Massive MIMO for Future Vehicular Networks: Compressed-Sensing and Low-Complexity Detection Schemes (Invited Paper)

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Abstract. The fast development of the fifth generation (5G) mobile communications system has brought a bright prospect of the next generation vehicular networks. Especially, a typical application in future vehicular networks is to deploy intelligent transportation systems (ITS), aiming to providing high level user experience on the move. To support the deployment of ITS, high rate communications and energy efficiency, low-latency transmission and low-complexity detection schemes are highly demanded. Massive multiple-input multiple-output (MIMO) has been seen as a promising candidate for the demand. The architecture that many vehicles access the roadside infrastructure is quite suitable for the employment of massive MIMO as large-scale antennas can be deployed at the roadside unit. However, the challenges along with massive MIMO is low complexity and efficient data detection schemes. In this paper, we provide an overview of low-complexity detection schemes in massive MIMO, and summarize the challenges and possible solutions.

Keywords: Vehicular networks · Massive MIMO · Low-complexity

1 Introduction

1.1 Intelligent Transportation Systems

With increasing number of vehicles on road nowadays, driving safety, traffic efficiency, and high quality in-vehicle entertainment service, have drawn much attention in both academia and industry [1–4]. The emerging intelligent transportation systems (ITS) have been widely studied aiming to meeting these requirements. Generally, both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications are required in ITS [1,2]. Specially, all vehicles on the road collect sensor data, including traffic information and road

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conditions, and share with neighboring vehicles through V2V communications or report to roadside infrastructure through V2I communications. To fulfill these tasks, each vehicle is equipped with on-board unit (OBU), while the roadside unit (RSU) is deployed along the roadside infrastructure. OBU and RSU are acting as the radio interface to establish the dependable connection [1]. It is reported that 90% of vehicles will be connected via wireless links by 2020 [3]. Therefore, the deployment and investigation of ITS becomes significant.

Fig. 1. A typical vehicular network to support ITS service

A typical application scenario for ITS service is shown in Fig. 1, where multiple RSUs are deployed along the traffic road, serving numbers of vehicles on the street. Vehicles are connected through V2V communication links, so that information about traffic status and road conditions can be shared among vehicles. Besides, the vehicles can also access the RSU through V2I communication links, which supports various in-vehicle entertainment service such as video streaming and social interactions. Suppose an ambulance vehicle is committing an emergence and a huge number of cars are crowded in a busy street. On the one hand, the emergence information can be reported to all vehicles through V2V communications, and then all vehicles make proper action to cooperate. On the other hand, an alternative solution might be that the RSU collects this information and broadcasts in the vehicular network. By doing that, all vehicles in its communication range will be aware of this information. Actually, the important role of the RSU playing in ITS service has been demonstrated in [3–5]. Therefore, we mainly focus on V2I communication in this paper.

1.2 Massive MIMO in Vehicular-to-Infrastructure Communications

Using massive multiple-input multiple-output (MIMO) in next generation vehicular networks, has been investigated recently [5,6]. It is known that in current traditional small-scale MIMO system, the antenna size is limited since the wave length of the microwave signal is relatively large. However, millimeter wave frequency band has been proposed in vehicular communication, which enables the antenna elements at RSU reach up to 256 [6]. Besides, the massive MIMO architecture is suitable for multiple vehicles accessing RSU since hundreds of antennas can be deployed at roadside infrastructure. Massive MIMO has shown significant potential in improving system spectrum efficiency and energy efficiency [7,8]. These improvements, are beneficial to future vehicular networks.

Along with the benefits of massive MIMO, some practical issues need be addressed. Typically, in massive MIMO, the large array signal processing at RSU is a high computational load. The processing delay associated with the detection has great impact on the system latency requirement. To deal with these practical issues, we need low-complexity and efficient detection schemes. Besides, compressed-sensing based techniques have been widely applied to communication systems. For example, it is employed in [9] for channel estimation. In massive MIMO, it also has many possible roles to play, and one of them is data detection, as will be discussed in this paper.

