# 에너지 효율적 반복 SIC-MMSE MIMO 검출

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# Energy efficient joint iterative SIC-MMSE MIMO detection

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**요 약**

본 논문에서는 연판정 간섭 소거 최소 자승-오류(soft interference cancellation and minimum mean squared-error; SIC-MMSE) 방법을 이용한 새로운 에너지 효율적 다중안테나(multi-input multi-output; MIMO) 검출 기법을 소개한다. SIC-MMSE 방법의 가장 큰 계산 복잡도는 복소 행렬에 대하여 안테나 개수 만큼의 여러 번 역행렬 계산을 해야 하는데 있다. 본 논문에서는 행렬에 대한 테일러 시리즈 확장(Taylor series expansion) 기법을 이용하여 안테나 개수에 상관없이 단 한번의 역행렬 계산만을 필요로 하는 방법을 제안하며, 이와 같은 방법을 이용하여 계산의 복잡도를 감소시킬 수 있다. 본 논문에서 제안한 기법의 복잡도 감소 효과는 안테나 개수가 증가함에 따라 더 크게 나타난다. 본 논문에서 제시한 시뮬레이션 결과를 통하여 제안한 기법이 기존의 SIC-MMSE 기법에 비하여 더 적은 복잡도로 거의 동일한 성능을 도출할 수 있음을 알 수 있다.

Key Words : multiple-input multiple-output (MIMO), minimum mean squared-error (MMSE), iterative detection, soft detection

**ABSTRACT**

In this paper, we propose a new computationally efficient joint iterative multi-input multi-output (MIMO) detection scheme using a soft interference cancellation and minimum mean squared-error (SIC-MMSE) method. The critical computational burden of the SIC-MMSE scheme lies in the multiple inverse operations of the complex matrices. We find a new way which requires only a single matrix inversion by utilizing the Taylor series expansion of the matrix, and thus the computational complexity can be reduced. The computational complexity reduction increases as the number of antennas is increased. The simulation results show that our method produces almost the same performances as the conventional SIC-MMSE with reduced computational complexity.

## Ⅰ. Introduction

In most of wireless systems with multiple-input multiple output (MIMO) technique, a powerful error correction coding scheme with an iterative decoder is employed in order to meet the performance requirement [1]. The low-complexity iterative detection and decoding technique based on soft interference cancellation and minimum mean squared-error (SIC-MMSE) detection has received considerable attention recently due to its good performance-complexity tradeoff for coded MIMO systems [2]. The basic concept of the SIC-MMSE detection is to compute estimates of the transmitted symbols based on the a priori log-likelihood ratio (LLR) obtained from the channel decoder. The estimates are then utilized to calculate soft symbols and cancel the interference in the received signal vector.

During the soft interference cancellation process, the SIC-MMSE detector requires to perform $N_t$ times of the matrix inversion process in complex domain, where $N_t$ is the number of transmit antennas. A number of attempts have been made to reduce the complexity of the SIC-MMSE schemes [3]-[5]. In order to reduce the complexity of matrix inversion process, singular value decomposition (SVD) method was used in [3], while eigen value decomposition (EVD) and Cholesky decomposition methods were utilized in [4] and [5], respectively. However, all of these methods still need $N_t$ times of the

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matrix inversion process. Reference [6] proposed a complexity reduced method for the SIC-MMSE scheme which requires only a single MMSE filtering processes, by deriving a non-layer dependent matrix, but its performance was only demonstrated with non-iterative decoder such as soft-output Viterbi algorithm (SOVA) for convolutional codes.

In this paper, we propose a new efficient approach which can largely reduce the complexity of matrix inversion process for the SIC-MMSE schemes, using the Taylor series expansion. The proposed method requires only a single matrix inversion process instead of $N_t$ times, and thus the complexity reduction effect becomes greater with increase in the number of antennas. In addition, we demonstrate the performance of the proposed scheme with an iterative decoder for turbo codes for joint iterative detection with the SIC-MMSE scheme.

The paper is organized in the following way. In Section II, we first introduce the concept of iterative detection and decoding for a coded MIMO system using the conventional SIC-MMSE scheme. Section III presents a computationally efficient matrix inversion scheme. Simulation results are provided in section IV, and our conclusion is followed in section V.

