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Novel Soft Decision Generation Technique for Performance Improvement of 3GPP LTE-Advanced Systems with Multiple Antennas

Jaeyoung Park[1] and Jaekwon Kim[1*]
[1]Division of Computer and Telecom. Engineering, Yonsei University, Wonju

다중 안테나를 사용하는 3GPP LTE-Advanced 시스템의 성능향상을 위한 새로운 연판정 값 생성방식

박재영[1], 김재권[1*]
[1]연세대학교 원주캠퍼스 컴퓨터정보통신공학부

Abstract 3GPP LTE-Advanced systems adopt multiple antennas for high speed data transmission. In general, the receiver complexity of a spatially mutiplexed (SM) multiple-input multiple-output (MIMO) system grows in proportion to the number of candidate vectors. A large number of candidate vectors increases the reliability of the soft output values. The maximum likelihood (ML) signal detection with a large number of candidate vectors achieves high performance. On the other hand, low complexity receiver techniques with a small number of candidate vectors provide soft output values, such as low reliability. This paper addresses the improving reliability of the soft output obtained from a small number of candidate vectors. The improved performance of the proposed technique with the aid of computer simulations is reported.

요 약 LTE-A 시스템은 고속 데이터 전송을 위해 다중안테나를 장착하고 있다. 일반적으로 공간다중화 다중안테나 시스템의 수신기 복잡도는 후보벡터의 개수에 따라 증가한다. 후보벡터의 개수가 증가함에 따라 연판정 값의 신뢰도가 향상된다. 많은 수의 후보벡터를 생성하는 최우도 신호검출방식을 사용하면 우수한 성능을 달성할 수 있다. 반면 적은 개수의 후보벡터를 생성하는 저복잡도 수신기는 신뢰도가 낮은 연판정 값을 생성한다. 본 논문에서는 적은 수의 후보벡터를 사용해서 얻게되는 연판정 값의 신뢰도를 향상시키는 새로운 기술을 제안하고 모의실험을 통해 개선된 성능을 확인한다.

Key Words : 3GPP LTE-Advanced, LLR, Signal detection, Soft decision

1. Introduction

When soft input channel decoder is used at the receiver, the overall system performance significantly depends on the soft output quality from signal detectors. In general, ML metric values are used for soft output calculation in spatially multiplexed(SM) multiple input multiple output(MIMO) systems. The reliability of soft output increases in proportion to the number of available candidate vectors. In ML detection, all possible transmitted signal vectors are candidate vectors, thus the resulting soft output is of high reliability, however, its complexity is also high.

In order to reduce the complexity, various suboptimal methods have been proposed such as QRM-MLD [1,2], QR-LRL [3,4], lattice reduction aided detection [5,6], sphere decoding [7]. In those methods, the number of candidate vectors is set to a fixed value in order to reduce the complexity, unfortunately, the reliability of soft output is also reduced.

*Corresponding Author : Jaekwon Kim(Yonsei Univ.)
Tel: +82-33-760-2263 email: jaekwon@yonsei.ac.kr
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When the candidate vector set is small, the problem of null ML metric for a bit value arises. The problem occurs to all suboptimal detectors including QRM-MLD and QR-LRL. In [1][2](applied to QRM-MLD) [3] (applied to QR -LRL), a threshold value was determined to replace the null ML metric value. However, there is another performance degrading factor when the candidate vector set is small.

In this paper, we analyze two reliability degrading factors when only a small number of candidate vectors are available. Then, we describe methods to increase soft output reliability resolving the problems without increasing the number of candidate vectors. One method is to use Euclidian distance instead of squared Euclidian distance [1,2]. Then we propose a method that clips ML metrics using a clipping threshold. Both methods outperform the conventional method in [3]. We also show that the conventional Euclidian distance method [1,2] is theoretically very similar to the proposed method. The soft output improvement methods can be added to all suboptimal detection methods with a small number of candidate vectors. As an example, we use the recently proposed QR-LRL method to confirm our analysis.

