Transmit Antenna Selection Using CNN-Based Multiclass Classification with Linear Interpolation of Wideband Channels

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***Abstract*—This study proposes a transmit antenna selection (TAS) method. The proposed TAS selects a transmit antenna based on the predicted channel quality by using a convolutional neural network (CNN)-based multi-class classification. The designed CNN directly determines the transmit antenna index based on the past signal-to-noise ratio (SNR), which is obtained through the received signals before the transmission. Since the channel states vary over time, the future SNRs are implicitly predicted through the CNN, and the predictive antenna index is explicitly determined. Here, the channels in the receiving and transmitting periods are symmetric, i.e., a time-division duplex (TDD) system is assumed. Further, various interpolation methods are examined to fill the missing received SNRs. Based on numerical results, it is verified that the proposed CNN-based TAS outperforms two conventional benchmarking methods: i) a TAS method based on the previous SNR and ii) a TAS method based on the average SNR.**

***Index Terms*—Convolutional neural network (CNN), transmit antenna selectin (TAS), channel prediction, wideband channel**

I. Introduction

To alleviate the hardware complexity issues in multiple antenna systems, transmit antenna selection (TAS) scheme has been studied in [1]–[3]. However, the performance of the existing TAS using channel information can be degraded in the fast-varying channel due to a large amount of required channel feedback overhead in the time-division duplex (TDD) systems. To this end, several machine learning approaches were considered in TAS systems, which can reduce the amount of channel feedback and the selection complexity [4], [5]. In this study, a convolutional neural network (CNN)-based TAS is proposed to further reduce the amount of channel feedback. Specifically, it selects the best transmit antenna based on the previously received signal-to-noise ratio (SNR) of each antenna. To cope with the SNR measurement failures, various SNR interpolation methods are also presented. Among various interpolation methods, a linear interpolation provides relatively better prediction accuracy than other methods. Simulation results verify that the proposed method outperforms the conventional schemes in the time-varying channel. It is worth noting that this is the first work to design a CNN architecture to improve the TAS performance in the time-varying channels.

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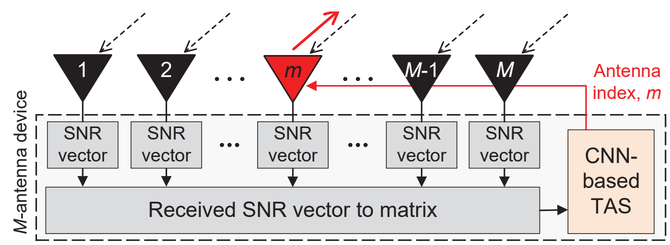
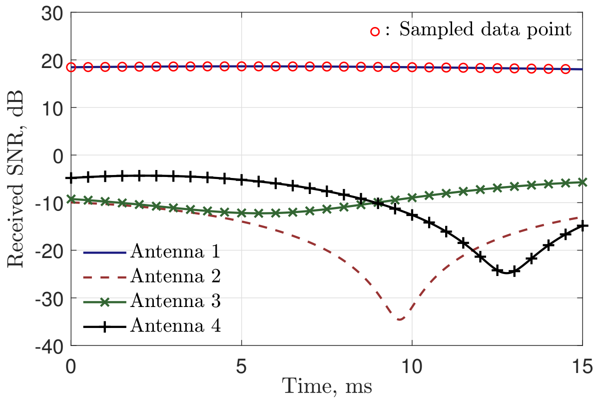


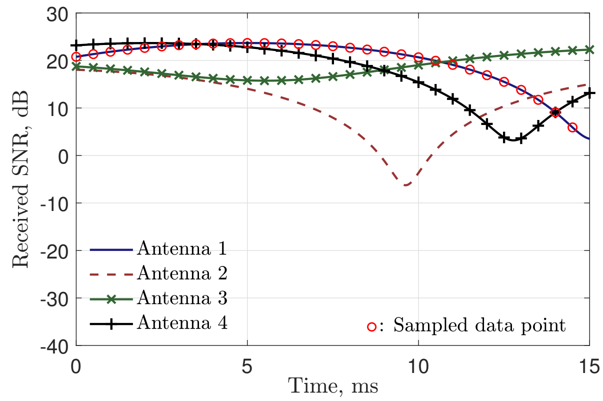
Fig. 1. CNN-based TAS scheme in an M-antenna device. Using the received SNR measurements for each antenna, a single antenna is selected for the next data transmission.

