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Phase-Shifted DMRS-Aided Automatic Modulation Classification for PDSCH in 5G New Radio

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ABSTRACT

In this letter, a novel automatic modulation classification (AMC) scheme is developed for physical downlink shared channel (PDSCH) in 5G New Radio (NR). We design a convolutional neural network (CNN) to classify modulation types of the received PDSCH. To improve the classification accuracy, an enhanced demodulation reference signal (DMRS) structure is proposed where the phase of the DMRS is shifted depending on the modulation types. Simulation results verify that the proposed AMC scheme achieves 31.5% gain compared to the legacy scheme in terms of classification accuracy.

Key Words : AMC, PDSCH, 5G NR, CNN, DMRS

Ⅰ. Introduction

With the large-scale commercial rollout of 5G and a new breakthroughs for 6G, mobile communication is developing toward intelligent communication[1]. Automatic modulation classification (AMC) for intelligent communication has got significant attention due to its wide range of applications in wireless communication[2,3]. An intelligent receiver can preprocess the received signal to identify the modulation type of the transmitted signal without prior information. Consequently, the control signal overhead can be reduced. Minimizing control signal overhead is particularly important for low complexity and battery-limited devices since it contributes to improve the reliability of physical downlink control channel (PDCCH) reception and reduces the power consumption associated with PDCCH blind decoding of the terminal[4]. Recently, deep learning-based AMC techniques have been widely studied[2,3]. Compared to the traditional maximum likelihood method, deep learning approach shows robust classification performance under fading channels and low signal-to-noise ratio (SNR) environments[2].

In 5G NR systems, the data channel, i.e., physical downlink shared channel (PDSCH), is transmitted with its demodulation reference signal (DMRS). Based on the current specification, the data symbols of a PDSCH can be modulated with one of modulation types among quadrature phase shift keying (QPSK), 16-quadrature amplitude modulation (QAM), 64-QAM, and 256-QAM. On the other hand, DMRS symbols are modulated with QPSK[5]. When AMC is applied to the NR PDSCH including DMRS, the classification accuracy is degraded due to the presence of the fixed QPSK symbols of DMRS.

In this paper, we develop a novel AMC method based on phase-shifted DMRS for NR PDSCH. To this end, we design a low complexity convolutional neural network (CNN) structure to classify one of four modulation types. In addition, we propose an enhanced DMRS structure where the phase of DMRS is associated with the modulation type of data. The modulation order-specific DMRS derives positive impacts on AMC performance, leading to improved classification accuracy.

Ⅱ. System Model

We consider NR PDSCH structure based on 5G NR specification[5]. A PDSCH can be transmitted in a slot which consists of 14 orthogonal frequency division multiplexing (OFDM) symbols. In frequency do-

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main, a PDSCH is allocated to multiple physical resource blocks (PRBs) consisting of 12 subcarriers. The data bits are modulated to complex-valued symbols based on one of modulation types among QPSK, 16-QAM, 64-QAM, and 256-QAM.

The DMRS for PDSCH is modulated by QPSK as

$$r(n) = \frac{1}{\sqrt{2}}\big(1 - 2c(2n)\big) + j\frac{1}{\sqrt{2}}\big(1 - 2c(2n+1)\big), \quad (1)$$

where the pseudo-random sequence $c(i)$ is defined in clauses 5.2.1 and 7.4.1.1 in TS 38.211[5]. The DMRS is mapped to resource element (RE) (k, l) according to the following equation:

$$\alpha_{k,l} = \beta w_f(k') w_t(l') r(2n + k'), \quad (2)$$

where k is subcarrier index, l is OFDM symbol index, β is a scaling factor, $k' = 0,1$, $l = l + l$, $k = 4n + 2k' + \Delta$ for configuration type 1, and $k = 6n + k' + \Delta$ for configuration type 2[5].

