**International Journal of Electrical and Computer Engineering (IJECE)**
Vol. 12, No. 4, August 2022, pp. 3911~3921
ISSN: 2088-8708, DOI: 10.11591/ijece.v12i4.pp3911-3921 

# Data detection method for uplink massive MIMO systems based on the long recurrence enlarged conjugate gradient

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**Article Info**

***Article history:***

Received Apr 22, 2021
Revised Jan 11, 2022
Accepted Feb 10, 2022

***Keywords:***

Conjugate gradient
Large-scale MIMO systems
Long-recurrence enlarged conjugate-gradient
Multiple-input multiple-output
Neumann series approximation

**ABSTRACT**

Although the mean square error (MMSE) approach is recognized to be near optimal for uplinking large-scale multiple-input-multiple-output (MIMO) systems, there are certain difficulties in the procedure related to matrix inversion. The long recurrence enlarged conjugate gradient (LRE-CG) approach is proposed in this study as a way to iteratively realize the MMMS algorithm while avoiding the complications of matrix inversion. In addition, a diagonal-approximate starting solution to the LRE-CG approach was used to speed up the conversion rate and reduce the complications required. It has been discovered that the LRE-CG-based approach has the ability to significantly reduce computational complexity. By comparing simulation results, it is clear that this new methodology surpasses well-established ways like the Neumann series approximation-based method and the Gauss-Siedel iterative method. With a small number of iterations, the suggested approach achieves near-optimal performance of a standard MMSE algorithm.

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## 1. INTRODUCTION

Many communication systems, including the fourth generation (4G) cellular system, IEEE 802.11n wireless local area network system [1], [2], long-term evolution advanced (LTE-A) [1], [2], and many more, have demonstrated the benefits of using multiple inputs and multiple outputs (MIMO). In [3] has received widespread praise from communication specialists as a promising core technology that has the potential to be used to a variety of wireless communication systems in the near future. Large-scale MIMO differs from the more common small-scale MIMO technology. In LTE-A, regular MIMO is typically equipped with eight antennas; however, large scale MIMO is provided with a huge number of antennas, which might be as many as 128 or even more. This technology, according to a newly proposed method, would allow these antennas in the base station to simultaneously service many user equipment devices [4]. There are theoretical evidences that large-scale MIMO systems are capable of achieving high energy efficiency while still achieving orders of magnitude increases in spectrum [5].

In the course of evaluating the practical advantages of large scale MIMO, various difficulties have been observed. For example, increasing the performance of the practical signal detection algorithm in the uplink to accommodate multiuser interferences. Growth in the number of transmit antennas has been shown to cause a fast increase in the complexity of ideal maximum likelihood (ML) detectors [6]. As a result, it becomes impracticable for large-scale MIMO systems, and their relevance diminishes as a result of this. In order to achieve near-optimal performance while reducing the degree of complexities, nonlinear detection algorithms, such as fixed-complexity sphere decoding [7] and tabu search [8] are proposed. However, this low degree of complexity continues to be a concern when the MIMO system is vast in size or when the modulation order is high [9] (for example, when there are 128 antennas at the base station and 64-quadrature amplitude modulation) (QAM). Every user equipment (UE) in the coverage area is serviced by every access point (AP) in the communication range in the traditional cell-free massive MIMO topology [10]–[12]. In research [13], a typology is proposed in respect of uplink receiver coordination across APs with CPU, ranging from entirely dispersed (level 2) to totally centralized (level 4) implementations, with the highest level of cooperation being the most cooperative. Although scalability issues for channel estimation, data decoding/precoding, and fronthaul signaling have been highlighted in recent work [14], [15], it is imperative that these issues be overcome in order to enable large-scale deployments of cell-free networks on a global scale. It has encouraged researchers to propose user-centric ways to selectively service a subset of APs in wide coverage areas, due to the fact that the majority of APs in a broad coverage area have insignificant channel gains to one or more specific UEs [16], [17].

In order to deal with the complexities while maintaining high performance, a low-complexity linear detection algorithm such as zero-forcing and minimum mean square error (MMSE) could potentially be used for up-linking the multiuser large-scale MIMO systems [18]. MMSE is a linear detection algorithm with near-optimal performance for up-linking the multiuser large-scale MIMO systems. This approach, on the other hand, employs a matrix inversion that is both difficult and unfavorable in nature. For translating matrix inversion into matrix-vector multiplication series [19], the Neumann series approximation approach was recently introduced. Although this algorithm has the potential to reduce complexity, the reduction is not very substantial.

