Blind Signal Classification for Non-Orthogonal Multiple Access in Vehicular Networks

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Abstract—For downlink multiple-user (MU) transmission based on non-orthogonal multiple access (NOMA), the advanced receiver strategy is required to cancel the inter-user interference, e.g., successive interference cancellation (SIC). The SIC process can be applicable only when information about the co-scheduled signal is known at the user terminal (UT) side. In particular, the UT should know whether the received signal is OMA or NOMA, whether SIC is required or not, and which modulation orders and power ratios have been used for the superposed UTs, before decoding the signal. An efficient network, e.g., vehicular network, requires that the UTs blindly classify the received signal and apply a matching receiver strategy to reduce the high-layer signaling overhead which is essential for high-mobility vehicular networks. In this paper, we first analyze the performance impact of errors in NOMA signal classification and address ensuing receiver challenges in practical MU usage cases. In order to reduce the blind signal classification error rate, we propose transmission schemes that rotate data symbols or pilots to a specific phase according to the transmitted signal format. In the case of pilot rotation, a new signal classification algorithm is also proposed. The performance improvements by the proposed methods are verified by intensive simulation results.

Index Terms—Non-orthogonal multiple access (NOMA), blind signal classification, signaling overhead, spectrum efficiency, 5G-enabled vehicular networks

I. INTRODUCTION

In order to utilize radio spectrum efficiently for a massive number of user terminals (UTs), non-orthogonal multiple access (NOMA) based on power multiplexing has been widely studied [1]–[5]. For next-generation communication systems, ultra-high data rates are required, and efficient and flexible uses of energy and spectrum have become critical issues [6], [7]. To this end, NOMA has been actively researched as a promising technology to improve system performance in 5G networks [8]–[10] and to provide robustness in high-mobility vehicular networks [11], [12]. Recently, 3GPP has also studied the deployment scenarios and receiver designs for a NOMA system in Rel-14 in the context of a working item labeled multiple user superposition transmission (MuST) [13].

NOMA superposes the multiple-user (MU) signals within the same frequency, time or spatial domain, so advanced receivers with successive interference cancellation (SIC) are typically considered for detection of the non-orthogonally multiplexed signals [4], [5]. Theoretically, NOMA is known to provide significant benefits in improving the cell throughput [14]; nevertheless, such gains can be obtained only when the receiver is able to cancel or sufficiently suppress interference from the co-scheduled users. Performance and complexity analysis of interference cancellation have been the subject of intense research [15], [16]. Based on the well-designed SIC, NOMA has been extensively researched in conjunction with various technologies. There have been some studies on the system applying NOMA to MIMO [17], [18], and NOMA in cooperative networks has been researched in [19]–[22]. Most of existing researches on NOMA have assumed ideal SIC with the knowledge of channel state information (CSI), but the recent work in [23] has handled the imperfect CSI for NOMA by using deep learning.

Even before an attempt is made to handle interference in a NOMA system, the receiver must first determine the presences of the co-scheduled users. If SIC is to be used, then the modulation order and power allocation ratio of the co-scheduled user should also be known to the receiver. The information required for signal classification and data detection can possibly be transmitted to the receiver via a high layer, but the required signaling overhead is a concern. Further, high-layer signaling may or may not be used at the receiver side depending on the MU channel condition, therefore it can be a waste of valuable resources. Especially in vehicular networks with the limited energy and resource (e.g., time limits due to high mobility in vehicular networks) [11], [12], this motivates blind signal classification at the receiver side followed by appropriate data detection. Moreover, vehicular networks have to cope with periodic short burst communications for safety information and alarm service [24], [25]. Since a concern of signaling overhead becomes more critical for short burst communications, blind signal classification could be emerged as a promising technology to reduce signaling overheads in vehicular communications [26].

For orthogonal multiple access (OMA), there have been extensive research efforts on modulation classification (MC). In [27], an ML-based classifier was presented to provide the optimal performance in the presence of white Gaussian noise when candidate modulation schemes are equally probable. MC was originated from military applications, such as electronic warfare; so the existing MC techniques have been typically developed for systems without knowledge of the signal amplitude, phase, channel fading characteristics and noise distribution [28], [29]. Since ML-based classification requires high computational complexity, on the other hand, the feature-based approaches of blind MC in [30] take advantage of the fact that good statistical features enable robust blind MC.
Furthermore, the convolutional neural network (CNN)-based feature extraction processes have been recently studied in [31]–[34]. However, the existing researches on blind signal classification are primarily limited in MC techniques in an OMA system.

Blind MC is also important in the NOMA system, however there are additional and necessary signal classification steps as follows: 1) multiple access classification between OMA and NOMA, 2) co-scheduled UT’s MC, and 3) classification of the signal based on the necessity of SIC. This paper studies the theoretically optimal ML-based approach for blind signal classification of the NOMA signal. There are some key differences between the existing works and this paper. Previous NOMA works assume that the receiver is given the perfect signal information, whereas this paper considers all three stages of signal classification for practical NOMA systems in vehicular networks. This paper assumes a two-user cellular model in this work owing to large computational complexity of ML-based blind signal classification. Therefore, the last step can be interpreted as near/far UT classification, because only the near UT which experiences the stronger channel condition than far one performs SIC.

Note that blind MC has not been previously studied in the literature in the context of NOMA to our best knowledge except for [35]. While the existing MC techniques aim at finding the UT’s modulation, the NOMA receiver attempts to classify the co-scheduled user’s modulation to perform SIC. In addition, the NOMA system should perform multiple access classification between OMA and NOMA as well as determine whether SIC is required or not for the received signal. The recent work in [35] focused only on signal classification with respect to the necessity of SIC, and jointly optimized both power allocation and user scheduling scheme which guarantee the reliable classification performance. This paper analyzes the performance impact of errors in blind NOMA signal classification and addresses ensuing receiver challenges in practical MU cases. In addition, two transmission policies are proposed to improve the performances of ML-based blind NOMA signal classification.

The main contributions of this paper are summarized as follows:

- This paper organizes the blind signal classification in three steps: 1) multiple access classification between OMA and NOMA, 2) co-scheduled UT’s modulation classification, and 3) classification of the signal with respect to the necessity of SIC.
- SINR and capacity analyses for the performance impact of errors in three blind NOMA signal classification steps are shown.
- The phase-rotated modulation is proposed for blind NOMA signal classification. Rotated data symbols make the constellations of the modulation candidates easier to distinguish from one another. This method is based on the existing ML-based classification algorithms.
- The pilot-rotation transmission method and the corresponding new signal classification algorithm are proposed. In this algorithm, a receiver estimates the rotation value of pilots and utilizes the estimated value for blind signal classification. Since the proposed scheme only depends on rotated phases of the pilots not on the pilot values, it requires no extra pilot overhead if phase estimation is correct.
- Numerical results verify the performance analysis of blind signal classification in NOMA system. Moreover, the proposed phase-rotated modulation and the pilot-rotation transmission scheme are shown to provide better classification performances than the conventional ML-based way.

