Selection of Optimum Transmit Antenna Based on Convolutional Neural Networks in Mobile Fading Channels

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Abstract

This paper proposes a new technique for selecting optimal transmit antennas using convolutional neural network (CNN) in mobile communication environments. The communication system considered in this paper has multiple antennas and time-division duplexing (TDD) mode. In a receiver mode, it utilizes all the antennas but uses only one antenna in a transmitter mode. The proposed method is an optimal antenna selection technique based on CNN for future transmission time. The input of the CNN the signal to ratios (SNRS) for the past received signals. Conventional method selects the optimal antenna based on the average of the past received SNRs or the most recently received SNR. We compare the proposed method with two conventional methods through computer simulation. According to the simulation results, by changing the mobile speed and the probability (or frequency) of receiving, the proposed CNN method has the highest accuracy in wideband signals while the convolutional method using the recent received SNR has the highest accuracy in narrowband signals.

Keywords: Antennal diversity, antenna selection, MIMO, deep learning, CNN, Multi-class classification.

1. Introduction

In general, wireless mobile communication systems experience fading that is multiple paths due to the influence of obstacles such as various topographical features on the radio path (Dighe et al., 2003; Sesia et al., 2011). For reliable communication in multipath fading channels, various diversity techniques have been proposed. In particular, spatial diversity using multiple-input and multiple-output (MIMO) systems provides significant improvements in system capacity and transmission reliability without increasing system bandwidth (Telater et al., 1999). However, the hardware cost, signal processing complexity, power consumption and component size are increased and it limit the general application of MIMO technology. In fact, the price and complexity of the RF chain of MIMO systems increase exponentially as the number of antennas increases (Heath et al., 2016). Therefore, the use of the antenna selection (AS) technique among MIMO technologies can overcome the shortcomings of MIMO (Sanayei et al., 2004; Tarokh et al., 1999). In the meantime, various studies on antenna selection have been conducted (Chen et al., 2005; Gucluoglu et al., 2008; Li et al., 2013; Ramya et al., 2009; Zhang et al., 2008).

In this paper, we propose a convolutional neural network (CNN) technique for selecting the optimal transmit antenna using the past received signal-to-noise ratio (SNR) obtained from each antenna on the move (Jeong et al., 2020). The communication system considered in this paper has multiple antennas and communicates bi-directionally using the same frequency and time division duplex (TDD) mode. Therefore, the transmit and receive channels are reciprocal. When receiving, all the antennas are used for antenna diversity, but only one antenna is selected and transmitted when transmitting. The proposed method is multi-class classification CNN, which uses the past received SNRs to select the optimal transmit antenna in the future. Conventional method selects the optimal antenna based on the average of the past received SNRs or the most recently received SNR. The performance comparison of the conventional method and the proposed method is performed through computer simulation. Specifically, the antenna selection accuracy is observed while changing the mobile and the probability (or frequency) of receiving. According to the simulation results, by changing the mobile speed and the probability (or frequency) of receiving, the proposed CNN method has the highest accuracy in wideband signals while the convolutional method using the recent received SNR has the highest accuracy in narrowband signals Therefore, it is advantageous to apply the proposed method in a wideband signal environment.

The structure of this paper is as follows section 2 describes the system model for selecting the transmit antenna, and section 3 describes the antenna selection technique. Section 4 shows the antenna selection accuracy of the conventional method and the proposed method through computer simulation.

2. System Model

In communication using multiple antennas, antenna selection is a technology that can increase communication reliability and reduce implementation costs. In general, feedback from a receiver is required when selecting an optimal transmit antenna. In a TDD mode, however, an optimal transmission antenna can be selected based on the quality of the past signal received from each antenna because the transmit and the receive channels are reciprocal. When the channel is time-varying the problem is not easy. The best antenna at the receive mode does not always the best transmit antenna in the future. In this case, it is reasonable to select the optimal transmit antenna based on the change over time of the received SNR. If artificial intelligence is used, the most optimal transmit antenna can be selected based on the SNR of the received signal in the past. This is motivation of this paper.