The complications caused by the linear detector with perfect inversion matrix increased in tandem with the increase in the number of users in large scale MIMO systems, making them prohibitively expensive. There have been a number of studies undertaken that have focused on the Neumann serious expansion (NSE) for approximation purposes in order to overcome the precise matrix inversion [20]–[27]. However, it has been shown that when the NSE number is greater than 2, the amount of complexity increases significantly once again. There have been other iterative linear algorithms suggested recently to achieve a better balance between performance and complexity, including the conjugate (CG) method [28]–[32] the Gauss-Seidel (GS) algorithm [33]–[35], and the successive over-relaxation (SOR) algorithm [36]–[38] among others. In order to get better MIMO detection with less complexity, these techniques are believed to be beneficial. Pyla *et al.* in [39], they propose to include the dynamic cooperative grouping methodology from the connectivity MIMO research [40], [41] into cell-free massive MIMO. There may be overlap between the AP groupings that service various UEs, and the groups are chosen based on the demands of the users.

Jiang *et al.* [42] take the position that the dynamic cooperative grouping may be used with both centralized (level 4) and completely dispersed (level 2) uplink implementations in the same network. However, with DCC, the level 3 implementation (based on the taxonomy in [43]) has not been addressed because it is not required. When the CPU reaches level 3, it adds a second layer of decoding, known as largescale fading decoding (LSFD), in order to reduce interference. When compared to level 2 in the original cell-free massive MIMO [44], this distributed processing technique has been demonstrated to significantly enhance the SE. However, this method has not been investigated in user-centric networks. The best SE performance among the levels is achieved by using level 4, but this requires the computation of centralized receive combiners at the CPU, which has significantly higher dimensions when contrasted to level 3 and level 2 local beamforming and thus increases the complexity of the algorithm of the level.

To further examine the problem associated with the previously mentioned issue, we suggest in this work that the matrix inversion-less signal detector technique with a low degree of complexity attached to it might be employed for a large scale MIMO system in an effort to investigate the problem. The suggested technique is based on the long recurrence expanded conjugate gradient (LRE-CG) method [45], which makes it suitable for large-scale MIMO systems due to its low computational complexity. Instead than focusing on identifying new research areas, we believe that establishing an orthonormal basis for Krylov subspace with a big dimension is far more important at this time. In addition to being utilized to update the solution, the full basis is also employed to prevent the occurrence of excessively intricate matrix inversions. The method's convergence rate is also projected to be increased to a more acceptable level as a result of this improvement. The convergence of the suggested signal detection method is also demonstrated in this work, hence ensuring its practicability and viability in the real world. This paper's approach, which has been validated with the help of stimulation results, has the ability to efficiently address the matrix inversion issue inside the iterative procedure up to the point where the required accuracy direction is attained. According to a survey of current literature and research effort relevant to this subject matter, this paper represents the first and only attempt to employ the LRE-CG approach for the process of signal detection in an uplink large scale MIMO system [46], [47] that has been made.

This paper has been divided into sections to help readers to have a comprehensive and clear grasp of the problem that has been recognized and the solution that has been suggested in the study. Section 2 of this document offers a brief overview of the system modeling methodology. It has been attempted in section 3 to define the suggested low complexity signal detection method, as well as the process of its convergence and a study of its complexity associated with it. Section 4 presents the findings of the bit error (BER) stimulation of the performance of our suggested systems' performance. Section 5 concludes with a synopsis of the complete piece of work.

In this paper, there are lowercase and uppercase boldface letters have been used to dignify the vector and matrices respectively $(\cdot)^T$, $(\cdot)^H$, $(\cdot)^{-1}$, and $|\cdot|$ is used for denoting the transpose, conjugate transport, matrix inversion and absolute operators, respectively. On the other hand notations $Re\{\cdot\}$ and $Im\{\cdot\}$ are used to denote the real part and imaginary part of a complex number, respectively; and finally, $I_N$ is the representative of the $N \times N$ identity matrix.

