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A CNN Technique for MCS Selection in 5G NR Mobile Communication Systems

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ABSTRACT 5G NR is a wireless mobile communication system that supports ultra-high speed mobile communications, high reliability services, and large-scale Internet of Things. In a mobile communication environment, the Doppler effect, which is proportional to the speed of travel, causes channel changes over time, which can lead to communication performance degradation. In order to achieve optimal communication performance in a mobile communication environment, it is necessary to predict the Signal to Noise Ratio (SNR) between the base station and the terminal and select and transmit the most appropriate Modulation and Coding Scheme (MCS) accordingly. In this paper, we propose a method for selecting the MCS level of a single antenna based on Convolutional Neural Network (CNN) in 5G NR mobile communication systems. The proposed system assumes a time division duplex (TDD) scheme, measures the SNR at the time of reception, predicts the SNR at the time of future transmission using CNN based on the measured past channel information, and selects the MCS level based on the predicted SNR. Experimental results through computer simulation show that the proposed CNN-based MCS selection method has a lower probability of communication disconnection and higher transmission rate at all speeds compared to the existing average value method based on the average of SNR and the recent value method based on the most recently received SNR. In particular, the transmission speed of the proposed method is about 46% and 4.6% better than the existing average value method and recent value method, respectively, and can be utilized as a technology to increase the transmission speed in 5G mobile communication environment.

Keywords: 5G NR, SNR Prediction, CNN, TDD, MCS, Deep Learning

1. INTRODUCTION

The development of major technologies such as Virtual Reality (VR), Augmented Reality (AR), Autonomous Vehicle (AV), and Internet of Things (IoT), which are the core technologies of the Fourth Industrial Revolution, require high-speed and high-capacity data transmission, leading to the introduction of 5G New Radio (5G NR) as defined by 3GPP (Osseiran et al, 2014 & Seol et al, 2023).

The three characteristics of 5G NR technology are Enhanced Mobile Broadband (eMBB), which can handle high-speed communication speeds and large amounts of data with no data delay; Mission-Critical Control, which provides a highly reliable, ultra-low latency, and highly available communication network; and finally, Massive Internet of Things, which uses less power and has a wide communication range to accommodate the rapid growth of IoT, and is recognized as a key element of the wireless communication system (Zaidi et al., 2017; Säily et al., 2020; Imam-Fulani et al., 2023 & Li et al., 2022). Therefore, research has been conducted to improve the efficiency and reliability of 5G networks, such as Ka-band CMOS variable gain amplifiers for 5G communications (Zhang et al, 2020), performance evaluation of 5G wireless access systems using four-way antennas (Takahashi et al. 2017), 5G-IoT architectures (Kar et al, 2021), and adaptive modulation and coding techniques for 5G systems (Wang et al, 2021).

In the case of non-line-of-sight communication in 5G NR mobile communication environment, communication performance degradation occurs due to the fading channel caused by surrounding obstacles and the Doppler effect proportional to the movement speed. Therefore, it is necessary to track the quality of the communication channel between the base station and the terminal in real time and select and transmit the communication method that is optimal for the channel quality (Zhao et al, 2024). One way to increase transmission speed and communication reliability is to adjust the Modulation and Coding Scheme (MCS) level. Each MCS level has a different reliability and transmission rate, and there is a trade-off relationship between higher MCS level and higher transmission rate at the expense of communication reliability, and lower MCS level and lower transmission rate at the expense of communication reliability. The optimal MCS level is determined by the channel quality at the time of communication, and if a higher MCS is selected, the communication reliability is not obtained, and if a lower MCS is selected, the transmission rate is reduced. Therefore, selecting the optimal MCS level is very important (Ngo et al. 2020; Fan et al, 2020). In addition, with the rapid growth of artificial intelligence, several researchers are conducting research on MCS selection using artificial intelligence (Wang et al, 2021; Oh et al, 2023).

Thyagarajan et al., 2021 propose a technique to predict the SNR at future transmissions using the past received SNR using Convolutional Neural Network (CNN) in 5G NR mobile communication environment and select the optimal MCS level based on the predicted SNR. We assume that the communication system under consideration is a time-division duplexing (TDD) system that communicates in both directions at the same frequency, and that one antenna is used for both transmitting and receiving. Therefore, the transmit and receive bidirectional channels are identical. Common methods for determining the MCS in this environment include the mean value method, which selects the MCS based on the average value of the received SNR, and the recent value method, which selects the MCS based on the most recently received SNR. However, if the transmitter or receiver is moving fast and the time difference between reception and transmission is large, the selected MCS may not be suitable. The proposed method uses a CNN to predict the SNR at future transmissions and selects an MCS based on the predicted SNR. Simulation experiments show that the proposed method based on CNN outperforms the existing methods in the 5G NR wireless mobile communication environment with better communication disconnection probability and higher transmission rate. Specifically, the proposed method outperforms the existing mean value method and recent value method by about 46% and 4.6%, respectively. These results show that the transmission rate can be improved by applying the proposed method in 5G mobile communication systems.

