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Transmit Antenna Selection Based on SNR prediction in TDD Systems Using Convolutional Neural Network

A-Min Jo[1], Jeong-Eun Oh[2] and Eui-Rim Jeong[3*]

[1]*Department of Mobile Convergence Engineering, Hanbat National University, Daejeon, Republic of Korea, whdkals18@gmail.com*

[2]*Department of Mobile Convergence Engineering, Hanbat National University, Daejeon, Republic of Korea, wjddms1199@gmail.com*

[3]*Department of Artificial Intelligence Software, Hanbat National University, Daejeon, Republic of Korea, erjeong@hanbat.ac.kr*

***Correspondence:** Eui-Rim Jeong; erjeong@hanbat.ac.kr; Tel.: +82-42-821-1752 (Eui-Rim.Jeong.)

ABSTRACT- This paper proposes a method for predicting future signal-to-noise ratio (SNR) in a time-division-duplexing (TDD) mobile communication environments using a convolutional neural network (CNN). The communication system uses multiple receive antennas and transmit using only one or two antennas among them. A CNN model is proposed to predict the SNR at a future transmission time based on past SNRs received from multiple antennas. The probability of reception at a certain is set to 10-100%. In case that SNR cannot be measured due to the absence of reception, linear interpolation is performed using two adjacent recorded SNRs. If even two adjacent SNRs do not exist, the SNR is set to 0dB. Comparing the predicted SNRs at multiple antennas, the antenna with the highest SNR value is selected for future transmission. To verify antenna selection accuracy, computer simulation is conducted. The simulation results substantiate the superiority of the proposed method over conventional method in single antenna selection. Regarding multi-antenna selection, the proposed method demonstrates diminished accuracy relative to conventional methods at lower speeds. Nevertheless, a comprehensive evaluation considering the root mean square error (RMSE) demonstrates the overall superiority of the proposed method across all speeds.

Keywords: TDD, SNR Prediction, MIMO, CNN, Antenna Selection.

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1. INTRODUCTION

Terrestrial military communications involve exchanging data and information between military vehicles and other entities in the environment, such as personnel and command centers. This communication relies on various technologies, including radio, satellite, and cellular networks [1-4]. Military vehicle communications play a critical role in military operations, allowing real-time information sharing and coordination. In the past, monopole antennas were installed on military vehicles for this purpose [5]. However, monopole antennas can cause signal quality deterioration and interference due to aerodynamics of the vehicles. Therefore, a method of integrating skin antennas into a vehicle's surface or structure has been proposed. Skin antennas are often preferred over external antennas because they are advantageous for aerodynamic, aesthetically pleasing, and can provide better performance in certain situations [6-8]. Designed a multi-band smart skin antenna for flight demonstration in an aircraft, while [8] incorporated an FBG sensor to adaptively compensate for radiation pattern degradation due to structural deformation [7]. Proposed an inkjet-printed microstrip patch antenna design for wearable applications. However, skin antennas can only communicate in one direction, requiring all nodes to be attached with skin antennas to transmit and receive in all directions.

This paper considers an antenna selection method for time-division-duplexing (TDD) systems. Multiple patch or skin antennas are installed. Data reception utilizes all the antennas, but data transmission is done using only one or two antennas among them. Multi-antenna systems can provide reliable communication in multipath fading channels. The TDD system is more bandwidth-efficient than frequency division duplexing (FDD) system [9]. This paper aims to predict the signal-to-noise ratio (SNR) of such systems and select optimal transmit antenna. Looking at conventional studies related to SNR prediction, there have been several recent works exploring different techniques for predicting SNR in various communication systems [10]. Used regression models to predict the SNR of GPS signals in urban environments, which could be useful for applications such as autonomous driving and location-based services [11]. Proposed a new interpretation model for predicting SNR in coherent optical communication systems using the Jones matrix, which can increase high-speed data transmission distance and transmission rate [12]. Used the wavenumber spectrum segmentation filters bank (WSSFB) technique for CQI prediction in high-speed mobility environments, while [13] proposed a deep learning technology to predict CQI for vehicle communication. Other studies have