## 2. SYSTEM MODEL

For the system model, first we will consider an uplink large scale MIMO system where N antennas are employed at the base system and K selected single antenna UE devices are simultaneously served for communicating. The N >> K assumption is made in this case, e.g., N=128 and K=16 [31]. In the parallel transmitted bit stream, K different users' signals are encoded separately at first. In order to map it to the constellation system, the channel encoder encode the data first. In order to conduct the mapping, values are extracted from the energy normalized modulation constellation Q. s in this model represents the K×1 transmitted signal vector which includes the transmissions from all the K users and $H \in C^{N \times K}$ is used to denote the flat Rayleigh fading channel matrix with zero mean and unit variance in which all the entries are considered to be independent as well as identically disturbed. The signal vector $y$ in the N×1 receiver can be expressed as:

$$y = Hs + n \tag{1}$$

In (1), $n$ is a $N \times 1$ additive white Gaussian noise vector whose entries follow $CN(0, \sigma^2)$. Multi-user signal detection work has been performed at the base station BS in order to get the estimated about the transmitted signal vector s from the noisy signals vector y received. It is important to note here that the channel matrix H is usually obtainable through time domain and frequency domain training pilots [42], [43]. Now, the estimated transmitted signal vector $\hat{s}$ that is obtained by the MMSE linear detection method can be expressed as (2):

$$\hat{s} = (H^H H - \sigma^2 I_K)^{-1} H^H y = W^{-1} y_{MF} \tag{2}$$

Here the $y_{MF} = H^H y$ is the matched-filter output of $y$, and the MMSE filtering matrix $W$ is denoted by (3):

$$W = G - \sigma^2 I_K \tag{3}$$

where $G = H^H H$ represents of the Gram matrix. Using the estimated results for soft-input channel decoding, the log-likelihood ratios (LLRs) of the transmitted signal vector can be derived. The assumption at this point is that the equivalent channel matrix is $E = W^{-1} G$ and $U = W^{-1} H^H (W^{-1} H^H)^H = W^{-1} G W^{-1}$. Therefore, with (1) and (2) combined, the MMSE estimate $\hat{s}$ is:

$$\hat{s} = Es + W^{-1} H^H n \tag{4}$$

According to (5), we may predict that the sent symbol for the $k^{\text{-th}}$ user will be:

$$\widehat{s_k} = \mu_k s_k + \delta_k \tag{5}$$

where $s_k$ denotes the symbol employed to represent the $k^{\text{-th}}$ element of the vector of the transmitting signal $s$. $\mu_k = E_{kk}$ denotes the channel gain, and $\delta_k^2 = \sum_{m \neq k}^{K} |E_{mk}|^2 + U_{kk}\sigma^2$ represents the noise plus interference (NPI) variance; $U_{kk}$ denotes the one component of matrix $U$ in the $k^{\text{-th}}$ row and $k$-th column and $E_{mk}$ denote the one component of matrix $E$ in the $m^{\text{-th}}$ row and $k^{\text{-th}}$ column. However, the LLR $\mathcal{L}_{k,b}$ of the $k^{\text{-th}}$ user can be expressed [24]:

$$\mathcal{L}_{k,b} = \hbar_k \left( \min_{\tau \in S_b^0} \left| \frac{\widehat{s_k}}{\mu_k} - \tau \right|^2 - \min_{\bar{\tau} \in S_b^1} \left| \frac{\widehat{s_k}}{\mu_k} - \bar{\tau} \right|^2 \right) \tag{6}$$

where $\hbar_k = {\mu_k^2}/{\delta_k^2}$ denotes the signal to interference plus noise ratio for the $k$-th user, and $S_b^0$, $S_b^1$ represents the groups that consist of the signs of the constellation $Q$.

From the above, it is clearly demonstrated that the MMSE linear detection algorithm is almost optimal for the process of uplink the multiuser large scale MIMO systems. However, it has also been verified that it is not possible to avoid the sophisticated matrix inversion $\mathrm{W}^{-1}$ included in MMSE algorithm. To calculate the final LLRs for soft-input channel decoding, MMSE estimates, channel gain and noise plus interference (NPI) variance are essentially needed where they can be computed by using the matrix inversion. The complexity computing of matrix inversion is $\mathrm{O}(\mathrm{K}^3)$ which is considered high because K is typically very large in the uplink large scale MIMO system [21].

