OPTIMIZED MIMO DETECTION TECHNIQUE

K.Rithik[1], N.Pradeep[2], P.Vyshnavi[3], P.Rajshekar[4], K.Deepthi[5]

[1] K.Rithik, Electronics and Communication, VNRVJIET, Telangana, India
[2] N.Pradeep, Electronics and Communication, VNRVJIET, Telangana, India
[3] P.Vyshnavi, Electronics and Communication, VNRVJIET, Telangana, India
[4] P.Rajshekar, Electronics and Communication, VNRVJIET, Telangana, India
[5] K.Deepthi, Electronics and Communication, VNRVJIET, Telangana, India

ABSTRACT

Linear detectors like Zero Forcing (ZF) or Minimum Mean Square Error (MMSE) are crucial for large/massive MIMO systems for both downlink and uplink situations. However, these linear detectors require matrix inversion, which is computationally costly for such large systems. In this paper we note that it is not necessary to compute an exact inverse to find the ZF/MMSE solution and that an approximate inverse would produce similar performance. This is possible when the quantized solution computed with using the approximate inverse is the same as that computed with the exact inverse. We quantify the amount of approach that can be tolerated for this to happen. Motivated by this, we propose to use existing iterative methods to obtain approximate inverses with low complexity. We show that after a sufficient number of iterations, inversion using iterative methods can yield similar error performance. Furthermore, we also show that the benefit of using an approximate inverse is not limited to linear detectors, but can be extended to non-linear detectors such as the sphere decoders (SD). An approximate inverse can be used for any SD that requires matrix inversion. We show that applying the approximate inverse leads to a smaller radius, which in turn reduces the search space, resulting in reduced complexity. The numerical results support our claim that using approximate matrix inversion reduces decoding complexity in large/massive MIMO systems without performance loss due to errors.

Keyword : ***- Multi Input Multi Output, Linear Detector, Zero Forcing, Minimum Mean Square Error, Sphere Decoding .***

1. INTRODUCTION

Multiple-input multiple-output (MIMO) communication techniques have been an important area of focus for next-generation wireless systems because of their potential for high capacity, increased diversity, and interference suppression. In practice, the main challenge for MIMO systems is the receiver design that can obtain low error-rate performance with acceptable computational complexity.

With the increasing demand for high performance, Multiple-Input-Multiple-Output (MIMO) systems with a large number of antennas are expected to become an indispensable part of fifth-generation radio technology. It uses a large number of antennas at once. Base station (on the order of hundreds) operated to serve relatively fewer users. However, we know that as the number of antennas increases, the complexity of the detection algorithms increases. Therefore, there is a need for techniques that, while exploiting the additional degrees of freedom, are able to efficiently decode the transmitted signal in terms of complexity and error behavior. downlink and as a decoder in a massive MIMO uplink. Even complex decoders for uplink transmission require calculation of the IF/MMSE solution. For example, neighborhood-based algorithms or scatter-based detectors use such linear detectors for initialization. a ZF or MMSE solution requires an array investment. However, finding an inverse is computationally expensive, especially when a large number of antennas are used. In this article we argue that an approximate inverse matrix is sufficient to find a ZF/MMSE solution. In other words, using an approximate inverse does not degrade the quality of an IF/MMSE solution. Since the solution obtained using linear detectors still needs to be quantized, it is clear that there is a way to use an approximate inverse as long as the quantized solution remains unchanged. We derive bounds on the approximation such that their quantized IF/MMSE solutions equal the exact approximate inverse and in the expected sense. Furthermore, we show that the benefits of using an approximate inversion are not limited to linear detectors.

2. LITERATURE SURVEY

This is possible if the quantized solution calculated using the approximate inverse is same as the one calculated using the exact inverse. We quantify the amount of approximation that can be tolerated for this to happen.

Motivated by this, we propose to employ existing iterative methods for obtaining low complexity approximate inverses. We show that, after a sufficient number of iterations, the inverse using iterative methods can provide a similar error performance.