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focused on SNR prediction in cellular communication systems [14, 15]. Proposed a technique for predicting SNR based on channel charting, while [15] estimated SNR prediction and resolution probability using the MSE threshold in noise cancellation and signal estimation techniques [16]. Proposed a machine learning technique for predicting CQI using channel change information in a 5G system, while [17] used deep learning technology for SNR prediction in LTE and 5G. Most existing studies related to SNR prediction deal with SNR estimation, and few focuses on predicting future SNR values. Nonetheless, these works demonstrate the growing interest in developing accurate and effective techniques for SNR prediction in different communication systems.

This study proposes an algorithm that utilizes artificial intelligence to predict the SNR value at a future transmission time based on the SNR information measured in the past at each antenna. To achieve this, a convolutional neural network (CNN) is utilized, using the SNR values received from all antennas over a period of time. However, if the SNR cannot be measured at a particular time due to the absence of a received signal, linear and edge-zero interpolation methods are used to fill it. In this method, the SNR values of two neighboring records are used for linear interpolation, setting 0dB if no neighboring SNR values are available. The proposed CNN is a multi-output model, and the number of outputs varies depending on the number of transmit antennas (one or two). The neural network outputs a predicted SNR at each antenna for single transmit antenna case or a predicted combined SNR for two transmit antenna case. Among the predicted SNR values, the antenna with the highest value is selected for the future transmit antenna. The performance of the proposed method is verified through computer simulation. The verification criteria are the antenna selection accuracy for the moving speeds of the communication node and the root mean square error (RMSE) between the actual SNR value and the predicted SNR value. According to the simulation, the method for selecting a single transmit antenna has better accuracy than the method for selecting multiple transmit antennas, but the method for selecting multiple transmit antennas has better overall performance as checked by the RMSE. Comparing the proposed method with the conventional method, the proposed method outperforms the conventional method in both antenna selection accuracy and RMSE.

The structure of the thesis is as follows. *Section 2* reviews previous studies, and *Section 3* describes the overall system model. *Section 4* describes the SNR prediction methods for the conventional method and the proposed method, and *Section 5* compares the performance of the proposed method and the conventional method, and also compares the performance of Single transmit antenna selection and multiple transmit antenna selection. Finally, *Section 6* presents the conclusions.

2. MULTI-ANTENNA TDD SYSTEM MODEL

The communication system under consideration performs transmission and reception by attaching several patch-type antennas to a communication vehicle, and the communication counterpart uses a Single antenna. In addition, since the TDD method is used, the same radio channel is used in two-way communication using the same frequency. When receiving, the communication vehicle may receive using all antennas, record, and store the received SNR. During transmission, based on the past received SNR record, the SNR at the future transmission time point is predicted, and an antenna is selected for transmission based on this. There are two types of antennas that can be selected during transmission: a Single antenna and multiple antennas. In the case of selecting multiple antennas, two antennas are selected. The method for selecting a Single antenna is referred to as “Single”, and the method for selecting multiple antennas is referred to as “Dual”.