Here, it has been proposed to use a low complexity signal detection technique in which the iterative LRE-CG algorithm is been employed to estimate the MMSE without the need of matrix inversion. Adding a diagonal approximate initial solution [25] to the LRE-CG method, we have used it to enhance the convergence and reduce the degree of complexity. Alongside, we also propose for estimating the channel gain and NPI variance for LLR computation by employing an approximated method that is not required to compute the exact matrix inversion. To sum up, the overall analysis of the proposed LRE-GC algorithm has been presented to demonstrate that there are certain advantages of this algorithm over other typical and conventional sophisticated methods found in the literature.

## 3. THE PROPOSED TECHNIQUE

For an uplink large scale MIMO system, the channel matrix H is an asymptotically orthogonal column full rank matrix according to the suggested technique. It guarantees the Hermitian positive definiteness of the MMSE filtering matrix W. The LRE-CG technique [15] may be used to iteratively solve (2) in the absence of matrix inversion because of its particular characteristic. $N$-dimensional linear equation $Ax = b$ has been solved using the LRE-CG technique, while, $A$ represents the $N$-dimensional Hermitian positive definite matrix, $x$ denotes the $N$-dimensional solution vector and $b$ represents the $N$-dimensional measurement vector. With the LRE-CG approach, which differs from the usual method in that it does not use a computer at all to solve the equation of $\mathrm{A}^{-1}\mathrm{b} = x$ repeatedly, the complexity of solving $Ax = b$ is kept to an absolute minimum. $W$ is a Hermitian positive definite matrix, hence we may decompose it as a Hermitian positive definite matrix.

$$W = D + L + L^H \tag{7}$$

Matrix $W$'s diagonal and lower triangular halves are referred to as $D$ and $L$, respectively. LRE-CG technique is used to estimate the transmitted signal vector s once this step has been completed. Krylov projection technique of the LRE-CG is used to solve a linear system of equations [15]. Without the matrix inversion, the LRE-CG approach may be able to solve the issue of (3) by addressing the following optimization problem,

$$\hat{s} = arg \min_{\hat{s} \in C^U} \| H^H b - A\hat{s} \| \tag{8}$$

where $A = H^H H + N_0 I_U \in C^{U \times U}$ denotes a positive definite matrix, which represents the regularized uplink Gram matrix. The method in [15] may be used to iteratively compute the solution, utilizing LRE-CG technique with minimal computational cost. As an alternative, LRE-CG may be used to determine the transmitted signal vector $s$ at the $i$-th iteration,

$$\hat{s}_i = \hat{s}_{i-1} + P_i \alpha_i \tag{9}$$

where $P_i$ represents the $U \times t$ matrix that consists of the $t$ sub-domain search-directions, and $\alpha_i$ represnets the vector of size $t$. Our LRE-CG-based technique to soft output data identification is summarized in algorithm 1. Our LRE-CG approach is based on algorithm in [15]. Even with an infinite number of repeats, the suggested algorithm reduces the complexity of the MMSE technique from $O(K3)$ to $O(K2)$ in algorithm 1.

| Algorithm 1. LRE-CG for soft-output MMSE detection | Flops |
|---|---|
| Input: | |
| $A$, the $n \times n$ symmetric positive definite matrix | |
| $b$, the $n \times 1$ observed vector | |
| $x_0$, the initial guess | |
| $\epsilon$, the stopping tolerance. | |
| $t$, Number of the Subdomains (search directions) | |
| $Itr_{max}$, the maximum allowed iterations | |
| Output: | |
| $x_{itr}$, the approximate solution | |
| 1. $r = b - Ax_0$, $Itr = 1$ | $2nnz - 1$ |
| 2. $W = \mathcal{T}(r_0)$, $Q = W$ | $2nnz + n(t-1)$ |
| 3. A-orthonormalize $P_1$ | |
| 4. *While* $(Itr < Itr_{max})$ *do* | |
| 5. $G = (Q^t AQ)$ | $(2nnz - n)t + (2n-1)t^2$ |
| 6. $\alpha = G^{-1}(Q^t r)$ | $(2n-1)n$ |
| 7. $x_{itr} = x_{itr-1} + Q\alpha$ | $2nt$ |
| 8. $r = r - AQ\,\alpha$ | $2nt$ |
| 9. $W = AW$ | $(2nnz - n)t$ |
| 10. A-orthonormalize $W$ using modified Gram Shmidt | $nnzt^2 + nt^2$ |
| 12. $Q = QW$ | $(2nnz - n)t$ |
| 13. $Itr = Itr + 1$ | 1 |
| 14. *End While* | |

