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Session 4C: Wireless Communications

Chair: Hiroyuki Otsuka (Kogakuin University, Japan)

Rooms D (A406), Time 15:30 ~ 17:00

[4C-1] Classification of Analog Modulated Signals Using Convolutional Neural Networks
Bo-Seok Seo, Yearn-Gui Yi and Kang Solsong (Chungbuk National University, Korea (South))

[4C-2] Consideration of Frequency Domain Adaptive SIC for Full-Duplex Communication
Kazuma Matsushima, Takumi Yasaka and Hiroyuki Otsuka (Kogakuin University, Japan)

[4C-3] MUSIC-Based Channel Estimation with Adaptive Reconfiguration of Diagonal RIS
Yaser Dorrazehi, Anna Guglielmi and Stefano Tomasin (University of Padova, Italy)

[4C-4] Design Flexibility of Picocells in HetNets with Respect to Number of Picocell-Sectors
Naoto Inagaki and Hiroyuki Otsuka (Kogakuin University, Japan)

[4C-5] Joint Optimization of Task Splitting and Cell-Free MIMO Transmission for Multi-Tier Computing Systems
Dogon Kim and Seok-Hwan Park (Jeonbuk National University, Korea (South))

July 5, 2024 (Friday)

Session 5A: Satellite Networks

Chair: Jihwan Moon (Hanbat National University, Korea)

Room B (B404), Time 9:30 ~ 11:00

[5A-1] Energy Efficiency Maximization for Multi-LEO Satellite Networks
Jihwan Moon (Hanbat National University, Korea (South)); Hoon Lee (Ulsan National Institute Science and Technology, Korea (South))

[5A-2] Machine Learning-Based NOMA in LEO Satellite Communication Systems
Min Jeong Kang and Jung Hoon Lee (Hankuk University of Foreign Studies, Korea (South)); Seong Ho Chae (Tech University of Korea, Korea (South))

[5A-3] Analysis of LEO Satellite Network Performace According to Phasing Factor: Polar Region Boundary, Minimun Elevation Angle
Heon-Woo Chu (University of Ajou, Korea (South)); Tae-Yoon Kim (Ajou University, Korea (South)); Jae-Hyun Kim (Ajou University, South Korea, Korea (South))

Session 5B: UAV Mobility

Chair: Masoud Ardakani (University of Alberta, Canada)

Room C (A405), Time 9:30 ~ 11:00

[5B-1] Group-Wise Coding for Coded Distributed Computing Systems with Group Heterogeneity and Communication Delay
Maryam Ardakani and Masoud Ardakani (University of Alberta, Canada); Chintha Tellambura (The University of Alberta, Canada)

[5B-2] Horizontal Soft Handover Management in Cell-Free Massive MIMO Networks
Murad Khan, Basil Alothman and Chibli C. Joumaa (Kuwait College of Science and Technology, Kuwait); Dongkyun Kim (Kyungpook National University, Korea (South))

[5B-3] Investigating Robustness of Trainable Activation Functions for End-To-End Deep Learning Model in Autonomous Vehicles
Ahmed D. M. Ibrahum, Manzoor Hussain, Zhengyu Shang and Jang-Eui Hong (Chungbuk National University, Korea (South))

[5B-4] GRU-Based MCS Selection for UAV Communication in 5G Environment
Woong Jong Yun, Seok Jin Hong and Eui-Rim Jeong (Hanbat National University, Korea (South))

Session 5C: Radio Resource Management

Chair: Sangheon Pack (Korea University, Korea)

Rooms D (A406), Time 9:30 ~ 11:00

[5C-1] Data Acquisition and Visualization for AI/ML-Based Radio Resource Management Optimization in the ns-O-RAN Framework
Seung-Eun Hong (ETRI, Korea (South)); Jung Mo Moon (Electronics and Telecommunications Research Institute, Korea (South)); Jaewook Lee (Pukyong National University, Korea (South))

[5C-2] ARQ Delay in Underwater Acoustic Communications
Andrej Stefanov (IBU Skopje, Macedonia, the former Yugoslav Republic of)

[5C-3] PAPR Reduction for OTFS Signals Based on Time-Domain Window
Huang Chang Lee (Chang Gung University, Taiwan)

[5C-4] Chirp Index Space Partitioning Based Multiple Access Technique
Hinata Sakamoto and Koichi Adachi (The University of Electro-Communications, Japan)

