CNN-Based DMRS Pattern Optimization for 5G Vehicle-to-Everything Communications

Gayeon Kim
dept. Information and Communication Engineering
Soonchunhyang University
Asan, Republic of Korea
bobo4131@sch.ac.kr

Taejun Choi
dept. Information and Communication Engineering
Soonchunhyang University
Asan, Republic of Korea
20184123@sch.ac.kr

Jeonghoon Bae
dept. Information and Communication Engineering
Soonchunhyang University
Asan, Republic of Korea
albert1022@sch.ac.kr

Daegun Jang
dept. ICT Convergence
Soonchunhyang University
Asan, Republic of Korea
wowhensum@sch.ac.kr

Taehyoung Kim
dept. Information and Communication Engineering
Soonchunhyang University
Asan, Republic of Korea
th.kim@sch.ac.kr

***Abstract*— In this paper, we optimize the demodulation reference signal (DMRS) pattern of the physical sidelink shared channel (PSSCH) based on a deep learning approach to maximize the channel estimation performance for 5G vehicle-to-everything (V2X) communication systems. For the DMRS optimization, we design a convolutional neural network (CNN) which classifies the optimal DMRS pattern index for the given received signals. It is shown that the proposed CNN structure achieves 91% accuracy for the optimal DMRS pattern index. The simulation results verify that the proposed scheme achieves 4 dB performance gain in terms of mean square error (MSE) compared to the legacy DMRS pattern.**

Keywords—Vehicle-to-everything (V2X), Sidelink, Physical layer, PSSCH, DMRS, CNN

I. Introduction

The recent advancements in artificial intelligence and communication technology have enabled the development of reliable communication in fast time-varying selective fading environments, which is also contributing to the progress of autonomous driving. Out of that, vehicle-to-everything (V2X) is a communication method that exchanges information between vehicles and road infrastructure, and it has received attention as technology has advanced.

For the sidelink data transmission, a demodulation reference signal (DMRS) is transmitted with the corresponding data, i.e., physical sidelink shared channel (PSSCH), to obtain the channel coefficients necessary for data demodulation at the receiving side. Depending on the statistical characteristics of the channel, e.g., delay spread and doppler shift, there exists an optimal DMRS pattern which maximizes the channel estimation performances. For this reason, in the current 5G specification, multiple DMRS patterns are supported for PSSCH [1]. However, it is very challenging task to adequately adopt an optimal DMRS pattern for a given channel since the channel characteristics are randomly changed for every moment. Motivated by this, in this paper, we propose a method to find the optimal DMRS pattern suitable for the given channel environment based on the deep learning approach.

This paper proposes a channel estimation technique employing the optimal DMRS pattern based on the convolutional neural network (CNN) for V2X communication systems. To this end, we first propose a CNN structure which classifies the optimal DMRS pattern index for the given received signal. Then, the obtained optimal DMRS pattern is transmitted and used for channel estimation at the receiver side. The proposed scheme improves the channel estimation performance compared to the legacy DMRS transmission strategy.

II. System Model

A. PSSCH frame structure

The physical channel of the sidelink consists of four channels such as physical sidelink control channel (PSCCH), PSSCH, physical sidelink feedback channel (PSFCH), physical sidelink Broadcast channel (PSBCH). PSCCH transmits 1st stage sidelink control information (SCI) and 2nd stage SCI, which includes control information related to PSSCH. PSSCH transmits data payload and additional control information composed of the 2nd stage SCI and transport block (TB).

TABLE I. PSSCH DMRS Time-Domain Location.

