Performance Analysis of Cloud-based Deep Learning Models on Images Recovered without Channel Correction in OFDM System

Ijaz Ahmad Dept. of Computer Engineering Chosun University Gwangju, South Korea ijazahmad@chosun.kr Nazmul Islam Dept. of Computer Engineering Chosun University Gwangju, South Korea nazmul@chosun.kr Seokjoo Shin Dept. of Computer Engineering Chosun University Gwangju, South Korea sjshin@chosun.ac.kr

Abstract—Channel correction plays an important role in performance of wireless communication systems. In conventional systems, channel estimation is one of the blocks at receiver side to compute channel impulse response. Various algorithms have been proposed to make them efficient and improve their performance. However, precise channel estimation incurs additional computational cost and increases complexity of the overall system. In this study, we have considered the otherwise to bypass channel estimation of an Orthogonal Frequency Division Multiplexing (OFDM) based image communication system designed to enable cloud-based deep learning (DL) computation. The simulations present performance analysis of OFDM system with and without channel correction in-terms of bit error rate (BER), and two image quality measures. Recovered image quality difference between the two systems significantly increases with higher E_b/N₀. For inferencing analysis, in higher E_b/N₀ regions, model performance on images recovered with correction is same as on the original images while lags behind by 6% on images without correction. In lower E_b/N₀ regions, the model accuracy reduces by 10% on average for both systems. In addition, the model accuracy shows overlapping pattern in that region and for 3 dB, it has performed better on images recovered without correction.

Keywords—Cloud-computing, Deep learning, OFDM system

I. INTRODUCTION

Over the past years, growth of mobile terminals and smart devices has grown exponentially and demand for high data rate and spectral efficiency is greater than ever for users and applications. 5G is result of this demand as it promises to provide 1000 times more capacity and improved spectrum efficiency by 5-15 times [1]. Besides these advantages, 5G integrates diverse technologies that demand for higher communication features such as security, sustainability, and mobility to realize the Internet of Things (IoT) ecosystem. The high data rate and spectrum efficiency in 5G systems are attainable using bandwidth efficient systems such as Orthogonal Frequency Division Multiplexing (OFDM) [2].

Image communication system is becoming an integral part of the IoT ecosystem to enable computer vision (CV) based applications, such as event monitoring, human activity recognition, surveillance to name a few. Given recent success of artificial intelligence (AI) techniques in various fields, most of CV applications are AI driven. However, IoT devices are characterized as computational and power constrained devices [3]. Therefore, most of the times, AI computation is offloaded to edge computing or cloud computing for processing. However, large volume of image data requires high data rate to enable real time applications. To overcome these challenges, OFDM is an efficient method to improve bandwidth efficiency and data rate. However, image data transmission over a wireless channel is susceptible to various types of distortion and interference [3]. Interferences such as inter-carrier interference (ICI) and inter-symbol interference (ISI) increase Bit Error Rate (BER) at receiver side. To alleviate such interference, hybrid techniques such as space diversity techniques are implemented along with OFDM methodologies. Channel correction plays an important role in performance of communication systems [2]. In conventional systems, channel estimation is one of the blocks at receiver side to compute channel impulse response. Various algorithms have been proposed to make them computationally efficient and improve their performance. Mainly, the techniques can be grouped into non-data-aided and data-aided [2], [4]. The first one is a blind technique that exploits statistical information of a received signal to estimate channel response. However, their efficiency is limited by the amount of available data. On the other hand, data aided methods require training signals (also called reference signals) to be transmitted for channel response estimation. The number of reference signals depends on the degree of channel variation. Several studies have investigated image transmission over OFDM communication systems under different factors, such as different modulation algorithms, channel models, and varying number of antennas. A comparative study of the method can be found in [5]. However, they did not consider performance of an application on the received distorted images. In our recent work [3], we have implemented OFDM based image communication system to enable cloud-based DL tasks. The system is based on QPSK modulation technique and performed channel correction. Although channel correction plays an important role in performance of a communication receiver, we have considered a system without it in order to avoid additional cost incurred by precise channel estimation.

In this study, we have considered OFDM based wireless communication system to enable cloud-based DL services. Specifically, we have considered Discrete Fourier Transform (DFT) based OFDM system with Quadrature Amplitude Modulation (QAM) technique. For channel modelling, we have implemented multipath channel with Additive White Gaussian Noise (AWGN). On the receiver side for the channel correction, we have used data aided estimation technique called comb-type pilot based channel estimation with linear interpolation. Further, we have analyzed performance of a trained DL model on the received images with channel correction and without channel correction.