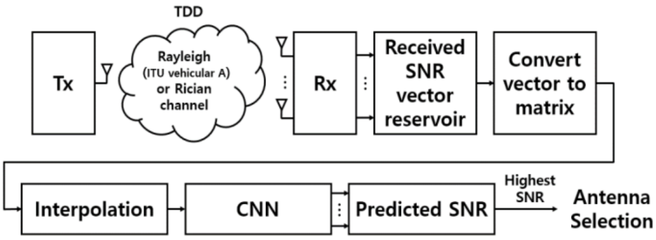

Figure 1: Block Diagram of a Multi-Antenna TDD System Model

Figure 1 depicts a block diagram of a multi-antenna TDD system. Signals are transmitted from the transmitting antenna to the receiving antenna through either a Rayleigh fading channel or a Rician fading channel. A Rayleigh fading channel refers to a non-line-of-sight environment where only reflected waves exist, while a Rician fading channel refers to a line-of-sight environment where direct waves and reflected waves coexist. Each receiving antenna can measure the received SNR, which is then recorded and stored in an SNR vector. The received SNR is measured per 1 orthogonal frequency division multiplexing (OFDM) symbol, where 1 OFDM symbol consists of symbols with the size of the OFDM FFT. *Equation 1* shows how to measure the j^{th} received SNR at the i^{th} receive antenna, where $t(n)$ is the transmitted symbol and $r(n)$ is the received symbol that has passed through the equalizer. N_{fft} represents the OFDM FFT size. The SNR is estimated using the average of the squared absolute differences between the channel-compensated symbols passed through the equalizer and the transmitted symbols. All antennas record the received SNR simultaneously. This can be expressed as *equation 2* represents the received SNR vector that has undergone the above process at a specific time f.

$$s_{i,j} = \frac{1}{N_{fft}} \sum_{n=(j-1)\times N_{fft}+1}^{j\times N_{fft}} |t_i(n) - r_i(n)|^2 \tag{1}$$

$$\boldsymbol{s}_f = [s_{1,f}, s_{2,f}, \dots, s_{M,f}]^T \tag{2}$$

The SNR matrix is created by combining the SNR vectors generated by repeating the above process for the length of the SNR record (N). The received SNR matrix (S) can be expressed as *equation 3*. The matrix S consists of rows representing the SNR vectors received by each antenna over time, and columns

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representing the received SNR vectors obtained at a particular reception point by using multiple antennas. The received SNR matrix signal S varies depending on the number of operating antenna combinations and the length of the past received SNR record (N). C is the number of antenna combinations. This varies depending on the number of operating antennas (M) and the number of transmitting antennas (A).

$$\boldsymbol{S} = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,N} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ s_{C,1} & s_{C,2} & \cdots & s_{C,N} \end{bmatrix} \quad (3)$$

The communication system proposed in this study may not receive signals all the time, which can make it difficult to measure the SNR of the received signal in the absence of any signal. This can be a problem in CNN models, where the size of the model inputs must be consistent. To address this issue, linear and edge-zero interpolation methods are utilized to replace missing incoming signal values. The predicted future SNR vector, denoted as y, represents the SNR at time index $N+1$ across all antennas. At this time, both y and the m^{th} element of y (denoted as y_m) can be expressed by *equations 4 and 5*, respectively.

$$y = [s_{1,N+1}, s_{2,N+1}, \dots, s_{C,N+1}]^T \quad (4)$$

$$y_m = s_{m,N+1} \quad (5)$$

3. SNR PREDICTION AND ANTENNA SELECTION

In this paper, a new CNN model is proposed that predicts the SNR of future transmission based on the SNR information of the previously received signal recorded for a certain period of time. The conventional method is a method of predicting a future signal SNR using an average of recorded received SNR information. To select the best antenna, among the predicted signal SNR and selects the antenna with the highest predicted value. This ensures that the antenna with the best signal quality is used for the next transmission.

3.1 Conventional SNR Prediction Method

The conventional antenna selection method estimates the signal SNR for a future transmission time by computing the average SNR for each antenna in the received signal SNR matrix (S). In this context, M represents the number of antennas in operation, while N represents the length of the received signal SNR recording. This average-based method is widely used in mobile environments where channels change over time [18] and is considered one of the most common methods for antenna selection.

3.2 Proposed SNR Prediction Method

The proposed antenna selection method utilizes a CNN that predicts the SNR for a future transmission point using the received SNR matrix S as its input. In cases where the SNR cannot be measured due to the absence of the received signal, linear interpolation is applied based on the two adjacent SNRs. If adjacent SNRs are do not exist, the SNR is recorded as 0dB. Linear interpolation can be achieved through *equations 6 and 7*. To calculate the SNR change(Δ_k) between two adjacent SNRs, *equation 6* is employed. Specifically, s_p and s_l denote the previously measured SNR and the subsequently measured SNR, respectively, while n_c indicates the number of SNRs not received between s_p and s_l. Meanwhile, k represents the index for which the received SNR is missing. Linear interpolation is performed using the SNR change obtained from *equation 6*. If either s_p or s_l does not exist, the SNR is recorded as 0dB. The interpolated received SNR matrix S is utilized as the input for the CNN to predict the SNR at the transmission time.