II. TAS System Model

Figure 1 shows a device having M antennas. Considering the TDD system, the device receives signals from the counterpart communication device. From the received signals, the device measures the received SNR and selects a transmit antenna to deliver data to the counterpart device. Here, the channel can vary significantly, as shown in Fig. 2, owing to the relative changes in the locations of the devices, i.e., mobility. In Fig. 2, the examples of the received SNR measurements are illustrated in both line-of-sight (LoS) and non-LoS (NLoS) channels. Wideband signal transmission with bandwidth $W = 2$ MHz is considered. The received SNR is measured once in every N_s received symbol, where N_s is a sampling period. The sampled SNR points of the first antenna are depicted in the red '$\circ$' mark in Fig. 2. Given sampling period N_s, the window size is determined by $N = \frac{T}{t_s N_s}$, where T and t_s denote the total observation time and symbol duration, respectively. Here, t_s is reciprocal to the signal bandwidth W.



(a)



(b)

Fig. 2. Examples of the received SNR measurements in time-varying channels when the speed of device is 60 km/h, sampling duration $N_s = 250$, and the total observation time $T = 15$ ms, i.e., widow size $N = 30$. (a) LoS channel. (b) NLoS channel.

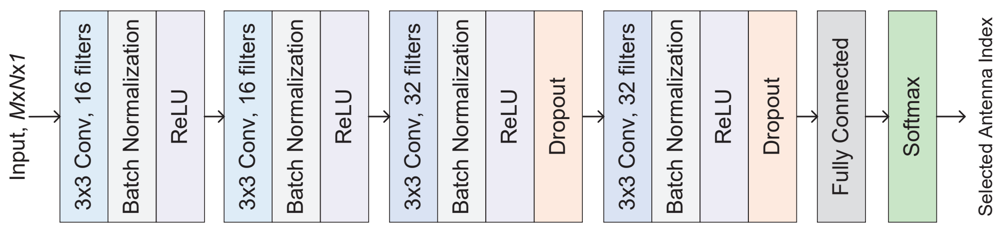


Fig. 3. Structure of CNN with $M \times N$ received SNR input. The output is the index of the selected transmit antenna.

To select the best transmit antenna, the channel quality for each antenna should be predicted based on the previously received SNR data. Using the past MN SNR measurements as input data of a designed CNN, the network is trained to directly obtain the index of the best antenna.

III. Proposed Method

In this section, the CNN-based TAS is designed to directly obtain the index of the best antenna among M available antennas, i.e., multi-class classifier. To construct full MN-sized training data sets, the interpolation methods are applied to generate omitted SNR measurements from received failure. The descriptions of the proposed CNN-based TAS model are then presented in detail.

A. Training Data Construction

In practice, the received SNR measurement failure can occur due to a significant loss in wireless channel quality, e.g., deep fading, obstacles, and abrupt motion changes in the device. Here, three interpolation methods are introduced to generate SNR values for measurement failures.

- "Zero": insert 0 dB in the omitted SNR measurements.
- "Linear": interpolate linearly based on two adjacent SNR measurements. If the last SNR measurement fails, the previous two measured SNR values are used in interpolation.
- "Linear and edge zero": similar to "Linear", while inserting 0 dB in the omitted measurements if the last SNR measurement fails.

B. CNN-Based Multi-Class Classifier Design

The proposed learning system utilizes 2D-CNN as the main feature extraction network, as shown in Fig. 3. The clean $M \times N$ SNR matrix is fed to 2D-CNN as the input for training. The proposed 2D-CNN model includes four hidden layer groups followed by fully connected and softmax layers. Each hidden group is constructed by one convolutional layer with a rectified linear unit (ReLU) layer between them, followed by a batch normalization layer.

The hidden non-linear features can be implicitly extracted by four alternating convolutional and ReLU layers. Further, to effectively extract the unknown and various features from the received SNRs, multiple filters are employed at each layer. The convolution layers of the four hidden groups are as follows:

- Convolutional layers 1 and 2: 3×3 filters, kernel (filter) size 16, stride 2, padding 0's
- Convolutional layers 3 and 4: 3×3 filters, kernel size 32, stride 2, padding 0's

The batch normalization between the convolutional and ReLU layers normalizes the hidden layer input and also resolves an issue caused bu the distribution change of the input [6]. At the end of each hidden layer, the most widely used activation function, i.e., a ReLU, is employed [7] for better and fast learning. At the end of the third and fourth hidden layers, the 30% output data of the batch normalization is dropped out (set to zeros or disconnected) in the dropout layer by randomly removing 30% of neurons during the training (i.e., the hyperparameter dropout rate is 0.3). The dropout prevents

TABLE I
SIMULATION PARAMETERS.