### 3.1. Computational complexity

According to algorithm 1, the computational complexity is assessed as follows. The calculated number of multiplications for each step in the proposed approach are used to calculate the final result. At each iteration, the total number of multiplications is given by:

$$O = 4Ut^2 + 8Ut + 2U$$

where $t$ denotes the number of search directions. Since the presented method aims to decrease the computational cost, $Itr_{max}$ should be made considerably less than $U$ so that the presented algorithm's computational complexity is less than $O\ (U^3)$. Also, we investigate computational complexity as it pertains to various approaches found in the literature for comparison in the next section.

## 4. RESULTS AND DISCUSSION

Monte-Carlo simulations have been carried out in a coded 20-MHz multiple-output orthogonal frequency-division multiplexing (MIMO-OFDM) uplink system with 2,048 subcarriers in order to evaluate the performance of the proposed technique in terms of error-rate performance. 1,200 of these are used for data transmission, such as in LTE advanced (LTE-A) [31] and other networks. The 64-QAM modulation scheme is used in conjunction with Gray mapping and a rate-3/4 turbo code. The channel matrices were also created in order to get the spatial and frequency correlation, for which we utilized the WINNER-Phase-2 model [34] with 7.8 cm antenna spacing, similar to the models used in [11] and [22]. It has been decided to use a logarithmic maximum a posteriori (Log-MAP) turbo encoder for the purpose of decoding the channel. A bit error rate is also supplied, which is calculated by coding over one OFDM signal with 1,200 data subcarriers and calculating the bit error rate. In this regard, we concentrate on a number of massive MIMO detection systems. The experiments were conducted out due to MATLAB program on Intel Core i7 CPU with a 2.4-GHz processor and 4G MB RAM, as well as a MATLAB environment.

Figure 1 shows a comparison of the bit error rate (BER) for the presented method in the study, as well as for other precise and approximate data-detection algorithms utilized for huge MU-MIMO systems with various antenna configurations, as shown in the paper. We have specifically acquired the BER findings for the Neumann series detection [7], the CG-based detection [10], and the Gauss-Seidel (GS)-based detection [13] techniques. In addition to this, we have supplied a reference equalization that is an exact linear MMSE equalizer as well. Three rounds of BER versus signal to noise ratio (SNR) of the described techniques are shown in Figure 1 with simulation results for each iteration. It is set up with the following parameters: N=128 antennas, U=8 users, and SNR values ranging from -10 to 20 decibels (decibels per kilometer). Figure 1 illustrates that the suggested technique, which is based on the LRE-CG method, is capable of approaching the performance of the MMSE algorithm while consistently delivering the lowest BER when compared to other algorithms described in the literature. Also included is a comparison of the average CPU timings for the various techniques, which is presented in Table 1. As demonstrated in Table 1, the suggested approach is comparable to the other algorithms, and it even outperforms the other methods when it comes to BER.

Furthermore, it is undeniable that the CG technique and the Richardson method are less difficult algorithms than the other algorithms available. However, with the introduction of increasingly powerful computer systems, such as graphics processing units (GPUs), the accuracy of performance measurements has gained in importance.

Figures 2 and 3 show the performance of the suggested algorithm, which is based on the LRE-CG technique and the other methods discussed above, when $N = 128$ and $U = 16$, respectively. As seen in Figures 2 and 3, the suggested method comes close to the performance of the MMSE algorithm while outperforming other algorithms that have been reported in the literature. Table 2 also includes a comparison of typical computation times, which illustrates the difference between the two approaches. As demonstrated in Table 2, the suggested technique is comparable to the other methods, and it even outperforms them in terms of BER performance.