The rest of the paper is organized as follows. The NOMA system model and the blind classification steps for received NOMA signal are illustrated in Section II. SINR analysis for three steps of blind NOMA signal classification and capacity of a NOMA UT with signal classification errors are provided in Sections III and IV, respectively. The phase-rotated modulation is proposed in Section V. In Section VI, the pilot-rotation transmission method and the corresponding new signal classification algorithm are proposed. In Section VII, performance improvements of the proposed algorithms are verified by intensive numerical simulations.

II. SYSTEM MODELS

A. NOMA Signal Model and Receiver Structure

In downlink power-multiplexing NOMA, a base station (BS) intentionally superposes the signals for target UTs with some power weightings. With the help of SIC, NOMA can serve multiple users simultaneously with the same resource. However, when information of the received NOMA signal is unknown at the receiver side, computational complexity of the ML-based signal classification in the NOMA system grows significantly with the number of co-scheduled UTs [35]. Therefore, this paper considers a two-user NOMA system. The received signal in a two-user downlink NOMA transmission is given by

\[ y = h(s_f + s_n) + w, \]

where \( y, s, h, \) and \( w \) correspond to the received signal, the transmitted symbol, the channel gain, and thermal noise, respectively, and the subscripts \( f \) and \( n \) denote far and near UTs. In addition, \( E[|s_f|^2] = P_f \) and \( E[|s_n|^2] = P_n \), where \( P_f \) and \( P_n \) are power allocation ratios of far and near UTs, respectively. The BS normally schedules UTs having the large channel gain difference, and allocates larger power to far UT (weak UT) to compensate its low channel gain, i.e., \( P_f > P_n \). Suppose that there is a normalized power constraint, \( P_f + P_n = 1 \), and the noise variance is \( \sigma^2 \). With large power allocation, the far UT does not perform SIC and just detects its data while ignoring the near UT’s signal. Meanwhile, SIC is necessary for the near UT to cancel the far UT’s signal, so only the near UT is considered as a NOMA-serviced user in general. For this reason, all statements in this paper are focused on the near UT of the NOMA system.

For SIC at the near UT, interference, i.e., the far UT’s signal, can be regenerated from the decoder or the detector, corresponding to codeword-level interference cancellation (CWIC) or symbol-level interference cancellation (SLIC), respectively.
For our study, CWIC is mainly performed to mitigate the inter-cell interference unless otherwise noted, and signal classification is required before CWIC is applied.

Let $\mathcal{M} = \{M_0, M_1, \cdots, M_L\}$ be a set of modulation modes, including $L$ NOMA modes, $M_l$ for $l = 1, \cdots, L$, and an OMA mode, $M_0$. The constellation set of the modulation mode $M_l$ is denoted by $\chi_l$ for all $l \in \{0, \cdots, L\}$. For $l \in \{1, \cdots, L\}$, $\chi_l$ is constructed by combinations of power-scaled near and far UTs’ constellation sets, $\chi_l = \chi_l^f \bigoplus \chi_l^n$, where the average powers of symbols in $\chi_l^f$ and $\chi_l^n$ are $P_f$ and $P_n$, respectively. Let $\mathcal{N}$ be a set of the constellation points of all NOMA modes, i.e., $\mathcal{N} = \chi_1 \cup \cdots \cup \chi_L$.

B. ML-based Signal Classification

The existing ML-based MC algorithm [27] which is optimal in OMA based on hypotheses testing can be directly applied to NOMA signal classification. We define some hypotheses to identify the received signal information as follows:

- $\mathcal{H}_l$: the hypothesis of the signal modulated by the $l$-th mode $M_l$ for all $l \in \{0, 1, \cdots, L\}$
- $\mathcal{H}_N$: the hypothesis of the NOMA signal, i.e., $\mathcal{H}_N = \mathcal{H}_1 \cup \cdots \cup \mathcal{H}_L$.
- $\mathcal{H}_l^f$: the hypothesis of the NOMA signal which does not require SIC.
- $\mathcal{H}_l^n$: the hypothesis of the NOMA signal which SIC is necessary for.
- $\mathcal{H}_N^f$: the hypothesis of the received signal which is modulated by the $l$-th NOMA mode and does not require SIC for all $l \in \{1, \cdots, L\}$.
- $\mathcal{H}_N^n$: the hypothesis of the received signal which is modulated by the $l$-th NOMA mode and requires SIC for all $l \in \{1, \cdots, L\}$.

The ML-based hypothesis testing can classify the received signal according to whether it is modulated by OMA or NOMA, which modulation and power weightings are used, and whether SIC is required or not. For example, let the $l$-th modulation mode is used for the NOMA signal and the signal requires SIC, i.e., the hypothesis $\mathcal{H}_N^n$ is true. Then, the likelihood probabilities of the hypothesis $\mathcal{H}_N^n$ is computed by

$$p(y|\mathcal{H}_N^n) = \frac{1}{|\mathcal{N}|} \sum_{\chi_l \in \mathcal{N}} \frac{1}{\pi \sigma^2} e^{-\frac{|y - \chi_l|^2}{\sigma^2}} ,$$ (2)

where $\sigma_n^2$ is the noise variance and $|\chi_l|$ is the number of symbols in the constellation set $\chi_l^n$. If $K$ symbols are used for blind signal classification and are not correlated, the joint likelihood function of the $K$ symbols of $y = [y_1, \cdots, y_K]$ is given by

$$\Gamma(y|\mathcal{H}_N^n) = \prod_{k=1}^{K} p(y_k|\mathcal{H}_N^n).$$ (3)

According to the maximum likelihood criterion, the detected hypothesis $\hat{\mathcal{H}}$ can be found by

$$\hat{\mathcal{H}} = \arg \max_{\xi \in \mathcal{H}} \Gamma(y|\xi),$$ (4)

where $\mathcal{H} = \{\mathcal{H}_0, \mathcal{H}_1^f, \cdots, \mathcal{H}_L^f, \mathcal{H}_1^n, \cdots, \mathcal{H}_L^n\}$. If $\hat{\mathcal{H}} = \mathcal{H}_0$, the received determines that the signal is modulated by OMA.

![Fig. 1: Processes of ML-based signal classification in NOMA systems](image-url)

On the other hand, if $\hat{\mathcal{H}} = \mathcal{H}_1^f$, then the received signal is classified into the NOMA signal of the $l$-th modulation mode which does not require SIC. In addition, $\mathcal{H}_N^n$ represents that the received signal is the NOMA one of the $l$-th modulation mode which SIC is necessary for. Since the accuracy of hypothesis testing would be significantly degraded as the number of hypotheses grows, however, this paper considers the hierarchical classifications of the NOMA signal to reduce the number of hypotheses in each classification step.