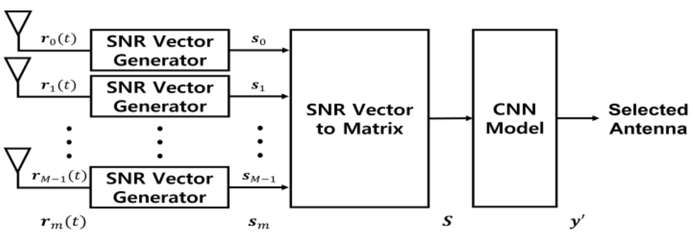


Fig. 1; Transmit Antenna Selection System Model

Figure 1 is a block diagram of the transmit antenna selection system of interest. The system receives using M reception antennas and transmits using $\mathrm{M_t}$ $(\mathrm{M_t} < \mathrm{M})$ antennas. In the reception process, $\mathrm{r_m(t)}$ is the received SNR for m-th antenna at certain time t in the receiver mode. m $(\mathrm{m} = 0, 1, \dots, \mathrm{M}-1)$ represents the index of the receiving antenna. $\mathrm{s_{m,n}}$ generated by sampling the analog signal $\mathrm{r_m(t)}$ at regular intervals can be represented as

$$\mathrm{s_{m,n}} = \mathrm{r_m(t)}|_{\mathrm{t}=\mathrm{L_s}\times \mathrm{n}} \quad (1)$$

$\mathrm{L_s}$ $(= \mathrm{k} \times \mathrm{T_s})$ is a value obtained by multiplying the symbol period $\mathrm{T_s}$ by k, and the received SNR collection interval becomes $\mathrm{L_s}$. n $(\in \{0, 1, \dots, \mathrm{N}-1\})$ is the index of the input data column. n represents time. The generated $\mathrm{s_{m,n}}$ is converted into an SNR vector signal $\mathrm{s_m}$. The SNR vector signal $\mathrm{s_m}$ is represented as

$$\mathbf{s}_{\mathrm{m}} = [\mathrm{s_{m,0}}, \mathrm{s_{m,1}}, \dots, \mathrm{s_{m,N-1}}] \quad (2)$$

An $\mathrm{M} \times \mathrm{N}$ SNR matrix signal S is generated by combining the SNR vector signals $\mathrm{s_m}$ for all antennas. S can be represented as

$$\mathrm{S} = \begin{bmatrix} \mathrm{s_{0,0}} & \mathrm{s_{0,1}} & \cdots & \mathrm{s_{0,N-1}} \\ \mathrm{s_{1,0}} & \mathrm{s_{1,1}} & \cdots & \mathrm{s_{1,N-1}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{s_{M-1,0}} & \mathrm{s_{M-1,1}} & \cdots & \mathrm{s_{M-1,N-1}} \end{bmatrix} \quad (3)$$

Each column of S consists of M SNR elements measured per $\mathrm{nL_s}$. The observation time is from 0 to $(\mathrm{N}-1)\mathrm{L_s}$. N determines the past time interval observed. The total observation time $\mathrm{T_{obs}}$ can be represented as (4).

$$\mathrm{T_{obs}} = \mathrm{L_s} \times \mathrm{N} \quad (4)$$

Figure 2 shows an example of input data S. The shaded block is a case where a reception SNR exists, and the white block is a case where a reception SNR does not exist because there is no received packet.

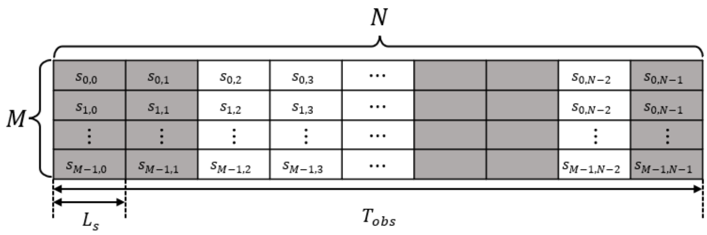


Fig. 2; Example of S in Proposed Method

It is assumed that the transmit time is $\mathrm{n} = \mathrm{NL_s}$. That is, the problem to be solved by this paper is to select the optimal transmission antenna at $\mathrm{n} = \mathrm{NL_s}$. The $\mathrm{M} \times 1$ label vector y is used to train the CNN. y is generated using the SNR signal $\mathbf{s}_{\mathrm{m,N}}$ at the transmit time N. $\mathbf{s}_{\mathrm{m,N}}$ can be written as