2. SYSTEM MODEL

In 5G NR wireless mobile communication environments, it is necessary to select an MCS level that ensures optimal communication reliability and transmission rate considering the time-varying channel. In this study, we predict the SNR at the time of transmission based on the past antenna channel quality in a TDD environment and then select the most appropriate MCS level. In the SNR prediction process, we consider a dense network model that utilizes CNNs to achieve high accuracy in channel estimation. First, the SNR is estimated at regular intervals from the receiving antenna and combined into a vector. Then, since the size of the input data is fixed for artificial intelligence models, the input data is preprocessed to fit the CNN model input and fed into the CNN for prediction. The system uses 100 downlink and 6 uplink data to ensure proper transmission and reception times, and uses a fixed 45-bit structure with equal downlink and uplink ratios among the standard formats of 5G NR.

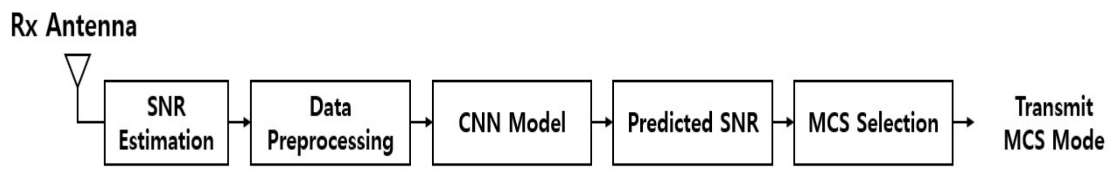

Figure 1. *Proposed System Model*

Figure 1 is a block diagram of the proposed MCS level selection system. The receiving antenna measures the SNR at regular intervals, then combines the SNR into a vector and stores it. In order to use the proposed CNN method, data preprocessing is required. To preprocess the data, we perform the process as shown in Figure 2, and then input it to the CNN model to predict the SNR and select the MCS.

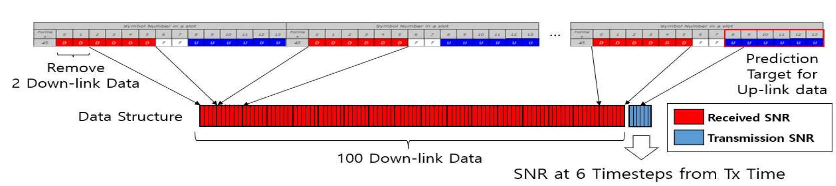

Figure 2. Input Data Structure Using 5G NR Format 45 Scheme

Figure 2 shows the input data preprocessing. The data slots used in this paper use the SNR 5G NR 45 format, which has 14 OFDMs per slot, with 6 uplink symbols, 2 guard bands, and 6 downlink symbols. In the above diagram, the red color indicates the past received SNR and the blue color indicates the SNR at the time of transmission, and it is designed in such a way that the SNR of the 6 uplink data can be predicted from the total 100 downlink data. In other words, this format predicts the SNR of the 6 time-varying data at the time of reception.

3. Prediction of Transmission Antenna SNR and MCS Level Selection Method

3.1. Existing methods

There are two existing methods for selecting a transmit antenna. The first is the recent value method. The recent value method uses the most recently measured receive SNR to predict the correct SNR at the time of transmitting and then selects the MCS level. The second method is the average value method, which calculates the average of the received SNRs measured over a period of time and predicts the correct SNR at the time of transmission to select the MCS level. These methods are used in a variety of wireless communication environments, and each has its own advantages and disadvantages. For example, the recent value method is good for fast-changing environments in real time, while the average value method can make stable predictions in slow-changing environments.

3.2. Proposed CNN method

Table 1: *CNN Overall Architecture*

Layers	Filters	Proposed CNN
Convolution	32	3 x 3 Conv, stride 1
Batch Normalization		
Convolution	32	3 x 3 Conv, stride 1
Batch Normalization		
Convolution	16	3 x 3 Conv, stride 1
Batch Normalization		
Convolution	16	3 x 3 Conv, stride 1
Batch Normalization		
Convolution	16	3 x 3 Conv, stride 1
Batch Normalization		
Regression Layer	Fully-Connected, Linear	

The proposed method in this paper uses CNNs to predict the future transmission SNR to select MCSs. Table 1 shows that it consists of five convolutional layers and one fully connected layer. In all layers, each convolutional layer includes a batch normalization layer and uses a 3x3 convolutional filter with a stride of 1. It also uses a Rectified Linear Unit (ReLU) as the activation function, with the following formula.