1.3 Main Contributions

In [10], MIMO Detection schemes in fifty years have been summarized by the year of 2014. However, at that time, few works have been done on massive MIMO detection. As we know, the turbo receivers show great performance in the traditional small scale MIMO-OFDM systems for data detection [11,12]. For massive MIMO, many new works on data detection have been proposed recently, including using compressed sensing technique [13–15], and iterative methods [16–18]. In this paper, we will extensively overview these new detection schemes and summarize the challenges and possible solutions in the applications to vehicular communications.

1.4 Organization

The rest of the paper is organized as follows. In Sect. 2, we briefly introduce the massive MIMO system model. Compressed-sensing based data detection schemes are illustrated in Sect. 3. We present a class of low-complexity near linear minimum mean-square error (MMSE) detection schemes in Sect. 4. Finally, the conclusions are drawn in Sect. 5.

2 System Model

Consider a massive MIMO system with N_B antennas equipped at RSU, and N_U vehicular users are under service ($N_B \geq N_U$). The relationship between the received vector and the transmitted symbols can be expressed as

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{z}, \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{N_B \times 1}$ denotes the received vector at base station. $\mathbf{H} \in \mathbb{C}^{N_B \times N_U}$ denotes the channel matrix, with the u-th column vector $\mathbf{h}_u = \mathbf{H}\mathbf{e}_u$ representing the channel impulse response from the u-th user to the base station. $\mathbf{x} \in \mathbb{C}^{N_U \times 1}$ is the transmitted symbol vector. $\mathbf{z} \in \mathbb{C}^{N_B \times 1}$ is the additive white Gaussian noise vector, satisfying $\mathrm{E}\left\{\mathbf{z}\mathbf{z}^{\mathrm{H}}\right\} = \sigma_z^2 \mathbf{I}_{N_B}$.

In [10], massive MIMO systems are divided into two groups, according to $\lim\limits_{N_B, N_U \to \infty} \frac{N_U}{N_B} = c$ or $\lim\limits_{N_B \to \infty} \frac{N_U}{N_B} = 0$. However, we can see this classification is not practical. This is because in real system configuration, the number of antennas and users will not be infinite. In this paper, we define $r = \frac{N_B}{N_U}$, $r \geq 1$. When r is sufficiently large, it corresponds the case that $\lim\limits_{N_B \to \infty} \frac{N_U}{N_B} = 0$; and $r \to 1$, it corresponds to the case that the number of users is comparable to the number of antennas at base station. For different range, different detection schemes can be applied.

In the case r is close to 1, compressed-sensing based data detection schemes can be applied. In the case r is sufficiently large, low-complexity near Linear MMSE detection schemes can be adopted.

3 Compressed-Sensing Based Data Detection

When $r \to 1$, the performance of the linear MMSE detection scheme is far away from the optimal system performance [13]. By noting that the detected symbol vector after conventional detectors is generally acceptable in the operating regime, the error vector $\mathbf{e} = \mathbf{x} - \widehat{\mathbf{x}}$ is sparse. Therefore, we can use compressed-sensing techniques to recover the sparse error vector, hence the transmitted symbols. The block diagram of the compressed-sensing based detection schemes are shown in Fig. 2.

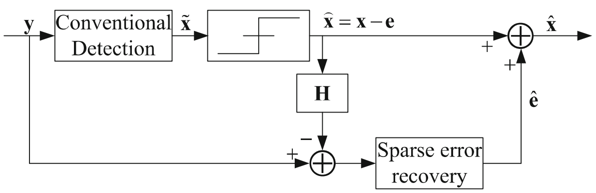

Fig. 2. Block diagram of the compressed-sensing based detection schemes

3.1 Transform to Sparse Vector Estimation Model

As the original transmitted symbols in (1) is non-sparse, the compressed-sensing techniques cannot directly applied to (1). Therefore, we need to transform the detection model to a sparse vector estimation one.