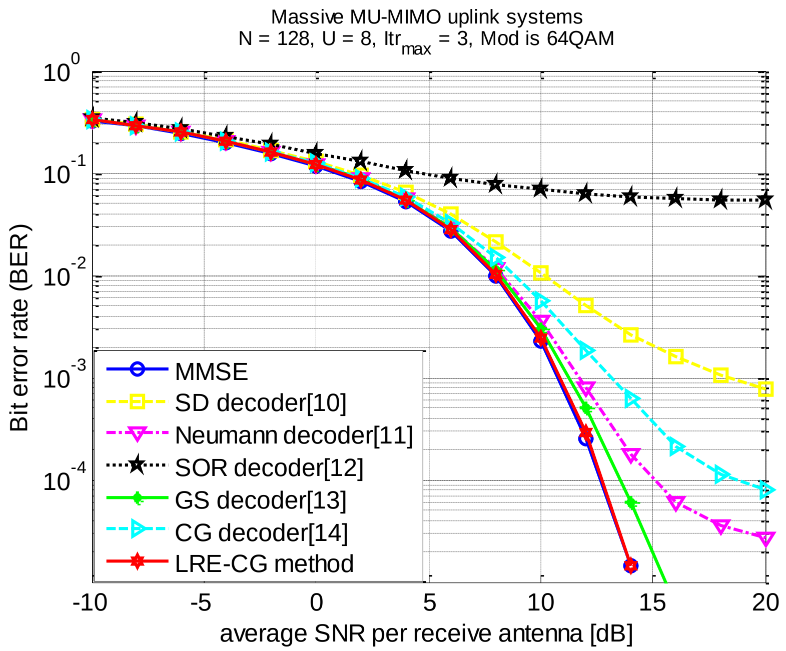


Figure 1. The BER compared the proposed estimated technique and alternative ways to calculate LLRs for $N = 128$ antennas with 8 users and different SNRs

Table 1. Average computational times for each method (in sec) for $U \times N = 8 \times 32$ case

| | MMSE | CG | SOR | Neurmann | Richardson | GS | LRE-CG |
|---|---|---|---|---|---|---|---|
| $Itr_{max} = 3$ | 1.03 e-04 | 8.15e-05 | 1.31 e-04 | 1.26 e-04 | 5.41e-05 | 1.31 e-04 | 5.53e-05 |

After that, in Figure 4, we compare the BER performance of the proposed algorithm with the SOR technique, the GS-based approach, the standard algorithm based on Neumann, and other algorithms in the literature using a variety of situations. It has been found that the suggested method operates admirably with a variety of antenna and user configurations. It is also demonstrated that when the number of iterations of the MMSE algorithm increases, the BER performance of the method approaches that of all traditional techniques in terms of BER. However, when a comparable number of iterations is used, the suggested technique is found to be more superior when compared to the other approaches in terms of performance. As shown in Figure 4, we also offer simulation results that are based on a comparison between the number of antennas at the base stations and the BER performance of the proposed method when a certain number of users is taken into consideration. It can be observed that as the value of N grows, the performance of the MMSE technique improves in a corresponding fashion. The precise performance of the algorithm may be attained by the suggested technique, regardless of the number of antennas used, when the number of iterations is kept to a bare minimum, such as three iterations. On the contrary, the performance of the GS-based and Neumann-based algorithms improves when the number of iterations is increased, while there is still a performance loss due to the lack of negligibility in the algorithms. According to the results of this comparison, the other standard algorithms in the literature are less superior than the suggested method. The Neumann series approach also performs well in the scenario (N × U = 128 × 8) which reinforces the impression in [12] that this method requires a high user to BS ratio ($p = N/U$), which is supported by the results of this study.

