CSI Classification for 5G Via Deep Learning

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***Abstract*—5G communication requires continuous exchanges of channel state information (CSI) between the base station and user equipment (UE) to adjust the physical layer parameters. CSI classification in a noisy environment is challenging, since CSI can get corrupted. To address this problem, we apply a convolutional neural network (CNN) to classify several key CSI parameters. In a simulation study, our CNN method classifies the CSI parameters with accuracy ranging between 84–98%, which is approximately 24–38% higher than the 3GPP recommendations for UEs [1].**

I. Introduction

Typically, a wireless communication system designer first designs and analyzes an end-to-end communication system using standard channel models [1], [2]. Such an analysis consists of rich mathematical theories and proofs-of-concept for robust communication in noisy environments. In a real-world environment, however, an implemented system may not prove as robust as seen in the analysis for various reasons [3]–[10]. From the physical (PHY) layer perspective, unforeseen variations in parameters and conditions, such as delays, Doppler effects, signal correlations, atmospheric effects, scattering, fading, hardware non-linearities, and power failures, result in performance degradation of well-studied models in the real-world. This gap between the theory and practice at the PHY layer requires the designer to investigate alternative approaches to tackle these challenges for building efficient 5G wireless systems.

5G communication requires continuous channel state information (CSI) exchanges between the base station (BS) and user equipment (UE) for robust communication. Based on CSI, a BS and UE adjust the physical layer parameters [1], [2]. In this paper, we convert CSI frames to a 2D data structure by exploiting the fact that CSI is organized in a specific pattern according to the 3GPP recommendations [1]. After mapping CSI to the data structure, we apply neural network techniques to learn and classify CSI parameters in noisy environments. Specifically, we apply the convolutional neural network (CNN) methodology very effective and robust in classification [11].

CNN technology itself is well established especially for computer vision. CNNs have also been applied to support mobile wireless applications, e.g., multiple-input multiple-output (MIMO) modulation recognition [3], activity recognition [12], traffic forecasting [13], anomaly detection [14], and power efficiency [15]. However, much less work has been done to apply CNNs to CSI classification [16], [17]. Duan et al. [16] apply CNNs to classify OFDM-QAM, UFMC, and FBMC-OQAM using an additive white Gaussian noise model that is rather ideal and may fail to model real-world channel conditions. In [17], a CNN and long short-term memory, which is a type of a recurrent neural network, are used together to predict CSI based on historical CSI data; however, the authors do not focus on classifying CSI parameters in a noisy environment. As CSI can be corrupted in a noisy environment, this is a serious issue and, therefore, more work is needed to enhance CSI classification. In this paper, we use more realistic and noisier models—the pedestrian A (EPA), extended vehicular A (EVA), extended typical urban (ETU) channel models—that subsume the channel models used in [16], [17]. Moreover, we consider a more comprehensive set of key 5G CSI parameters: the delay spread, Doppler spread, signal interference to noise ratio (SINR), precoding matrix indicator (PMI), channel quality indicator (CQI), and rank indicator (RI). The main contribution of this paper is effectively applying CNN techniques to support more comprehensive 5G CSI parameter classification using more realistic channel models. Thus, it is different from and complementary to related leading-edge works discussed above [3], [12]–[17].

In this paper, we design, train, and evaluate a CNN framework for CSI classification. In a simulation study, our CNN classifies the aforementioned CSI parameters with high accuracy that range between 84–98%, which is approximately 24–38% higher than the 3GPP recommendations for UEs [1].

The rest of this paper is organized as follows. Section II provides background on CSI. Section III discusses the overall 5G system structure. Section IV describes our approach to designing a CNN for CSI classification. Section V evaluates the performance of the proposed CNN. Finally, Section VI concludes the paper and discusses future work.

II. Channel State Information

As the frequency spectrum is the most precious resource in wireless communication, a wireless system designer needs to design a system that utilizes available frequency resources efficiently. To design a spectrally efficient system, a designer typically uses higher order MIMO, 5G new radio (NR) waveforms, 5G-NR modulation and coding schemes (MCS) in the PHY layer [2]. However, unforeseen channel conditions can degrade the overall system performance as discussed in Section I. Hence, the BS and UE need to continuously exchange CSI