## Ⅱ. Concept of Iterative Detection and Decoding Based on SIC-MMSE

### 1. System Model

We consider an iterative MIMO system based on bit-interleaved coded modulation (BICM) transmission strategy, with $N_t$ transmitters and $N_r$ receivers. During the transmission process, information bits, **c** is firstly channel encoded to sequence, **d**, with an error correction code. At the second step, after bit-interleaving of **d**, the coded sequence is divided into $N_t$ independent streams. Each stream consists of $M$ bits, where $M$ denotes the number of bits per symbol. Therefore, $N_t \times M$ information bits are transmitted in a MIMO frame [1].

Information bits in each frame are then mapped onto symbols for transmission, denoted by $\mathbb{S} = \left[s_1, s_2, s_3, \ldots, s_{N_t}\right]^T$, where $s_i$ ($i$=1,2,3,..,$N_t$) is identically chosen from a complex constellation $X$, with cardinality $|X|=2^M$. We assume energy at each transmit antenna is equally distributed, and channel coefficients are known at the receiver. Then, the received signal, denoted by $\mathbb{Y} = \left[y_1, y_2, y_3, \ldots, y_{N_r}\right]^T$, can be represented with an $N_r \times N_t$ complex channel matrix $\mathbb{H}$ as follows [1]:

$$\mathbb{Y} = \mathbb{H}\mathbb{S} + \mathbb{N}, \tag{1}$$

where $\mathbb{N}$ is an $N_r \times 1$ complex noise vector.

At the receiver, the SIC-MMSE detector calculates the LLRs for $N_t \times M$ bits from $\mathbb{Y}$. Then, the de-interleaved version of LLRs is sent to the channel decoder. After that, LLR values are utilized either to make decision for information bits, or feedback bit-interleaved version to the MIMO detector. The same process is repeated until a fixed number of iterations.

### 2. Conventional SIC-MMSE Algorithm

The basic concept of the SIC-MMSE detection is to compute estimates of the transmitted symbols, based on the a priori information provided by the channel decoder in each iteration and cancel the interference. During the detection process, the SIC-MMSE algorithm first estimates, the soft symbol for the $i$-th layer, $\hat{s}_i$ as follows [2][7]:

$$\hat{s}_i = E[s_i] = \sum_{b=1}^{2^M} \mathrm{Pr}ob[s_i = s_b].s_b \ , \tag{2}$$

where $E[s_i]$ is the expected value of $s_i$ and, $s_b \in X$.

The a priori probability of the symbol $s_i$ is denoted by:

$$\mathrm{Pr}ob[s_i = s_b] = \prod_{m=1}^{M} \mathrm{Pr}ob[x_{i,m} = x], \tag{3}$$

where $x_{i,m} = [s_b]_m$ represents the $m$-th bit associated with the symbol $s_b$, and

$$\Pr[x_{i,m} = x] = \frac{\exp\left(\dfrac{xL_a(x_{i,m})}{2}\right)}{\exp\left(\dfrac{xL_a(x_{i,m})}{2}\right) + \exp\left(\dfrac{-xL_a(x_{i,m})}{2}\right)}, \tag{4}$$

with $x_{i,m} \in \{-1, +1\}$. The LLR values provided by the channel decoder as a priori information, $L_a(x_{i,m})$ is set to zero at the first iteration for all the $M$ bits associated with the $i$-th symbol. The variance of $i$-th transmitted symbol is computed by [8]:

$$Var[s_i] = \left(\sum_{b=1}^{2^M} |s_b|^2 . \mathrm{Prob}[s_i = s_b]\right) - |\hat{s}_i|^2 . \tag{5}$$

After computing the estimate of soft symbols and its variance, the second step is to cancel the interference from all other layers. Then, the interference cancelled $i$-th vector is given by:

$$\hat{\mathbb{Y}}_i = \mathbb{Y} - \sum_{j, j \neq i}^{N_t} h_j \hat{s}_j = h_i \hat{s}_i + \ddot{\mathbb{N}}_i \ , \tag{6}$$

where $h_j$ denotes the $j$-th column of $\mathbb{H}$ and the residual interference plus noise can be represented by:

$$\ddot{\mathbb{N}}_i = \sum_{j, j \neq i}^{N_t} h_j e_j + \mathbb{N} . \tag{7}$$

