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Low Complexity And High Performance Sphere Detection Technique For MIMO Communication Systems

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***Abstract*—In literature many authors reported that in multiple input multiple output (MIMO) detection methods sphere-decoding (SD) is one of the efficient detection technique. In general, Euclidean norm is used for traversing a tree in sphere detection. By using the proposed method circuit complexity can be reduced with negligible performance loss. This is due to the reduction in the number of nodes visited in the critical path of the search tree. This paper presents the performance of complexity of 4x4 MIMO with 16-QAM modulation. The performance is compared with maximum likelihood detection (MLD) and L^2 norm with the help of MATLAB simulation results. It was observed that the complexity is reduced when mean of real multiplications and mean of real additions are calculated. Proposed $L\infty$ sphere detection shows better performance as the number of transmitting antennas increased. The tree pruning behavior of proposed SD is aggressive than the previously reported ones. Proposed $L\infty$ sphere detector follows new approach of radius selection for reducing the computational complexity as compared to the L^2 sphere de-coding algorithm and with the ideal ML decoder. It was also observed that using the infinity-norm reduces the hardware complexity of sphere detector considerably at only a minor performance loss.**

Keywords— MIMO; Sphere Detection; Circuit Complexity; Bit Error Rate

I. Introduction (*Heading 1*)

Engineers have been forced to develop innovative techniques to enhance spectral efficiency and consistency in wireless networks as the need for greater data rates and improved service quality grows [1]. MIMO is a technique for improving spectrum efficiency or diversity. Traditional Multiple Input Multiple Output (MIMO) detection techniques such as Zero Forcing (ZF), Minimum Mean Square Error (MMSE), Successive Interference Cancellation (SIC), and others are used when computational complexity is low and performance is modest. These low computing complexity [2] MIMO detection techniques perform poorly in terms of bit error rate (BER).

In MIMO detection the major problem is to achieve optimum performance with less computational complexity. Maximum likelihood detection (MLD) provides the greatest performance in MIMO detection techniques, but it has a major disadvantage that its high computational complexity which is exponentially increases when the modulation order or the number of transmitting antennas increases. So the Maximum Likelihood algorithm practically not feasible and the investigation of near optimal and low computational complexity MIMO detector is needed. So one of the solutions is to use Sphere Detection method based on Maximum Likelihood which is an optimal solution and with reduced computational complexity. When utilizing the ML detection strategy, the computational difficulty of exhaustive search grows exponentially with the number of transmitting antennas, but the complexity of the Sphere Detection methodology grows polynomially with the number of antennas over a wide range of SNR.

The remainder of the article continues with a brief description of the MIMO system model in Section 2, followed by a discussion of the sphere detection technique in Section 3. The findings of Bit Error Rates (BER) of several MIMO detection algorithms are shown in Section 4. In Section 5, the author discusses how the proposed detector achieves near-ML performance while requiring less complexity.

II. System Model

A. Basic Idea

The sphere identification technique's basic concept is to restrict the search to just locations that are inside a sphere with a centre at the supplied vector x and radius r. The sphere's closest point to x is definitely the lattice's closest point to x. Calculation time and computational complexity are decreased when the search space is minimized. The advantage of the sphere decoding method is that it eliminates the need to use the traditional maximum likelihood decoding algorithm, which searches the whole vector constellation for the most likely transmit signal vector. The sphere detection algorithm is a refined version of the ML algorithm. Its basic concept is to minimize computing complexity by narrowing the search range, or to search just the grid points within the received signal's hyper sphere[3] rather than the full grid. Key issues affecting the sphere decoding are: (1) How to select the search radius d. If d is too large, contains too many points inside the sphere, the complexity will approach or reach the exponential complexity of the maximum likelihood decoding. If d is too small, the point may be within a grid are not included, then the sphere decoding algorithm will not be a reasonable solution. (2) How to determine whether a point is within a sphere. Clearly it is an unverified approach where one has to check every point to see whether it is located within the sphere or not. If this approach is followed then the resulting calculation is exponential so this approach is not ideal. Sphere detection addresses an issue by splitting the task of finding the points in a one-dimensional (actual) hyper or a two-dimensional (complex) hyper sphere into m Problems with the identification of which symbols are in a 1D (real part) or 2D (complex) hyper sphere into m difficulties to determine if symbols have one (true) or two-dimensional (complex). This implies that in the present world it is essential to identify the numbers of the set constellation within a certain interval, while in the complicated case it is necessary to identify all symbols that fall inside a particular circle. Below figure 1 shows the MIMO system model.