In addition, we also show that the advantage of using an approximate inverse is not limited to linear detectors but can be extended to nonlinear detectors such as sphere decoders (SD). An approximate inverse can be used for any SD that requires matrix inversion.

We show that the advantages of using an approximate inversion are not limited to linear detectors. Thus, a class of Sphere Decoding (SD) algorithms require the ZF solution for computing the Babai Radius (BR) consequently requiring matrix inversion. Hence, one can think of utilizing an approximate matrix inverse even in complex decoding schemes like SD.

The approximate inverse has two advantages. Firstly, it reduces the complexity of matrix inversion. But secondly, and more importantly, we prove that it results in a smaller BR. This is a bigger advantage as complexity of decoding in such SD algorithms is largely governed by the choice of BR. Simulation's results for large/massive MIMO systems corroborate that the proposed SD provides a low complexity solution with no loss in error performance.

Our SD approach incorporates both the strategies wherein we initialise with a BR computed using a low complexity iterative matrix inverse and also update the radius adaptively with every excellent point. The amount of updates while employing this approach will be substantially reduced, as the radius would be adjusted only when a new point is closer to the broadcast signal than ZF.

3. PROPOSED SOLULTION

Consider a massive MIMO downlink with N transmit antennas at the base station and K users, each with a single receive antenna. Such a system can be represented by

$y_d = H_d s_d + n_d$, (1)

where sd = Wxd, W is the linear precoder such as ZF or MMSE and xd is the N-dimensional signal vector transmitted by the base station. Each element in xd is drawn from a set Ω whose entries belong to an MQAM constellation with an average symbol energy Es. Hd represents the K × N channel matrix whose elements are independently and identically distributed (i.e.) with zero mean and unit variance, and nd is an i. Zero-mean Gaussian noise vector with dimension K × 1 and variance N0. The ith input of the yd vector, yi,d, is the signal destined for the ith user, for i = 1, 2, · · ·, K. Similarly, in the uplink Case be represented by.

$y_u = H_u x_u + n_u$, (2)

where x_u is the K-dimensional transmitted signal vector whose ith entry is the symbol transmitted by the ith user, for i = 1, 2, , K .Again, each element in x_u is drawn from the set Ω, with an average symbol energy Es. Similarly, $H_u$is the i N × K channel matrix, where each coefficient has zero mean and unit variance. The noise vector n_u is i.N × 1 Gaussian, with each element having zero mean and N_0 variance, and y_u is the N-dimensional received signal vector at the base station.This results in a signal-to-noise ratio (SNR) KE_s/N_0 at each receiving antenna

Linear detectors such as ZF and MMSE are useful for both uplink and downlink (as precoders) in Massive MIMO systems. The expressions for these detectors can be expressed as

$$x_{ZF} = [(H^H H)^{-1} H^H y] \quad (3)$$

$$x_{MMSE} = [(H^H H + N_0/E_s I_K)^{-1} H^H y], \quad (4)$$

where ⌈.⌋ is the quantization operator for the set Ω and H is the N × K -Channel Matrix Quantization allows us to use approximate inversion instead of exact inversion while getting the same IF/MMSE solution. Since the operations are similar in both uplink and downlink, we only consider the uplink scenario for the analysis.

3.1. A LINEAR DETECTOR USING APPROXIMATE INVERSE

Maximum likelihood (ML): This is the optimal detector from the point of view of minimizing the probability of error (assuming equiprobable x). The maximum likelihood detector with Gaussian noise at the receiver antennas solves the following problem. The minimization is over $x \in X^{Mt}$, i.e. over all possible transmitted vectors. Unfortunately, solving this problem involves computing the objective function for all X^{Mt} potential values of x. Hence the ML detector has prohibitive (exponential in Mt) complexity.

Minimum Mean Square Error (MMSE): it minimizes the square error between the received and the transmitted vectors, taking into account the noise and operating on each component, separately. This method is not able to reach the maximum diversity order MrMt , but it is limited to $Mr - Mt + 1$. This causes a low Bit Error Rate (BER) at high SNRs.