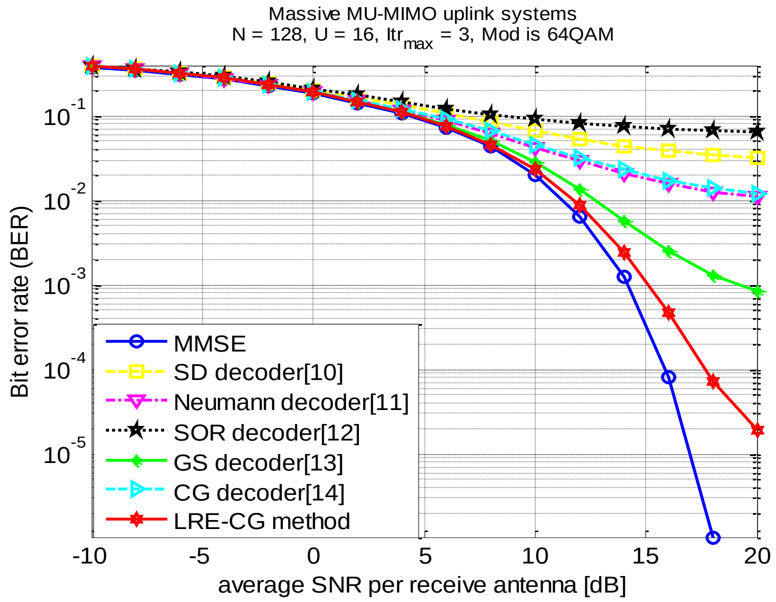


Figure 2. The evaluation of proposed approximation technique's BER to alternative approaches for calculating LLRs for a system with 128 antennas and 16 users, using $Itrmax = 3$

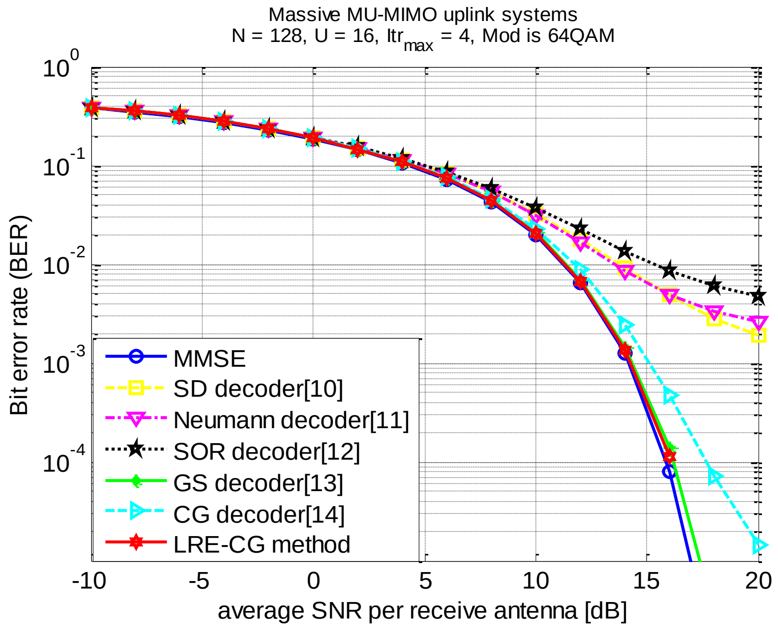


Figure 3. The evaluation of proposed approximation technique's BER to alternative approaches for calculating LLRs for a system with 128 antennas and 16 users, using $Itrmax = 4$

Table 2. Average computational times for each method (in sec) for U × N = 16 × 128 case

| | MMSE | CG | SOR | Neurmann | Richardson | GS | LRE-CG |
|---|---|---|---|---|---|---|---|
| $Itr_{max} = 3$ | 1.42e-04 | 9.32e-05 | 2.35e-04 | 3.25e-04 | 1.05e-04 | 2.27e-04 | 1.11e-04 |
| $Itr_{max} = 4$ | 1.44e-04 | 1.23e-04 | 2.84e-04 | 4.12e-04 | 1.27e-04 | 2.83e-04 | 1.26e-04 |