$$\Delta_k = \frac{s_l - s_p}{n_c + 1} \quad (6)$$

$$s_k = s_p + W \times \Delta_k, (W = 1,2,\cdots,n_c) \quad (7)$$

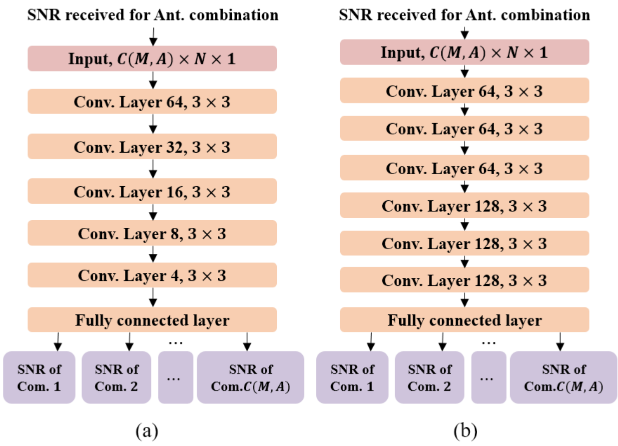

Figure 2: Proposed CNN Model Structure (a) Single (b) Dual

Figure 2 shows the structure of the proposed CNN model.

Figure 2(a) represents the model structure of Single, while (b) represents the model structure of Dual. The inputs of both models are in the form of a matrix S, but the size and output of the inputs vary depending on the number of selected transmit antennas. The inputs and outputs are the SNR and predicted SNR values for each antenna combination ($C(M,A)$) Single consists of 5 convolutional layers and 1 fully connected layer. The number of filters in each layer is 64, 32, 16, 8, and 4 respectively, with a filter size of 3 × 3. The output of every convolutional layer passes through a batch normalization layer and a Rectified Linear Unit (ReLU) activation function. The final predicted SNR value is output through flattening after converting the output of the last convolutional layer into a 1-dimensional vector. Dual has the same structure as Single, with the only difference being the number of convolutional layers and filters. Dual consists of 6 convolutional layers and 1 fully connected layer, with the number of filters being 64, 64, 64, 128, 128, and 128 respectively. The total number of parameters in these neural networks is 28,240 for Single and 630,150 for Dual. As a result, approximately the same number of multiplications and additions are required to perform SNR

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prediction once for both models. Therefore, Dual has a structure that is about 22 times more complex than Single.

4. SIMULATION RESULTS

4.1 Simulation Environments

Data generation for the simulation is performed using MATLAB, and the generated data is used for training and testing in Tensor Flow 2.0. The communication system parameters are set as shown in *table 1*, with 4 operating receiving antennas (M). The number of future transmit antennas (A) is set to 1 or 2. The SNR record length (N) is set to 40, bandwidth is set to 2MHz, and the carrier frequency is set to 512MHz. The OFDM FFT size (N_{fft}) is set to 512, and the cyclic prefix (CP) is set to 64. The channels are evenly distributed between Rician and Rayleigh (ITU Vehicular A) channels. The k-factor of a Rician channel is set to 10dB. Probability of recording received SNR is 1 OFDM symbol, and the reception SNR range, reception probability, and speed are uniformly generated between 0 to 30dB, 10 to 100%, and 0 to 100km/h, respectively.

