MCS Selection Based on Convolutional Neural Network in Mobile Communication Environments

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***Abstract*— In this work, we propose using a CNN to select the MCS for future transmit times in mobile communication environments. The CNN predicts the MCS level from the past measured SNRs. We propose two techniques: the first selects the MCS directly from the past SNRs, and the other predicts the SNR at future transmit times first and then selects the MCS based on the predicted SNR. A typical conventional method selects the MCS based on the most recently measured SNR. According to our simulation results, the proposed methods show lower outage probabilities and higher throughput compared to the conventional method.**

Keywords—MCS prediction; CNN; Classification; Regression; SNR prediction

I. INTRODUCTION

In wireless communications, there are several modulation and coding schemes (MCSs) from which the transmitter selects one to transmit information. Different MCSs have different data rates and reliability. For instance, when the channel quality is low, a lower MCS level may allow for reliable communication without outage, but at the cost of a decrease in throughput. The selection of an MCS is based on signal-to-noise ratio (SNR) or the channel quality [1-3]. It is possible to measure the SNR during data reception in a time division duplex (TDD) system. Based on past SNRs, the MCS to be used in future transmission can be determined. If either the transmitter or receiver is in motion, the channel or SNR can fluctuate over time, which means that the previously selected MCS based on past SNRs might not be appropriate for future transmission. To select the appropriate MCS without experiencing an outage or significant loss in data rate, prediction of the future SNR based on past SNRs may be necessary.

This work uses artificial intelligence to choose an appropriate MCS for TDD systems operating in a mobile environment. Specifically, we suggest using a convolutional neural network (CNN) to select the MCS. The input for the CNN is the past SNRs. In a TDD system, the transmission and reception use the same frequency but different time. Therefore, the transmit and receive channels are the same. When receiving, the channel quality or SNR can be measured, and the MCS can be determined based on the past measured SNRs. The method commonly used to determine the MCS is by utilizing the SNR received in the recent past. However, if the transmitter or receiver is moving rapidly and the time gap between reception and transmission is significant, the selected MCS may not be appropriate for the transmit channel. To address this problem, we propose using a CNN to predict the future SNR at the time of transmission. We propose two techniques: one is selecting the proper MCS directly from the past SNRs, and the other is predicting the future SNR first and then selecting the MCS based on the predicted SNR. The aforementioned techniques are named the *direct* and *indirect* methods, respectively. We evaluate the performance of MCS selection methods through computer simulation, and the performance evaluation metrics are outage probability and throughput. According to our results, the proposed techniques outperform the conventional method for both outage probability and throughput. These results indicate that the proposed MCS selection techniques can reduce outage events and increase data rate. When comparing the two proposed methods, the proposed *indirect* method outperformed the *direct* method on all performance metrics.

II. MCS SELECTION SYSTEM MODEL

The channel environment changes over time while moving, so the MCS mode should be changed accordingly. In actual communication, it is possible to measure the channel environment only during reception. The duplexing mode used in the proposed system is time-division duplexing (TDD). Since the TDD mode transmits and receives using the same frequency, the transmission channel and the reception channel are same. Accordingly, MCS mode selection for transmission can be based on the quality of signals received in the past.

Fig. 1 shows the block diagram of the proposed MCS selection system. In the case of an OFDM system, the SNR is estimated using the average of the equalizer's output. Following the estimation of the received signal's SNR, the SNRs are vectorized to a set length and stored. Then, Data preprocessing is performed to preprocess the data for missing SNR values due to signal loss. Data preprocessing means linear interpolation using measured data before and after missing data. If there is no measured data before and after, it is filled with 0 dB.

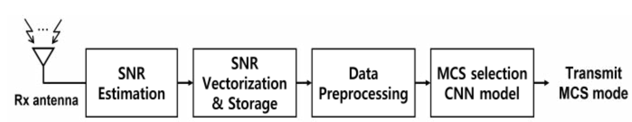

Fig. 1. Proposed MCS selection system block diagram.

The preprocessed data is fed into the MCS selection CNN model to select the MCS with the lowest probability of communication disconnection and the highest throughput at the time of transmission.

III. MCS Selection Methods

In this paper, there are one conventional method and two proposed methods for MCS selection. Table 1 shows the MCS table used by the proposed system.