$$\mathbf{s}_{\mathrm{m,N}} = \begin{bmatrix} \mathrm{s_{0,N}} \\ \mathrm{s_{1,N}} \\ \vdots \\ \mathrm{s_{M-1,N}} \end{bmatrix} \quad (5)$$

The elements of y are composed of 0 and 1, and the number of 1 is $\mathrm{M_t}$. 1 is assigned to the corresponding indices of the highest SNR values in $\mathrm{s_{m,N}}$. CNN is trained using the input matrix S and label y. The trained CNN model selects an optimal antenna at a future transmission time. A predicted antenna is denoted by $\mathrm{y'}$ from the proposed CNN model.

3. Proposed CNN Antenna Selection Technique

3.1. Conventional Select Method

For conventional techniques, two schemes are considered for performance comparison with the proposed method. The first one is selecting an antenna having the highest average SNR during 0 to N-1 of the received SNRs. The second method selects the antenna having the highest SNR at the most recent received SNRs among M antennas. For example, the method of using the average SNR is to obtain the average in rows of shaded blocks in Figure 2, and to select the antenna corresponding to the highest average SNR. The second technique is to select the last column of the shaded block in Figure 2 and select the antenna showing the highest SNR in that column.

3.2. Proposed Select Method

In the proposed method, we design a multi-class classification CNN that selects the optimal antenna. Specifically, the SNR matrix S is input to the CNN, and the CNN output indicates the optimal transmission antenna. In the proposed method, if there is no received signal, the empty value is filled through linear interpolation. Linear interpolation is performed using the nearest previous index r_1 and the subsequent time r_2 where the received signal. $s_{m.n}$ in which the reception signal does not exist can be calculated as

$$s_{m,n} = s_{m,r_1} + (n - r_1) \times \frac{s_{m,r_2} - s_{m,r_1}}{r_2 - r_1}, r_1 \leq n < r_2 \quad (6)$$

However, the most front part and the last part of the input data S have only one adjacent received SNR. Therefore, this part must be filled in another way. If it is not received at the very beginning, it is filled using (7), and if it is not received at the very end, the empty SNR is filled using (8).

$$s_{m,n} = s_{m,n+1} - \left(s_{m,n+2} - s_{m,n+1}\right), (n = r_2 - 1, \dots, 0) \quad (7)$$

$$s_{m,n} = \left(s_{m,n-1} - s_{m,n-2}\right) + s_{m,n-1}, (n = r_1 + 1, \dots, N - 1) \quad (8)$$

The structure of the proposed CNN model is designed in two ways depending on the bandwidth of the signal. Figure 3(a) is the proposed CNN model for wideband signals, consisting of a total of four convolutional layers and one fully connected layer, and Figure 3(b) is the proposed CNN model for narrowband signals, consisting of a total of seven convolutional layers and one fully connected layer. Each convolutional layer of all models includes a batch normalization layer, with the convolutional filter of size 3x3, stride 1, and all activation functions of each layer are Rectified Linear Unit (ReLU). Models for wideband use a total of two dropout. Thereafter, the optimal transmission antenna selected through the classification layer. In training, the optimization method uses Adam, and the learning rate is 0.01, the batch size is 512, and the epoch is 150. It also uses three ensembles. The loss function uses cross-entropy (CE).

