Next Generation Wireless Systems," *Communications Magazine, IEEE*, vol. 52, no. 2, pp. 186–195, February 2014.

[3] L. Lu, G. Li, A. Swindlehurst, A. Ashikhmin, and R. Zhang, "An Overview of Massive MIMO: Benefits and Challenges," *Selected Topics in Signal Processing, IEEE Journal of*, vol. 8, no. 5, pp. 742–758, Oct 2014.

[4] T. Marzetta, "Noncooperative Cellular Wireless with Unlimited Numbers of Base Station Antennas," *Wireless Communications, IEEE Transactions on*, vol. 9, no. 11, pp. 3590–3600, November 2010.

[5] A. Hyvarinen, "Fast and Robust Fixed-Point Algorithms for Independent Component Analysis," *Neural Networks, IEEE Transactions on*, vol. 10, no. 3, pp. 626–634, May 1999.

[6] H. Hijazi, E. Simon, M. Lienard, and L. Ros, "Channel Estimation for MIMO-OFDM Systems in Fast Time-Varying Environments," in *Communications, Control and Signal Processing (ISCCSP), 2010 4th International Symposium on*, March 2010, pp. 1–6.

[7] V. Sharma and S. Kumar, "Recent Developments in MIMO Channel Estimation Techniques," in *Digital Information and Communication Technology and it's Applications (DICTAP), 2012 Second International Conference on*, May 2012, pp. 1–6.

[8] D. Zhang, K. Nikitopoulos, I.-W. Lai, G. Ascheid, and H. Meyr, "Iterative Channel Estimation Control for MIMO-OFDM Systems," in *Information Sciences and Systems (CISS), 2010 44th Annual Conference on*, March 2010, pp. 1–6.

[9] H. Q. Ngo and E. Larsson, "EVD-Based Channel Estimation in Multicell Multiuser MIMO Systems with Very Large Antenna Arrays," in *Acoustics, Speech and Signal Processing (ICASSP), 2012 IEEE International Conference on*, March 2012, pp. 3249–3252.

[10] A. Hu, T. Lv, and Y. Lu, "Subspace-Based Semi-Blind Channel Estimation for Large-Scale Multi-Cell Multiuser MIMO Systems," in *Vehicular Technology Conference (VTC Spring), 2013 IEEE 77th*, June 2013, pp. 1–5.

[11] X. Gao, F. Tufvesson, and O. Edfors, "Massive MIMO Channels - Measurements and Models," in *Signals, Systems and Computers, 2013 Asilomar Conference on*, Nov 2013, pp. 280–284.

[12] L. Liu, C. Oestges, J. Poutanen, K. Haneda, P. Vainikainen, F. Quitin, F. Tufvesson, and P. Doncker, "The COST 2100 MIMO Channel Model," *Wireless Communications, IEEE*, vol. 19, no. 6, pp. 92–99, December 2012.

[13] K. P. Bagadi and P. S. Das, "MIMO-OFDM Channel Estimation Using Pilot Carries," *International Journal of Computer Applications*, vol. 2, no. 3, pp. 81–88, May 2010, published By Foundation of Computer Science.