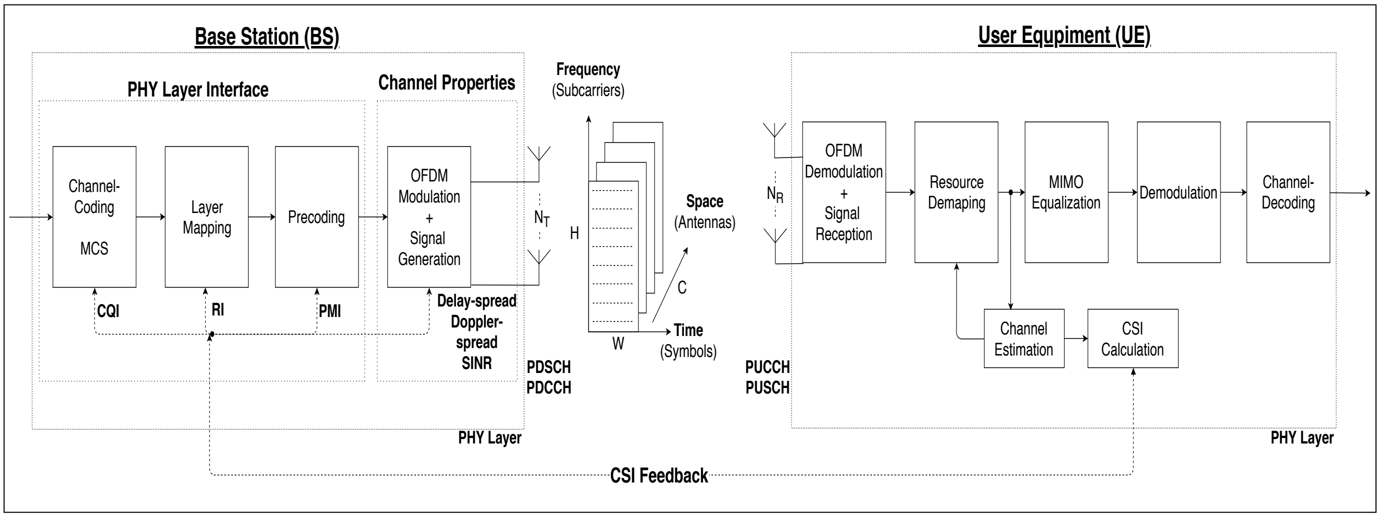


Fig. 1: Overall 5G System Structure

and adjust the PHY layer parameters accordingly to achieve robust performance even in a noisy environment. [1], [2].

As shown in Figure 1, CSI exchanged between a BS and UE is 3D data with the size of $H \times W \times C$ where H, W, and C represent the number of sub-carriers, the number of symbols, and the number of MIMO antennas, respectively. CSI contains many parameters; however, in this paper, we mainly focus on the PHY layer and consider several key CSI parameters useful to design an adaptive 5G PHY layer. They are classified into two broad categories as follows:

1) Communication channel properties allow a UE to estimate the conditions of incoming BS signals.
   - The delay spread allows the UE to estimate the delay propagation with recommended propagation scenarios, such as EPA, EVA, and ETU.
   - The Doppler spread lets the UE estimate the mobility with recommended velocities, such as 5Hz, 70Hz, and 300Hz.
   - Based on the SINR, the UE estimates the noise level of the channel between the BS and UE.
2) PHY layer interference parameters allow the UE to adjust the PHY layer configuration as per the BS.
   - RI denotes the number of independent data streams coming toward the UE.
   - PMI informs the UE of the codebook for downlink transmission. It determines how to map the individual data streams to the antennas.
   - CQI measures the downlink channel quality to specify the best possible MCS for the UE.

III. Overall Communication System Structure

Figure 1 shows the overall 5G communication system structure used for our work presented in this paper. It mainly consists of two parts: a BS and UE. For simplicity, we depict just one UE assuming that all the other UEs have the same PHY layer. As illustrated in Figure 1, the BS applies channel coding to the incoming signal based on CQI, layer mapping based on RI, and precoding based on PMI in sequence. After that, it applies OFDM modulation and signal generation based on the delay spread, Doppler spread, and SINR. In the UE, a similar process takes place in reverse order. In addition, channel estimation and CSI calculation are performed to distinguish among different uplink/downlink channels.

Based on the CSI parameters, the BS and UE adapt channel coding, layer mapping, and precoding to optimize wireless communication. To adjust the PHY layer parameters in a noisy channel environment, the UE and BS exchange the CSI through a feedback link as shown in Figure 1. Specifically, the UE provides CSI feedback through the physical uplink control channel (PUCCH) and the physical uplink shared channel (PUSCH) as shown in Figure 1. The BS transmits its CSI information to the UE through the physical downlink shared channel (PDSCH) and physical downlink control channel (PDCCH) [2]. In this paper, we extract CSI frames exchanged between the BS and UE through these channels and label them to design and train the CNN for CSI classification.