GRU-Based MCS Selection for UAV Communication in 5G Environment

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***Abstract*— This paper proposes a modulation and coding scheme (MCS) selection method using Gated Recurrent Unit (GRU) to improve the transmission speed and communication quality between Unmanned Aerial Vehicles (UAVs) and ground stations in the 5G NR (New Radio) environment. The proposed system assumes a Time Division Duplex (TDD) mode and measures the Signal-to-Noise Ratio (SNR) at the receiver. The proposed method predicts the SNR at future transmission points based on the measured channel information using GRU, and then selects the MCS level accordingly. Simulation results show that the proposed GRU-based MCS selection outperforms conventional methods such as the average methods, recent-value method, and Convolutional Neural Network (CNN) model in terms of lower communication outage probability and higher transmission speed across all speeds. Thus, it can contribute to enhancing communication performance in 5G UAV communication environments.**

Keywords—UAV, 5G NR, MCS, GRU, SNR Prediction

I. Introduction

In recent years, rapid advancements in technology have led to the widespread use of unmanned aerial vehicle (UAV) in various fields including military, public, and civilian applications. UAV, characterized by their small size and high maneuverability, are utilized extensively for tasks that are either hazardous or critical, as they operate without onboard pilots or passengers. For instance, UAV are employed in applications such as data collection, security, collaborative reconnaissance, satellite communication, surveillance of high-rise buildings for fire incidents, and medical transportation. Seamless mission execution necessitates stable communication between UAV and ground stations [1-3]. Particularly, due to the high mobility of drones, wireless channel fluctuations are prevalent, requiring receivers to be designed considering such channel environments [4].

One application of 5G communication is communication between UAV and ground stations. 5G communication is designed to accommodate high-speed mobility and select the optimal communication methods for transmission based on channel conditions. Specifically, 5G communication encompasses numerous combinations of modulation and coding schemes (MCS), allowing for the selection of the optimal MCS for transmission depending on the quality of the communication channel. Lower-level MCS enables transmission at low speeds even at low signal-to-noise ratios (SNR), whereas higher-level MCS permits communication only at high SNR. Channel quality is typically represented by SNR, and at specific SNR, there exists an MCS level that ensures reliable communication with the highest transmission rate. Thus, selecting the optimal MCS is crucial for ensuring communication reliability and transmission speed. Communication systems like 5G employ the time-division duplex (TDD) method, wherein transmission and reception are performed using the same frequency but at different time slots. In this case, the transmission and reception channels can be considered identical. Typically, the optimal MCS is selected for transmission based on measuring the channel quality during reception. Selecting an MCS level higher than the channel's quality may result in communication interruptions, while choosing a lower MCS level allows communication but at a reduced transmission rate [5].

This paper proposes a technology for selecting MCS based on the Gated Recurrent Unit (GRU) in the 5G UAV communication environment. The proposed technology predicts the future SNR at the transmission time point using GRU with the past measured SNR as input. Subsequently, the optimal MCS level is selected based on the predicted SNR and transmitted. As comparative subjects, the paper considers the average method, which selects MCS based on the average of received SNR, the recent value method, which selects MCS based on the most recent received SNR, and the method utilizing Convolutional Neural Network (CNN) to predict SNR and then select MCS. Received SNR can be viewed as time-series data that varies over time, and the proposed method using GRU for processing time-series data demonstrates an advantage over the existing CNN techniques. Through simulation results, the proposed GRU-based method shows superior communication interruption probability and higher transmission speed compared to existing methods. These results indicate that applying the proposed method not only enhances communication reliability in the 5G UAV communication environment but also improves transmission speed in ground mobility scenarios.

II. System Model

Utilizing antennas attached to UAVs to select MCS based on their movements can enhance communication reliability and optimize transmission speed. The system proposed in this study operates in a TDD environment, where the transmission and reception frequency channels are identical, enabling the prediction of SNR at the transmission time point based on the quality of the antenna's channel and selecting the optimal MCS. Given these characteristics, in the 5G UAV environment, where channel quality changes rapidly, it is essential to monitor the fluctuating channel quality over time and select MCS accordingly. Therefore, leveraging GRU, the proposed system can select the optimal MCS level for future transmissions based on past received signal SNR.

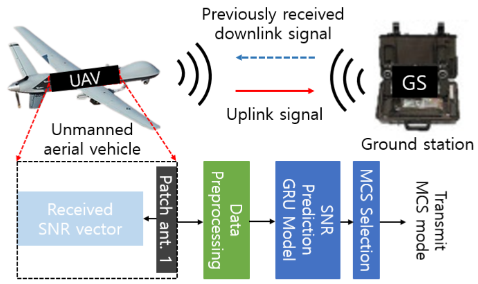

Fig. 1. Proposed System Model

Figure 1 illustrates the model of the MCS selection system in the proposed 5G UAV communication environment. The process of MCS selection is as follows: SNR is measured at intervals set by the UAV antenna, and the SNR of the received signals is stored and vectorized. For the utilization of the proposed GRU, preprocessing of the input data is necessary, following the 5G NR format defined by the 3rd Generation Partnership Project (3GPP). After undergoing input data preprocessing, the data is inputted into the transmission antenna SNR prediction model. Based on the predicted SNR, the optimal MCS level for future transmission points is selected.