Table 1. Simulation parameters

Parameter	Value
Number of Rx antennas (M)	4
Number of Tx antennas (A)	1 or 2
SNR record length (N)	40
Bandwidth	2MHz
Carrier frequency	512MHz
OFDM FFT size (N_{fft})	512
Cyclic prefix	64
Channel	Rician or Rayleigh (ITU vehicular A)
K-factor of Rician channel	10dB
SNR recording period	1 OFDM symbol
SNR range	0~30dB (Uniform random)
Probability of recording received SNR	10~100% (Uniform random)
Speed	0~100km/h (Uniform random)

For learning parameters, 200,000 pieces of learning data are created using the parameters shown in *table 1*, and 20,000 pieces of test data are created at intervals of 10km/h from 0km/h to 100km/h. The optimizer is AdaGrad, and the learning rate is 0.01. The batch size is 512, and the loss function is the mean squared error (MSE).

$$MSE = \frac{1}{D_{train}} \sum_{n=1}^{D_{train}} \sum_{i=1}^{M} (y_{i,n} - \hat{y}_{i,n})^2 \qquad (8)$$

Equation 8 represents the mean squared error (MSE). $y_{i,n}$ is the actual SNR at the i^{th} antenna of the n^{th} training data, and $\hat{y}_{i,n}$ is the predicted SNR at the i^{th} antenna of the n^{th} training data. D_{train} is the number of training data. That is, the MSE is a value obtained by accumulating the squared difference between the actual answer and the prediction and dividing by the total number of training data.

4.2 Results

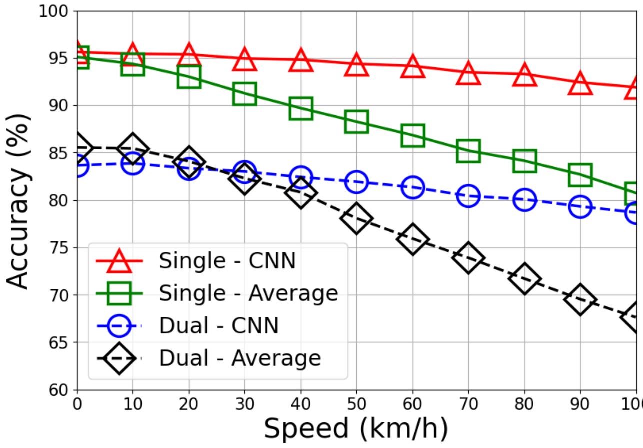

Figure 3: Accuracy for Number of Transmit Antennas Selection

Figure 3 shows the accuracy according to the number of transmit antennas. The red solid triangle (Δ) represents the case of the Single proposed method, and the circle (○) of the blue dotted line represents the case of the Dual proposed method. The green solid square (□) represents the case of the Single conventional method, and the black dotted diamond (◊) represents the case of the proposed Dual method. As the speed increases, the accuracy of the proposed Single method decreased from about 95.62% to 91.90%, and the accuracy of the proposed Dual method decreased from about 84.00% to 78.98%. The conventional Single method showed a decrease in accuracy from about 95.10% to 80.74%, and the Dual method showed a decrease in accuracy from about 85.55% to 67.63%. In the single method, the proposed method outperforms conventional methods at all speeds. However, in the dual method, it is superior to the conventional method for speeds of 20 km/h or higher.

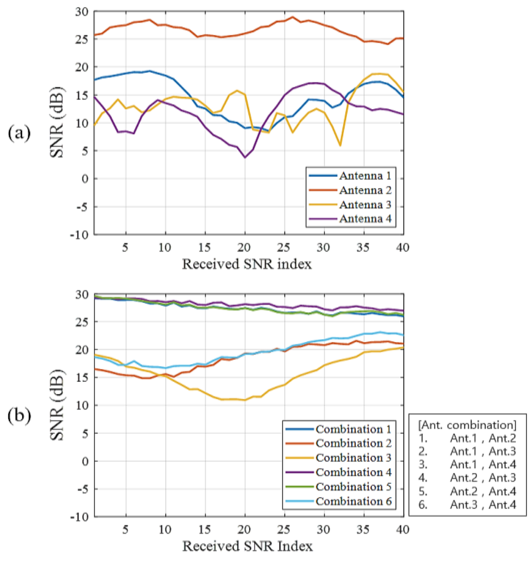

Figure 4: The Received SNR After Passing Through a Rician Channel (a) Single (b) Dual

Figure 4 shows the received SNR signal passing through a Rician channel. Upon analyzing the reason for the large difference in accuracy between the Single and Dual proposed methods by checking the received SNR, it was confirmed that just one signal had a high SNR from a Single antenna, while Dual had similar SNR values from multiple antenna combinations. This is a phenomenon caused by the addition of the signal of the antenna with the highest signal quality and the signal of another antenna because it was created with a combination of operational antennas in the signal generation method of Dual.