IV. CNN Design

In this paper, we map CSI frames to our data structure. Using the data structure, we design a CNN to classify CSI parameters.

- As communication data involve complex numbers, existing CNN techniques (e.g., image processing) are not directly applicable. To address this issue, we put the real and imaginary parts of each data in two consecutive columns to distinguish them and process them accordingly in our CNN. For example, if there is a complex number $5 + 3i$, we write 5 and 3 into two columns. Although one may argue that this conversion is straightforward, it allows us to avoid any data loss that can significantly degrade the performance of CSI classification.

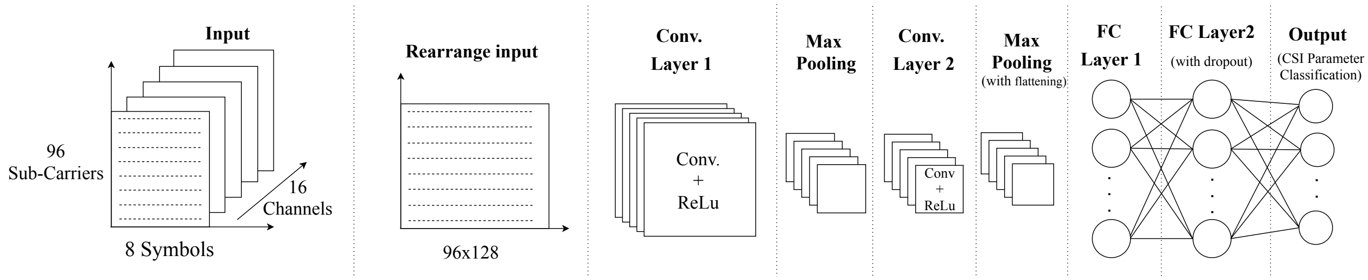


Fig. 2: CNN for CSI Parameter Classification

- In 5G communication, there are multiple channels depending on the MIMO antenna array configuration. For example, there are 16, 64, and 256 channels for 4×4, 8×8, and 16×16 MIMO antennas, respectively. To address this issue, we rearrange the 3D CSI input data into the 2D and put multiple antenna frames next to each other as shown in Figure 2. In this way, we can classify CSI data for any number of MIMO antennas rather than being restricted to a specific MIMO antenna configuration.
- In communication data, there is the smallest amount of data in the W axis for symbols as shown in Figure 1. To deal with the small region of interest, we stack multiple 2D data structures as depicted in Figure 2.
- In this paper, we choose LeNet [11], which has two hidden layers, as our CNN model, since the CSI data is relatively small and it is reduced to half after going through each convolution layer. We have investigated several other state-of-the-art CNN models, including ResNet, VGG, and inception, effective for classification [11], [18]–[20]; however, they require deeper networks.

Given that, our CNN model performs feature extraction and CSI classification:

1) Feature extraction aims to extract the features of input CSI frames and create a feature map. The first convolutional layer in Figure 2 learns the features from input by shifting the filter (kernel) across the CSI frames. By doing this, it produces a mid-level feature representation of the CSI frames. To the feature representation, we apply the rectified linear unit (ReLu) activation function that is a very effective nonlinear activation function. In the pooling layer following the first convolution layer in Figure 2, we apply the max-pool function to the result produced by ReLu for down-sampling. In the second convolutional layer, convolution and ReLu activation are performed, similar to the first convolutional layer. Subsequently, max pooling is applied for another sub-sampling. The output is flattened and provided as the input to the following layers for CSI parameter classification.
2) In the classification stage, we use two fully-connected (FC) layers that take the feature map as the input as shown in Figure 2 for high accuracy classification of CSI. We also apply the dropout method [11], [18]–[20] to the second fully connected layer to avoid overfitting the network and enhance the CSI classification accuracy for new data unseen in model training. Finally, we employ the softmax function for CSI parameter classification in the output layer.

V. Performance Evaluation

In this section, we evaluate the performance of our proposed CNN method for CSI parameter classification. First, we build and simulate the 5G link-level system structure according to the 3GPP standard requirements [1] and extract the CSI frames by mapping them to our data structure as discussed in Section IV. Second, we label the extracted CSI parameters to collect data necessary for training the CNN. Third, we train and validate the CNN using the labeled data in the training and validation sets, while tuning the hyper parameters of the CNN. Moreover, we evaluate the accuracy of CSI parameter classification using the test set not used for training and validation.