The received signal on (k, l), $x_{k,l}$, is given by

$$x_{k,l} = \rho \cdot c_{k,l} \cdot s_{k,l}^{(q)} + n_{k,l}, \quad (2)$$

where ρ is transmit SNR, $c_{k,l}$ is channel impulse response, $s_{k,l}^{(q)}$ is the transmitted symbol modulated by q-th modulation type where q = 0, 1, 2, 3, and $n_{k,l}$ is additive white Gaussian noise (AWGN) with zero mean and unit variance.

Ⅲ. Proposed AMC scheme

The classifier is designed to provide the probability of a given type of predictive modulation as follows:

$$\Pr\left(s_{k,l} \in M(q) \middle| x_{k,l} \text{ for } k,l \in \Omega_{pdsch}\right), \quad (4)$$

where $M(q)$ represents the q-th modulation type and Ω_{pdsch} is a set of REs where the PDSCH is received.

The CNN architecture for AMC of PDSCH is shown in Fig. 1. The designed network uses real-valued raw data as the input. The received signal consists of in-phase and the quadrature components, and the length of the signal is set to $N_{sym}N_{sc}$, where N_{sym} is the number of symbols and N_{sc} is the number of subcarriers. In Fig. 1, "Conv" means the convolution layer, "BN" represents a batch normalization layer that normalizes the input to a standard normal distribution, "ReLU" means rectification linear activation. We set 2 × 1 and 16 × 1 pooling kernel sizes for the maximum pooling layer and the average pooling layer, respectively. "FC" is a fully connected layer and "SoftMax" is a softmax layer which is an activation function of a fully connected layer. Finally, the output is a classified modulation type. The proposed CNN is designed to have much lower complexity compared to the existing networks such as TRNN[2] and ResNet[3]. The number of training parameters of CNN, TRNN, and ResNet are 96.7k, 223.8k, and 121.8k.

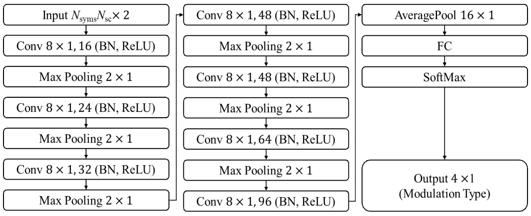

Fig. 1. CNN architecture of AMC for NR PDSCH.

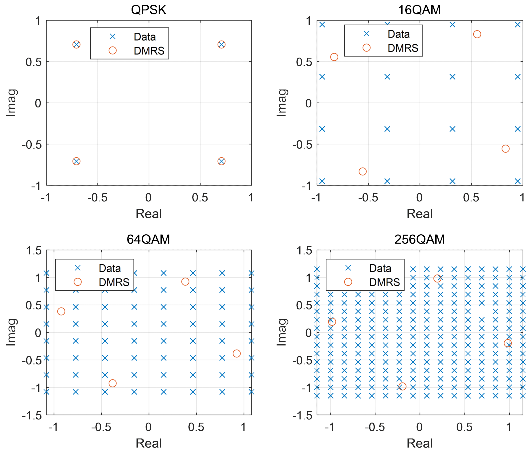

Fig. 2. Proposed phase-shifted DMRS structure.

Fig. 2 illustrates the proposed phase-shifted DMRS structure. As shown in Fig. 2, the phase for QPSK constellation of DMRS is determined by the modulation type of data. Specifically, the proposed DMRS is modulated based on the following equation:

$$r'(n) = e^{j\theta(q)}\left(\frac{1}{\sqrt{2}}\left(1-2c(2n)\right) + j\frac{1}{\sqrt{2}}\left(1-2c(2n+1)\right)\right), \quad (5)$$

where $\theta(q) = (q - 1) \cdot \pi/16$ is the phase shift value for q-th modulation type. Although DMRS still uses QPSK modulation, the additional phase information associated with modulation type can contribute to extract feature for the specific modulation type.