Zero forcing can cause noise amplification if the minimum singular value of H is too small. This may be quantified by the notion of the condition number of the matrix H. The condition number of the matrix H is a measure of the relative magnitudes of the singular values of H. It is defined as the ratio between the largest and the smallest singular values of H. When the condition number is unity or close to unity, the matrix is said to be well conditioned. When the condition number is large, the matrix is ill conditioned. To reduce the sensitivity of linear receivers to the conditioning of the matrix H, we can add a regularization term to the objective function . Note that the minimization is only over all affine functions of y, which is parametrized by A and b. The expectation is over the randomness in x and n (the channel matrix H is assumed to be known and non random). If x were to be Gaussian (instead of being from discrete constellation points), this is also the MMSE detector. Compared to the ML detector, both the linear detectors are simpler to implement, but the BER performances are worse.

3.2. SPHERE DECODING USING ITERATIVE MATRIX INVERSE

Now, let us investigate the advantages of using iterative matrix inverses for non-linear detectors, such as SD. Presently, there are two main versions of SD. The first is the SchnorrEuchner enumeration, that updates the radius for SD adaptively, where after starting with an infinite radius, the search space shrinks with each good point until we get the optimal solution. In large/massive MIMO systems, such a technique would result in a huge decoding complexity. The other one is Fincke-Pohst algorithm based SD, which uses a fixed radius approach, and all the points that are inside the search space defined by the radius are compared for detecting the transmitted signal.

Algorithm 1: Proposed SD Scheme
Input: y, H, Ω, k
Output: $\hat{x}$
Initialization $i = K$, $cost = r_k$, $\tilde{c}_i = 0$;
[Q R] $\leftarrow$ QR decomposition of H and $z = Q^H y$;
$\hat{x} \leftarrow$ DFTS (z, R, Ω, cost, $\tilde{c}_i$, d, i);
Function: DFTS (z, R, Ω, cost, $\tilde{c}_i$, i)
for $j \leftarrow 1$ to length(Ω) do
  $c_j = |z_i - r_{i,i} x_j|^2, \ \forall x_j \in \Omega$;
end
Sort c_j's in ascending order and keep only those symbols for which $c_j < (cost - \tilde{c}_i)$;
if $c_j \nless (cost - \tilde{c}_i)$ then
  return $\hat{x}$, cost;
else
for $u \leftarrow 1$ to length(c) do
  $\hat{x}_i = x_u$;
  $\tilde{c}_i \leftarrow \tilde{c}_i + c_u$;
  if $i = 1$ then
    if $cost_{temp} < cost$ then
      cost $\leftarrow \tilde{c}_i$;
      return $\hat{x}$, cost;
    end
  else
    $\tilde{z} = z - R_{:,u}\, x_u$;
    Extend the tree T for all Ω;
    [$\hat{x}$, cost] $\leftarrow$ DFTS($\tilde{z}$, R, Ω, cost, $\tilde{c}_i$, $i - 1$);
  end
end
end

This technique is extremely sensitive to the choice of the radius. It has been shown in the literature that both these approaches provide near ML performance. In this section, we propose a mechanism to reduce the complexity of SD. Our SD algorithm combines both the strategies wherein we initialize with a BR computed using a low complexity iterative matrix inverse and also update the radius adaptively with every good point. The number of updates when using this algorithm would be significantly less, as the radius will be updated only when a new point is closer to the transmitted signal than ZF. Also, we are always guaranteed a solution as the ZF solution is always inside the searched domain. In Algorithm 1, we show the steps of the proposed SD scheme.

4. SIMULATION RESULT

We have shown the advantages of using an approximate matrix inverse for detectors in large/massive MIMO systems. We obtained the maximum error which can be tolerated in the inverse to arrive at the same quantized ZF/MMSE solution.

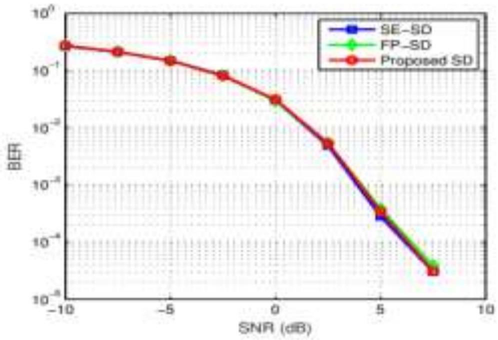

fig -1 :Bit error performance for different SD schemes for a massive MIMO system with 32 base antennas and 8 users for 4-QAM.