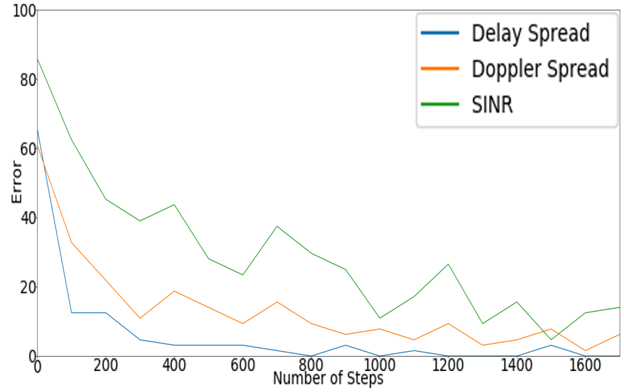
A. CSI Data Generation

Parameters	**Labels**
Delay Spread	EPA, EVA, ETU
Doppler Spread	5Hz, 70Hz, 300Hz
Signal Interference to Noise Ratio (SINR)	-10:2:20
Rank Indicator (RI)	0-4
Precoding Matrix Indicator (PMI)	0:16:255
Channel Quality Indicator (CQI)	0-15

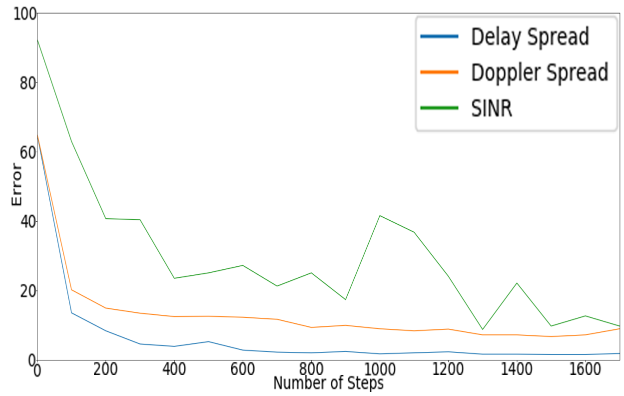
TABLE I: CSI Parameters and their Labeling

To generate CSI data, we design and simulate the 5G link-level system framework in Figure 1 using the MATLAB LTE Toolbox. A generated CSI frame has the dimension of $96 \times 8 \times 16$ as discussed in Section IV. After generating CSI data, we label the dominant CSI parameters in Table I discussed in Section II. As shown in Table I, we have considered six CSI parameters and manually labeled the parameters by examining all CSI frames. In this paper, we have generated 43,200 CSI frames.[1] After generating CSI data and labeling them, we train and validate the CNN as follows.

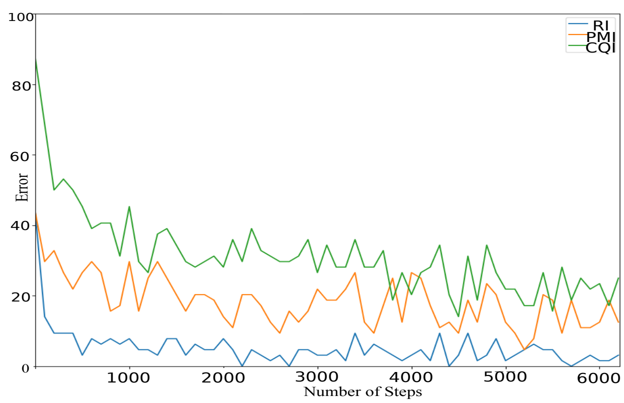
[1]In addition, an extensive set of real-world communication data was used while Ankur Vora worked at Cadence System Design as an intern in 2018. The evaluation results were similar to the ones presented in this paper; however, we no longer have access to the Cadence data. Neither can we present the results produced using the Cadence data due to the nondisclosure agreement.