Ⅳ. Simulation Results

In this section, we provide simulation results to evaluate the classification performance for the proposed AMC scheme. Table 1 describes detailed simulation parameters. For training and test, we generate PDSCHs containing data symbols which is randomly modulated by one of QPSK, 16-QAM, 64-QAM, and 256-QAM. DMRSs are generated based on the fixed parameters given in Table 1 and inserted to the REs corresponding to eq. (2). The generated physical frame is transmitted via fading channel with AWGN. Then, it is input to the deep learning network in frequency domain after FFT.

Fig. 3 illustrates the classification accuracy depending on the transmit SNR. The proposed AMC with enhanced DMRS achieves 96 % accuracy, while that

Table 1. Simulation Parameters

Parameter	Value
Channel model	TDL-A
Carrier frequency	6 GHz
Delay spread	$10^{-8.3}$ sec
Velocity	30 km/h
Subcarrier spacing	30 kHz
Number of PDSCH symbols	12 symbols
Number of RB	10 RBs
DMRS configuration type	2
DMRS length	2
DMRS additional position	1
DMRS scrambling ID	10
Number of training data	480,000
Number of validation data	120,000
Number of test data	200,000
Epoch	25
Mini batch size	1024

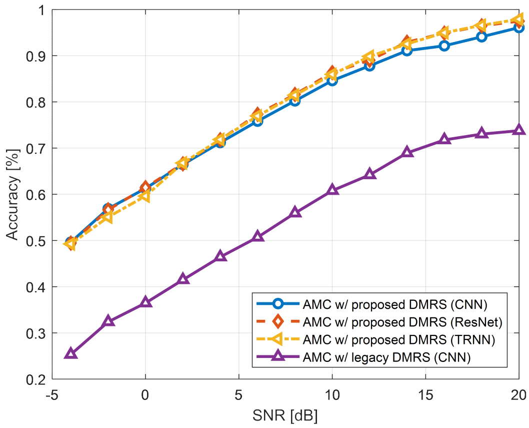

Fig. 3. Classification accuracy for the proposed AMC.

with legacy DMRS shows 73% accuracy at 20 dB SNR, i.e., 31.5 % performance gain is achieved. In addition, the proposed CNN shows similar classification accuracy compared to the legacy TRNN[2] and ResNet[3] although the CNN has much lower complexity. Therefore, the proposed

AMC scheme is effective for realizing the real-time AMC technique for NR PDSCH.

Ⅴ. Conclusion

In this letter, a novel CNN-based AMC method is proposed for NR PDSCH. We develop a low complexity CNN to classify modulation types of the received PDSCH. In addition, an enhanced DMRS structure which applies different phase shift value according to the modulation order is proposed. Based on the simulation, it is verified that the proposed AMC scheme achieves improved classification accuracy compared to legacy scheme.

References

[1] C.-X. Wang, et al., "On the road to 6G: visions, requirements, key technologies, and testbeds," *IEEE Commun. Surv. & Tut.*, vol. 25, no. 2, pp. 905-974, Secondquarter 2023.

[2] L. Zhang, et al., "Real-time OFDM signal modulation classification based on deep learning and software-defined radio," *IEEE Commun. Lett.*, vol. 25, no. 9, pp. 2988-2992,

Sep. 2021.

[3] T. J. O'Shea, T. Roy, and T. C. Clancy, "Over-the-air deep learning based radio signal classification," *IEEE J. Sel. Top. Sig. Proc.*, vol. 12, no. 1, pp. 168-179, Feb. 2018. (https://doi.org/10.1109/JSTSP.2018.2797022)

[4] T. Kim, Y. Kim, M. Jung, and H. Son, "Intelligent partial sensing based autonomous resource allocation for NR V2X," *IEEE Internet of Things J.*, vol. 11, no. 2, pp. 3144-3160, Jan. 2024. (https://doi.org/10.1109/JIOT.2023.3295024)

[5] 3GPP TS 38.211, "NR; Physical channels and modulation," V17.2.0, Release 17, Jun. 2022.