The three hierarchical steps of the signal classification are investigated as follows: OMA/NOMA classification, modulation classification (i.e., the necessity of SIC), and near/far UT classification (i.e., the necessity of SIC). The relevant likelihood probabilities and the hypothesis testing results can be computed by

1) OMA/NOMA Classification:

$$p(y|\mathcal{H}_0) = \frac{1}{|\mathcal{N}|} \sum_{\chi_l \in \mathcal{N}} \frac{1}{\pi \sigma^2} e^{-\frac{|y - \chi_l|^2}{\sigma^2}}$$ (5)

$$p(y|\mathcal{H}_N) = \frac{1}{|\mathcal{N}|} \sum_{\chi_l \in \mathcal{N}} \frac{1}{\pi \sigma^2} e^{-\frac{|y - \chi_l|^2}{\sigma^2}}$$ (6)

$$\hat{\mathcal{H}} = \arg \max_{\xi \in \{\mathcal{H}_0, \mathcal{H}_N\}} \Gamma(y|\xi)$$ (7)

2) Modulation Classification:

$$p(y|\mathcal{H}_l^f) = \frac{1}{|\mathcal{N}|} \sum_{\chi_l \in \mathcal{N}} \frac{1}{\pi \sigma^2} e^{-\frac{|y - \chi_l|^2}{\sigma^2}}$$ (8)

$$\hat{\mathcal{H}} = \arg \max_{\xi \in \{\mathcal{H}_1^f, \cdots, \mathcal{H}_L^f\}} \Gamma(y|\xi)$$ (9)

3) Near/Far UT Classification:

$$p(y|\mathcal{H}_l^n) = \frac{1}{|\mathcal{N}|} \sum_{\chi_l \in \mathcal{N}} \frac{1}{\pi \sigma^2} e^{-\frac{|y - \chi_l|^2}{\sigma^2}}$$ (10)

$$p(y|\mathcal{H}_l^f) = \frac{1}{|\mathcal{N}|} \sum_{\chi_l \in \mathcal{N}} \frac{1}{\pi \sigma^2} e^{-\frac{|y - \chi_l|^2}{\sigma^2}}$$ (11)

$$\hat{\mathcal{H}} = \arg \max_{\xi \in \{\mathcal{H}_N^n, \mathcal{H}_l^n\}} \Gamma(y|\xi).$$ (12)
The overall processes of ML signal classification are shown in Fig. 1. To sum up, OMA/NOMA classification should be performed first, and the next is classification of the modulation orders and power ratios of the UTs. Near/far UT classification requires the constellations of the superposed signal as well as the far UT’s, therefore it is the last step. Since we assume that a UT already knows the modulation order of itself, if the far and near UTs’ modulation orders from the classified modulation mode are different, then the UT does not require near/far UT classification. Otherwise, near/far UT classification is necessary.

Compared to hypothesis testing with respect to the whole set of modulation modules in (4) which $2L+1$ hypotheses are compared, the hierarchical classification steps could reduce the dimension of hypothesis testing and increase the accuracy. In the OMA/NOMA and near/far UT classification steps, only two hypotheses are compared, and $L$ hypotheses are in the modulation classification step. In addition, a decrease of the number of comparing hypotheses also reduces computational complexity.

III. SINR Analysis for NOMA UT with Signal Classification Errors

In this section, the effects of signal classification error on SINR and capacity are investigated. The near UT is only considered as the NOMA-serviced user in general, so SINR analysis for near UT is investigated.

A. OMA/NOMA and near/far UT Classification Errors

When the BS transmits the NOMA signal but the near UT incorrectly classifies it as OMA, severe performance degradation is expected. The transmitted signal contains the far UT’s signal component but an OMA decision would make the receiver do nothing for interference, i.e., SIC does not work. Similar results happen when the OMA signal is transmitted but the receiver classifies the signal as NOMA. In this case, the receiver performs SIC, but there is no interference in the OMA signal. Both cases cannot guarantee reliable performance. Accordingly, zero throughput is reasonably considered for OMA/NOMA classification errors in this paper.

In a similar way, erroneous near/far UT classification is critically harmful for the system performance. If wrong near/far UT classification occurs, the far UT of the NOMA system cancels the target signal, and the near UT does not perform SIC. Therefore, an error in the near/far UT classification step is assumed to yield no throughput. The classification results of the far UT’s modulation order and power ratio become meaningful only when the signal is classified as NOMA and near UT.

B. Classification Errors of Power Ratio

For the NOMA system, there are some modulation modes having the same modulation orders but different power ratios for two UTs. Modulation classification among these modes can be interpreted as classification of power ratio. Although the receiver incorrectly classifies the power ratio as one of the competing modes, it is still possible to detect data correctly. The reason is that the incorrectly classified modulation mode may have a constellation point indicating the same bit-labeling as the transmitted one. However, the SINR may still degrade due to the erroneous decision of power ratio.

For simplicity, consider a flat fading channel and two competing modulation modes, $M_1$ and $M_2$, having the same order but different power allocation ratios for two NOMA UTs. Suppose that $M_1$ is transmitted, then the received signal is given by

$$y = h(s_{f,1}(i) + s_{n,1}(k)) + w.$$  \hspace{1cm} (13)

where $s_{f,1}(i)$ and $s_{n,1}(k)$ are the $i$-th and $k$-th data symbols of $x_1^f$ and $x_1^n$ for the far and near UTs, respectively, and $E_s[|s_{f,1}(i)|^2] = P_{f,1}$ and $E_s[|s_{n,1}(k)|^2] = P_{n,1}$.

Assuming perfect SIC, correct modulation classification yields the SINR of

$$\eta_{1 \rightarrow 1} = \frac{P_{n,1}}{\sigma^2}. \hspace{1cm} (14)$$

where $\sigma^2 = \frac{\sigma^2}{|h|^2}$. Th subscript $l \rightarrow m$ in (14) means that the transmitted mode is $M_l$ but $M_m$ is decided.

However, when classification of power ratio is incorrect, SIC is not accurate. Suppose the same index $i$ of $s_{f,1}(i)$ and $s_{f,2}(i)$ indicates the same bit-labeling, then the detected interference by SIC is highly likely to be $s_{f,2}(i)$, not $s_{f,1}(i)$. Then, $s_{f,2}(i)$ is subtracted from the received signal of (13) by SIC, and the signal after SIC is denoted by

$$y_{SIC} = h(s_{f,1}(i) + s_{n,1}(k) - s_{f,2}(i)) + w \hspace{1cm} (15)$$

$$= h(s_{n,2}(k) + h(s_{f,1}(i) - s_{f,2}(i)) \hspace{1cm} (16)$$

$$+ h(s_{n,1}(k) - s_{n,2}(k)) + w.$$

If $s_{n,2}(k)$, whose bit-labeling is the same as that of the transmitted signal $s_{n,1}(k)$, is detected, data detection could be still correct, even if incorrect modulation mode is detected. The SINR becomes

$$\eta_{1 \rightarrow 2} = \frac{P_{n,2}}{E_s[|s_{f,1}(i) - s_{f,2}(i)|^2] + E_s[|s_{n,1}(k) - s_{n,2}(k)|^2] + \tilde{\sigma}^2}. \hspace{1cm} (17)$$

Note that when $P_{n,1} \geq P_{n,2}$, an incorrect power ratio classification obviously results in a SINR degradation, i.e., $\Delta \eta = \eta_{1 \rightarrow 1} - \eta_{1 \rightarrow 2} \geq 0$. However, if $P_{n,1} < P_{n,2}$, $\Delta \eta > 0$ only when

$$P_{n,1}(E_s[|s_{f,1}(i) - s_{f,2}(i)|^2] + E_s[|s_{n,1}(k) - s_{n,2}(k)|^2] + \tilde{\sigma}^2)$$

$$> P_{n,2} \tilde{\sigma}^2. \hspace{1cm} (18)$$

which holds in the high SNR region. If (18) is not satisfied, the SINR can increase even when the power ratio is incorrectly classified. Accordingly, classification of power ratio is more important as the power ratio of the near UT, i.e., $P_{n,1}$, increases.