A. Conventional method

Conventional MCS selection methods typically use the SNR of the most recently received signal (called ‘recent value’). Use the recent received SNR to select the MCS mode which the highest throughput among all MCS levels available in the MCS table. The performance of the *recent value* method is affected when the length of the input (or observation time) is too short to have a low probability of reception, but after a certain length, the performance is similar.

B. Proposed methods

CNN is one of the popular artificial intelligence models for analyzing images or graphs [4]. Since SNR vectors have a correlation between the SNR and time, it is appropriate to use CNN in MCS selection problems. We propose two methods for selecting MCSs using CNN. The first is to select the MCS directly (called ‘direct’). The second is to estimate the SNR using CNN and then select the optimal MCS (called ‘indirect’). The direct method is a classification problem, whereas the indirect method is a regression problem. Fig. 2 shows the model structure of proposed MCS selection CNN. The model structure of the direct method, which includes two convolutional layers and one fully connected layer, is presented in (a) of Fig. 2. Both convolutional layers of the direct method contain 64 filters. The model structure of the indirect method, which includes six convolutional layers and one fully connected layer, is presented in (b) of Fig. 2. The convolutional layers of the indirect method consists of two layers of 16, 32, and 64 filters in sequence. We set the filter size to 3 and the stride to 1. In addition, all layers use batch normalization, and the activation function uses ReLU (Rectified Linear Unit). Subsequently, the direct method uses the softmax activation function in the fully connected layer.

TABLE I. MCS Table

MCS index	Modulation & code rate	Threshold SNR [dB]	Throughput [Mbps]
0	Communication unavailable	SNR < 3.9	0
1	QPSK, 1/6	3.9 < SNR < 8.0	1.2459
2	QPSK, 1/3	8.0 < SNR < 12.6	1.8690
3	QPSK, 1/2	12.6 < SNR < 15.5	2.4919
4	16 QAM, 1/2	15.5 < SNR < 19.5	2.8034
5	32 QAM, 2/3	19.5 < SNR < 26.7	3.7379
6	256QAM, 5/6	26.7 < SNR	5.6068

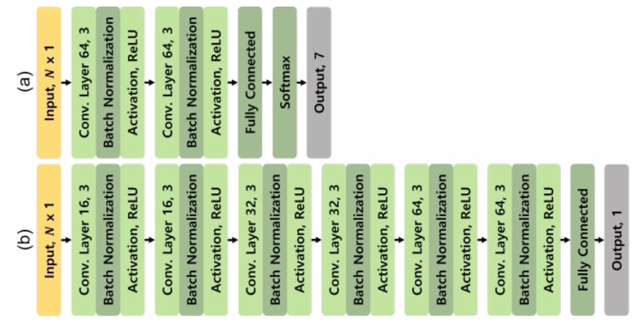

Fig. 2. Proposed MCS selection CNN model structure. (a) Direct (b) Indirect

IV. Simulation Result

A. Simulation environment

To verify the system's performance, we conducted simulations in both Tensorflow 2.0 and MATLAB. A summary of the simulation parameters is provided in Table 1. Both Rician and Rayleigh fading channels are considered for the channels. The Rician fading channel has a K-factor of 10 dB, which represents the power ratio of the direct and reflected waves. The period for sampling the received SNR is 1 OFDM symbol. This means that the SNR is estimated and updated every 1 OFDM symbol interval. The carrier frequency is 512 MHz, and the bandwidth is set to 2 MHz. Generate a range of SNR from 0 to 30 dB. Adjust the likelihood of recording received SNRs to range from 10% to 100%. Simulate SNR recording periods in increments of 10 from 10 to 100, and then choose the most suitable duration. The received SNRs' length is 50 for the *recent value* method and *direct* method, and 40 for the *indirect* method.