2. Spatially Multiplexed MIMO System

In this paper, we consider a wireless channel with n_T transmit antennas and n_R receive antennas. The relation between the transmitted signal $\mathbf{x}=[x_1\, x_2 \cdots x_{n_T}]^T$ and the received signal $\mathbf{y}=[y_1\, y_2 \cdots y_{n_R}]^T$ is expressed as

$$\mathbf{y}=\mathbf{Hx}+\mathbf{z} \tag{1}$$

$$\mathbf{H}=[\mathbf{h}_1\, \mathbf{h}_2 \cdots \mathbf{h}_{n_T}] \tag{2}$$

where $x_i,\, i=1,2,\cdots,n_T$ is the signal transmitted from the i-th transmit antenna; $y_i, j=1,2,\cdots,n_R$ is the received signal at the j-th received antenna; and $h_{i,j},\ j=1,2,\cdots,n_R,\ \ i=1,2,\cdots,n_T$ is the channel gain between the i-th transmit antenna and the j-th receive antenna, forming the channel gain vectors $\mathbf{h}_i=[h_{1,i}\, h_{2,i} \cdots h_{n_R,i}]^T,\ i=1,2,\cdots,n_T$. Also $z_i \sim CN(0,\sigma_z^2),\ \ j=1,2,\cdots,n_R$ is the circularly symmetric white Gaussian noise, forming the noise vector $\mathbf{z}=[z_1\, z_2 \cdots z_{n_R}]^T$. In this paper, we assume that the transmitted signal $x_i, i=1,2,\cdots,n_T$ is drawn from a quaternary amplitude modulation(QAM) constellation.

First, we consider the LLR values when all the possible vectors and their ML metric values are available. Using the max-log approximation, the LLR values of $b_{k,m},\ k=1,2,\cdots,\log_2|\mathrm{C}|,\ m=1,2,\cdots,n_T$ are described as follows.

$$L(b_{k,m}|\mathbf{y}) \approx \min_{\mathbf{x}\in\chi(k,m)^-} D(\mathbf{x}) - \min_{\mathbf{x}\in\chi(k,m)^+} D(\mathbf{x}) \tag{3}$$

where, $D(\mathbf{x})=\|\tilde{\mathbf{y}}-\mathbf{Rx}\|^2, \chi(k,m)^-$ is the set of candidate vectors that satisfy $b_{k,m}=-1,\ \ \chi(k,m)^+$ is the set of candidate vectors with $b_{k,m}=+1$. If 16-QAM is used for 3×3 MIMO system, the size of the candidate vectors $|\chi(k,m)^-|=|\chi(k,m)^+|$ are $\mathrm{C}^{n_T}/2=16^3/2$. The ML detection achieves high performance, however, its complexity is very high, requiring a large number of ML metric calculations.

3. Performance Degradation

In this section, we point out the performance degradation factors of soft output when only a small number of candidate vectors are available. Although there exist various suboptimal signal detection methods, we use the QR-LRL in order to generate a small set of candidate vectors.

Assume $\mathbf{H}=\mathbf{QR}$, $\tilde{\mathbf{y}}=\mathbf{Q}^H\mathbf{y}$, $n_T=3$, the QR-LRL is described as follows.

```
B = [];
metric = [];
For i = 1 : |C|
    x_{3,temp} = C(i)
    x_{2,temp} = Q((ỹ_2 − r_23 x_{3,temp}) / r_22)
    x_{1,temp} = Q((ỹ_1 − r_12 x_{2,temp} − r_13 x_{3,temp}) / r_11)
    x = [x_{1,temp} x_{2,temp} x_{3,temp}]^T
    metric temp = ‖ỹ − Rx‖^2
    B = [B x]
    metric = [metric  metric temp];
End
```

In the algorithm description, C stands for constellation point set, $C(i)$ is the i-th constellation point, $|C|$ stands for the number of elements in the set C. The function $Q(\tilde{x})$ is the slicing function defined as $Q(\tilde{x}) = \arg\min_{x \in C} |x - \tilde{x}|$. Using the above QR-LRL, we obtain $|C|$ candidate vector and corresponding ML metric values. At the end of QR-LRL, the set $\mathbf{B}$ is the candidate vector set, and the number of vectors in $\mathbf{B}$ is the same as $|C|$. When 16-QAM is used $|\mathbf{B}| = |C| = 16$. In QRM-MLD detection method, the parameter M is involved, and the candidate vector set is of size $M \times |C|$, thus as M increases, its performance get closer to the optimal ML performance.

When a suboptimal signal detection is used, the following approximated LLR values can be used.

$$L(b_{k,m}|\mathbf{y}) \approx \min_{\mathbf{x} \in S(k,m)^-} D(\mathbf{x}) - \min_{\mathbf{x} \in S(k,m)^+} D(\mathbf{x}) \quad (4)$$

where, $S(k,m)^-$ is the set of candidate vectors that with $b_{k,m} = -1$ and is a subset of the candidate vector set $\mathbf{B}$. The set $S(k,m)^+$ is similarly defined. If we use the approximated LLR values in (4), we have the following problems.

Problem 1: The value for a bit is the same for all the vectors in $\mathbf{B}$, i.e., $S(k,m)^- = \varnothing$ or $S(k,m)^+ = \varnothing$, thus we can calculate only one term in (4).