	Number of DM-RS	**l_d in symbols**		
PSCCH duration 2 syms.	2	1,5 (l_d : 6,7,8)	3,8 (l_d : 9,10)	3,10 (l_d : 11,12,13)
	3	1,4,7 (l_d : 9,10)	1,5,9 (l_d : 11,12)	1,6,11 (l_d : 13)
	4	1,4,7,10 (l_d : 11,12,13)		
PSCCH duration 3 syms.	2	1,5 (l_d : 6,7,8)	4,8 (l_d : 9,10)	4,10 (l_d : 11,12,13)
	3	1,4,7 (l_d : 9,10)	1,5,9 (l_d : 11,12)	1,6,11 (l_d : 13)
	4	1,4,7,10 (l_d : 11,12,13)		

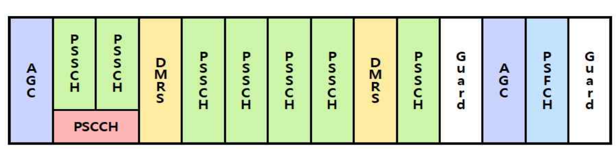

Fig. 1. Example of PSSCH frame structure.

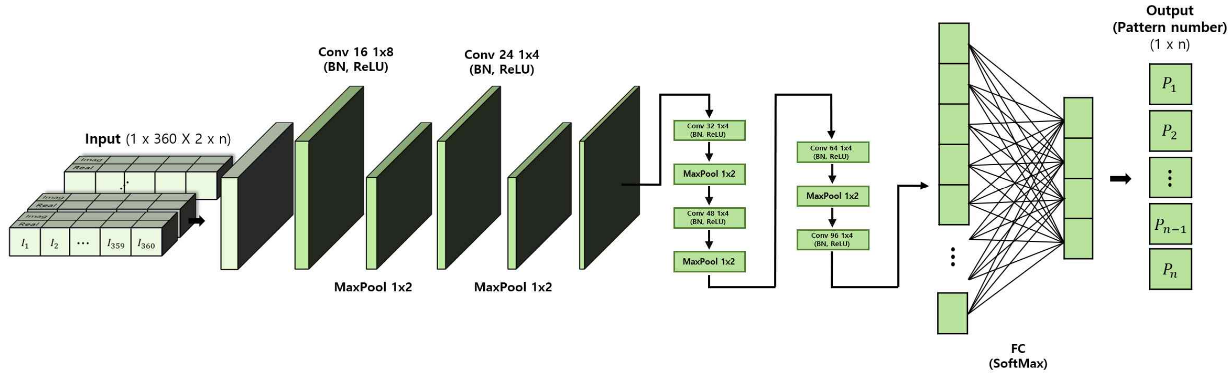

Fig. 2. CNN strutcture.

PSFCH transmits feedback related to the success or failure of sidelink transmission, and PSBCH transmits information to support synchronization in sidelink [2]. The 1st stage SCI contained in PSCCH includes the priority of PSSCH, frequency and time resource allocation, resource reservation period, and DMRS pattern information. The 2nd stage SCI transmits information used to decode PSSCH and support HARQ feedback and the channel state information (CSI) report. It also contains 1 bit of new data indicator (NDI), 16 bits of destination ID, and 8 bits of source ID [3].

DMRS is a signal used to demodulate a signal, and PSSCH's DMRS is used to decode the 2-step SCI. PSSCH DMRS is transmitted at different positions within a slot. As shown in Table 1, l_d is the duration of the scheduled resources for transmission of PSSCH and the associated PSCCH, there are nine DMRS patterns, each consisting of two, three, or four sidelink symbols transmitted at different time slots [1]. Each DMRS pattern has an optimal pattern that suits the characteristics of the channel, such as delay spread and doppler shift. Additionally, the different patterns vary in the number of symbols for PSCCH, PSSCH DMRS, and PSSCH symbols within a slot.

Fig. 1 shows an example of a PSFCH, two PSCCH, and nine PSSCH slots containing two PSSCH DMRS symbols for a normal cyclic prefix (CP) [1]. Therefore, in V2X sidelink, the DMRS pattern is selected according to the channel characteristics, and each pattern has a different number of data symbols transmitted. For example, if communication is performed on a channel with relatively small delay spread or low-speed doppler shift, channel estimation is possible with a small amount of DMRS symbols. In other words, a large amount of data can be transmitted.