Communication parameters	**Values**
# of antennas, M	4
Bandwidth / Carrier frequency	2 MHz / 512 MHz
Average of SNR	0-30 dB
Speed	0-100 km/h
Prob. of Sig. Reception	10-100%
$\kappa-$factor of Rician channel	14 dB
Hyperparameters for CNN	**Values**
# of training data	80000
# of validation data	10000
# of test data	40000
Optimizer in CNN	Adagrad
Learning rate	0.01
# of maximum epochs	500
Loss function	Cross-entropy

a nonsensical action from significantly relying on a particular input, reducing over-fitting and generalization [8]. After the dropout layer, each batch goes through a fully connected layer and then is provided to the softmax layer to determine the selected antenna index.

IV. Simulation Results and Discussion

In this section, the antenna selection accuracy of the proposed CNN-based TAS methods is evaluated. The communication parameters and CNN hyperparameters are presented in Table. I. In Fig. 4, the accuracies of the proposed CNN-based TAS are compared under three different interpolation methods. Here, the window size N and sampling period N_s are set to 100 and 1000, respectively. It is verified that the accuracy of each interpolation method is higher than 90 %. Also, the linear interpolation method shows the highest accuracy among the others.

Fig. 5 compares the performance of the proposed CNN-based TAS scheme with two benchmarks. For each benchmark scheme, the antenna index is chosen as one of the following criteria: i) the antenna with the largest lastly received SNR and ii) the antenna with the largest received average SNR. Following the comparison results in Fig. 4, the linear interpolation method is applied. The window size N and sampling period N_s are set to 10 and 250, respectively. It is shown that the proposed method outperforms the other two benchmarks when the device's speed is higher than 30 $\mathrm{km/h}$.

V. Conclusion

In this study, the CNN-based TAS method was proposed in wideband channels considering the TDD systems. The proposed method can directly predict the best transmit antenna index in the presence of channel variation. Considering the SNR measurement failure, three interpolation methods are utilized to generate omitted SNR values. Numerical results showed that the proposed CNN-based TAS with linear interpolation method outperforms the other benchmarks in antenna index prediction accuracy. The proposed method will be further extended to be adopted in narrowband channel models.

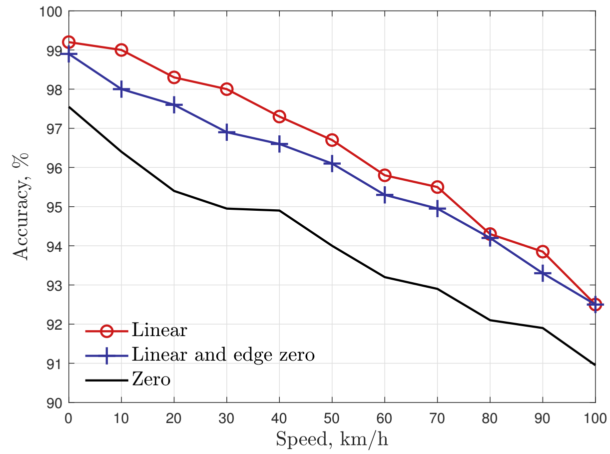


Fig. 4. Selection accuracy comparison of various interpolation methods over speed.

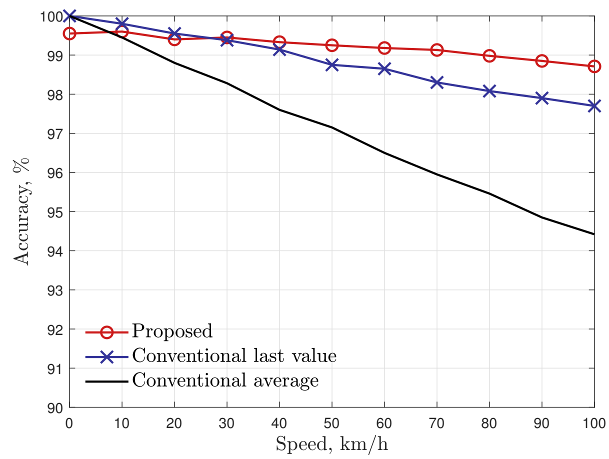


Fig. 5. Selection accuracy comparisons between the proposed and benchmark schemes.

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