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MCS Selection Based on Convolutional Neural Network in TDD System

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ABSTRACT- In this paper, a convolutional neural network (CNN) is proposed for selecting modulation and coding schemes (MCSs) at the time of future transmission in time-division-duplex (TDD) systems. The proposed method estimates the signal-to-noise ratio (SNR) obtained by the average of the equalizer's output in the orthogonal frequency division multiplexing (OFDM) system and records it to select the most suitable MCS for future transmission. Two methods are proposed: one that directly selects an MCS and one that predicts the SNR first before selecting an MCS. The conventional method commonly used is to select an MCS based on the SNR of the most recently received signal. Computer simulations show that the outage probability and throughput of all proposed methods (direct and indirect) are superior to conventional methods (recent value). Shorter SNR sampling periods perform better than longer ones, and the accuracy of MCS selection decreases as mobile speed increases.

Keywords: MCS Selection, TDD, CNN, Classification, Regression.

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1. INTRODUCTION

In wireless communications, there are several different modulation and coding schemes (MCS) that a transmitter can choose to transmit a message. Each MCS has a different throughput and reliability, and there is a trade-off between the two [1]. For example, using a lower MCS level results in lower throughput but higher reliability, while a higher MCS results in higher throughput and lower reliability. Therefore, the MCS level is often selected based on channel condition of the communication system being used [2, 3]. Indeed, many communication systems use channel quality or signal-to-noise ratio (SNR) to select the level of MCS.

In a time-division-duplex (TDD) system, transmission and reception have the same frequency but different time. In a TDD system, the SNR can be measured during data reception. If the transmitter or receiver is moving, the channel or SNR may change over time. Therefore, an MCS selected based on the SNR at one point in the past may not be valid for future transmissions. In order to select or predict an appropriate MCS without causing outages or reducing the throughput, the MCS should be selected based on the variation of the historical received SNR over time.

This paper utilizes artificial intelligence to select the transmit MCS in a TDD system. Specifically, two convolutional neural networks are proposed for MCS selection. The historical received SNR is used for MCS selection. Two types of convolutional neural network (CNN) are proposed: one is to directly select the appropriate MCS, and the other is to predict the future SNR first and then select the MCS based on the predicted SNR. The two methods are referred to as *direct* and *indirect* methods, respectively. The most common way to determine the MCS is to use the recently received SNR value [4]. However, if the transmitter or receiver is moving fast and the time interval between reception and transmission is large, the selected MCS may not be suitable for the transmission channel. The proposed methods are proposed to cope with the problem by predicting the future channel based on the CNN. To evaluate the performance, computer simulations are conducted, and the outage probability and throughput are compared. According to the result, the proposed methods outperform the conventional method in both outage probability and throughput. These results indicate that the proposed MCS selection methods can reduce the occurrence of failure events and increase the throughput.

2. RELATED WORKS

There has been extensive research on the use of deep learning (DL) in telecommunications, with more expected in the future [5-7]. Some of the previous works that have applied DL to telecommunications include a deep learning-based approach for channel estimation and signal detection in orthogonal frequency division multiplexing (OFDM) systems [8]. The authors proposed a neural network architecture that could estimate the channel impulse response and detect the transmitted signal from the received OFDM symbols. These papers offer valuable insights into the potential of DL to enhance the performance of OFDM systems.

Moreover, DL-based solutions have been developed to solve classification problems, such as the frequency user classification problem, which plays an important role in radio resource management [9]. The book also discusses other problems, such as channel state identification (CSI) that can be solved using DL. The authors suggest that DL is a useful technique for addressing classification problems in wireless communications and can be applied in various fields, including radio resource management, signal classification, CSI, and sensor networks.

In addition, SNR is an essential element for many signal processing algorithms and techniques. Previous studies have focused on estimating the SNR at a specific time point in the past [10, 11]. In this paper, two methods are proposed for selecting MCSs for DL-based future transmissions. First, a regression-based approach is discussed for predicting the signal-to-noise ratio (SNR) at a future time point and selecting the appropriate MCS. In this method, the MCS can be chosen based on the predicted SNR at the desired time. In the second method, the MCS selection problem is solved as a classification problem using DL. Based on the results, it is concluded that DL is an efficient tool for selecting the optimal MCS to be used in future transmissions.