B. Convolutional Neural Network

CNNs are deep learning algorithms primarily used for processing image and video data. Unlike other neural networks, CNNs are capable of learning directly from data without requiring feature extraction. The network architecture of a CNN is composed convolutional layer, activation function, polling layer, and fully connected layer.

The convolution layer extracts features from input matrices using filter and convolution operations. The features obtained through the filter are called feature maps. The activation function transforms input signals into output signals and plays a role in determining the activation based on the total of the input signals. It is also used to add nonlinearity to the network. This paper utilizes the ReLU activation function, which outputs positive values as they are and returns 0 for negative values, as in (1). The ReLU function not only avoids the gradient loss problem that the sigmoid function had but also has the advantages of simple implementation and fast learning speed in CNNs that learn with large amounts of data.

$$f = \begin{cases} (x < 0) & f(x) = 0 \\ (x \geq 0) & f(x) = x \end{cases} \tag{1}$$

To achieve high accuracy, CNNs require many filters, which in turn increase the size of feature maps. Since we need to reduce the increased dimensions, we use a pooling layer. The operation of the pooling layer includes max pooling to extract the maximum value and average pooling to extract the average value.

Finally, the fully connected layer connects every neuron in one layer to every neuron in the next layer. It is used to train two-dimensional array data by flattening the data into one-dimensional form.

III. Proposed DMRS Pattern Optimization Based on CNN

A. Input data

The channel was set to TDL-A with delay spread and velocity values varied in specific ranges. Table II provides all simulation parameters [1][4]. The pattern index values from Table I were used to generate input data for CNN training, and DMRS symbols were randomly created using QPSK. The smallest MSE between the estimated and original channel values is calculated based on the delay spread and velocity parameters in TDL-A, using the MSE equation (2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{2}$$

where Y_i is correct answer of the ith learning data, $\hat{Y}_i$ is predicted value of the ith learning data and n is number of iterations.

Using the best DMRS pattern, data sets for training and validation are created for training a CNN, respectively. These data sets use symbols from unused time slots (index [3, 5, 6]) and have a resource grid size of 120 x 3, with only three of the 14 time slots and 120 subcarriers. The correct answer has a matrix size of 2000 x 1.

TABLE II. SIMULATION PARAMETERS.

Parameter	Value
Subcarrier spacing	30 [kHz]
Number of PSSCH Subcarrier	120
Number of OFDM Symbols	14
DMRS Pattern number	3 (for fixed pattern)
Size of FFT	2,048
Sample rate	61,440,000
Carrier frequency	6 [GHz]
SNR [dB]	0:10
Iiteration	10,000
Channel Model	TDL-A
Velocity	10:30:100 [km/h]
Delay Spread	10:100:1000 [ns]
Channel Estimator	MMSE

B. Traning

The structure of the neural network being trained consists of an input layer and six CNN layers. Each CNN layer uses a 1 x 4 sized filter, with 16, 24, 32, 48, 64, and 96 filters, respectively. To solve the overfitting and gradient vanishing problems during training, a batch normalization layer was added to each layer. The activation function used was the ReLU function, and a 1 x 2 sized filter and max pooling were used for the pooling layer. To match the size of the input data and filter used in the convolution layer, the complex matrix of size 120 x 3 is converted to a matrix of size 1 x 360. Since this matrix is a complex matrix, a 1 x 360 x 2 matrix is used as the input data, divided into the real and imaginary domains. The output layer consists of a fully connected layer, and the activation function used was the softmax function. The artificial neural network is trained with 2000 DMRS patterns obtained through simulation, which are the correct answer values. Therefore, the artificial neural network is trained with a predicted value of size 1 x 360 x 2 and the correct answer value of 2000 DMRS patterns.

IV. SIMULATION RESULTS

The simulation of this paper derives the results according to the parameters in Table II. As mentioned in Section 3, the model is constructed based on the structure of the designed CNN and the input data and correct answer. In addition, the validation phase is carried out using validation data to fine-tune the hyper-parameters of the neural network. The epoch was set to 5, which refers to the number of successful samples in the entire dataset after completion of training.