After interference cancelation process, the MMSE filtered vector is computed by [2][8]:

$$\mathbb{P}_i^H = h_i^H \mathbb{A}_i^{-1} , \tag{8}$$

where

$$\mathbb{A}_i = (\mathbb{H} \Lambda_i \mathbb{H}^H + \sigma^2 \mathbb{I}_{N_t}) \ , \tag{9}$$

and $\Lambda_i$ is an $N_t \times N_t$ diagonal matrix with entries

$$\Lambda_{j,j} = \begin{cases} E_j, \ j \neq i \\ E_s, \ j = i \end{cases} .$$

The estimate of the $i$-th transmitted symbol after filtering process, $\ddot{s}_i$ is given as,

$$\ddot{s}_i = \mathbb{P}_i^H \hat{\mathbb{Y}}_i = \alpha_i \hat{s}_i + \mathbb{P}_i^H \ddot{\mathbb{N}}_i \ , \tag{10}$$

with

$$\alpha_i = \mathbb{P}_i^H h_i . \tag{11}$$

Finally, the a posteriori LLR, $L(x_{i,m})$ is approximated to the system as $N_t$ single-input single-output which are statistically independent, and thus the weighted residual interference plus noise (RIN) term $\mathbb{P}_i^H \ddot{\mathbb{N}}_i$, follows a Gaussian distribution[2][9]. This results in

$$L(x_{i,m}) \approx \min_{s \in X_{i,m}^{(0)}} \left( \frac{|\ddot{s}_i - \alpha_i s|^2}{\ddot{\beta}_i^2} - \sum_{m=1}^{M} \frac{x L_a(x_{i,m})}{2} \right) \\ - \min_{s \in X_{i,m}^{(1)}} \left( \frac{|\ddot{s}_i - \alpha_i s|^2}{\ddot{\beta}_i^2} - \sum_{m=1}^{M} \frac{x L_a(x_{i,m})}{2} \right) , \tag{12}$$

where $X_{i,m}^{(0)}$ and $X_{i,m}^{(1)}$ denotes the set of candidates symbol vectors corresponding to $x_{i,m} = 0$ and $x_{i,m} = 1$, respectively, and $\ddot{\beta}_i^2$ represents the variance which is given by:

$$\ddot{\beta}_i^2 = Var[\ddot{s}_i] = \mathbb{P}_i^H \left( \sum_{j, j \neq i}^{N_t} h_j h_j^H + \sigma^2 \mathbb{I}_{N_r} \right) \mathbb{P}_i \ . \tag{13}$$

## Ⅲ. Proposed Method with Computationally Efficient Matrix Inversion

A large amount of computational jobs of the conventional SIC-MMSE algorithm is occupied by the multiple inverse operations during the detection process. This is because the matrix $\mathbb{A}_i$ in (8) is layer dependent in the conventional SIC-MMSE algorithm. Therefore it requires the same number of inverse operations as the transmit antenna.

In this section we present a new approach which efficiently computes the inverse of the matrix, using the Taylor series expansion. The proposed method needs a single matrix inversion per iteration. The Taylor series expansion formula can be used for a complex matrix $\mathbb{X}$ with size of $n \times n$, as follows [10]:

$$(\mathbb{I} + \mathbb{X})^{-1} = \mathbb{I} - \mathbb{X} + \mathbb{X}^2 - \mathbb{X}^3 + \cdots + \mathbb{X}^k = \sum_{k=0}^{\infty} (-\mathbb{X})^k . \tag{14}$$

The eigen values for $\mathbb{X}$ should satisfy the following condition:

$$|\lambda_p| < 1 \text{ , for } p = 1, \cdots, n. \tag{15}$$

Meaning that,

$$\begin{cases} \max_{1 \leq p \leq n} \left( \sum_{q=1}^{n} |\wp(\chi_{pq})| + |\Im(\chi_{pq})| \right) < 1, \\ \max_{1 \leq q \leq n} \left( \sum_{p=1}^{n} |\wp(\chi_{pq})| + |\Im(\chi_{pq})| \right) < 1, \end{cases} \tag{16}$$

where $\chi_{pq}$ represents the element of the $p$-throw and $q$-th column of $\mathbb{X}$. $\wp(\chi_{pq})$ and $\Im(\chi_{pq})$ represent the real and imaginary part of $\chi_{pq}$, respectively.