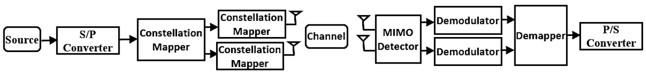

Fig. 1. MIMO System Model.

The sphere detection technique has to compute how many constellation points are located inside the search sphere [4] and the sphere detector needs to verify the euclidean distance of every node s to identify which point is located within the radius D search sphere. Thus, it is still feasible to search thoroughly. Determining which gill nodes fall within the m-dimensional sphere is challenging to achieve, but in a single-dynamic scenario m = 1[5] is unimportant.

By finding all nodes in lesser dimensions (1, 2, . m), and the same distance from the centre of the sphere within the hyper-sphere. This permits the process to stretch from k to k + 1. The method to sphere detection is therefore illustrated through the branches of a tree K^{th}layer are the grid nodes which are within the radius d sphere.

B. Signal Model

Having M transmitting antennas, N receiving antennas ($N \geq M$) of the system signal model can be expressed as:

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

When r is the signal vector received at a given moment, the channel matrix H is a complicated N*M matrix field, the matrix $h_{ij}(i = 1,...,N, j = 1,...,M)$ element represents the j from the transmitting antenna to the receiving antenna i channel between fading coefficients, which statistically independent, and subject to $\mathcal{N}(0,1)$ distribution. The term n is zero mean complex white Gaussian noise and its covariance matrix: $E(nn^H) = \sigma_n^2 I_N$.

III. Sphere Detection

3.1 Sphere Detection Algorithm based on L^2 norm

Sphere detection performs exhaustive search by ML detection solution is

$$\hat{s} = \min_{s \in D \subset Z^m} \left\| r - Hs \right\|_2 \tag{2}$$

In above equation Z^m is an integer lattice point set, s is the transmitted signal. But tree search is subjected to a sphere constraint

$$d_s^2 \geq \left\| r - Hs \right\|_2^2 \tag{3}$$

Where d_s is the appropriate radius of the sphere.

The radius ds should be properly determined and large enough for the search area to contain at least one point. If d_s selected too large many points will lies in the sphere and all these points satisfy the sphere constraint criteria and the complexity of Euclidean norm will be high. Thus the sphere restriction [6] is projected by conducting QR decomposition as a weighted tree research issue, and the technique is as follows.

1. The QR Decomposition (QRD) method is used to decompose the channel matrix H.

$$H = [Q_1, Q_2] \begin{bmatrix} R \\ 0_{(N-M)*M} \end{bmatrix} \tag{4}$$

Where $Q_1 \in R^{N*M}, Q_2 \in R^{N*(N-M)}$

And if R is an upper triangular matrix of size M x M and 0 is an all zeros matrix of size (N-M)*M, it may be represented as

$$d_2^2 = d_s^2 - \left\| Q_2^H y \right\|_2^2, y = Q_1^H r \tag{5}$$

According to equation (5) equation (3) becomes

$$d_2^2 \geq \left\| y - Rs \right\|_2^2 \tag{6}$$

Based on the definition of Euclidean norm of the vector and expression the right side is the sum of the squares.

$$d_2^2 \geq \left\| y_{k:M} - R_{k:M,k:M} s_{k:M} \right\|_2^2 + \left\| y_{1:k-1} - R_{1:k-1,1:k-1} s_{1:k-1} - R_{1:k-1,k:m} s_{k:m} \right\|_2^2 \tag{7}$$

Now in above equation by ignoring the second part the equation becomes

$$d_2^2 \geq \left\| y_{k:M} - R_{k:M,k:M} s_{k:M} \right\|_2^2 \tag{8}$$

2. Start from k=M and substitute

$$d_2^2 \geq (y_M - R_{M,M} s_M)^2 \tag{9}$$

3. Start iteration k=M-1 and substitute in equation then

$$d_2^2 \geq (y_M - R_{M,M} s_M)^2 + (y_{M-1} - R_{M-1,M-1} s_{M-1} - R_{M-1,M} s_M)^2 \tag{10}$$

3.2 Sphere Detection Algorithm based on L^∞ norm

Previous section explains about 2-norm sphere decoding [7] and infinity norm sphere decoding obtained by replacing 2 with ∞ in equation 6 and it can be written as

$$d_\infty^2 \geq \left\| y - Rs \right\|_\infty^2 \tag{11}$$

It can be observed that the infinity norm spherical decoding operation is similar to 2-norm sphere decoding and Infinity norm sphere decoding complexity is less than 2-norm sphere decoding, but there is a slight loss of performance.