III. Input Data Preprocessing

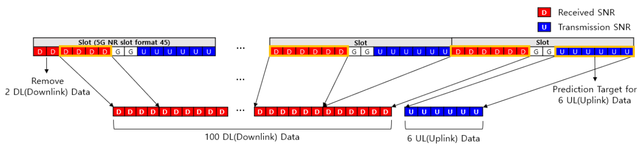

Fig. 2. Input Data Structure Using 5G NR Format 45 Scheme

Figure 2 illustrates the process of input data preprocessing. The data slot used in this paper follows the 5G NR format, specifically the 45th format. This structure consists of 14 Orthogonal Frequency Division Multiplexing (OFDM) symbols per slot, comprising 6 uplink symbols, 2 guard bands, and 6 downlink symbols. In the diagram above, the red represents past received SNR, while the blue represents SNR at the transmission point. It is designed to predict the SNR of 6 uplink data using a total of 100 downlink data points. In other words, this format is structured to predict the SNR of 6 uplink data points at the reception point.

IV. MCS Selection Method

A. *Conventional MCS selection method*

There are mainly three methods for selecting MCS based on communication parameters. The first method is the average value method, where the SNR received by the antenna during the specified observation period is predicted as the target SNR, and the MCS level is selected. The second method is the recent value method, which predicts the SNR received most recently as the target SNR at the transmission time and selects the MCS level. Lastly, there is the method of using CNN to predict SNR and then select MCS. CNN is a model that can be effectively applied in various domains such as images or time series. Therefore, the method involves using a CNN regression model to predict future SNR values and then select the MCS level. The overall architecture of the CNN model is as shown in Figure 3.

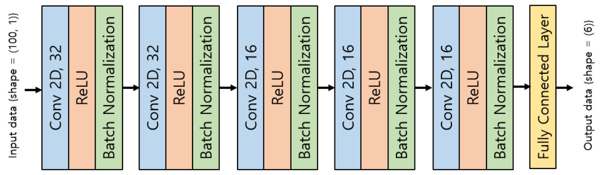

Fig. 3. Conventional CNN Overall Architecture

In summary, all three methods select MCS in different ways, and the CNN-based method utilizes deep learning to predict future SNR values and perform MCS selection.

B. *Proposed GRU-based MCS selection method*

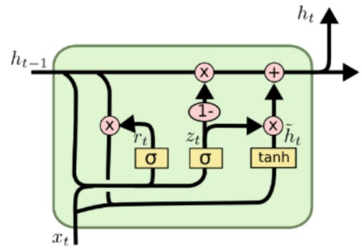

Fig. 4. GRU Sell with its Gates

Figure 4 depicts the structure of the GRU model. GRU is an improved model of Recurrent Neural Networks (RNN), proposed based on Long Short-Term Memory (LSTM) networks to address the gradient vanishing problem. LSTM networks consist of input gates, forget gates, and output gates. GRU combines the forget gate and input gate of LSTM into an update gate, while simultaneously combining the memory unit and the implicit layer into a reset gate, simplifying the overall structural operation and enhancing performance. The update gate controls the flow of information into the memory, while the reset gate controls the flow of information within the memory. The determination of information to be outputted is governed by the update gate and reset gate, enabling the model to learn how to maintain past knowledge while discarding irrelevant information. The formulas used in GRU are computed as shown in equations (1) to (4) below.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{1}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{2}$$

$$\tilde{h}_t = tanh(W \cdot [r_t * h_{t-1}, x_t]) \tag{3}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \tag{4}$$

The GRU model used in this paper consists of a total of 3 GRU layers, with layer normalization applied to each layer. The overall architecture of the CNN model is as shown in Figure 5.

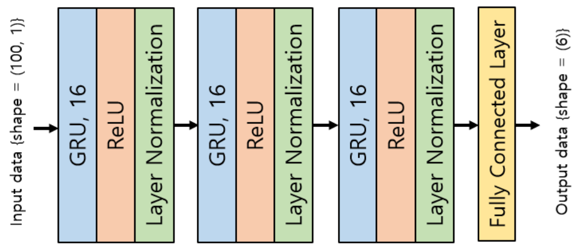

Fig. 5. GRU Overall Architecture

The training parameters are set as follows: 200 epochs, batch size of 128, Adam optimizer, Tanh activation function, and learning rate of 0.001. Additionally, Mean Squared Error (MSE) is employed as the loss function.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (5)$$

MSE is defined as follows: Here, n represents the number of data points, y_i is the actual value, and $\hat{y}_i$ is the predicted value by the model.