3. MCS SELECTION SYSTEM

It is necessary to select an MCS level that ensures optimal communication reliability and transmission rate by considering the changes in the channel environments over time. The system proposed in this study is an OFDM system that supports TDD. Therefore, transmit and receive frequencies are the same, and the channel characteristics in both directions are identical. Based on these characteristics, it is reasonable to select the MCS level for future transmissions based on the quality of the received channel in the past (*i.e.*, the channel quality of the received signal). Artificial intelligence can be utilized to select the optimal MCS level for future transmissions based on the SNR trend of the received signal in the past.

Figure 1 shows an example of MCS level selection based on received SNR. MCS selects the level that satisfies the required communication quality and has the highest throughput. As demonstrated in the example, the suitable MCS mode changes over time, and a long sampling period of the received SNR (i.e., SNR measurement period) can result in communication loss if the channel quality deteriorates quickly. Therefore, the shorter the sampling period of the SNR, the more optimal the MCS selection becomes.

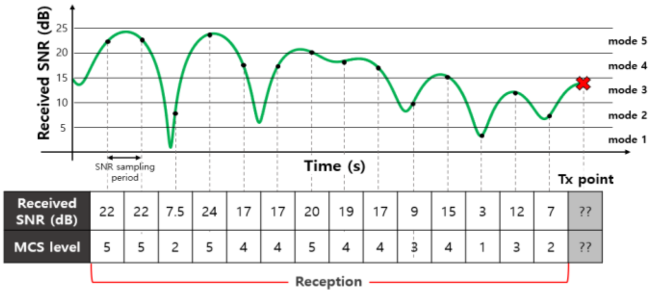

Figure 1: Example of MCS level selection process

Figure 2 shows a block diagram for the proposed MCS selection systems. The MCS selection process is as follows: After estimating the SNR of the received signal by averaging over the output of the equalizer, the SNRs of the past received signals are collected and vectorized. The SNR of the received signal is recorded in every reception. However, missing data caused by the absence of a signal needs to be preprocessed. For missing data, the beginning and end of the data are filled with 0 dB, and the middle of the data is processed by linear interpolation. After preprocessing, the data is input to the CNN model. At this point, two CNN models are proposed: one directly selects the MCS, and the other predicts the SNR and selects the MCS based on the predicted SNR.

4. MCS SELECTION METHODS

In this paper, two methods are proposed for selecting the optimal MCS for future transmissions based on past received SNR information. The conventional method uses the SNR of the most recently received signal to select the MCS mode.

4.1 Conventional method

A typical MCS selection technique is to use the SNR value of the most recently received signal to select the MCS mode that can communicate and has the fastest transmission speed (referred to as the ‘recent value’ method). However, this method is expected to perform poorly in two situations.

The first situation is when the channel quality is highly variable over time, which can be seen in *figure 3* where the received SNR changes rapidly when moving at high speeds in a moving environment. The *recent value* method does not consider the change over time, and therefore is expected to perform poorly when the communication quality changes over time. The second situation is when there is a large time interval between reception and transmission. Again, this method does not consider changes in communication quality over time, and selecting an MCS using this method may result in a situation where the best throughput is not achieved, or communication is not possible at all.