C. Classification Errors of Modulation Order

Consider two competing modes of $M_1$ and $M_2$ having different modulation orders of their far UTs. It is very important...
for the near UT to find the modulation order of the far UT in order to perform SIC appropriately. If a classification error for the far UT’s modulation order arises, estimated interference by SIC, \( s_{f,2}(l) \), would be incorrect. Then, the signal after SIC is given by
\[
y_{SIC} = h(s_{f,1}(i) + s_{n,1}(k) - s_{f,2}(l)) + w
\]
\[
= hs_{n,2}(k) + h(s_{f,1}(i) - s_{f,2}(l)) + h(s_{n,1}(k) - s_{n,2}(k)) + w.
\] (19)

Then, the SINR of \( \eta \rightarrow 2 \) becomes
\[
\eta_{1 \rightarrow 2} = \frac{P_{n,2}}{\mathbb{E}_i[|s_{f,1}(i) - s_{f,2}(l)|^2] + \mathbb{E}_k[|s_{n,1}(k) - s_{n,2}(k)|^2 + \sigma^2].} \] (20)

Comparing (20) with (17), the only difference is that \( s_{f,2}(l) \) is replaced by \( s_{f,1}(i) \) in the denominator of (20). \( s_{f,2}(l) \) in (20) is completely different from \( s_{f,1}(i) \) in (17), because \( M_1 \) and \( M_2 \) have different modulation orders and \( s_{f,1}(i) \) and \( s_{f,2}(l) \) cannot represent a symbol of the same bit-labeling as transmitted \( s_{f,1}(i) \).

Similarly to Section III-B, a classification error for the far UT’s modulation order always causes SINR degradation at the near UT when \( P_{n,1} \geq P_{n,2} \). However, when \( P_{n,1} < P_{n,2} \), \( \Delta \eta_n > 0 \) only when the system satisfies the condition:
\[
P_{n,1}(\mathbb{E}_i[|s_{f,1}(i) - s_{f,2}(l)|^2] + \mathbb{E}_k[|s_{n,1}(k) - s_{n,2}(k)|^2 + \sigma^2]) > P_{n,2} \sigma^2. \] (21)

Similar to (18), (21) is satisfied in high SNR region. Therefore, when (21) is satisfied, SINR does not degrade even with incorrect classification of the far UT’s modulation order, but this situation is much less likely to happen than the case of incorrect power ratio classification. The reason is \( |s_{f,1}(i) - s_{f,2}(l)| > |s_{f,1}(i) - s_{f,v}(i)| \) in general, with the assumption that far UT’s modulation orders of \( M_1 \) and \( M_v \) are different, and far UT’s modulation orders of \( M_l \) and \( M_v \) are the same but their power ratios are different.

There is another problem for incorrect classification of far UT’s modulation order. As mentioned in Section II, decision feedback for SIC can be generated at either symbol or codeword level. However, incorrect classification for the far UT’s order does not allow the use of CWIC because of a mismatch in the codeword length. Since CWIC outperforms SLIC substantially, this is highly undesirable for the system-level performance.

IV. CAPACITY OF NOMA UT WITH SIGNAL CLASSIFICATION ERRORS

Based on the SINR analysis, we can compute capacity of NOMA UT, \( C \), including the effect of the signal classification error. With the assumption that the transmitted mode is \( M_l \), let \( p_{l \rightarrow m} \) be the probability that the classified modulation mode is \( M_m \). Capacity can be computed as
\[
C = \sum_{l=1}^{L} \pi_l \mathbb{E}_h \left[ \left\{ p_{l \rightarrow m} q^n_{m} \log_2(1 + \eta_{l \rightarrow m}) \right\} + \sum_{m \neq 1} p_{l \rightarrow m} q^n_{m} \log_2(1 + \eta_{l \rightarrow m}) \right], \] (22)

where \( \pi_l \) is the probability which the signal is transmitted with one of NOMA modes \( M_l \) for all \( l \in \{1, \ldots, L\} \) and \( q^n_{l} \) is the probability which the signal of the modulation mode \( M_l \) is for the near UT (i.e., the signal requires SIC). The equally probable modulation mode is assumed, i.e., \( \pi_l = \frac{1}{L} \). Again, since only the near UT of the two-user NOMA system represents the NOMA user, the capacity in (22) is achieved for the near UT cases. In addition, \( \eta_{l \rightarrow m} \) is achieved in Section III. Since the errors in OMA/NOMA and near/far UT classification arise zero throughput, those classification errors is not included in (22).

The ML-based signal classification performance strongly depends on how the constellations of the competing modulation modes can be distinguished well from one another. To quantify this effect, we denote the minimum distance between the constellation sets of two different modulation modes of \( M_l \) and \( M_m \) by \( d_{min}(M_l, M_m) \), \( l \neq m \). \( d_{min} \) can be generally defined for \( L \) modulation modes as follows:
\[
\forall s_1 \in \chi_l, \ldots, \forall s_L \in \chi_l, \\
d_{min}(M_1, \ldots, M_L) = \min d(s_1, \ldots, s_L), \] (23)

where \( \chi_l \) is the constellation set of the modulation mode \( M_l \) for all \( l \in \{1, \ldots, L\} \).

Fig. 2: Legacy constellations of two modulation modes

Fig. 2 gives an example of two competing modulation modes, \( M_l \) and \( M_m \), whose corresponding constellation sets are \( M_l \) and \( M_m \), respectively. In Fig. 2, \( d_{min}(M_l, M_m) \) is the distance between two closest points from different modes, as marked by the dashed circles. These symbols are very close to each other, therefore when ML signal classification is used, these pairs are expected to be main causes of incorrect classification. In this example, if all symbol points are equally probable, the probability of classification error can be computed as
\[
p_{l \rightarrow m} = \frac{1}{|\chi_l||\chi_m|} \sum_{i=1}^{|\chi_l|} \sum_{k=1}^{|\chi_k|} \frac{Q\left(\frac{|h(s_l(i) - s_m(k))/2}{\sigma/\sqrt{2}}\right)}{Q\left(\frac{h \cdot d_{min}(M_l, M_m)/2}{\sigma/\sqrt{2}}\right)} \] (24)

\[
\approx \frac{N_{min}}{|\chi_l||\chi_m|} Q\left(\frac{h \cdot d_{min}(M_l, M_m)/2}{\sigma/\sqrt{2}}\right). \] (25)
where $s_i(i)$ is the $i$-th constellation point of $M_i$. In addition, $N_{\text{min}}$ is the total number of symbol pairs giving the minimum distance $d_{\text{min}}(M_l, M_m)$.