Problem 2: Both values of a bit exist in the candidate vector set $\mathbf{B}$, i.e., $S(k,m)^- = \varnothing$ and $S(k,m)^+ = \varnothing$, however, the minimum ML metric for a specific bit value obtained form $\mathbf{B}$ is larger than the optimal minimum ML metric obtained when all the possible candidate vectors are available.

The first problem is obvious. Let us deal with the second problem in more detail. When the true ML vector is included in the set $\mathbf{B}$, assuming $b_{k,m,ML} = b_{k,m,ML,B} = -1$, the LLR value is expressed as follows.

$$L(b_{k,m}|\mathbf{y}) \approx D(\mathbf{x}_{ML}) - \min_{\mathbf{x} \in S(k,m)^+} D(\mathbf{x}) < 0 \quad (5)$$

In (5), the first term is correct, but the second term is larger than the true value $\min_{\mathbf{x} \in \chi(k,m)^+} D(\mathbf{x})$. When the true ML vector is not in the set, the LLR value, assuming $b_{k,m,ML} \neq b_{k,m,ML,B} = -1$, is expressed as follows.

$$L(b_{k,m}|\mathbf{y}) \approx D(\mathbf{x}_{ML,B}) - \min_{\mathbf{x} \in S(k,m)^+} D(\mathbf{x}) < 0 \quad (6)$$

In (6), the both terms have positive errors, i.e., $D(\mathbf{x}_{ML,B}) > D(\mathbf{x}_{ML})$ and $\min_{\mathbf{x} \in S(k,m)^+} D(\mathbf{x}) \geq \min_{\mathbf{x} \in \chi(k,m)^+} D(\mathbf{x})$.

4. LLR from Suboptimal Detectors

In this section, we describe three methods that attempt to resolve the two problems in section 3. We first consider the method in [3] that is described as follows.

4.1 A Previous Method in [3] and [4]

When we use QR-LRL, all the constellation points are tried as the first layer symbol, thus all the bit values of the first layer symbol exist in the candidate set. Using this fact, the following method was used to resolve the non-existing bit value problem. First, LLR value are calculated for the first layer symbol i.e., $m = n_T,\ 1 \le k \le \log_2|C|$.

$$L(b_{k,n_T}|\mathbf{y}) \approx \min_{\mathbf{x} \in S(k,n_T)^-} D(\mathbf{x}) - \min_{\mathbf{x} \in S(k,n_T)^+} D(\mathbf{x}) \quad (7)$$

Using the above ML metrics, threshold value Th is calculated.

$$T^+(k) = \min_{\mathbf{x} \in S(k,n_T)^+} D(\mathbf{x}),\ 1 \le k \le \log_2|C| \quad (8)$$

$$T^-(k) = \min_{\mathbf{x} \in S(k,n_T)^-} D(\mathbf{x}),\ 1 \le k \le \log_2|C| \quad (9)$$

$$T(k) = \max(T^+(k), T^-(k)), 1 \le k \le \log_2|C| \quad (10)$$

$$Th = \max_k T(k) \quad (11)$$

Once we obtain the above threshold value, the possible null ML metric value in (4) is replaced by Th. The previous method resolves the first problem, however, the second problem is not resolved.

4.2 Clipping Threshold Method (CTM)

We propose to clip all the ML metrics that are larger than a threshold. We first consider the case $\mathbf{x}_{ML} = \mathbf{x}_{ML,B}$, if we assume that $b_{k,n_T,ML,B} = -1$, the absolute value of LLR in (5) is decreased if the second term is clipped. In this case the first term is the optimal value, however, the second term can be larger than the optimal value due to the small size of the candidate vector set. In the case of $\mathbf{x}_{ML} \not\in \mathbf{B}$, i.e., $\mathbf{x}_{ML} \ne \mathbf{x}_{ML,B}$ the two terms are statistically expected to be larger than a threshold value, thus both are clipped. We note that when the two terms are clipped, the LLR value becomes "0". We also note that there are cases where the two terms have positive errors but only one of them are clipped or none of them are clipped, depending on Th_{clip}, however, the two terms are expected to be clipped statistically.

In order to use the proposed method, we need a clipping threshold value Th_{clip}. When the candidate vector is different from the transmitted symbol vector, the corresponding ML metric is expressed as follows.

$$\|\mathbf{y} - \mathbf{H}\mathbf{x}\|^2 = \|\mathbf{z} + \mathbf{H}(\mathbf{x}_T - \mathbf{x})\|^2 = \|\mathbf{z} + \mathbf{H}\mathbf{e}\|^2 \quad (12)$$

where $\mathbf{x}_T$ is the true transmitted signal vector.