In order to use the Taylor series expansion formular, we represent $\mathbb{A}_i^{-1}$ in (8) as follows:

$$\begin{aligned}\mathbb{A}_i^{-1} &= (\mathbb{H}\mathbb{V}_i\mathbb{H}^H + \sigma^2\mathbb{I}_{N_t})^{-1} \\ &= \left(\sum_{j\neq i}^{N_t} Var[s_j]h_jh_j^H + E_s h_i h_i^H + \sigma^2\mathbb{I}_{N_t}\right)^{-1} \\ &= \left(\sum_{j=1}^{N_t} Var[s_j]h_jh_j^H\,(E_s - Var[s_i])\,h_ih_i^H + \sigma^2\mathbb{I}_{N_t}\right)^{-1}.\end{aligned} \tag{17}$$

Let us define the matrix $\mathbb{C}$ as follows:

$$\mathbb{C} = \left(\sum_{j=1}^{N_t} Var[s_j]h_jh_j^H + \sigma^2\mathbb{I}_{N_t}\right) = (\mathbb{H}\Lambda\mathbb{H}^H + \sigma^2\mathbb{I}_{N_t}) \;, \tag{18}$$

and

$$\epsilon = E_s - Var[s_i] \;. \tag{19}$$

Then, (17) can be rewritten as,

$$\mathbb{A}_i^{-1} = ((\mathbb{I} + \epsilon h_ih_i^H\mathbb{C}^{-1})\mathbb{C})^{-1} \;. \tag{20}$$

Let

$$\mathbb{X}_i = \epsilon h_ih_i^H\mathbb{C}^{-1} \,, \tag{21}$$

then

$$\mathbb{A}_i^{-1} = \mathbb{C}^{-1}(\mathbb{I} + \mathbb{X}_i)^{-1} \;. \tag{22}$$

As we can see, matrix $\mathbb{C}$ is not layer dependent matrix. However, those modifications has some impacts on the system performance. The similar problem has been shown in reference [6]. Indeed, after a few iterations, $\Lambda$ can get close to zero and the inverse, $\mathbb{C}^{-1}$ might become very large. This implies (21) might not satisfy the conditions of convergence for Taylor series expansion in [10]. In order to meet those conditions, we modified the scaling approach proposed in reference [6]. The main idea of this scaling approach consist of scaling $\Lambda$ to $\widetilde{\Lambda}$ as follows:

$$\widetilde{\Lambda}_{i,i} = \frac{E_s + \Lambda_{i,i}}{2} \quad \text{for } i = 1,\cdots,N_t, \tag{23}$$

where $\widetilde{\Lambda}$ is a $N_t \times N_t$ diagonal matrix. The scaling ensures that, $E_s/2 \le \widetilde{\Lambda}_{i,i} \le E_s$ for $i = 1,\cdots,N_t$. Then the matrix $\mathbb{C}$ in (25) can be rewritten as

$$\widetilde{\mathbb{C}} = (\mathbb{H}\widetilde{\Lambda}\mathbb{H}^H + \sigma^2\mathbb{I}_{N_t}) \,, \tag{24}$$

and the matrix $\mathbb{X}_i$ in (18) can be re-computed based on (24) as follows:

$$\widetilde{\mathbb{X}}_i = \epsilon h_ih_i^H\widetilde{\mathbb{C}}^{-1}. \tag{25}$$

Then, (22) can be rewritten as,

$$\widetilde{\mathbb{A}}_i^{-1} = \widetilde{\mathbb{C}}^{-1}(\mathbb{I} + \widetilde{\mathbb{X}}_i) \;. \tag{26}$$

By applying the Taylor series expansion formula, the final expression is given by:

$$\widetilde{\mathbb{A}}_i = \widetilde{\mathbb{C}}^{-1}\sum_{k=0}^{\infty}(-\widetilde{\mathbb{X}}_i)^k \;, \tag{27}$$

and the MMSE filtered vector is computed by using (27) as follows:

$$\widetilde{\mathbb{P}}_i^H = h_i^H\widetilde{\mathbb{C}}^{-1}\sum_{k=0}^{\infty}(-\widetilde{\mathbb{X}}_i)^k \;, \;\; \text{for } i = 1,\ldots,N_t. \tag{28}$$

Then, the final estimation of transmitted symbol is found as follows:

$$\widetilde{s}_i = \widetilde{\mathbb{P}}_i^H\widetilde{\mathbb{Y}}_i \,, \text{ for } i = 1,\ldots,N_t. \tag{29}$$

With this modification, we can estimate the inverse of matrix in (8) per iteration, because (24) is not a layer dependent matrix, but only depends on the channel. Then, the complexity is largely reduced, compared with the conventional SIC-MMSE scheme.