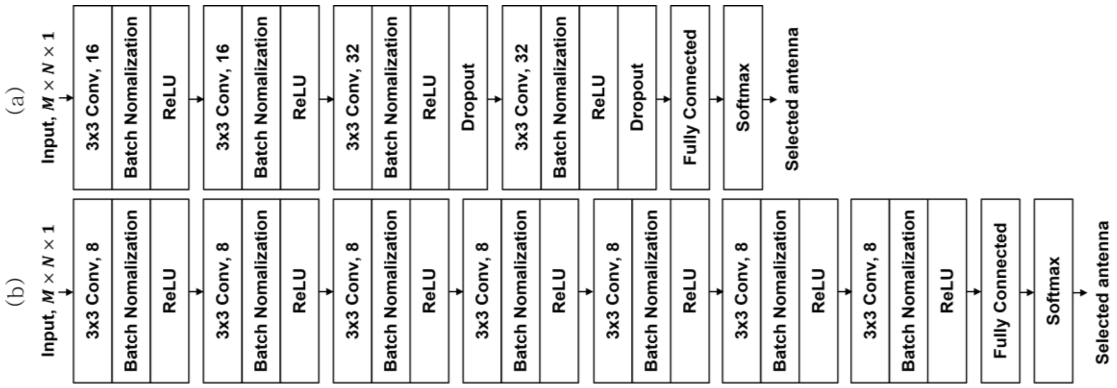


Fig. 3; Multi-class Classification CNN Model Structures for (a) Wideband (b) Narrowband

4. Simulation Results

4.1.Simulation Environment

For performance verification, simulations are performed using Tensorflow 2.0 and MATLAB. The parameters used in the simulation are summarized in Table 1.

Table 1. Simulation Parameters

Parameters	Value
Number of antenna (M)	4
Size of input data column (N)	100
Number of Tx antenna (M_t)	1
Symbol spacing (k)	1,000
Bandwidth	25 kHz, 2 MHz
Carrier frequency	88 MHz, 512 MHz
Average of SNR	0 ~ 30 dB
Speed	0 ~ 100 km/h
Probability of receiving signal	10~100 %
K-factor of Rician channel	14 dB

In the simulation, the number of antennas M is set to 4, the column length N of the input data X is 100, the transmit antenna M_t is 1, and the symbol interval k is 1,000. Bandwidth is $2\,\mathrm{MHz}$ for wideband and $25\,\mathrm{kHz}$ for narrow band, and carrier frequencies for each bandwidth are set to $88\,\mathrm{MHz}$ and $512\,\mathrm{MHz}$. The average SNR is randomly selected from 0 to $30\,\mathrm{dB}$ in $1\,\mathrm{dB}$ intervals, moving speed is 0 to$100\,\mathrm{km/h}$, and the probability of receiving (received SNR recording probability) is 10 to $100\,\%$. For example, a reception probability of 20% means that the received SNR exists only in 20% of the total time. In the Rician channel, the K-factor is $14\,\mathrm{dB}$.

4.2.Training CNN Model

A total of 80,000 matrices S are used to train the proposed CNN model. The number of data for validation is 10,000. The input size of the model is 4×100. The loss function of the CNN model is cross entropy:

$$CE(P,Q) = -\sum_{i=0}^{M_t-1} P(c_i)\log Q(c_i)$$
$$CE(P,Q) = -\{P(X=c_0)\log Q(X=c_0)\} + \cdots + \{P(X=c_{M_t-1})\log Q(X=c_{M_t-1})\} \tag{9}$$

M_t is the number of classes or the number of transmission antennas. In classification problems, the label of the data is expressed through one-hot encoding. These probability values are values that constitute the probability distribution Q estimated by the model. The actual probability distribution P of the data is the one-hot encoding probability distribution values.