To begin with, with conventional detectors, the output estimation can be quantized to the closest constellation symbol. In adequate operating regime, the quantization error is small, for example, less than 10^{-1}. That is to say, the error vector after quantization is sparse, hence we can establish a new detection model, given by

$$\widehat{\mathbf{y}} = \mathbf{y} - \mathbf{H}\widehat{\mathbf{x}} = \mathbf{He} + \mathbf{z}. \tag{2}$$

As $\mathbf{e}$ is sparse, we can adopt the compressed-sensing techniques to recover $\mathbf{e}$.

3.2 Prevailing Compressed-Sensing Methods

Since $\mathbf{e}$ in Eq. (2) is sparse, the intuitive solutions to Eq. (2) is to find a sparse vector under the system constrain. Hence, we can use convex optimization approaches such as basis pursuit de-nosing method [19]. However, the computational complexity of such algorithms (or its variations) are, generally, is the order of $\mathcal{O}\left(N_B^2 N_U^3\right)$. Low-complexity compressed-sensing techniques normally are generalized as greedy algorithms or iterative methods.

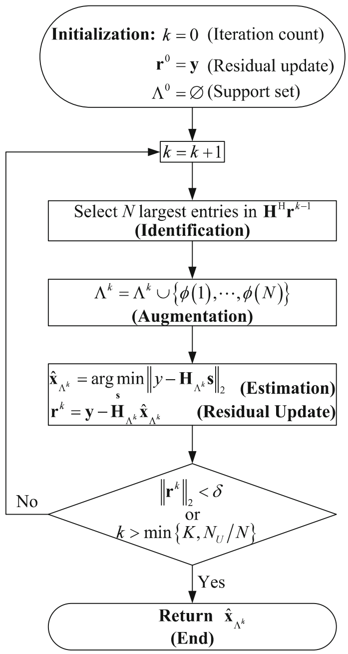

Fig. 3. The flow chart of the generalized OMP algorithm

The main process of the greedy algorithm consists of the following steps [13]: (1) identification; (2) augmentation; and (3) residual update. Specifically, the identification progress is to find the expected subset of the support sets. This is usually to use the correlation between the selected columns from $\mathbf{H}$ and the residual. The augmentation progress is to generate the new sparse vector. The residual update is to generate the new residual by removing the identified sparse vector from received signal for next iteration. The well-known orthogonal matching pursuit (OMP) method is to find one optimal candidate using the greedy strategy [20]. Therefore, the overall computational complexity is in the order of $\mathcal{O}\left(KN_BN_U\right)$, where K is the sparsity of the signal vector. Some other variations of OMP have been investigated, such as compressive sampling matching pursuit (CoSaMP) [21], generalized OMP [22], and the most recent multipath matching pursuit [23]. Generally, the main difference between those variations is the identification and the correspondent augmentation progress. For example, generalized OMP is to select N indices instead of one in identification progress, and it degrades to OMP when $N = 1$. However, by selecting N indices, the iterations required for the recovery can be speeded up. The flow chart of the gOMP is presented in Fig. 3. Note in Fig. 3, when $N = 1$, the gOMP becomes OMP as for each iteration, only one candidate is selected.

Another low complexity compressed-sensing technique is to use iterative methods for sparse signal recovery [24]. The iterative update step is given by

$$\hat{\mathbf{s}}^{(i+1)} = T\left(\hat{\mathbf{s}}^{(i)} + \mathbf{H}^{\mathrm{H}}\left(\mathbf{y} - \mathbf{H}\hat{\mathbf{s}}^{(i)}\right)\right), \tag{3}$$

where $T\left(\cdot\right)$ is the thresholding operator to generate the next estimation from the previous estimation. More references in this algorithm can be found in [25,26].