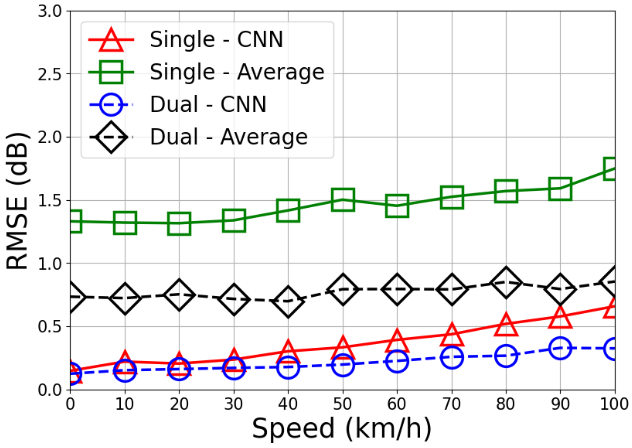

Figure 5: RMSE for Number of Transmit Antennas Selection

Figure 5 shows the RMSE according to the number of transmit antennas. As shown in *figure 3*, the line type and marker type are the same. In the case of Dual, since the three signals have similar values of SNR, the predicted SNR of the selected antenna and the actual SNR of the actual antenna were compared, considering that the difference between the selected antenna and the actual communication quality may be small. As a result, both single and dual show an error lower than 1dB in the proposed method, and an error lower than 2dB in the conventional method. In the dual method, from 0 to 20 km/h, the conventional method exhibits higher accuracy compared to the proposed method. However, upon examining the RMSE, it is observed that the error of the proposed method is approximately 0.5 dB lower than that of the conventional method at all speeds. This indicates that there is not much difference between the selected antenna and the actual communication quality, suggesting that it may not be a problem even if the actual antenna is not selected.

$$RMSE = \sqrt{\frac{1}{M}\frac{1}{D_{test}}\sum_{n=1}^{D_{test}}\sum_{i=1}^{M}(y_{i,n}-\hat{y}_{i,n})^2} \qquad (9)$$

Equation 9 represents RMSE. RMSE is obtained by taking the square root of the mean of the squared differences between the actual answer and the prediction, calculated over the total number of test data.

5. ACKNOWLEDGMENTS

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6. CONCLUSION AND FUTURE WORK

In this paper, a method is proposed to predict future SNRs using CNNs in TDD environments, select the antenna with the highest SNR as the future transmission antenna, and compare performance based on the number of selected transmission antennas. As a result of simulation antenna selection accuracy is the proposed method outperforms the conventional method at all speeds in the single method. In the dual method, the performance of the conventional method is superior at low speeds, but the performance of the proposed method surpasses it as the speed increases. However, upon examining the RMSE, it is found that the error of the proposed method is smaller than that of the conventional method at all rates for both single and dual methods. The reason for the low antenna selection accuracy but small RMSE in the duplex scheme is that the combination of the antenna with the best signal quality and other antennas results in multiple signals with similar signal quality. The antenna selection is wrong, but if the difference between the actual SNR and the predicted SNR is small, it is not a problem in real communication. Therefore, Dual antenna selection accuracy is not an issue. Furthermore, the performance of the proposed method is superior to that of the conventional method. If this method is applied to an actual communication system, SNR at the time of future transmission can be accurately estimated using signals received in the past, thereby securing a transmission speed. As the received SNR changes over time, a recurrent neural network (RNN) would be a more appropriate choice than a CNN. Therefore, in future studies, RNNs will be used to predict SNR at future transmission points and compared with CNNs.

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