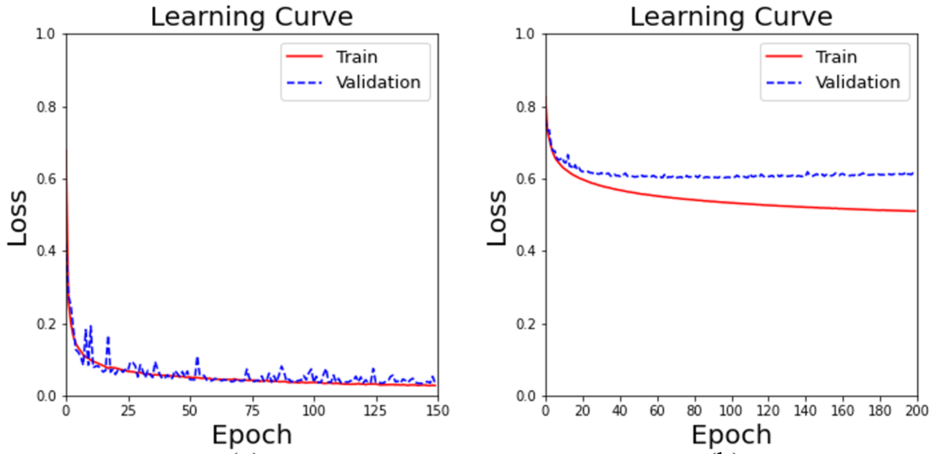
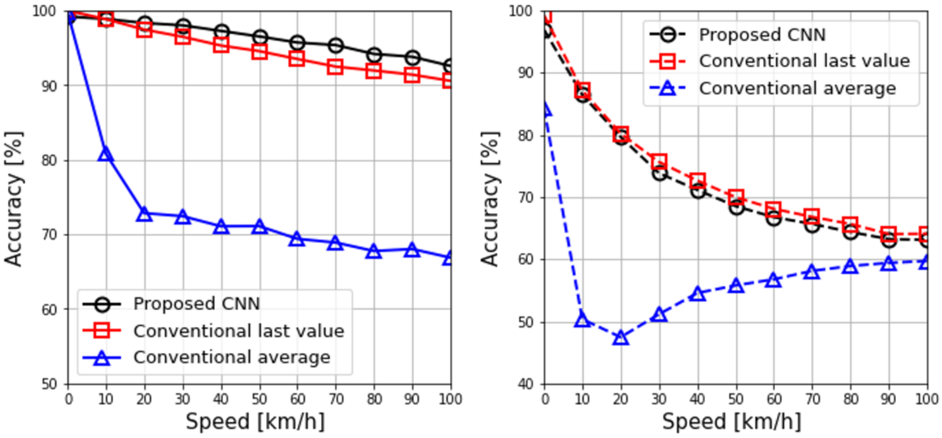


Fig. 4; Learning Curves for (a) Wideband (b) Narrowband

Figure 4 shows the learning curve of the proposed method. Figure 4 (a) is a learning curve for wideband signal, and Figure 4 (b) is a learning curve for narrowband signal. Through the learning curve, it can be confirmed that the training has been performed well. According to the results of validation, overfitting did not occur in the wideband signal, but a little overfitting occurred in the narrowband.

4.3.Performance Comparison

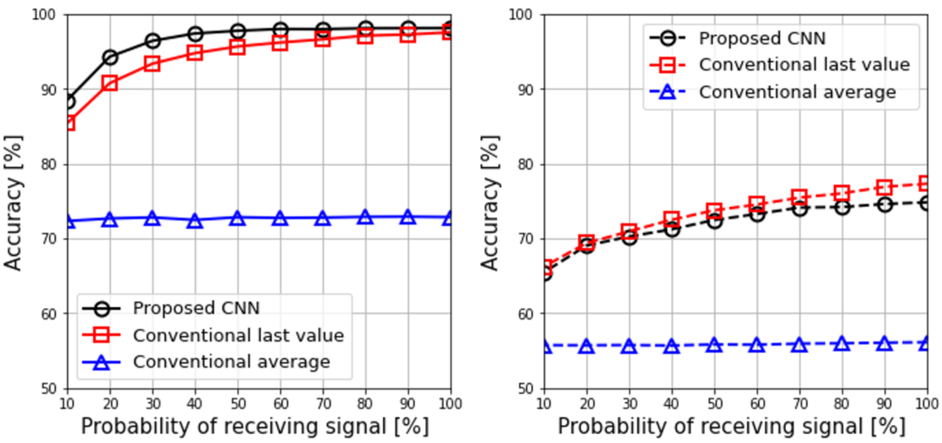
To verify the performance of the proposed method, test data are generated in two ways. The first is to observe the performance change by the moving speed, and 20,000 test data are generated at interval of 10 km/h from 0 to 100 km/h. The probability of receiving is randomly chosen between 10 and 100 %. The second is to observe the performance change by the probability of receiving SNRs, and 20000 test data are randomly generated at a moving speed of 0-100 km/h. The probability of receiving data is generated at intervals of 10 % to 100 %. Accuracy is used as a performance indicator for performance comparison.