The LLR value calculation is associated with the minimum ML metric values in (12). The expected minimum value is as follows.

$$E\{\min_{\mathbf{e}}(\mathbf{z}^H\mathbf{z} + \mathbf{z}^H\mathbf{H}\mathbf{e} + \mathbf{e}^H\mathbf{H}^H\mathbf{z} + \mathbf{e}^H\mathbf{H}^H\mathbf{H}\mathbf{e})\} = \sigma_z^2 n_T + \lambda_{min}^2 E\|\mathbf{e}_{min}\|^2 \quad (13)$$

where, λ_{min} is the minimum eigenvalue of $\mathbf{H}^H\mathbf{H}$, $\mathbf{e}_{min}$ is the minimizer of the ML metric. In deriving (13), we assumed infinite degree of freedom of the error vector. Even when we use a very large constellation to increase the degree of freedom of $\mathbf{e}$, the calculation of (13) is computationally costly, involving an eigen-decomposition. In this paper, we propose the following clipping threshold value.

$$T^+(k,m,n) = \min_{\mathbf{x} \in S(k,m,n)^+} D(\mathbf{x}) \quad (14)$$

$$T^-(k,m,n) = \min_{\mathbf{x} \in S(k,m,n)^-} D(\mathbf{x}) \quad (15)$$

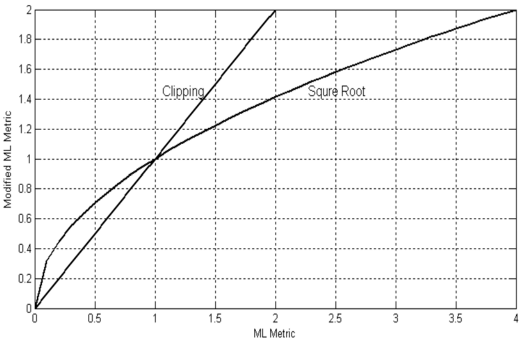
$$T(k,m,n) = \max(T^+(k,m,n),\ T^-(k,m,n)) \quad (16)$$

$$Th_{dip} = \frac{1}{\text{NMK}} \sum_n \sum_m \sum_k T(k,m,n) \quad (17)$$

where k is the bit index, m is the symbol index, n is the symbol vector index. It is assumed that a codeword involves multiple symbol vectors. We resolve the two problems in section 3 by the threshold value (17). When one of the two ML metric values can not be obtained, we replace the null value by Th_{clip}. We note that there is no case when both ML metrics are null. We also replace the other existing ML metric value by Th_{clip} when it is larger than Th_{clip}. For the case when both terms in (4) can be calculated, the terms are replaced by Th_{clip} when they are larger than Th_{clip}.

4.3 Euclidian Distance Method

In [1,2], it was shown that soft output generation using Euclidian distance instead of squared Euclidian distance improves the error performance of QRM-MLD. Since the same problems occur in QR-LRL, the same approach can also be used for QR-LRL. As can be seen in Fig. 1, the square root function is very similar to the clipping function. Since the ML metric becomes Euclidian distance after square root operation, we name the method *Euclidian distance method* (EDM). When the null ML metric value is replaced by the threshold value (17) and EDM is used to resolve the problem 2, the soft output calculation method can be considered as the old method [1,2] applied to QR-LRL.



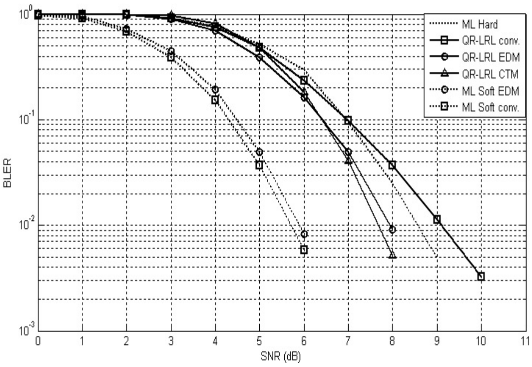
[Fig. 1] Square root function and a clipping function

5. Simulations

In this section, we compare the three methods in terms of block error rate. The simulation environment is summarized in Table1. Both the number of transmit antennas and the number of receive antennas are 4. The 16 channel gains are assumed to be i.i.d. Gaussian random variables with unit variance. A codeword involves 20 transmitted vectors. The channel coding is 1/2 rate convolutional coding with constraint length of 7. Thus, the block size is 80 bits when 4-QAM is used for symbol mapping.