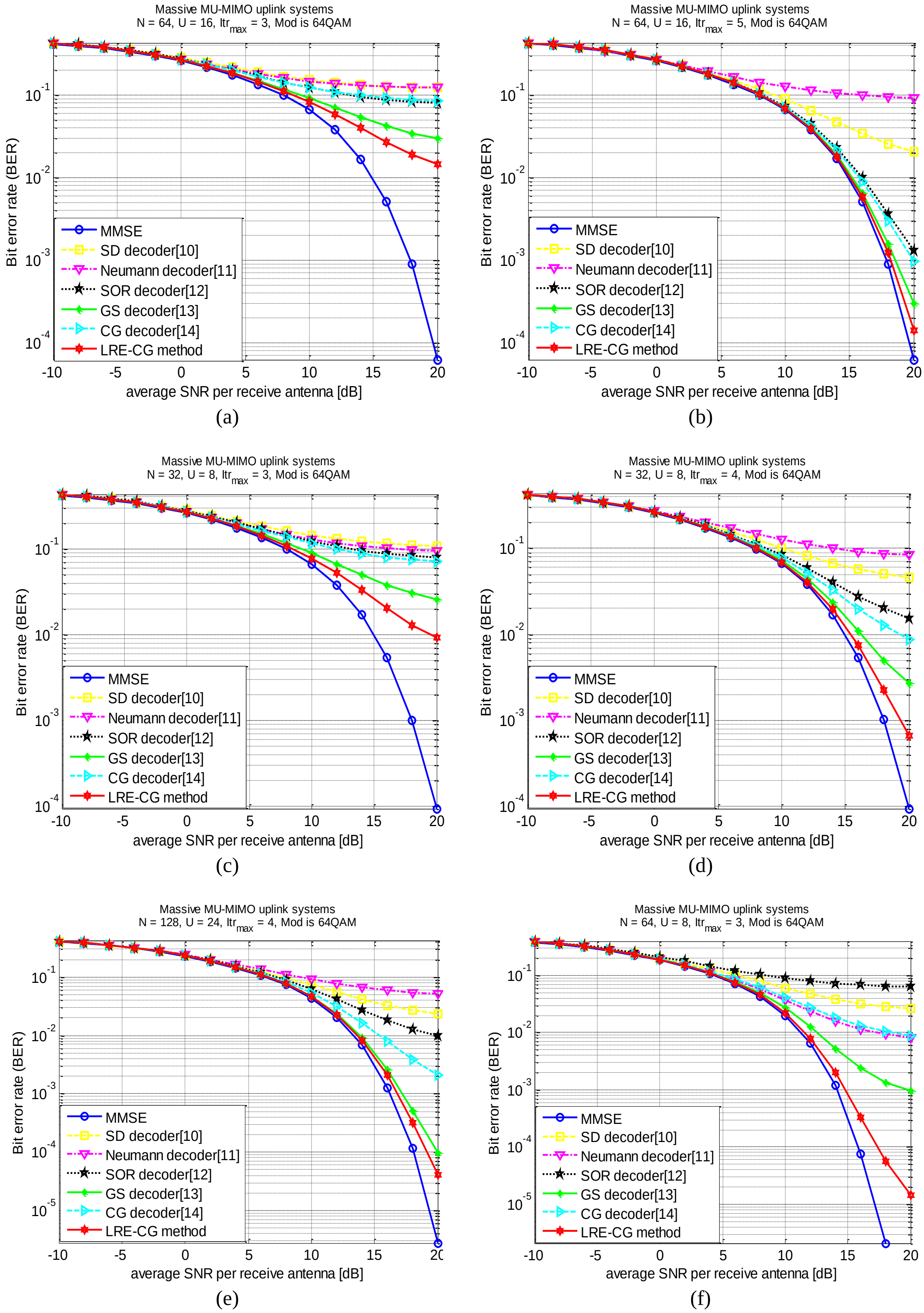


Figure 4. BER performance comparison in the massive MIMO uplink for (a) U×N=16×64 with $Itr_{max} = 3$, (b) U×N=16×64 with $Itr_{max} = 5$, (c) U×N=16×32 with $Itr_{max} = 3$, (d) U×N=16×32 with $Itr_{max} = 4$, (e) U ×N=24 × 128 $Itr_{max} = 4$, and (f) U×N=8×64 $Itr_{max} = 3$

## 5. CONCLUSION

As a conclusion, we state that the proposed detection using approximation LLR calculation has high resilience against changes in channel correlation and loading factor, which is summarized in this paper. In our numerical findings, it has been demonstrated that, for relatively high ratios between base station and user antennas, the proposed detection strategy rapidly corresponds to the performance of an accurate detection technique. So the proposed methodology is capable of producing performances that are comparable to those of an accurate inversion method while needing (in many cases) less computing complexity. Further to the point, the approximate Neumann series inversion and other schemes suggested in the literature are outperformed by the proposed scheme in terms of both efficiency and complication, and our system is less complicated. The proposed detector is efficient and can be used in a variety of antenna configurations in large MIMO systems with a variety of antenna types.

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