3.3 Challenges and Possible Solutions

Compressed-sensing based detection schemes have shown enhanced performance compared to the conventional linear MMSE detection schemes. However, most of the work requires hard decision on symbol detection. That is to say, in each iteration, when the estimation is given, it is always quantized to the closed constellation symbol. However, in real applications, the soft-input channel coding schemes are always adopted, which requires soft output from the symbol detector. Therefore, we need to derive the soft output compressed sensing based detection schemes.

In order to address these issue, we need to investigate the expected signal component from the estimation, and derive the *a posteriori* signal-to-interference-plus-noise ratio (SINR). Different from hard decision strategy, the afterward processing may put extra computational load. However, soft output compressed-sensing based schemes, which are designed to maintain low complexity but achieve near optimal performance, will be an interesting topic.

4 Low-Complexity Near Linear MMSE Detection

As demonstrated in [7,8,16], when r is sufficiently large, by employing linear detection schemes, such as MMSE, zero-forcing, or even matched filter, we can achieve near optimal system performance. Therefore, a class of these detection schemes have been widely studied recently [16–18,27–29]. Generally, these schemes can be categorized into two groups: to approach the matrix inversion [16,27] and to solve linear equations with iterative methods [17,18,28,29].

4.1 Methods to Approach Matrix Inversion

To begin with, the linear MMSE estimation in Eq. (1) is given by

$$\hat{\mathbf{x}} = \left(\mathbf{H}^{\mathrm{H}}\mathbf{H} + \sigma_z^2\mathbf{I}_{N_U}\right)^{-1}\mathbf{H}^{\mathrm{H}}\mathbf{y} = \mathbf{W}^{-1}\mathbf{y}^{\mathrm{MF}}, \tag{4}$$

where $\mathbf{W} = \mathbf{H}^{\mathrm{H}}\mathbf{H} + \sigma_z^2\mathbf{I}_{N_U}$, and $\mathbf{y}^{\mathrm{MF}} = \mathbf{H}^{\mathrm{H}}\mathbf{y}$ is the matched-filter output. With Neumann series expansion, the matrix inversion $\mathbf{W}^{-1}$ can be expanded as $\mathbf{W}^{-1} = \sum_{l=0}^{\infty}\left(\mathbf{X}^{-1}\left(\mathbf{X}-\mathbf{W}\right)\right)^{l}\mathbf{X}^{-1}$, where the convergence conditions are given by $\lim_{l\to\infty}\left(\mathbf{X}^{-1}\left(\mathbf{X}-\mathbf{W}\right)\right)^{l} = \mathbf{0}$. From the satisfied conditions, we can see that the higher order expansions can be omitted, leading to truncated approximation to matrix inversion, given by

$$\mathbf{W}^{-1} = \sum_{l=0}^{L-1}\left(\mathbf{X}^{-1}\left(\mathbf{X}-\mathbf{W}\right)\right)^{l}\mathbf{X}^{-1}. \tag{5}$$

When we select a matrix $\mathbf{X}$ that is very close to $\mathbf{W}$, the expansion order in Eq. (5) can be less than three, which is of low-complexity since the direct matrix inversion is in the order of $\mathcal{O}\left(N_U^3\right)$. Based on this idea, the authors in [16] select the diagonal matrix extracted from $\mathbf{W}$, and demonstrate that when $r \geq 16$, the expansion order $L \leq 3$.

However, using the diagonal matrix in the development may require large truncated orders when r is less than 16. To speed-up the convergence rate, Newton iteration has been introduced in [27]. However, Newton iteration involves matrix multiplications, and the computational complexity may be high even with only two iterations. Therefore, the authors in [27] propose to used the diagonal banded matrix in the development, and the iterations are limited to two. They also demonstrated that the performance with two iterations is better than that of the Neumann-series expansion based detection scheme when $r = 8$.