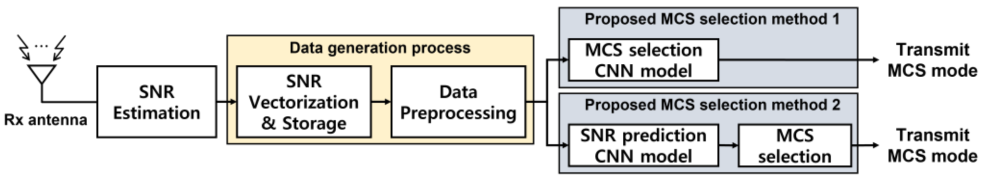

Figure 2. Block diagram of proposed MCS selection systems

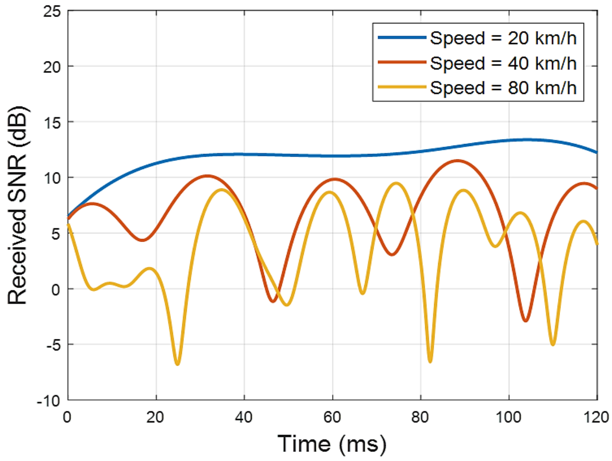

Figure 3. Received SNR over time according to speed

For these two reasons, it is important to consider the time evolution of the historical receive SNR to select the MCS for the desired transmission time.

4.2 Proposed methods

The proposed MCS selection method utilizes a CNN and can be implemented in two ways. The first method is to use a CNN to directly select the MCS (referred to as the 'direct' method). The second method is to use a CNN to predict the SNR, and then use the predicted SNR to select the optimal MCS (referred to as the 'indirect' method). The main difference between the two methods is that the *direct* method is a classification problem, while the *indirect* method is a regression problem.

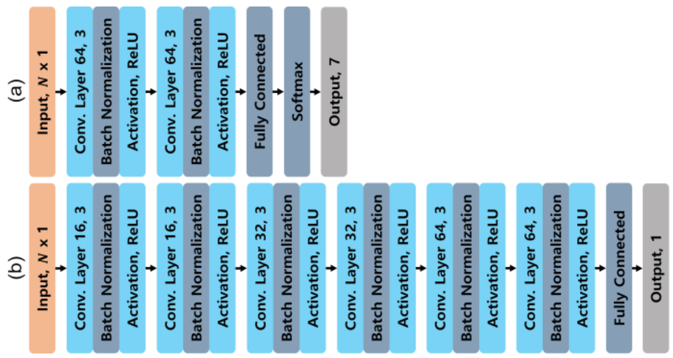

Figure 4. Proposed CNN architecture (a) *Direct* (b) *Indirect*

Figure 4 illustrates the model structure of the two proposed CNNs. *Figure 4 (a)* shows the model structure of the *direct* method, which consists of two convolutional layers and one fully connected layer. The convolutional layers in the *direct* method consist of a total of 64 filters. *Figure 4 (b)* shows the model structure of the *indirect* method, which consists of six convolutional layers and one fully connected layer. The *indirect* method consists of two successive convolution layers with the same number of filters. The number of filters increases by a factor of 2, ranging from 16 to 64. Both methods use batch normalization for all layers, and the activation function uses Rectified Linear Units (ReLU). The *direct* method utilizes Softmax as the activation function on the fully connected layer.

5. SIMULATION

5.1 Simulation environment

For performance verification, simulations are performed using Tensor flow 2.0 and MATLAB. The parameters used in the simulation are summarized in *table* 1.

Table 1. Simulation parameters

Parameter	Value
Wireless channel model	Rayleigh (ITU Vehicular A) / Rician
K-factor of Rician channel	10 dB
SNR sampling period	1 or 6 OFDM symbol
(OFDM) FFT size	512
Bandwidth	2 MHz
Carrier frequency	512 MHz
SNR variation range	0 ~ 30 dB
Speed range	0 ~ 100 km/h
Probability of signal reception	10 ~ 100 %

For channels, both Rician fading channels and Rayleigh fading channels are considered. In the Rician fading channel, the K-factor, the power ratio of the direct and reflected waves, is 10dB. The received SNR sampling period means the interval between SNR measurement and update. Experiments are conducted with 1 OFDM symbol and 6 OFDM symbols. The bandwidth is 2 MHz and the carrier frequency is 512 MHz. SNR ranges from 0 to 30 dB, and speed ranges from 0 to 100 km/h. Set the probability that the received SNRs is recorded (or present) to 10-100%. Simulate the received SNR recording length in 10 intervals between 10 and 100, then select the optimal length. The *direct* method uses a receive SNR length of 50 when the receive SNR period is 1 OFDM symbol and 70 when the receive SNR period is 6 OFDM symbols. The *indirect* method uses a receive SNR length of 40 when the receive SNR period is 1 OFDM symbol and 30 when the receive SNR period is 6 OFDM symbols. *Recent value* method has a received SNR length of 50 regardless of the received SNR period.