$$f(x) = \max(0, x) \quad (1)$$

The FC Layer uses a linear function. The regression layer gives the SNR prediction of the antenna, and the optimal MCS level is output. For training, the learning rate is 0.01, the batch size is 128, the epoch is 200, and the loss function is Cross-Entropy with the following equation.

$$H(p,q) = -\sum_i p(i)\log(q(i)) \quad (2)$$

4. SIMULATION RESULT

4.1. Simulation environment

Table 2: Simulation parameters

Parameters	Values
	5G NR
Num. of Rx antenna	1
Num. of Tx antenna	
Bandwidth	100MHz
Carrier frequency	3.6GHz
Channel model	Rayleigh(ITU Vehicular A) / Rician
K-factor of Rician channel	10dB
Num. of time step	100
SNR range	0 ~ 30dB
Speed	0 ~ 300km/h
LoS probability	50%

OFDM symbols per slot	14 OFDM symbol

For the simulation, we utilize MATLAB and TensorFlow 2.0 to generate data, validate and train the neural network model, and evaluate its performance. The following Table 2 shows the communication signal parameters of the simulation. Both the receiving and transmitting antennas use one antenna and are assumed to be directional. In this experiment, we consider the signal bandwidth specified by the 5G NR standard. The bandwidth is 100 MHz and the carrier frequency is assumed to be 3.6 GHz. The channel model is randomly selected between Line of Sight (LoS) and Non-LoS, utilizing the Rayleigh (ITU Vehicular A) and Lycian channel models. The K-index of the Lycian channel is 10 dB, and the length of the input data is set to 100. The input data is the received SNR of the generated signals according to the sampling interval in the channel model, and the average SNR of each generated signal is randomly selected from 0 to 30 dB. The traveling speed is randomly set from a minimum of 0 km/h to a maximum of 300 km/h. The travel speed and the average SNR of the signal are randomly generated for each training sample. The probability that a training sample is selected for line-of-sight and non-line-of-sight environments is 1:1, with 14 OFDM symbols per slot. Finally, the CNN model is trained with 200,000 training data and 20,000 validation data.

Table 3 shows the MSC table used in the simulation. In total, there are 15 types of threshold SNR values and transmission rate information that satisfy the SNR requirement performance of 5G NR [16].

Table 3: *5G NR MCS table*

CQI	MCS	Code rate × 1024	Spectral efficiency	SNR (dB) Perfect channel estimation	SNR (dB) Practical channel estimation
1	QPSK	78	0.1523	-11.2	-6.3
2	QPSK	120	0.2344	-6.9	-5.8
3	QPSK	193	0.377	-2.2	-1.4
4	16QAM	308	0.6016	2.7	3.9
5	16QAM	449	0.877	4.3	5.3
6	16QAM	602	1.1758	6.9	8.1
7	64QAM	378	1.4766	8.5	9.8
8	64QAM	490	1.9141	10.6	11.7
9	64QAM	616	2.4063	12.4	13.6
10	64QAM	466	2.7305	14.4	15.8
11	64QAM	567	3.3223	17.5	18.8
12	256QAM	666	3.9023	18.1	21.4
13	256QAM	772	4.5234	20.2	23.6
14	256QAM	873	5.1152	22.8	28.2
15	256QAM	948	5.5547	24.9	32

4.2. Simulation result

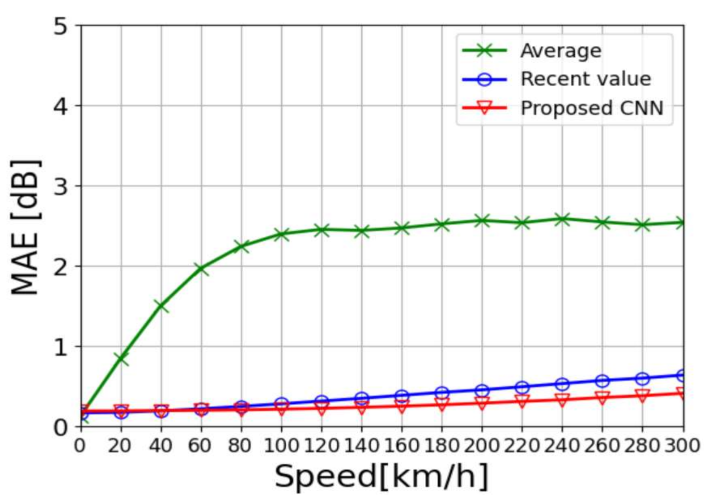

Figure 3. Compare All Methods MAE Performance

Generate a total of 20,000 test data at 20 km/h intervals in the same speed range. The evaluation metrics are the MAE and the communication disconnection probability and transmission rate for MCS selection based on the traveling speed using CNN. The formula for MAE is shown in Equation 3.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \quad (3)$$