## Ⅳ. Simulation Results

In this section, we compare the performance of conventional SIC-MMSE schemes with that of the the proposed method, in term of bit error rate (BER) for 4×4 and 8×8 MIMO systems over a Rayleigh fading channel. We used a turbo code with 16-quadrature amplitude modulation (QAM), and quaternary phase shift key

(QPSK) scheme. The 3GPP defined turbo code with information block size of 378 bits and a code rate of 1/3 was used, and the constraint length of each recursive systematic convolutional (RSC) component code was 3. Furthermore, we also analyze the complexity between the both algorithms, in term of multiplications and additions.

Fig. 1 and 2 show the BER performance of the 4×4 and 8×8 MIMO systems using QPSK, with different number of iterations. On the other hand, Fig. 3 and 4 show the BER performance of the 4×4 and 8×8 MIMO systems using 16-QAM. In the figures, $M_{it}$ and $D_{it}$ denote the number of inner iterations made at the SIC-MMSE detector and the number of outer iterations made at the decoder, respectively. In the simulation of our proposed scheme, we estimate $k$ values of the summation in (27) up to 1, i.e. two terms. As we can see, the proposed method produces nearly the same BER performance as the conventional SIC-MMSE scheme.

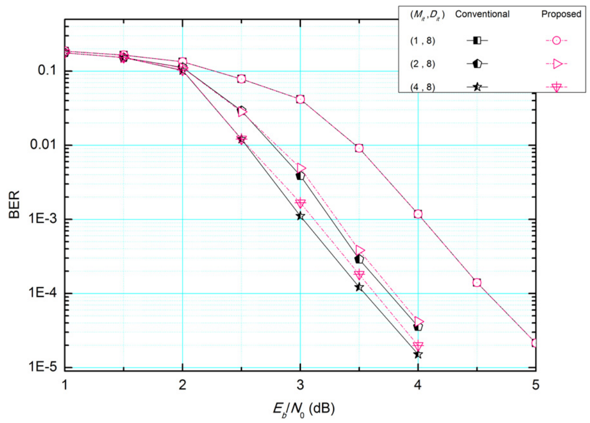


Fig. 1. BER performance comparison of 4×4 MIMO system using QPSK over a Rayleigh fading channel.

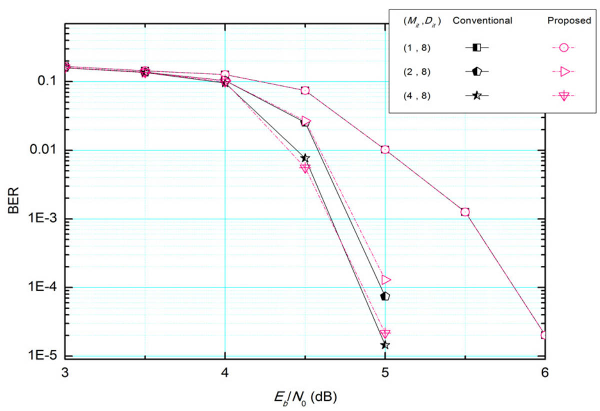


Fig. 2. BER performance comparison of 8×8 MIMO system using QPSK over a Rayleigh fading channel

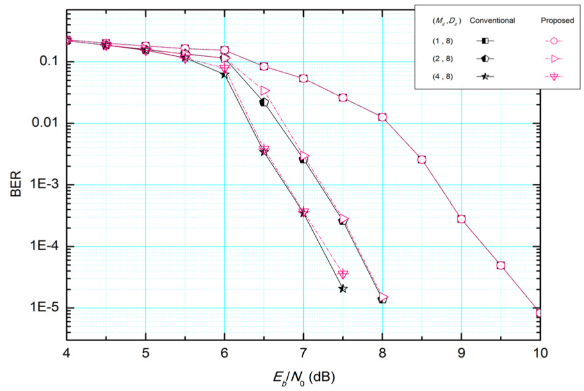


Fig. 3. BER performance comparison of 4×4 MIMO system using 16-QAM over a Rayleigh fading channel.

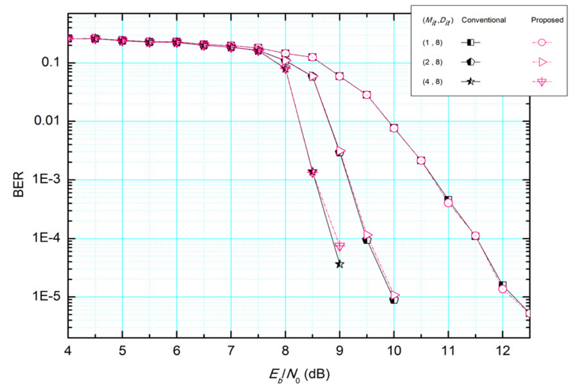


Fig. 4. BER performance comparison of 8×8 MIMO system using 16-QAM over a Rayleigh fading channel.