Table 2 is the MCS table used in the simulation. It consists of a total of seven types of MCS.

Table 2. Simulation parameters

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

5.2 Training CNN models

The training data and the validation data are generated randomly, with 200,000 and 20,000 samples, respectively, at speeds ranging from 0 to 100 km/h. The parameters required to train the CNN model are common to both proposed methods and are as follows: the optimizer is Ada grad, the learning rate is 0.01, the batch size is 512, and the epoch is 500. The loss functions used by the *direct* and *indirect* methods to train the

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CNN model are Cross-entropy and mean square error (MSE), respectively.

Figure 5 and *figure 6* show the learning curves of the proposed method. The learning curves indicate that the training is progressing well. And you can see that for both methods, when the SNR sampling period is large, the loss is large. From this, the performance can be expected to be worse when the SNR sampling period is 6 OFDM symbols compared to 1 OFDM symbol.

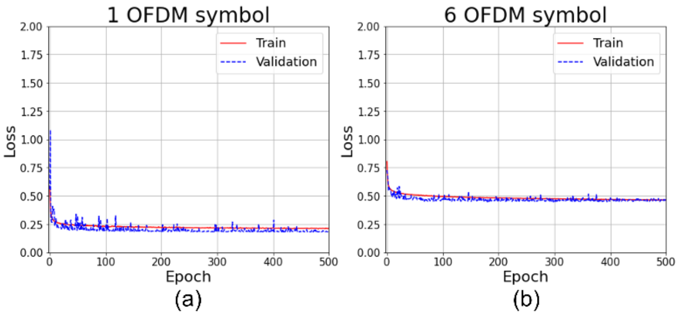

Figure 5: Learning curve of the *direct* method

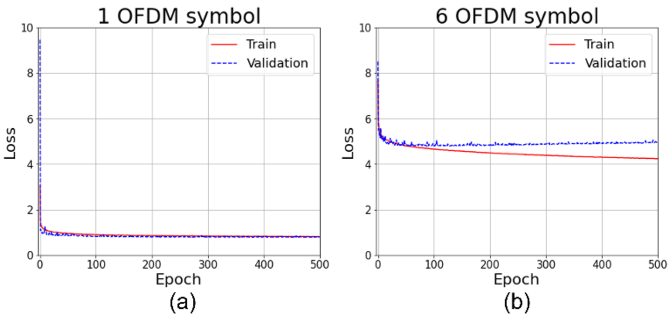

Figure 6: Learning curve of the *indirect* method

5.3 Simulation result

A total of 20,000 test data are generated at intervals of 10 km/h at the same speed range. The evaluation metrics are outage probability and throughput. Outage means that the predicted MCS is higher than the optimal MCS, and thus communication disconnection occurs. When outage occurs, the throughput is calculated as 0 Mbps. A lower outage probability is better, and a higher throughput is better.

The simulation is performed by setting the SNR sampling period to 1 OFDM symbol and 6 OFDM symbol. The performance of all methods is compared for each SNR sampling period. The color of each method's graph is red for the *direct* method, green for the *indirect* method, and black for the *recent value* method. Markers for the *direct* method are circles, squares for the *indirect* method, and crosses for the *recent value* method.

Figure 7 shows the probability of outage for all methods. *Figure 7 (a)* presents the performance when the SNR sampling period is 1 OFDM symbol. *Figure 7 (b)* shows the performance when the SNR sampling period is 6 OFDM symbols. According to *figure 7*, when the SNR sampling period is 1 OFDM symbol, the average probability of outage for all speed ranges is 3.38% for *direct*, 2.94% for *indirect*, and 4.41% for *recent value*.

