Proactive Prediction of Path Loss Using Multi-Input Recurrent Neural Network in an Urban Environment

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6th generation mobile communication systems are expected to be used in a variety of ways, and among them, there are high expectations for their use in self-driving cars. As a way to ensure the safety of autonomous driving, it is important to grasp the driving state such as remote monitoring using wireless communication [1]. However, there is a problem of deterioration in wireless communication quality due to movement. In this paper, we report a multi-input recurrent neural network (RNN) using building information as a method for predicting wireless communication quality in seconds, which is necessary to ensure the safety of autonomous driving [2].

Figure 1 shows the configuration of the proposed multi-input RNN model. Here, gated recurrent unit (GRU) layer was utilized as one of the RNN. The input of left side is the time-series data of the latest path loss. The time-series data is processed in gated recurrent unit (GRU) layer. The input of center and right side are building parameters at the current position and the future position as prediction target. The building parameters are processed in fully connected layer. Outputs of these GRU layer and fully connected layers are combined at the next fully connected layer. By combining them, it is possible to make proactive predictions that consider both path loss fluctuations and surrounding environment fluctuations. Building parameters include the average building height between transmitter (TX) and receiver (Rx), maximum building height between Tx and Rx, the height of the nearest building from Tx and Rx, distances to the nearest building from Tx and Rx, the density of buildings between Tx and Rx, density of buildings around Rx, and the distance between Tx and Rx.

The training data and validation data are the path losses measured in Yokosuka City, Kanagawa Prefecture, Japan, and the measurement frequencies are 2.2, 4.7, and 26.4 GHz. Using 50 points of path loss data about every 0.1 s, path loss after 5 s was predicted. With the prediction method using the proposed multi-input RNN model, the root mean squared error of the prediction results for the validation data was 3.6, 3.8, and 3.7 dB at 2.2, 4.7, and 26.4 GHz, respectively. The proposed model can improve the prediction accuracy compared to a deep neural network model using only building information and an RNN model using only the latest path loss. These details will be introduced in the presentation.

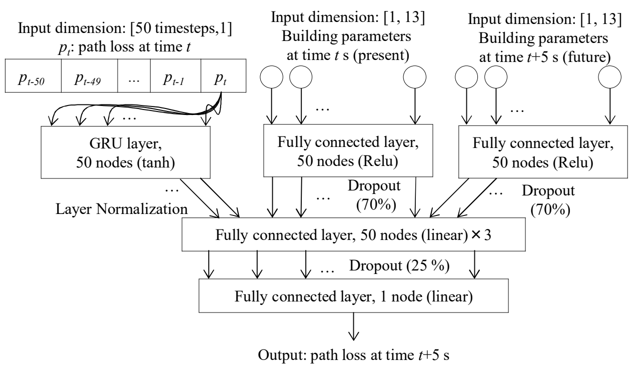

Figure 1. Proposed prediction model using multi-input RNN, which uses time-series data of latest path loss and map data of surround buildings at current and future positions for proactive prediction of path loss.

References

[1] S. Belcher, at.el., "Roadmap to vehicle connectivity," SFB Consulting, Sep. 2018.
[2] A. Seetharam, at.el, "A markovian model for coarse-timescale channel variation in wireless networks," IEEE Trans., Vehicular Technology, Vol. 65(3), pp. 1701–1710, 2016.