Generally, the methods to approach the matrix inversion suffers from matrix multiplications. Therefore, the applications of the methods in this category are limited to the scenario where r is sufficiently high (for example, $r \geq 8$).

4.2 Solving Linear Equations with Iterative Methods

By transforming the matrix inversion problem into linear equations, a class of iterative methods can be applied. To be specific, Eq. (4) is rewritten to

$$\mathbf{W}\hat{\mathbf{x}} = \mathbf{y}^{\mathrm{MF}}. \tag{6}$$

For Jacobi method [29], the iterative estimation is given by

$$\hat{\mathbf{x}}^{(i+1)} = \mathbf{D}^{-1}\left((\mathbf{D}-\mathbf{W})\,\hat{\mathbf{x}}^{(i)} + \mathbf{y}^{\mathrm{MF}}\right), \tag{7}$$

where $\mathbf{D} = \mathrm{diag}(\mathbf{W})$. It has been shown in [17,30] that when the initial estimation for Jacobi method is given by $\hat{\mathbf{x}}^{(0)} = \mathbf{D}^{-1}\mathbf{y}^{\mathrm{MF}}$, the estimation after L iterations is equivalent to results in Neumann series expansion based method with L orders. However, instead of approaching the matrix inversion, the Jacobi method is to approach the estimation vector and only matrix-vector product is involved in iterative process. Therefore, the computational complexity is much reduced, allowing large number of iterations.

Similarly, the Gauss-Seidel method proposed in [28] using the triangular matrix in the development. Since an successive detection manner is introduced in Gauss-Seidel method, the convergence performance (rate and probability that convergence conditions are satisfied) is greatly improved [28]. Using this idea, the development of using the stair matrix in massive MIMO uplink signal detection is presented in [17]. It has been demonstrated that by using the stair matrix, the probability that the convergence conditions are satisfied is improved compared to the use of the diagonal matrix, which indicates that the system requirement for large r can be released. Meanwhile, the convergence rate is also improved, which means less iterations are required for convergence.

4.3 Challenges and Possible Solutions

Iterative methods have the advantages of low complexity; however, the processing time introduced in iterative processing is significant. Therefore, to achieve fast processing time but maintain near optimal system performance is a critical challenge for implementation.

One possible solution to the challengeable issue mentioned above is to use parallel processing structure. For example, in [18], the authors propose a block Gauss-Seidel method based signal detection scheme for massive MIMO in V2I communications. The main idea behind that proposal is to implement the iterative estimation in several independent blocks. This is realized by using the block diagonal matrix in the development of the iterative method. Specifically, $\mathbf{W}$ is divided into $\mathbf{W} = \mathbf{P} + \mathbf{Q}$, with the block diagonal matrix $\mathbf{P}$ given by

$$\mathbf{P} = \begin{bmatrix} \mathbf{P}(1) & & & \\ & \mathbf{P}(2) & & \\ & & \ddots & \\ & & & \mathbf{P}(B) \end{bmatrix}.$$

In addition, the iterative estimation can be given as

$$\mathbf{P}\hat{\mathbf{x}}^{(i+1)} = \mathbf{y}^{\mathrm{MF}} - \mathbf{Q}\hat{\mathbf{x}}^{(i)}, \tag{8}$$

Since $\mathbf{P}$ is a block diagonal matrix, the iterative estimation in Eq. (8) can be updated on each individual block independently, each with a much degraded matrix size. The independent block update procedure can be implemented with parallel processing structure, and the processing time in each iteration can be greatly reduced. The parallel processing structure for the proposed detection scheme in [18] is shown in Fig. 4.