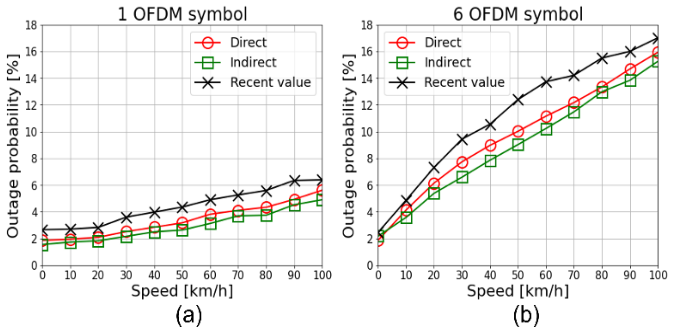

Figure 7: Comparison of outage probability by SNR sampling period

When the SNR sampling period is 6 OFDM symbols, the average probability of outage for all speed ranges is 9.64% for *direct*, 8.94% for *indirect*, and 11.22% for *recent value*. In all SNR sampling periods, performance is best in the order of *indirect*, *direct*, and *recent value*. Additionally, if the moving speed is faster and the SNR sampling period is longer, the performance worsens.

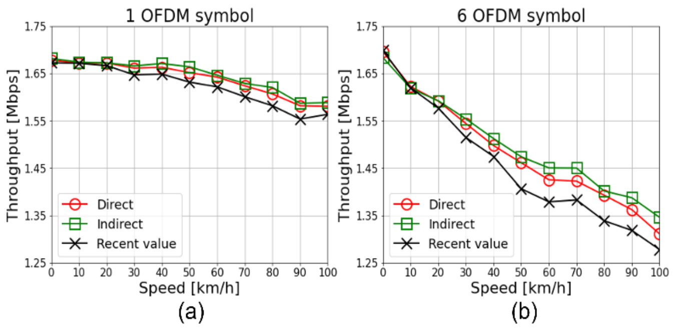

Figure 8: Comparison of throughput by SNR sampling period

Figure 8 shows the throughput for all methods. *Figure 8 (a)* presents the performance when the SNR sampling period is 1 OFDM symbol, and *Figure 8 (b)* shows the performance when the SNR sampling period is 6 OFDM symbols. When the SNR sampling period is 1 OFDM symbol, the average throughput for all speed ranges is 1.64 Mbps for *direct*, 1.65 Mbps for *indirect*, and 1.62 Mbps for *recent value*. When the SNR sampling period is 6 OFDM symbols, the average throughput for all speed ranges is 1.48 Mbps for *direct*, 1.50 Mbps for *indirect*, and 1.45 Mbps for *recent value*. In all SNR sampling periods, performance is best in the order of *indirect*, *direct*, and *recent value*. It can also be observed that the performance of the *recent value* method is more affected by the moving speed than the other two proposed methods. Additionally, as shown in *figure 7*, the longer the SNR sampling period, the worse the performance for all methods, and the performance deteriorates as the moving speed increases.

According to the simulation results, the two proposed methods demonstrate superior performance compared to the conventional methods in terms of communication disconnection probability and throughput. This indicates that a larger volume of data can be processed at a faster rate when communicating using the proposed method.

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6. CONCLUSION

In this paper, the use of convolutional neural networks (CNNs) is proposed for MCS selection at the time of transmission in TDD systems. The proposed method selects the most suitable MCS for future transmission based on the changes in received SNR over time. Computer simulation results show that all the proposed methods (*direct* and *indirect*) outperform the conventional methods (*recent value*). Shorter SNR sampling periods perform better than longer ones. Therefore, the shorter the SNR sampling period can be recorded in the communication system used, the better the performance. It is also observed that the performance of MCS selection degrades as the mobile speed increases, which is believed to be due to the rapidly changing channel conditions. In this study, the transmission rate in the event of a failure is calculated as *0* Mbps. However, this result does not consider the retransmission time in the event of a transmission failure. Therefore, the actual transmission rate is likely to be more affected by outages. Considering these factors, it is important to take into account the communication system and channel environment when selecting an MCS in a real-world situation.

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