TABLE II. Simulation Parameters

Parameters	Value
Wireless channel model	Rayleigh (ITU Vehicular A) / Rician
K-factor of Rician channel	10 dB
Bandwidth	2 MHz
Carrier frequency	512 MHz
SNR sampling period	1 OFDM symbol
(OFDM) FFT size	512
SNR variation range	0 ~ 30 dB
Probability of signal reception	10 ~ 100 %
Speed	0 ~ 100 km/h

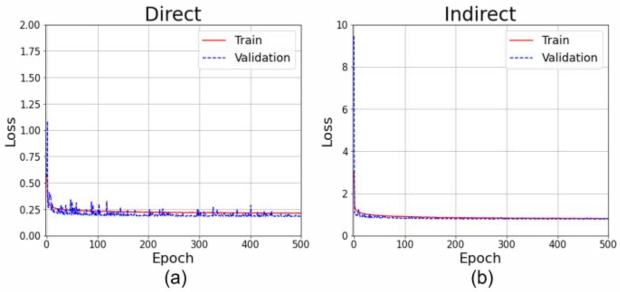

Fig. 3. Learning curve. (a) Direct method (b) Indirect method

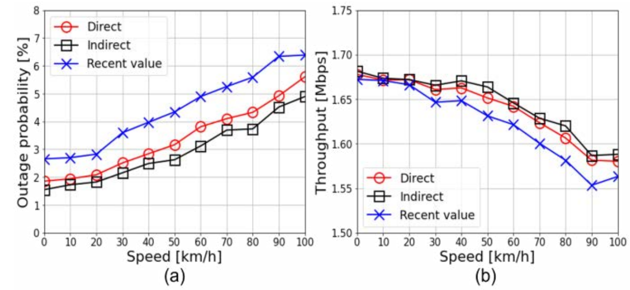

Fig. 4. Performance of MCS selection for speed.

B. *Training proposed CNN method*

The training and validation data are randomly generated at speeds ranging from 0 to 100 km/h, with 200,000 and 20,000 samples, respectively. The parameters required to train the CNN model, such as the optimizer, learning rate, batch size, and epoch, are common to both proposed methods and are as follows: Adagrad optimizer, 0.01 learning rate, 512 batch size, and 500 epochs. The direct and indirect methods use Cross-entropy and mean square error (MSE) loss functions, respectively, to train the CNN model. The learning curves of the proposed method are shown in Fig. 3, which shows that both models are trained well.

C. *Simulation result*

In the same speed range as training and validation, we generate a total of 20,000 test data with intervals of 10 km/h, and evaluate the performance using outage probability and throughput as metrics. Outage occurs when the MCS predicted by the model is greater than the optimal MCS, resulting in communication disconnection, and the throughput is set to 0 Mbps. Lower outage probability and higher throughput are desirable.

Fig. 4 shows the MCS selection performance for all methods. (a) in Fig. 4 represents the probability of outage occurrence according to the speed for each method, and (b) in Fig. 4 represents the throughput. The colors and marker styles of the graphs representing each method are as follows: the direct method is represented by a red circle, the indirect method is represented by a black square, and the recent value method is represented by a blue cross. According to the results of the simulation, the performance of all methods degrades as the moving speed increases. The outage probability at 50 km/h is 3.165 % for direct, 2.625 % for indirect, and 4.345 % for recent value. The throughput at 50 km/h is 1.651 Mbps for direct, 1.664 Mbps for indirect, and 1.631 Mbps for recent value. Performance comparison of the three MCS selection methods, the indirect method shows the best performance in both outage probability and throughput, while the recent value method performs the worst.

When comparing the performance in terms of throughput, as the mobile speed increases, the gap between the performance of the proposed methods and the conventional method widens. From this, we can see that using the proposed method is more effective as the moving speed increases.

V. Conclusion

This paper proposes the use of a CNN for selecting the MCS at the transmission time in a mobile environment. The proposed method uses the estimated SNR of past received signals as input to a CNN to select the most appropriate MCS for future transmission. According to computer simulations, the performance of all proposed methods (*direct* and *indirect*) was better than that of the conventional method (*recent value*). In addition, the performance of the MCS selection deteriorates as the mobile speed increases. This is because as the mobile speed increases, the channel state undergoes rapid changes, and therefore, the most appropriate MCS mode for future transmission also changes quickly.

In this study, the throughput was calculated as 0 Mbps when an outage occurred. However, this result did not consider the time for retransmission in case of transmission failure. As a result, outages are more likely to have a larger impact on the actual throughput. Therefore, when selecting the MCS in real-world scenarios, it is essential to consider the communication system and channel environment.

In this paper, we used a type of deep learning, CNN, for the proposed MCS selection method. This was because there is a correlation between the input data used in this study, which is the variation of received SNR over time. To further develop this study, recurrent neural network (RNN), which is one of the neural network types suitable for time series data, can be used for MCS selection.

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