The metric $\left\| T(s) \right\|_\infty$ can be computed recursively according to

$$\left\| T_k(s_k) \right\|_\infty = \max \left\{ \left\| T_{k-1}(s_{k-1}) \right\|_\infty, \left| [T(s)]_{M-k+1} \right| \right\} \tag{12}$$

As a result $\left\| T_k(s_k) \right\|_\infty = d_\infty$ (13)

The L^∞ solution is obtained by selecting one node with minimum $\left\| T(s) \right\|_\infty$, so the solution is

$$\hat{s} = \arg \min_{s \in D \subset Z^m} \left\| T(s) \right\|_\infty \tag{14}$$

If the performance is to be near optimal in comparison with the maximum likelihood detection performance, the initial radius [8] of the hyper sphere must be selected. . If d is less than the search for a suitable point in the range, it needs to increase the value of d.

In order to obtain high efficiency in SD, it is necessary to modify a critical constraint, the search sphere radius or the primary radius of an iterative upgradable search range method. The properly characterizing of d is important; if the scan is too large, the number of antennas or users will have an exponential complexity with little benefit above maximum probability detection. Moreover, the algorithm cannot detect any locations in the search field if the radius is too tiny. The simplest definition of d is the half-distance between two points in a constellation, or, to put it another way, the distance between an arrangement sign and the decision zone's boundary. Squared constellations are obviously outperformed by this approach. For near optimal performance selection of initial radius has $d = \alpha n \sigma^2$. Where n is the twice the number of transmit antennas, σ^2 is the noise variance and α is the test value.

IV. Results and Discussion

A. Performance Analysis

The following is a 4 x 4 MIMO system, transmits symbols using 16-QAM modulation, and the first result compares the ML maximum likelihood detection (red), the second norm sphere decoding (blue), the infinite norm sphere decoding (green) simulation respectively, in terms of SNR (dB) versus BER and simulation time.