Fig 3 shows the accuracy and verification of the trained model. The accuracy is 91.72% and loss is close to 0. The model was tested using test data, and the accuracy of the learned DMRS pattern and the optimal pattern was 91.509%.

Fig. 4. shows the simulation results for evaluating the performance of optimal DMRS pattern selection based on the MSE according to SNR obtained through the fixed DMRS pattern, the proposed DMRS pattern, and the optimal DMRS pattern. To ensure a 90% accuracy in the simulation based on the accuracy of the estimated values obtained through CNN, the simulation was designed. As the SNR increases, the MSE tends to decrease, and the MSE for the optimal DMRS pattern is the smallest, approximately 0.062, while the MSE for a fixed DMRS pattern is the largest, approximately 0.086. The DMRS pattern learned by CNN shows a similar performance

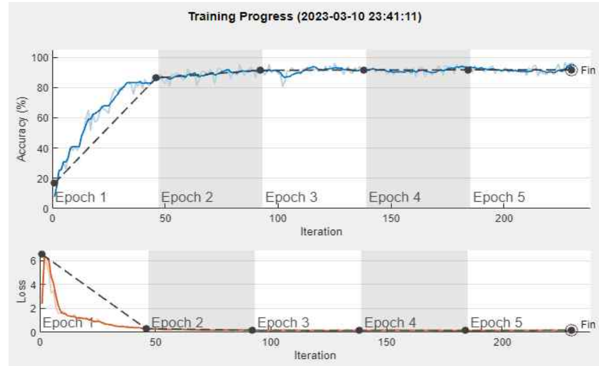

Fig. 3. Accuracy and cross-entorpy loss of the proposed CNN.

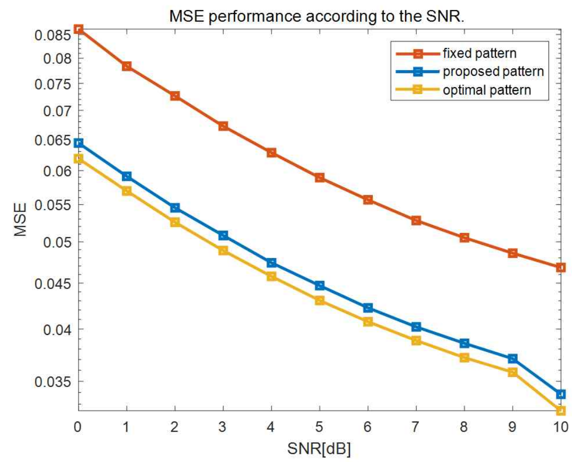

Fig. 4. MSE performance according to the SNR[dB].

to the optimal pattern, with an MSE of approximately 0.065, which differs by about 0.003.

V. CONCLUSION

This paper have proposed a channel estimation strategy based on the optimal DMRS pattern based on CNN according to the channel characteristics. The proposed CNN based DMRS pattern optimization have achieved 91% accuracy. It has been shown that the proposed scheme achieves 4 dB performance gain compared to the legacy channel estimation strategy by using the optimized DMRS pattern.

REFERENCES

[1] *TSG RAN; NR; Physical channels and modulation (Release 17)*, document TS 38.211 V17.0.0, 3GPP, Dec. 2021

[2] M. H. C. Garcia et al., "A Tutorial on 5G NR V2X Communications," *IEEE Commun. Surv. & Tut.*, vol. 23, no. 3, pp. 1972-2026, thirdquarter 2021.

[3] *TSG RAN; NR; Multiplexing and channel coding (Release 17)*, document TS 38.212 V17.0.0, 3GPP, Dec. 2021

[4] *ETSI; 5G; Study on channel model for frrequencies from 0.5 to 100 GHz (Release 17),* document TR 38.901 V17.0.0, 3GPP, Apr. 2022