Table 1 and 2 compare the complexity of the conventional and proposed algorithms in term of additions and multiplications per MIMO frame. We note that both algorithm require the same complexity for (6), (9), (10), (11), and (12). However, the complexities to estimate (8) and (26) are different. Because we used the $k$ values up to 1, the *order* to estimate (26) in the tables is set to 1.

Table 1. The number of additions required

| Process | Equation | Conventional | Proposed |
|---|---|---|---|
| Interf, cancel. | (6) | $N_t(4N_rN_t - 6N_r)$ | $N_t(4N_rN_t - 6N_r)$ |
| MMSE filtering | (8)/ (26) | $N_t(4N_r^2N_t + 4N_r^2 + 2N_t^2N_r - 2N_rN_t - 2N_r)$ | $(4N_r^2N_t + 2N_t^2N_r - 2N_rN_t) + N_t(14N_r^2 - 6N_r - 1 + (2N_r^2)^{order} + \sum_{k=1}^{order}(4N_r^3 - 2N_r^2)^{order-k})$ |
| Symbol estimation | (10) + (11) | $4N_rN_t$ | $4N_rN_t$ |
| LLR estimation | (12) | $N_t(2M(2^M + M + 1))$ | $N_t(2M(2^M + M + 1))$ |

Table 2. The number of multiplications required

| Process | Equation | Conventional | Proposed |
| --- | --- | --- | --- |
| Interf. cancel. | (6) | $N_t(4N_rN_t - 4N_r)$ | $N_t(4N_rN_t - 4N_r)$ |
| MMSE filtering | (8)/ (26) | $N_t(4N_r^2N_t + 5N_r^2 + 2N_t^2N_r)$ | $(4N_r^2N_t + N_r^2 + 2N_t^2N_r) + N_t(18N_r^2 - 1 + (2N_r^2)^{order} + \sum_{k=1}^{order}(4N_r^3)^{order-k})$ |
| Symbol estimation | (10) + (11) | $8N_rN_t$ | $8N_rN_t$ |
| LLR estimation | (12) | $N_t(2M(2^{M+1} + M))$ | $N_t(2M(2^{M+1} + M))$ |

Fig. 5 shows the complexity comparison between the conventional and the proposed methods, in terms of multiplications and additions. The number of operations presented in Fig. 5 are estimated at each MIMO frame when $M_{it}$ equal to 1, and these will be linearly increased by $M_{it}$. Since estimation process of (6), (10), (11) and (12) are the same, the complexities to estimate (8) and (26) are compared. We can see that the complexity is largely reduced with our proposed method as the antenna size is increased. This is mainly because the conventional SIC-MMSE detector requires $M_{it} \times N_t$ matrix inversion processes, while the proposed method requires only $M_{it}$ matrix inversion processes.

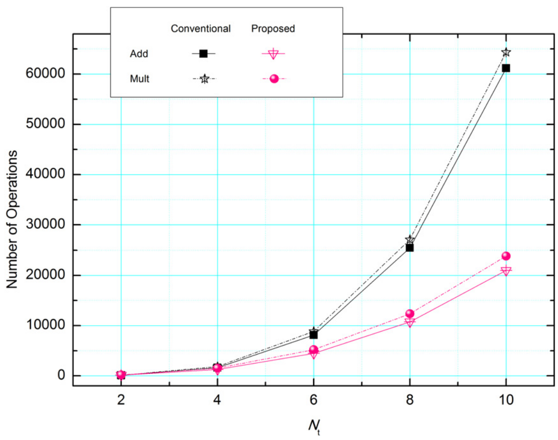


Fig. 5. Complexity comparison per MIMO frame when $M_{it}$ =1, ($N_t$=$N_r$).

# V. Conclusion

In this work, we proposed a new efficient approach to find an approximate of the matrix inverse for the SIC-MMSE scheme with less computational complexity. The proposed method utilized the Taylor series expansion, and needs only a single matrix inversion per iteration, and thus complexity is reduced by $N_t$ times compared with the conventional scheme. The proposed method produces almost the same BER performance as the conventional SIC-MMSE scheme, with low computational complexity.

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