(a) (b)

Fig. 5; Accuracy According to Speed (a) Wideband (b) Narrowband

Figure 5 shows the performance for the moving speeds. Figure 5(a) shows the accuracy when the bandwidth is 2 MHz, and Figure 5(b) shows the accuracy when the bandwidth is 25 kHz. When the bandwidth is 2 MHz, the antenna selection accuracy decreases in all methods as the speed increases. When speed is 100 km/h, the accuracy of the proposed CNN is 92.58 %, the accuracy of the conventional method using the last SNR is 90.57 %, and the accuracy of the conventional method using the average SNR is 66.86 %. When the bandwidth is 25 kHz, the proposed method and the conventional method using the last value have lower antenna selection accuracy as speed increases, but the conventional method using average has higher accuracy as speed increases when speed is 20 to 100 km/h. When speed is 100 km/h, the accuracy of the proposed CNN is 63.11 %, the accuracy of the conventional method using the last SNR is 64.08 %, and the accuracy of the conventional method using the average SNR is 59.71 %. In the wideband, the accuracy of the proposed method is higher than that of all conventional methods, but in the narrowband, the accuracy of the proposed method is about 0.97 % lower than that of the method using the last variable.



(a) (b)

Fig. 6; Accuracy According to Probability of Receiving Signal (a) Wideband (b) Narrowband

Figure 6 shows the performance for probability of receiving. Figure 6(a) shows the accuracy when the bandwidth is 2 MHz, and Figure 6(b) shows the accuracy when the bandwidth is 25 kHz. As the reception probability increases in all bandwidths, the antenna selection accuracy increases in all methods except for the conventional method using average. When the bandwidth is 2 MHz and probability of receiving signal is 100 %, the accuracy of the proposed CNN is 98.13 %, the accuracy of the conventional method using the last SNR is 97.57 %, and the accuracy of the conventional method using the average SNR is 72.86 %. When the bandwidth is 25 kHz and probability of receiving signal is 100 %, the accuracy of the proposed CNN is 74.84 %, the accuracy of the conventional method using the last SNR is 77.32 %, and the accuracy of the conventional method using the average SNR is 56.13 %. Similar to the performance according to speed, the accuracy of the proposed method is higher than all conventional methods in the wideband, but the accuracy of the proposed method in the narrowband is about 2.48% lower than that of the conventional method using the last value.

According to the above results, it is advantageous to use the proposed method when the signals is wideban. In a wideband signal, the method that proposes both the accuracy according to speed and reception probability is superior to all the existing methods. However, in a narrowband signal, the conventional method of selecting an antenna based on the last SNR is superior to the proposed method.

5. Conclusion

This paper proposed to use CNN when selecting transmit antenna among multiple antennas in a moving environment. The proposed method uses the received SNRs from the receiving antennas as an input to the CNN and selects the antenna with the highest SNR at the future time of transmission. As a result of computer simulation, the accuracy of the conventional method using the average was the lowest, and the accuracy of the proposed method and the conventional method using the last value showed similar performance. For the wideband signal, the proposed method was the best, and for the narrowband, the conventional method of selecting an antenna based on the recent SNR value was the best. Therefore, when selecting transmit antenna, it is recommended to use the proposed method in a wideband, and to use the conventional method of selecting the antenna with a high last SNR value in a narrowband. As a future research, we plan to compare the proposed method with the conventional method in a realistic situation where there is an observation error or noise in the received SNRs.

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