In (24), $s_m(k)$ is the closest one among the constellation points of $M_k$ to $s_i(i)$, so the case where $s_i(i)$ is confused with $s_m(k)$ is dominant for incorrect classification. Equation (25) is approximated one step further by only considering the symbol pairs from different modes, giving the minimum distance $d_{\text{min}}(M_l, M_m)$. $N_{\text{min}}$ is the number of these pairs, and $N_{\text{min}} = 4$ in Fig. 2.

Some conclusions are drawn at this point. First, we can find capacity analytically by substituting the expressions for the SINR and classification error probability to (22). Second, the tradeoff between the classification error rate $p_{l \rightarrow m}$ and the SINR degradation term of $\eta_{l \rightarrow m}$ is observed in (22). According to (25), the classification error rate decreases with $d_{\text{min}}(M_l, M_m)$. However, if the classification error occurs, then SINR would be increasingly degraded as $d_{\text{min}}(M_l, M_m)$ increases. Third, it is helpful to select appropriate power allocation ratios for the NOMA modulation modes which maximizes capacity in (22). However, the choice of power ratios is beyond our scope here, and will not be investigated in detail.

V. PHASE-ROTATED MODULATION BASED ON ML SIGNAL CLASSIFICATION

We propose phase-rotated modulation to increase the accuracy in signal classification in this section. As explained in Section IV, reliability of ML-based signal classification strongly depends on how well the competing modes can be distinguished from one another. Based on this observation, different phase rotations are assigned to individual modulation modes to make their constellation points more effectively separated. This idea can be seen by comparing Fig. 2 and Fig. 3, showing the legacy and phase-rotated composite constellations of two different modulation modes, respectively. In Fig. 3, $M_1$ is rotated by $\theta$, so it becomes $M_1 e^{i\theta}$. The symbol pairs from different modes giving the minimum distance $d_{\text{min}}(M_1 e^{i\theta}, M_2)$ are marked by the dashed ellipses in Fig. 3. Since $d_{\text{min}}(M_1 e^{i\theta}, M_2) > d_{\text{min}}(M_1, M_2)$, it is easily expected that phase-rotated modulation provides a lower classification error probability compared to the legacy one. If the same phase rotation is applied to every modulation mode, the rotated composite constellations of $M_1 e^{i\theta}$ and $M_2 e^{i\theta}$ still keep the same minimum distance of $d_{\text{min}}(M_1, M_2)$. Thus, the key point is to apply the different phase rotations to different modulation modes. We can make the phase list $\Theta = \{\theta_0, \theta_1, \ldots, \theta_L\}$, and its elements $\theta_i$ corresponds to $M_i$ for all $l \in \{1, \cdots, L\}$. The modulation mode table should be updated to include the phase rotations, as shown in Table I, and all UTs should know the rotation values also.

However, a larger $d_{\text{min}}(M_1 e^{i\theta}, M_2)$ does not guarantee better user capacity, because the SINR terms in (22) would be changed. As we mentioned the tradeoff between $p_{l \rightarrow m}$ and $\eta_{l \rightarrow m}$ in (22) in Section IV, even though phase-rotated modulation can provide a smaller classification error rate, SINR would degrade much more and finally capacity would not increase much, when a classification error occurs. The phase rotations of each modulation mode can be obtained so as to maximize capacity. We can formulate the optimization problem for the phase rotation list $\Theta$:

$$\Theta = \arg \max_{\Theta = \{\theta_0, \ldots, \theta_L\}} C$$

The above optimization problem is difficult to solve theoretically because of expectation over random channel realizations; we find the optimal phase rotations numerically in this paper. When there exist many modulation modes, however, numerically finding all rotation values requires too massive computations. This paper applies phase-rotated modulation for only OMA/NOMA classification, i.e., $\theta_0 \neq 0$ and $\theta_l = 0$ for all $l \in \{1, \cdots, L\}$, because incorrect OMA/NOMA classification cannot give any throughput, as we have seen in Section III. On the other hand, wrong decisions for the far UT’s modulation order or power allocation ratio are not as critical as OMA/NOMA classification.

However, near/far UT classification is not affected by phase-rotated modulation. According to (10) and (12), near/far UT classification depends on the constellation structures of $\chi_1$ and $\chi_1^f$. Phase-rotated modulation changes those constellations to $\chi_1 e^{i\theta_l}$ and $\chi_1^f e^{i\theta_l}$, but the minimum distance between them is not changed. Thus, phase-rotated modulation cannot influence on the performance of ML-based near/far UT classification.

VI. PILOT REUSE-BASED SIGNAL CLASSIFICATION

In Section V, the ML-based phase-rotated modulation scheme is proposed which uses data symbols for blind signal classification, and how capacity and classification accuracy change depending on phase rotations is investigated. However, since there exists the tradeoff between the classification
modulation. Assuming pilot rotation to prevent confusion with phase-rotated modulation. The symbol phase rotations are assigned to each modulation mode similarly and rotates the identical pilot for the second duration. Different transmit the legacy value for the first pilot symbol duration, static channel gain. In the proposed method, the BS should pilot symbol durations. Second, the identical value should assumptions. First, the channel should be static at least for two pilots. It just rotates the existing pilot symbols already used (22) do not change. This algorithm does not require additional constraints explained later. This signal classification algorithm based on pilot reuse does not require any change in the modulation scheme. In addition, since phase-rotated modulation cannot improve near/far UT classification owing to the independence of the symbol phase rotations on the modulation scheme. In addition, since phase-rotated modulation classification performance, the phase rotations are assigned to the pilot-based scheme has been presented not to affect the blind classification performance. Therefore, the pilot-based scheme has been presented not to affect the SINR in this section, however this scheme requires an additional constraint explained later. This whole processes of the pilot reuse-based signal classification algorithm are shown in Fig. 4. Overall, OMA/NOMA classification and selections for the modulation orders and power ratios are conducted simultaneously. Then, near/far UT classification follows.

A. Pilot Reuse-Based OMA/NOMA and Modulation Classifications

On the contrary to phase-rotated modulation, this subsection introduces phase rotations for existing pilots. Data symbols are modulated in the convention way, therefore the SINR terms in (22) do not change. This algorithm does not require additional pilots. It just rotates the existing pilot symbols already used for other purposes, e.g., estimation of carrier frequency offset.