V. SIMULATION

A. Simulation Environment

Performance validation is conducted through simulations using TensorFlow 2.0 and MATLAB. The parameters used in the simulations are summarized in Table 1 below.

TABLE I. 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

In this experiment, the performance of the GRU model is evaluated under various conditions by simulating the communication environment according to the 5G NR standard. The experiment utilizes a bandwidth of 100MHz and a carrier frequency of 3.6GHz. It assumes a TDD environment with a single antenna, where the reception and transmission environments are identical. Additionally, it is assumed that the antenna uses directional antennas with directionality. The channel model randomly selects between Line-of-Sight (LoS) and Non-Line-of-Sight (Non-LoS), modeling channel characteristics using Rayleigh (ITU Vehicular A) and Lician channels. The K factor of the Lician channel is set to 10dB. The input data consists of received SNR of signals with a length of 100. The average SNR of each generated signal is randomly selected between 0dB and 30dB. The velocity is randomly selected from a range of 0km/h to 300km/h, and the average SNR of the signal and the velocity are randomly generated for each training sample creation. The probability of selecting LoS and Non-LoS environments is 1:1, with 14 OFDM symbols per slot. Finally, the experiment trains the GRU model using 200,000 training data and 20,000 validation data points. Through these settings, the performance of the GRU model is evaluated compared to existing methods.

TABLE II. 5G NR MCS TABLE

CQI	MCS	Code Rate X 1024	Spectral efficiency	SNR (dB) Perfect channel estimation	SNR (dB) Practiacal 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

Table 2 represents the MCS table used in the simulation experiments. The MCS levels are selected based on the corresponding threshold SNR values. It contains threshold SNR values and transmission rate information that satisfy the 15 types of SNR performance requirements of 5G NR.

B. Simulation Result

The performance evaluation of the proposed method is conducted using test data generated with the same parameters as the training data. To experiment with the performance variation according to the velocity, 20,000 test data points are generated at intervals of 20km/h. The performance evaluation metrics include Mean Absolute Error (MAE), communication outage probability for MCS selection, and transmission rate.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (6)$$

MAE is defined as follows: Here, n represents the number of data points, y_i is the actual value, and $\hat{y}_i$ is the predicted value by the model.

Figure 6 and 7 depict the results of the simulation experiments, showing the communication outage probability and transmission rate for MCS selection, respectively.

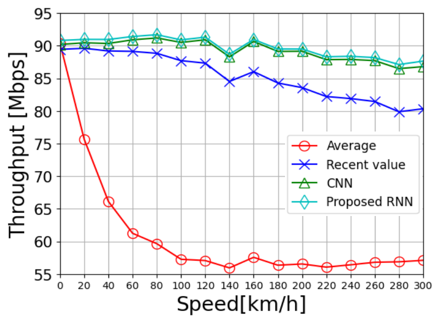

Fig. 6. Throughput of MCS selection

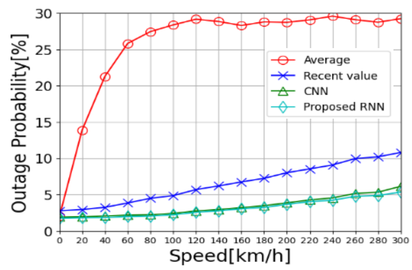

Fig. 7. Outage probability of MCS selection

When measuring the average communication outage probability for all velocities, the average method shows 25.52%, the recent value method shows 6.53%, the CNN method shows 3.39%, and the proposed GRU method shows 3.13%. Thus, the proposed GRU method demonstrates lower communication outage probability than the existing methods across all velocities. When measuring the average transmission rate for all velocities, the average method shows 61.06Mbps, the recent value method shows 85.34Mbps, the CNN method shows 89.28Mbps, and the proposed GRU method shows 89.76Mbps. The simulation results show that both the existing methods and the proposed method experience performance degradation as velocity increases. Additionally, the communication outage probability and transmission rate validate that the proposed method outperforms the existing methods. This indicates that when using the proposed method in the 5G UAV communication environment, more data can be processed at a faster rate.

VI. CONCLUSION

This paper proposes a MCS selection method using GRU to improve the transmission speed and communication quality between UAV and ground stations in the 5G NR environment. The proposed method demonstrates higher MCS level accuracy compared to existing methods at all velocities. Simulation results show that the proposed GRU-based MCS selection outperforms conventional methods such as average methods, recent-value methods, and CNN models in terms of lower communication outage probability and higher transmission speed at all velocities. Thus, this indicates the potential to enhance communication performance in the 5G UAV communication environment.

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