[Table 1] Simulation Environment

System model	4x4 MIMO systems (SM)
Channel model	i.i.d. Rayleigh fading channels
Channel estimation	Ideal estimation
Block size	20 X 4 X 2 X 1/2 = 80 bits
Constellation	4-QAM
Channel coding	convolution coding (rate =1/2)
Interleaving	16 x 10



[Fig. 2] Performance of the optimal ML hard detection (ML Hard), the optimal ML soft detection (ML soft Conv.), the ML soft detection with Euclidian distance method (ML soft EDM), the suboptimal QR-LRL soft detection in [3], the suboptimal QR-LRL with EDM (QR-LRL EDM)[1,2], and the proposed suboptimal QR-LRL with CTM (QR-LRL CTM).

Fig. 2 compares the performance of various soft output generation methods when applied to QR-LRL. In Fig. 2, QR-LRL conv. is the method in section 4.1, QR-LRL EDM is the method in section 4.3. We note again that QR-LRL EDM can be considered as the previous work [1,2] applied to QR-LRL. QR-LRL CTM is the proposed method in section 4.2. As can be observed in Fig. 2, the proposed method is superior to the previous method in [1-3] from the error performance perspective.

Before we compare the methods from the complexity perspective, we consider the complexity of Euclidian distance and squared Euclidian distance. When an n -dimensional complex vector $[y_{1,R}+jy_{1,I}\ \ y_{2,R}+jy_{2,I}\ \ \cdots\ y_{n,R}+jy_{n,I}]^T$ is considered, the squared Euclidian distance is $\sum_{l=1}^{l=n}(y_{l,R}^2+y_{l,I}^2)$ which requires $2\times n$ real multiplications. In order to compute Eudlidian distance, an additional square root operation is necessary after the calculation of squared Euclidian distance. Since we are addressing QR-LRL signal detection, the candidate vector set are the same regardless of the soft output generation method. Also, the threshold calculation in equation (17) is used for both EDM and the proposed CTM. We note that the Euclidian distance instead of squared Euclidian distance is used for (17) in EDM, and the squared Euclidian distance is used for (17) in the proposed CTM. Thus square root operations are necessary in EDM while the operations are not necessary for the proposed CTM. Therefore, the proposed CTM is slightly superior to the previous EDM from the complexity perspective.

Also provided is the ML soft performance with and without EDM. Fig. 2 demonstrates that when there exist a large number of candidate vectors, conventional ML metric based soft output achieves better performance than EDM, however, when there exist only a small number of candidate vectors, EDM shows better performance.

6. Conclusions

In this paper, we analyzed the soft output reliability degradation factors when only a small set of candidate vectors are available. Inspired by our analysis, we proposed CTM which is theoretically similar to EDM that can be considered as the previous work [1,2] applied to QR-LRL. With the aid of computer simulations, we showed that the proposed CTM shows the better performance than the previous works [1-3]. We also showed that EDM degrades performance when there exist a large number of candidate vectors. We note that performance comparison was provided for only the QR-LRL signal detection in the paper, the proposed CTM and EDM techqniues are applicable to all suboptimal detection methods that produce an insufficient number of candidate vectors for soft decision calculations.

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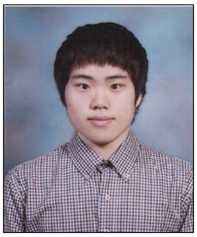
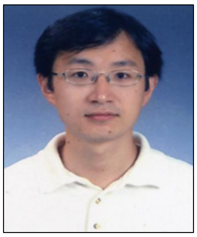
Jaeyoung Park [associate member]



- Feb. 2013 : B.S. Computer and Telecomm. Engineering Division, Yonsei Univ., Wonju.
- Feb. 2013 ~ current : Integrated M.S and Ph.D. student, Computer and Telecomm. Engineering Division, Yonsei Univ., Wonju

<Research Interests>
Wireless video transmission over MIMO-OFDM and SC-FDMA systems.

Jaekwon Kim [Regular member]



- Aug. 1995 : B.S., Electrical Eng., Chung-Ang Univ.
- Feb. 2000 : M.S., Electrical Eng., Chung-Ang Univ.
- May 2004 : Ph.D, Dept. of ECE., Univ. of Texas at Austin.
- Aug. 2004 ~ Aug. 2005 : Samsung Advanced Institute of Technology (SAIT), Researcher
- Sept. 2005 ~ current : Yonsei Univ., Computer and Telecomm. Engineering Division, Associate Professor

<Research Interests>
Signal detection for MIMO-OFDM/SC-FDMA sustems, Unequal error protection techniques for wireless video streaming