The proposed pilot-reuse-based scheme requires some assumptions. First, the channel should be static at least for two pilot symbol durations. Second, the identical value should be used for two consecutive symbols which experience the static channel gain. In the proposed method, the BS should transmit the legacy value for the first pilot symbol duration, and rotates the identical pilot for the second duration. Different phase rotations are assigned to each modulation mode similar to phase-rotated modulation. The symbol \( \phi \) is used for the pilot rotation to prevent confusion with \( \theta \) in phase-rotated modulation. Assuming \( M_{i_0} \) is transmitted, the received two consecutive pilot symbols are given by

\[
\begin{align*}
    r_u &= h p_u + w_u, \\
    r_r &= h p_r + n_r = h p_u e^{j \phi_0} + w_r,
\end{align*}
\]

where \( p \) and \( r \) are transmitted and received pilots. The subscripts of \( u \) and \( r \) mean unrotated and rotated, respectively. Also, \( w_u, w_r \sim \text{CN}(0, \sigma_n^2) \). The receiver can estimate the phase rotation of pilot in the second symbol duration, as given by

\[
\varphi = \angle \{ r_u^* r_r \} \approx \angle \{ |r_u|^2 e^{j \phi_0} \}.
\]

By comparing the estimated \( \varphi \) with the exact rotations, the modulation mode, \( M_{N,i} \), can be easily classified as follows:

\[
\hat{l} = \arg \min_{l \in \{0, \ldots, L_1\}} |\varphi - \phi_l|.
\]

In addition, we can give greater importance to OMA/NOMA classification than classification of the modulation orders or power ratios by introducing the phase ranges for OMA and NOMA with different intervals denoted by \( \Phi_O \) and \( \Phi_N \), respectively. Obviously, \( \phi_0 \in \Phi_O \) and \( \phi_1, \ldots, \phi_L \in \Phi_N \), and also assume that \( \Phi_O \cup \Phi_N = [0, 2\pi) \) and \( \Phi_O \cap \Phi_N = \{ \phi \} \), where \( \{ \phi \} \) is the empty set. Then, \( \varphi \) must be included in either \( \Phi_O \) or \( \Phi_N \), but not both. If \( \varphi \in \Phi_O \), the signal is classified as OMA, otherwise, NOMA. Similarly, the far UT’s modulation order can be classified by dividing \( \Phi_N \) into several nonoverlapping phase ranges corresponding to different far UT’s modulation orders. For example, let QAM, 16QAM and 64QAM are the candidates of far UT’s modulation. Then, we can generate \( \Phi_{N,0}^{QAM}, \Phi_{N,1}^{16QAM} \), and \( \Phi_{N,2}^{64QAM} \), corresponding to the NOMA modes using QAM, 16QAM, and 64QAM as far UT’s modulation, respectively. Those ranges satisfy \( \Phi_{N,0}^{QAM} \cup \Phi_{N,1}^{16QAM} \cup \Phi_{N,2}^{64QAM} = \Phi_N \). Therefore, if \( \varphi \in \Phi_N \), then \( \varphi \) must be included in only one range among \( \Phi_{N,0}^{QAM}, \Phi_{N,1}^{16QAM} \), and \( \Phi_{N,2}^{64QAM} \), and far UT’s modulation can be found.

Next, suppose that QAM is classified as far UT’s modulation and there are \( L_1 \) modulation modes whose far UT’s modulation is QAM. Then, classification of power ratio can be conducted by introducing nonoverlapping phase ranges of \( \Phi_{N,i}^{QAM} \) for all \( l \in \{1, \ldots, L_1\} \), satisfying \( \bigcup_{l=1}^{L_1} \Phi_{N,i}^{QAM} = \Phi_{N,i}^{QAM} \), in a similar way to the aforementioned classification steps. A series of the pilot reuse-based classification processes of OMA/NOMA and modulation are expressed in Algorithm 1. In Algorithm 1, we assume that the far UT’s modulation of the first \( L_1 \) modes, \( M_{L_1}, \ldots, M_{L_1} \), is QAM. In addition, the next \( L_2 \) modes, \( M_{L_1+1}, \ldots, M_{L_1+L_2} \), and remaining \( L_3 \) modes, \( M_{L_1+L_2+1}, \ldots, M_L \), use 16QAM and 64QAM for the far UT’s modulation, respectively.

This scheme performs OMA/NOMA and modulation classifications simultaneously, therefore blind signal classification becomes simpler. In addition, this scheme is not necessary to estimate the accurate rotation value, and it is sufficient to find the correct phase range which corresponds to the transmitted modulation mode. After modulation classification, the pilot symbols should serve their original purposes, therefore the rotated one has to be de-rotated, \( r_r e^{-j \phi_l} \). Thus, the proposed classification algorithm does not need to know any pilot value.


Algorithm 1 Pilot-Reuse Based OMA/NOMA and Modulation Classifications

Precondition: Phase ranges:

\[ \Phi_{O}, \Phi_{N}, \Phi_{N^{QAM}}, \Phi_{N^{16QAM}}, \Phi_{N^{64QAM}} \]

1: Compute \( \phi \) by (29)
2: if \( \phi \in \Phi_{N^{QAM}} \) then
3: Decide \( M_{O} \)
4: else
5: if \( \phi \in \Phi_{N^{16QAM}} \) then
6: \( \hat{\phi} \leftarrow \arg \min_{l=1,\ldots,L_{1}} |\phi_{l} - \phi| \)
7: else if \( \phi \in \Phi_{N^{64QAM}} \) then
8: \( \hat{\phi} \leftarrow \arg \min_{l=L_{1}+1,\ldots,L_{1}+L_{2}} |\phi_{l} - \phi| \)
9: else
10: \( \hat{\phi} \leftarrow \arg \min_{l=L_{1}+L_{2}+1,\ldots,L} |\phi_{l} - \phi| \)
11: end if
12: Decide \( M_{I} \)
13: end if

and channel gain.

The performance of the proposed algorithm depends on how phase rotation is assigned to each modulation mode. From a broad perspective, there are two phase assignment rules:

1) Uniform Assignment: The simplest rule is the uniform one, \( \phi_{l} = \frac{2\pi l}{L} \) for \( M_{I} \) and \( \phi_{O} = 0 \) for \( M_{O} \). In this case, \( \Phi_{N} = \{ 2\pi \frac{0}{L_{1}} \ldots, 2\pi \frac{L_{1}+L_{2}}{L_{1}+L_{2}} \} \) and \( \Phi_{O} = \{ 0, \frac{2\pi}{L_{1}}, \frac{2\pi}{L_{1}+L_{2}} \} \). The uniform assignment seems reasonable, but \( \Phi_{O} \) becomes smaller as \( L \) increases, therefore it is unfair when OMA is transmitted.

2) Non-uniform Assignment: The non-uniform assignment rule reflects an importance of each classification step. Since OMA/NOMA classification is more important than modulation classification, generations of \( \Phi_{O} \) and \( \Phi_{N} \) have the first priority, and then \( \Phi_{N^{QAM}}, \Phi_{N^{16QAM}}, \Phi_{N^{64QAM}} \) are settled. At last, the phase rotations of the NOMA modes having the same far UT’s modulation order but different power ratios are decided.