Figure 3 shows the MAE of SNR estimation as a function of speed in a cellular environment. For both the recent value, average value, and CNN, the MAE tends to increase with increasing speed. The Doppler effect and rapid signal changes at higher speeds cause the estimated SNR value to deviate from the correct value. The mean value method is less dependent on the SNR of the most recently received signal, showing increasing estimation error up to 100 km/h and converging at 2.5 dB. The recency method performs similarly to the proposed CNN at 0 km/h, and as the speed increases, the SNR variation over time becomes larger, with lower SNR accuracy after 140 km/h. Finally, the proposed CNN model also degrades as the speed increases, but it outperforms the existing methods in all speed bins except 0 km/h, especially at speeds above 140 km/h, where it outperforms all methods. The average MAE of the average value method and the recent value method are 2.1367 dB and 0.3722 dB, respectively, while the average MAE of the proposed CNN method is 0.2448 dB, which shows good performance. Through this study, it is expected that the higher prediction SNR accuracy in 5G NR communication will ensure greater communication reliability compared to the existing methods.

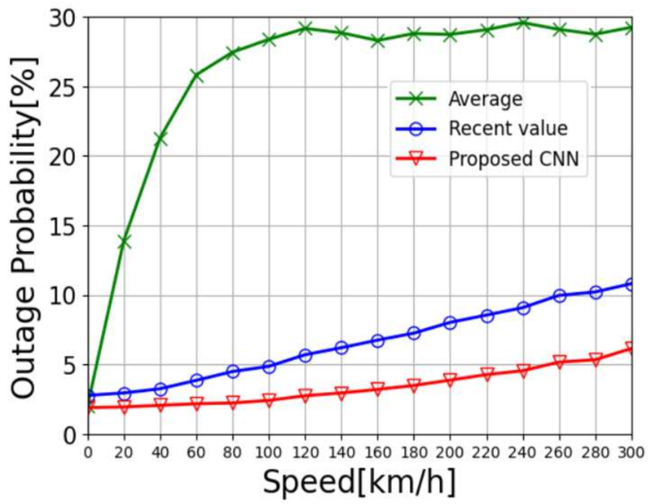

Figure 4. Outage probability of MCS selection

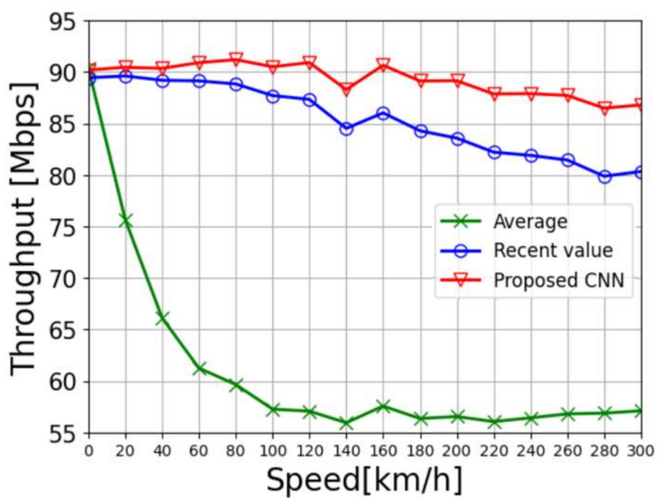

Figure 5. *Throughput of MCS selection*

Figure 4 and Figure 5 show the disconnection probability and transmission rate for the MCS selection, respectively. The average disconnection probability for all travel speeds is 25.52% for the average value method, 6.53% for the recent value method, and 3.39% for the proposed CNN method. At all speeds, the proposed CNN method has a lower disconnection probability than the existing methods. The average transmission rate is 61.06 Mbps for the average value method, 85.34 Mbps for the recent value method, and 89.28 Mbps for the proposed

CNN method at all travel speeds. The MAE of SNR estimation and the probability of communication disconnection as a function of speed in a mobile environment show similar trends. The simulation results show that the performance of both the existing method and the proposed CNN method degrades as the traveling speed increases, and we also observe that the performance difference between the existing method and the proposed method increases in the three performance evaluation metrics. This indicates that the proposed method can process more data at a higher speed when communicating in a mobile environment.

5. CONCLUSION

In this paper, we propose a method for selecting the MCS level of a single antenna based on CNN in 5G NR wireless mobile communication systems. The proposed method shows higher SNR prediction accuracy than existing methods at all speeds. In particular, experiments comparing three performance evaluation metrics, MAE, communication disconnection probability, and transmission rate, in a mobile environment show that the proposed CNN method outperforms the existing methods, the average value method and the recent value method. Through this study, it is expected that the proposed method can be used for one-to-one communication in a mobile communication environment to ensure high communication reliability and transmission speed by selecting the optimal MCS level with high SNR prediction accuracy.

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