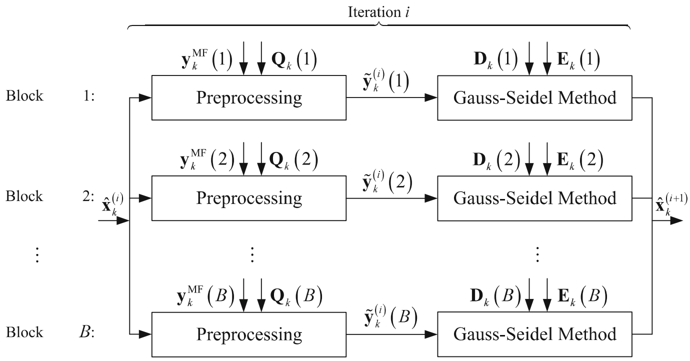

Fig. 4. The parallel processing structure of the block Gauss-Seidel method [18].

However, as the block diagonal matrix is adopted, the convergence performance (in terms of convergence rate and the probability that the convergence conditions are satisfied) will be another issue to be addressed.

5 Conclusions

In this paper, we start from the requirements of the ITS, and introduce a promising candidate technique, massive MIMO, for future vehicular networks. Especially, we specify that massive MIMO is quite suitable for multiple vehicles to access the roadside infrastructure where large scale antennas can be deployed. In addition, we overview the newly proposed compressed-sensing technique and a class of low-complexity near linear MMSE detection schemes in massive MIMO uplink data detection. We present the general procedure in implementation, and summarize future challenges and possible solutions along with these new techniques. Those challengeable issues brought in this paper can be valuable references for future research topics.

References

1. Mecklenbrauker, C., Molisch, A., Karedal, J., Tufvesson, F., Paier, A., Bernado, L., Zemen, T., Klemp, O., Czink, N.: Vehicular channel characterization and its implications for wireless system design and performance. IEEE Proc. **99**(7), 1189–1212 (2011)
2. Viriyasitavat, W., Boban, M., Tsai, H., Vasilakos, A.: Vehicular communications: survey and challenges of channel and propagation models. IEEE Veh. Technol. Mag. **10**(2), 55–66 (2015)