Fig. 5: Phase ranges of non-uniform phase rotation rule

The phase ranges of the non-uniform assignment are described in Fig. 5. Even though \( \Phi_{N^{QAM}}, \Phi_{N^{16QAM}}, \Phi_{N^{64QAM}} \) consist of \( L_{1}, L_{2} \) and \( L_{3} \) modes, those ranges occupy the same amount of interval as that of \( \Phi_{O} \). After generating \( \Phi_{O} \) and \( \Phi_{N} \), \( \Phi_{N} \) is divided into \( \Phi_{N^{QAM}}, \Phi_{N^{16QAM}}, \Phi_{N^{64QAM}} \), as shown in Fig. 5. The interval sizes of the phase ranges can be arbitrarily chosen depending on the transmission system, such as the number of modulation candidates. The exact phase rotation values for the NOMA modes, \( \phi_{1}, \ldots, \phi_{L} \), are uniformly chosen in the range in which each mode is included. For example, if \( \Phi_{N^{QAM}} = \{ \frac{2\pi}{3}, \frac{2\pi}{3} \} \), then \( \phi_{l} = \frac{2\pi}{3} + \frac{2\pi}{L_{1}} \cdot (l-1) \), for all \( l \in \{ 1, \ldots, L_{1} \} \).

Algorithm 2 Pilot reuse-based Near/Far UT Classification

Precondition: \( p_{0}^{f} \) is given.

1: Compute \( a_{f} \) and \( a_{n} \)
2: \( a_{f} = y - h\sqrt{P_{f}p_{0}^{f}} \)
3: \( a_{n} = y - h\sqrt{P_{n}p_{0}^{n}} \)
4: Compute \( \Delta_{f} \) and \( \Delta_{n} \)
5: \( \Delta_{f} = \min_{y \in \chi_{f}} |a_{f} - h\sqrt{P_{f}p_{0}^{f}}| \)
6: \( \Delta_{n} = \min_{y \in \chi_{n}} |a_{n} - h\sqrt{P_{n}p_{0}^{n}}| \)
7: if \( \Delta_{f} \geq \Delta_{n} \) then
8: Far UT Decision
9: else
10: Near UT Decision
11: end if

B. Pilot Reuse-Based Near/Far UT Classification

For proposing a near/far UT classification algorithm by reusing the existing pilots, it considers power multiplexing of pilot transmissions. The power-multiplexed legacy pilot becomes

\[ p_{l} = \sqrt{P_{f}p_{l}^{f}} + \sqrt{P_{n}p_{l}^{n}}, \quad (31) \]

where \( p_{l}^{f} \) and \( p_{l}^{n} \) are legacy pilots for the far and near UTs, respectively. The rotated pilot symbols used for OMA/NOMA and modulation classifications can also be utilized for near/far UT classification after de-rotating them. Each UT usually knows only its own pilot values, but does not recognize whether the known pilot symbols are for the far or near UT. Therefore, let \( p_{0}^{f} \) be a known pilot value, therefore \( p_{l}^{f} = p_{l}^{f} \) for the far UT and \( p_{l}^{n} = p_{l}^{n} \) for the near UT.

The proposed near/far UT classification algorithm in a two-user NOMA system is summarized in Algorithm 2. Algorithm 2 requires channel estimation and modulation classification to be previously completed. The UT computes two hypotheses, \( \Delta_{f} \) and \( \Delta_{n} \), and each one is obtained under the assumption that the receiver is the far or near UT, respectively.

To clearly explain the algorithm, an example is presented. From (27) and (31), the received pilot is given by

\[ y_{l} = h(\sqrt{P_{f}p_{l}^{f}} + \sqrt{P_{n}p_{l}^{n}}) + n_{l}. \quad (32) \]

Suppose channel estimation is perfect and the receiver is the near UT, i.e., \( p_{0}^{n} = p_{l}^{n} \), then

\[ a_{f} = y_{l} - h\sqrt{P_{f}p_{l}^{f}} = h(\sqrt{P_{f}(p_{l}^{f} - p_{l}^{n})} + \sqrt{P_{n}p_{l}^{n}}) + n_{l} \quad (33) \]

\[ a_{n} = y_{l} - h\sqrt{P_{n}p_{l}^{n}} = h\sqrt{P_{f}p_{l}^{f}} + n_{l}. \quad (34) \]

\( a_{f} \) and \( a_{n} \) are obtained under the assumption that the receiver would be far and near UTs, respectively. The next step is to
TABLE II: Case 1: Modulation Mode Table

| Modulation mode | Modulation (far UT) | Modulation (near UT) | Power ratio (far UT) |
|-----------------|---------------------|----------------------|----------------------|
| M₀              | QPSK                | -                    | 1.0                  |
| M₁,N,1          | QPSK                | QPSK                 | 0.8                  |
| M₁,N,2          | QPSK                | QPSK                 | 0.8621               |
| M₁,N,3          | QPSK                | QPSK                 | 0.9163               |

TABLE III: Case 2: Modulation Mode Table

| Modulation mode | Modulation (far UT) | Modulation (near UT) | Power ratio (far UT) |
|-----------------|---------------------|----------------------|----------------------|
| M₀              | 16QAM               | -                    | 1.0                  |
| M₁,N,1          | QPSK                | 16QAM                | 0.8653               |
| M₁,N,2          | QPSK                | 16QAM                | 0.95                 |
| M₁,N,3          | 16QAM               | 16QAM                | 0.95                 |

TABLE IV: Case 3: Modulation Mode Table

| Modulation mode | Modulation (far UT) | Modulation (near UT) | Power ratio (far UT) |
|-----------------|---------------------|----------------------|----------------------|
| M₀              | 16QAM               | -                    | 1.0                  |
| M₁,N,1          | QPSK                | 16QAM                | 0.7619               |
| M₁,N,2          | QPSK                | 16QAM                | 0.8653               |
| M₁,N,3          | QPSK                | 16QAM                | 0.9275               |
| M₁,N,4          | 16QAM               | 16QAM                | 0.95                 |
| M₁,N,5          | 16QAM               | 16QAM                | 0.97                 |

compute $\Delta_f$ and $\Delta_n$ as follows:

$$\Delta_f = \min_{q \in \chi^f} |a_f - h \sqrt{P_n} q|$$

(35)

$$\Delta_n = \min_{q \in \chi^l} |a_n - h \sqrt{P_f} q|.$$  

(36)

Since modulation classification is completed, $P_f$, $P_n$, $\chi^f$ and $\chi^l$ are known. Note that $\Delta^q_i$ remains the only noise component when $q = p^f_i$. On the other hand, $a_f$ includes the non-zero term in (33), i.e., $h \sqrt{P_f}(p^f_i - p^n_i)$, as well as the noise component. Thus, mostly $\Delta_f \geq \Delta_n$ and the near UT is decided.

VII. PERFORMANCE EVALUATION

A. Simulation Environments

This section provides a variety of performance comparisons of conventional ML signal classification with the proposed schemes. Acronyms are used for the methods of signal classification in the figures, “MLC” for ML classifier, “MLC-PRM” for phase-rotated modulation based on ML classification, and “PRC” for the pilot reuse-based classifier. For MLC and MLC-PRM, 10 data symbols are used to classify the received signals. PRC utilizes only one pair of pilots, because the number of pilots are usually less than data symbols. There are three example cases of the modulation modes.

1) Case 1: Case 1 is based on Table II. The far UT’s modulation is fixed, and it considers OMA/NOMA and power ratio classifications only. Suppose that $M_2$ is transmitted.

2) Case 2: Case 2 is based on Table III. The single power ratio is assigned to each mode, and it considers OMA/NOMA and far UT’s modulation order classifications only. Suppose that $M_1$ is transmitted.