Simulation results show that iterative inversion methods, used to calculate the ZF and MMSE solutions, reached the same performance as provided by the exact inverse for sufficient number of iterations. Extending the idea to complex detectors like SD, we show that the value of BR calculated using iterative methods is less than the BR obtained through the exact method. To this end, we proposed an adaptive SD scheme that uses BR as the initial radius. Simulation results show that the proposed SD scheme outperforms FP-SD and SE-SD in terms of complexity without any loss in performance.

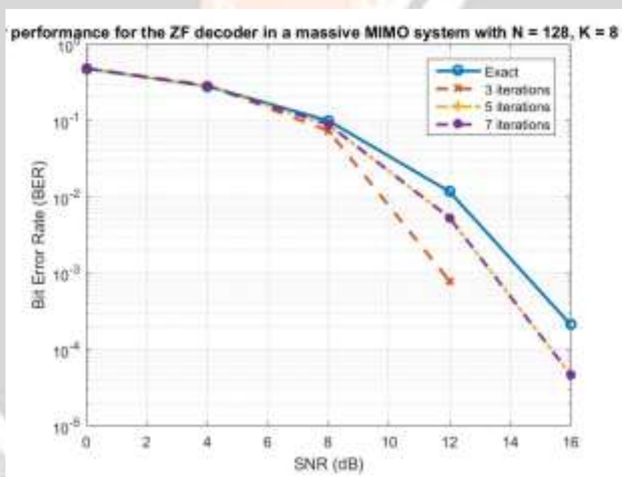

fig-2:Bit error performance for the ZF decoder in a massive MIMO system with N = 128, K = 8 for 16-QAM.

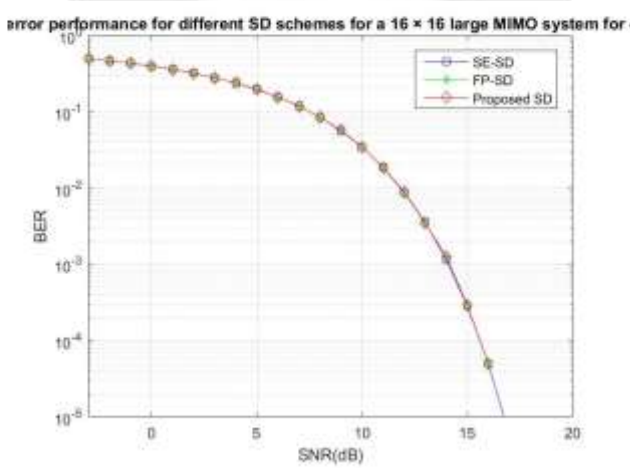

fig-3: Bit error performance for different SD schemes for a 16 × 16 large MIMO system for 4-QAM.

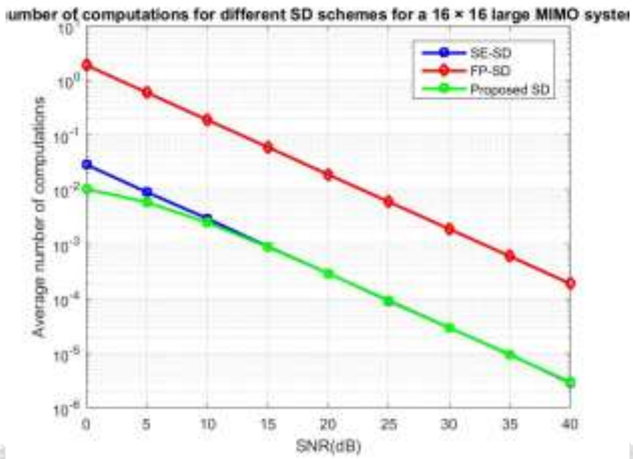

fig-4:Average number of computations for different SD schemes for a 16 × 16 large MIMO system for 4-QAM.