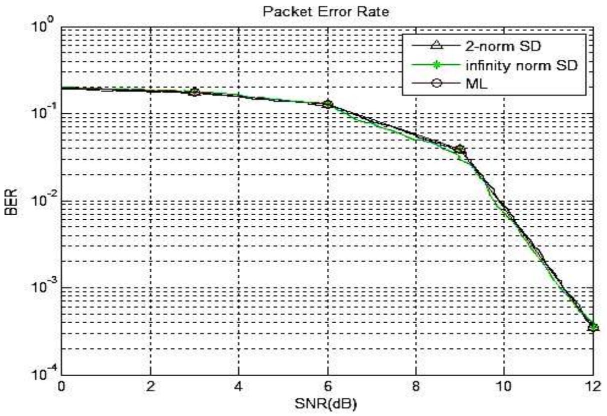

Fig. 2 Comparison of Bit Error Rate of different algorithms

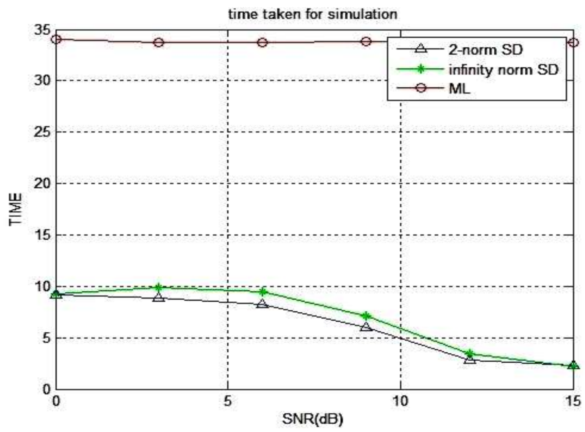

Fig. 3 Comparison of simulation time of different algorithms

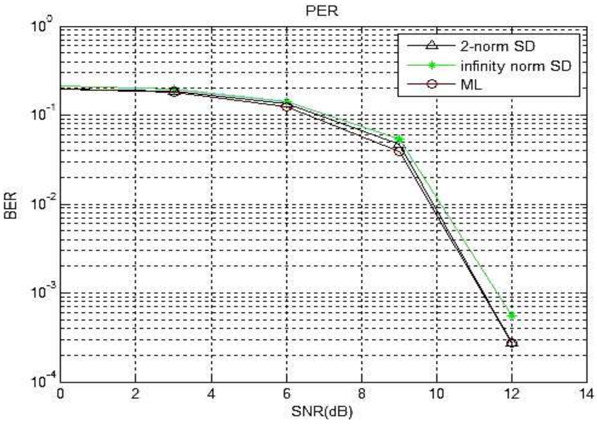

Fig. 4 Comparison of BER of algorithms with initial radius

Initial radius of the two-norm sphere decoding norm is given by the empirical formula. According to the above conditions, the simulation curve shown in Figure 2, 3, 4and 5.

The simulation time point of view, Maximum Likelihood Detection takes much time in comparison with L^2 norm sphere detection and L^∞ norm sphere detection, where L^∞ norm sphere detection takes less simulation time. Form the results it was observed that L^2 norm sphere decoding come close to the maximum likelihood detection performance and proposed detector complexity is less with some performance degradation. It may be noted that both the L^2 and L^∞ detection techniques preserved the diversity order same as ML detector. This can be noticed if the slope of BER curve at high SNR is analyzed.

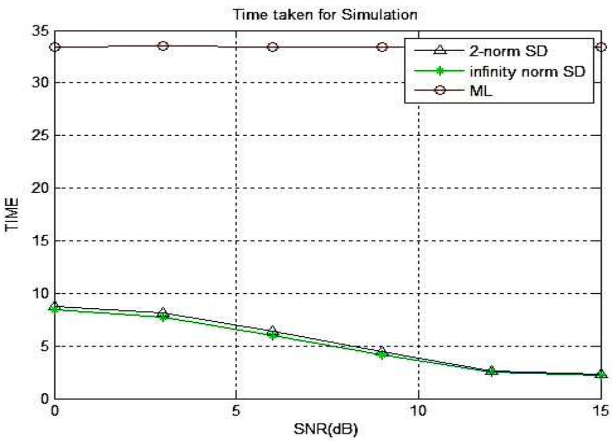

Fig. 5. Comparison of simulation time of algorithms with initial radius

B. Complexity Analysis

Complexity of proposed Sphere Decoder is analyzed by observing how many nodes are visited during traversing tree according to $\|T_k(s_k)\|_\infty \le d_\infty$ equation. Proposed technique with four transmit and receive antennas attains remarkable reduction in the average complexity as it can be seen in the figure 6. When the mean of real multiplication is considered, the suggested sphere decoder performs worse; however, when the mean of real addition is determined, the proposed method performs better. Also, it was observed that the number of counted flops are decreased in the proposed method.

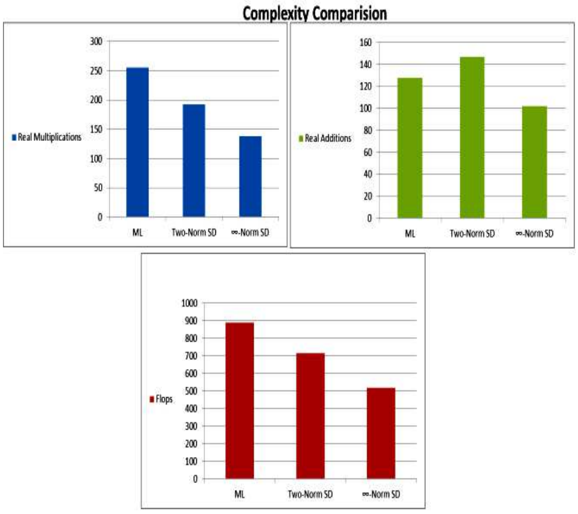

Fig. 6 Complexity comparison of algorithms

V. Conclusion

In this paper first the basic principles of sphere decoding are introduced, the proposed sphere detection importance is proved by reducing almost half of the hardware complexity and also algorithm complexity in comparison with the MLD and other SD. Proposed detector also achieved the same diversity as other detectors. Proposed detector complexity for metric computation is reduce by avoiding squaring operations and reduced the algorithmic complexity by reducing the number of nodes visited in search tree. Further there is a scope for VLSI implementation of this sphere detector which may turn to be useful in terms of silicon complexity, low power and area.

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