3) Case 3: Case 3 is based on Table IV. It considers OMA/NOMA, power ratio, and far UT’s modulation order classifications. Suppose that $M_2$ is transmitted.

The power ratios of the modulation modes whose far UT is modulated by QPSK in Table II-IV follow the MuST parameters of 3GPP [13]. Since MuST only considers QPSK for the far UT from now on, the power ratios of the far UT which uses 16QAM are arbitrarily chosen.

We consider a two-user cellular NOMA system assuming Rayleigh fading channel, $h \sim CN(0, 1)$. A ML equalizer and a low-density parity check (LDPC) 11ad decoder [37] are used for word error rate (WER) simulations. CWIC is basically used for SIC, but the system occasionally chooses SLIC when decoder-feedback is impossible to obtain, i.e., classification of the far UT’s modulation order is incorrect. The phase rotations of MLC-PRM are $\theta_1 = 0.6, 0.51,$ and $0.69$ radians optimized at 13dB, 20dB, and 20dB of SNR in Cases 1, 2 and 3, respectively. As explained before, these phase rotations are applied for only OMA/NOMA classification. Additionally, the uniform phase assignment rule is used for PRC.

Fig. 6: OMA/NOMA classification error rates in Case 1

Fig. 7: Near/far UT and modulation classification error rates in Case 1
Fig. 8: OMA/NOMA classification error rates in Case 2

Fig. 9: Near/far UT and modulation classification error rates in Case 2

Fig. 10: OMA/NOMA classification error rates in Case 3

Fig. 11: Near/far UT and modulation classification error rates in Case 3

B. Signal Classification Error Rates and User Capacity

Figs. 6, 8 and 10 show classification error rates in Cases 1, 2, and 3, respectively. We can easily find that PRC gives much better OMA/NOMA classification rates than those of MLC for every example. MLC-PRM is also obviously better than MLC, but its improvement is less than PRC. Since an OMA/NOMA classification error destroys correct data restoration, the proposed MLC-PRM and PRC are expected to be favorable for data detection.

The near/far UT classification error rates in Cases 1, 2 and 3 are the solid curves in Figs. 7, 9 and 11, respectively. Since the signals determined as OMA does not perform near/far UT classification, these error rate curves include incorrect decisions of OMA as well as far UT of NOMA. Compared to OMA/NOMA classification, performance improvements of MLC-PRM over MLC are reduced in near/far UT classification. The reason is the tendency of the signals which are classified as OMA by MLC but as NOMA by MLC-PRM. Those signals already contribute the OMA/NOMA classification error rate of MLC, therefore it does not make near/far UT classification error rate worse. On the other hand, even though MLC-PRM classifies them as NOMA, those signals can be classified as the far UT. A similar phenomenon appears in the PRC graphs, but the effect is not significant. Therefore, PRC still shows much better classification performance of the near UT signals compared to those of MLC and MLC-PRM.

Comparing the simulation cases, there is not much significant difference in near UT classification rates of the three methods in Fig. 7, compared to Fig. 9 and 11. This is because Case 2 and Case 3 are less sensitive to near/far UT classification than Case 1. Since every NOMA mode has the same modulation order for both UTs in Case 1, even when the signal is classified as NOMA, Case 1 should always perform near/far UT classification for correct data detection. On the other hand, in Case 2 and Case 3, there are some situations where near/far UT classification is not required, in other words, modulation orders for near and far UTs are different for some modes. Note that the receiver already knows its own modulation order.

The dashed curves in Figs. 7, 9, and 11 are the modulation classification error rates among the signals correctly classified as near UT of NOMA. Incorrect OMA/NOMA or near/far UT classification almost results in a packet error, therefore the modulation classification rates of the signals decided as near UT of NOMA are only meaningful. In the case of MLC-PRM, a data symbol rotation is applied for only OMA/NOMA classification, therefore the modulation classification rates of MLC and MLC-PRM are almost the same in every example case. On the other hand, PRC shows much better modulation classification rates than MLC and MLC-PRM. Especially for Cases 2 and 3, the incorrectly classified modulation mode may have a different far UT’s modulation order from the transmitted one. Therefore, the effects of the better modulation classification rates obtained by PRC on the data detection performance are expected to be large in Cases 2 and 3.

In addition, the capacity degradations of the signal classification methods with respect to the Genie scheme with ideal classification are shown in Fig. 12. In the SNR region lower than 20dB, MLC-PRM and PRC obviously give better capacity than MLC, and especially PRC shows almost similar capacity to that of Genie. In the high SNR region, the classification rates of all schemes are sufficient to achieve almost the same
C. Word Error Rates

The WER performances of the signal classification schemes are obtained to verify practical usefulness of the proposed schemes. Figs. 13, 14, and 15 correspond to Cases 1, 2, and 3, respectively.

In Case 1, the WER performance of every signal classification scheme is significantly worse than that of Genie. According to Fig. 7, the classification error rates of all schemes are still too poor to catch the performance of Genie at the SNR region lower than 10dB. As SNR increases above 10dB, the near/far UT classification rates obtained by MLC-PRM and PRC become eventually superior to those obtained by MLC, and this tendency is reflected in Fig. 13.

The WER graphs of Cases 2 and 3 shown in Figs. 14 and 15 respectively, are quite similar. In these figures, the performance of PRC is nearly the same as the Genie scheme. According to Figs. 9 and 11, since PRC shows remarkable superiority of the classification error rates to MLC and MLC-PRM around 15dB, PRC seems almost always successful to classify the NOMA signals in the operating SNR region.

MLC-PRM provides a 1dB SNR gain at the WER of 0.1 compared to MLC in Case 2 and Case 3, but the WER performances of MLC and MLC-PRM are still much worse than PRC and Genie even in the high SNR region. These results are consistent with the modulation classification error rates shown in Figs. 9 and 11. In the high SNR region, the near/far UT classification error rates of all methods are sufficiently improved and the effect of the modulation classification error becomes dominant. Thus, the WER performances of PRC is also much greater than those of MLC and MLC-PRM in the high SNR region. On the other hand, since MLC and MLC-PRM have the identical modulation classification rates, their WER performances are converging.

VIII. CONCLUSIONS

This paper considers one of the key issues in NOMA systems, namely, blind signal classification problem to reduce a high-layer signaling for informing the co-scheduled signal formats and to improve spectrum/resource efficiency in highly-mobile vehicular networks. We consider the classification steps of OMA/NOMA, near/far UT, modulation orders and power ratios for NOMA UTs. This work quantifies how much effects come from each type of the classification error in terms of SINR. Based on SINR analysis, capacity of the near UT in the NOMA system is obtained with inclusion of the signal classification errors. This paper also proposes a phase-rotated modulation scheme, which rotates the data symbols to make the constellations of the modulation modes easily distinguishable from one another. In addition, a pilot-reuse-based signal classification algorithm is proposed. The proposed schemes give better performances in terms of classification error rate, capacity and WER than conventional ML classification in various environment settings. Thus, the proposed schemes can be helpful in vehicular networks where only the limited energy and spectrum/resource/time are provided due to high mobility.
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