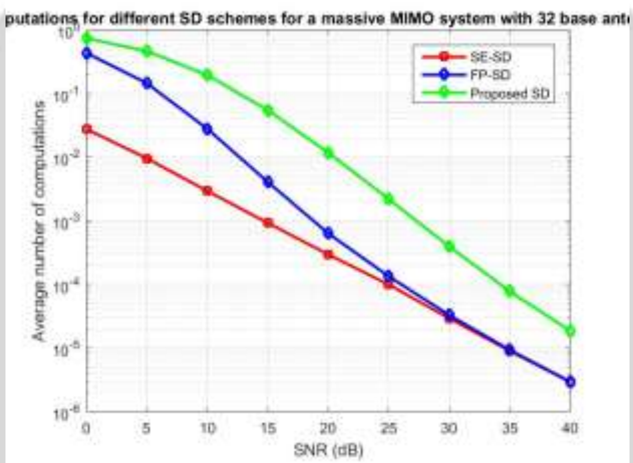

fig-5:Average number of computations for different SD schemes for a massive MIMO system with 32 base antennas and 8 users for 4-QAM.

5. CONCLUSIONS

We have shown the advantages of using an approximate matrix inverse for detectors in large/massive MIMO systems. We obtained the maximum error which can be tolerated in the inverse to arrive at the same quantized ZF/MMSE solution. Simulation results show that iterative inversion methods, used to calculate the ZF and MMSE solutions, reached the same performance as provided by the exact inverse for sufficient number of iterations.

Extending the idea to complex detectors like SD, we show that the value of BR calculated using iterative methods is less than the BR obtained through the exact method. To this end, we proposed an adaptive SD scheme that uses BR as the initial radius. Simulation results show that the proposed SD scheme outperforms FP-SD and SE-SD in terms of complexity without any loss in performance

6. ACKNOWLEDGEMENT

We would like to thank our guide K.Deepthi for his valuable guidance during project time period.

7. REFERENCES

[1] 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.

[2] F. Boccardi, R. Heath, A. Lozano, T. Marzetta, and P. Popovski, “Five disruptive technology directions for 5G,” Communications Magazine, IEEE, vol. 52, no. 2, pp. 74–80, 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 Proc., IEEE Journal of, vol. 8, no. 5, pp. 742–758, Oct 2014.

[4] J. Hoydis, S. ten Brink, and M. Debbah, “Massive MIMO in the UL/DL of Cellular Networks: How Many Antennas Do We Need?” Selected Areas in Communications, IEEE Journal on, vol. 31, no. 2, pp. 160– 171, February 2013.

[5] H. Li and V. Leung, “Low complexity zero-forcing beamforming for distributed massive MIMO systems in large public venues,” Comm. and Networks, Journal of, vol. 15, no. 4, pp. 370– 382, Aug 2013.

[6] A. K. Sah and A. K. Chaturvedi, “Reduced neighborhood search algorithms for low complexity detection in MIMO systems,” in GLOBECOM 2015. IEEE International Symposium on, Dec 2015.

[7] N. Srinidhi, T. Datta, A. Chockalingam, and B. Rajan, “Layered Tabu Search Algorithm for Large-MIMO Detection and a Lower Bound on ML Performance,” Communications, IEEE Transactions on, vol. 59, no. 11, pp. 2955–2963, November 2011.

[8] X. Peng, W. Wu, J. Sun, and Y. Liu, “Sparsity-boosted detection for large MIMO systems,” Communications Letters, IEEE, vol. 19, no. 2, pp. 191–194, Feb 2015.

[9] J. W. Choi and B. Shim, “New approach for massive MIMO detection using sparse error recovery,” in Global Communications Conference (GLOBECOM), 2014 IEEE, Dec 2014, pp. 3754–3759.

[10] Y. Wang and H. Leib, “Sphere decoding for mimo systems with newton iterative matrix inversion,” Communications Letters, IEEE, vol. 17, no. 2, pp. 389–392, February 2013.