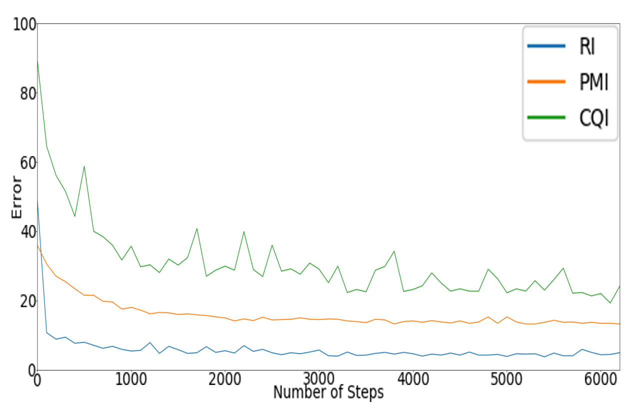
(a) Training Errors for Communication Channel Properties



(b) Validation Errors for Communication Channel Properties



(c) Training Errors for PHY Layer Interference Parameters



(d) Validation Errors for PHY Layer Interference Parameters

Fig. 3: Errors for Training and Validating CSI Parameters

B. Network Training and Validation

We design the LeNet in Figure 2 using TensorFlow [18]. We provide the CSI data and their labels as input to the LeNet and start training the network. We use 80% of the data for network training, 10% of the data for network validation, and the remaining 10% of the data for testing purposes. To optimize the classification accuracy, we tune the CNN hyper parameters. For the given data set, the best hyper parameters we found are presented in Table II.

Hyper Parameters	**Values**
Hidden Layers	2
Batch Size	128
Activation Function	ReLu
Learning Rate	0.01
Decay Rate	0.95
Conv. Layer Width	64,32
FC Layer Width	512
Dropout Probability	50%
Padding	same
Kernel Size	3×3

TABLE II: Hyper Parameters of the Proposed Network

Using the hyper-parameters, we have trained and validated the CNN again. As shown in Table I, each of the labeled CSI parameters has different complexity, noise, and labels associated with it. The results of our network training and validation using the hyper parameters are shown in Figure 3 and discussed in the following.

First, we evaluate the CSI parameters of channel properties: 1) delay-spread, 2) Doppler-spread, and 3) SINR. In Figures 3a and 3b, the training and validation results observed after more than 1600 iterations are plotted. As shown in Figures 3a and 3b, the errors of delay and Doppler spread generally reduce toward zero. However, the training data of SINR are noisier. Thus, it has relatively large errors than the delay and Doppler spread.

Further, we evaluate the CSI parameters that estimate PHY layer interference: 1) RI, 2) PMI, and 3) CQI. Among them, PMI and CQI have more complex data structures and more subject to corruption in a noisy environment [1], [2]. In fact, reducing their complexity is a separate research problem for effective wireless communication [21]–[24]. To address this issue, we have undertaken much more iterations (over 6000) for training and validation. As shown in Figures 3c and 3d, the error of RI generally decreases toward zero, but the errors of PMI and CQI do not reduce toward zero due to the noisy, complex nature.

C. Classification Accuracy

The testing results using the saved 10% test set that the LeNet has never seen are presented in Table III. The classification accuracy of delay spread, Doppler spread, and RI range between 93–98%, which is higher than the 3GPP recommendations for UE manufactures [1] by 33–38%.

The accuracy of SINR classification is 90%, since it is noisier than delay spread and Doppler spread are as discussed before. Due to the noisy and complex nature, PMI and

Parameters	Accuracy
Delay Spread	98%
Doppler Spread	93%
Signal-Interference-to-Noise-Ratio (SINR)	90%
Rank Indicator (RI)	96.7%
Precoding Matrix Indicator (PMI)	84.7%
Channel Quality Indicator (CQI)	86.6%

TABLE III: CSI Parameter Classification Accuracy Results

CQI classifications achieve the lowest accuracy of 84.7% and 86.6%, respectively. However, their accuracy is higher than the 3GPP recommendations [1] by 24.7–26.6%. A more effective approach is needed to further enhance the accuracy. A thorough investigation is reserved for future work.

VI. Conclusions

In 5G communication, the channel state information (CSI) is continuously exchanged between the base station and a user equipment. Thus, CSI is essential for effective 5G communication; however, CSI can be corrupted in a noisy environment. In this paper, to support effective CSI parameter classification in noisy environments, we effectively apply convolutional neural network (CNN) techniques. Although the CNN methodology itself is well established, related work on its application to CSI parameter classification in noisy environments is relatively scarce (discussed in Section I). In our simulation study, our CNN achieves 84–98% accuracy of CSI classification, which is approximately 24–38% higher than the 3GPP recommendations [1]. In this paper, the classification accuracy is measured for a single channel at the physical and link layers. In practice, however, a UE has multiple uplink and downlink channels. It is desirable for the UE to pick the channel with the lowest noise to further enhance the classification accuracy. In the future, we will explore whether it is feasible to effectively integrate channel selection and CSI classification by applying machine learning techniques, such as deep reinforcement learning.

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