3. Su, Z., Hui, Y., Yang, Q.: The next generation vehicular networks: a content-centric framework. IEEE Wirel. Commun. Mag. **24**(1), 60–66 (2017)
4. Li, P., Zhang, T., Huang, C., Chen, X., Fu, B.: RSU-assisted geocast in vehicular ad hoc networks. IEEE Wirel. Commun. Mag. **24**(1), 53–59 (2017)
5. Zhang, R., Zhong, Z., Zhao, J., Li, B., Wang, K.: Channel measurement and packet-level modeling for V2I spatial multiplexing uplinks using massive MIMO. IEEE Trans. Veh. Technol. **65**(10), 7831–7843 (2016)
6. Choi, J., Va, V., Gonzalez-Prelcic, N., Daniels, R., Bhat, C., Heath, R.: Millimeter wave vehicular communication to support massive automotive sensing. IEEE Commun. Mag. **54**(12), 160–167 (2016)
7. Marzetta, T.: Noncooperative cellular wireless with unlimited numbers of base station antennas. IEEE Trans. Wirel. Commun. **9**(11), 3590–3600 (2010)
8. Ngo, H., Larsson, E., Marzetta, T.: Energy and spectral efficiency of very large multiuser MIMO systems. IEEE Trans. Commun. **61**(4), 1436–1449 (2013)
9. Zhang, Y., Venkatesan, R., Dobre, O.A., Li, C.: Novel compressed sensing-based channel estimation algorithm and near-optimal pilot placement scheme. IEEE Trans. Wirel. Commun. **15**(4), 2590–2603 (2016)
10. Yang, S., Hanzo, L.: Fifty years of MIMO detection: the road to large-scale MIMOs. IEEE Commun. Surv. Tutor. **17**(4), 1941–1988 (2015)
11. Jiang, F., Zhang, Y., Li, C.: A new SQRD-based soft interference cancelation scheme in multi-user MIMO SC-FDMA system. IEEE Commun. Lett. **21**(4), 821–824 (2017)
12. Li, C., Jiang, F., Meng, C., Gong, Z.: A new turbo equalizer conditioned on estimated channel for MIMO MMSE receiver. IEEE Commun. Lett. **21**(4), 957–960 (2017)
13. Choi, J., Shim, B.: New approach for massive MIMO detection using sparse error recovery. In: IEEE Proceedings of the GLOBECOM, Austin, TX, USA, pp. 3754–3759 (2014)
14. Peng, X., Wu, W., Sun, J., Liu, Y.: Sparsity-boosted detection for large MIMO systems. IEEE Commun. Lett. **19**(2), 191–194 (2015)
15. Choi, J., Shim, B., Ding, Y., Rao, B., Kim, D.: Compressed sensing for wireless communications: useful tips and tricks. IEEE Commun. Surv. Tutor. **19**(3), 1527–1550 (2017)
16. Wu, M., Yin, B., Wang, G., Dick, C., Cavallaro, J., Studer, C.: Large-scale MIMO detection for 3GPP LTE: algorithms and FPGA implementations. IEEE J. Sel. Top. Signal Process. **8**(5), 916–929 (2014)
17. Jiang, F., Li, C., Gong, Z., Su, R.: Stair matrix and its applications to massive MIMO uplink detection. Submitted to IEEE Trans. Commun. (2017, under review)
18. Jiang, F., Li, C., Gong, Z.: Block Gauss-Seidel method based detection in vehicle-to-infrastructure massive MIMO uplink. In: IEEE Proceedings of the GLOBECOM (2017)
19. Chen, S., Donoho, D., Saunders, M.: Atomic decomposition by basis pursuit. SIAM J. Sci. Comput. **20**(1), 33–61 (1998)
20. Tropp, J., Gilbert, A.: Signal recovery from random measurements via orthogonal matching pursuit. IEEE Trans. Inf. Theory **53**(12), 4655–4666 (2007)
21. Needell, D., Tropp, J.: CoSaMP: iterative signal recovery from incomplete and inaccurate samples. Appl. Comput. Harmon. Anal. **26**, 301–321 (2009)
22. Wang, J., Kwon, S., Shim, B.: Generalized orthogonal matching pursuit. IEEE Trans. Signal Process. **60**(12), 6202–6216 (2012)
23. Kwon, S., Wang, J., Shim, B.: Multipath matching pursuit. IEEE Trans. Inf. Theory **60**(5), 2986–3001 (2014)

24. Maleki, A., Donoho, D.: Optimally tuned iterative reconstruction algorithms for compressed sensing. IEEE J. Sel. Top. Signal Process. **4**(2), 330–341 (2010)
25. Blumensath, T., Davies, M.: Iterative hard thresholding for compressed sensing. Appl. Comput. Harmon. Anal. **27**(3), 265–274 (2009)
26. Bayati, M., Montanari, A.: The dynamics of message passing on dense graphs, with applications to compressed sensing. IEEE Trans. Inf. Theory **57**, 764–785 (2011)
27. Tang, C., Liu, C., Yuan, L., Xing, Z.: High precision low complexity matrix inversion based on Newton iteration for data detection in the massive MIMO. IEEE Commun. Lett. **20**(3), 490–493 (2016)
28. Dai, L., Gao, X., Su, X., Han, S., Wang, Z.: Low-complexity soft-output signal detection based on Gauss-Seidel method for uplink multiuser large-scale MIMO systems. IEEE Trans. Veh. Technol. **64**(10), 4839–4845 (2015)
29. Qin, X., Yan, Z., He, G.: A near-optimal detection scheme based on joint steepest descent and Jacobi method for uplink massive MIMO systems. IEEE Commun. Lett. **20**(2), 276–279 (2016)
30. Jiang, F., Li, C., Gong, Z.: A low complexity soft-output data detection scheme based on Jacobi method for massive MIMO uplink transmission. In: 2017 IEEE International Conference on Communication, pp. 1–5. IEEE Press, Paris (2017)