The rest of the paper is summarized as: Section II provides an overview of the proposed OFDM based image communication system and channel estimation techniques. Section III presents simulation results and discussion. The paper is concluded in Section IV.

II. METHODS

A. OFDM based Image Communication System

An image communication system based on Orthogonal Frequency Division Multiplexing (OFDM) is shown in Fig. 1. The main idea of OFDM is to divide a high-rate serial data stream into parallel low-rate sub streams that are modulated onto orthogonal subcarriers [4]. For this purpose, the binary data (for example, image data in our case) is encoded as a high-rate data stream by using a modulation technique such as Phase Shift Keying (PSK) or Quadrature Amplitude Modulation (QAM) constellation. The mapper block groups the binary data, which are then mapped into complex-valued constellation symbols in the mapping block according to the chosen modulation technique. The serial-to-parallel blocks groups the mapped data into parallel low-rate sub streams. The parallel symbols goes through the Inverse Discrete Fourier Transform (IDFT) to create OFDM symbols. The IDFT to obtain time-domain OFDM symbol is defined as

$$x(n) = \frac{1}{N} \sum_{k=0}^{N-1} X(k) e^{\frac{j2\pi kn}{N}},$$
(1)

where $j = \sqrt{-1}$ and *N* is the DFT length, X(k), for $k = 0, 1, \dots, N-1$ are the complex data symbols, and x(n) is the resultant time domain representation of an OFDM symbol. In order to avoid inter-symbol interference (ISI) guard interval is inserted after the IDFT block. For which the guard time must be chosen larger than the expected delay spread. To prevent inter-carrier interference (ICI) the guard time includes cyclic prefix (CP), which cyclically extended part of OFDM symbol. As a result, the CP turns linear convolution with the channel into a circular convolution. After the guard interval with length N_g insertion, the OFDM symbol becomes

$$x_f(n) = \begin{cases} x(N+n), & -N_g \le n \le \cdots, N-1 \\ x(n), & otherwise \end{cases}$$
(2)

The OFDM symbols are then concatenated to obtain the transmitted signal. When a signal is transmitted over a wireless channel, it is often diffracted, reflected and scattered, which results in overlapping copies of the same signal on the receiver side with different amplitudes, delays and phases.

Such wireless channel can be modelled by the use of channel impulse response given as

$$h(m) = \alpha(m)e^{j\theta(m)}, \qquad m = 0, 1, \cdots, M - 1$$
 (3)

where *M* is the total number of received signal paths. The m^{th} path attenuation is $\alpha(m)$ and phase shift is $\theta(m)$. In addition to multipath fading, the transmitted signal is also susceptible to additive noise originated from a receiver amplifiers and interference. The noise in an OFDM system can be modeled as additive white Gaussian noise (AWGN) with a uniform spectral density and zero-mean Gaussian probability distribution [4]. Because of the multipath effects and additive noise, the received OFDM signal is

$$y_f(n) = x_f(n) \otimes h(n) + w(n) \tag{4}$$

where h(n) is the channel impulse response, w(n) is the AWGN and \otimes is convolution. Once the signal is received, receiver performs inverse of the transmitter steps in a reverse order. The first step is to remove guard interval as

$$y(n) = \begin{cases} y_f(n), & -N_g \le n \le \cdots, N-1 \\ y_f(n+N_g), & otherwise \end{cases}$$
(5)

In the next step, y(n) goes through forward DFT defined by

$$Y(k) = \frac{1}{N} \sum_{n=0}^{N-1} y(n) e^{\frac{-j2\pi kn}{N}},$$
 (6)

In the presence of attenuation resulted from multipath effect and additive noise as in (4), the relation between recovered OFDM symbols Y(k) at this stage and X(k) in (1) can be expressed as

$$Y(k) = X(k)H(k) + W(k)$$
⁽⁷⁾

The H(k) is DFT transformed channel impulse h(n) and W(k) is DFT transformed additive noise w(n). For simplicity, we have assumed no ISI and ICI in (7). To mitigate the attenuations, DFT is followed by channel estimation block where estimated channel $H_e(k)$ is obtained. Once the channel is estimated for the data sub-carriers, the transmitted modulated data \hat{X} is recovered as

$$\hat{X} = \frac{Y(k)}{H_e(k)},\tag{8}$$

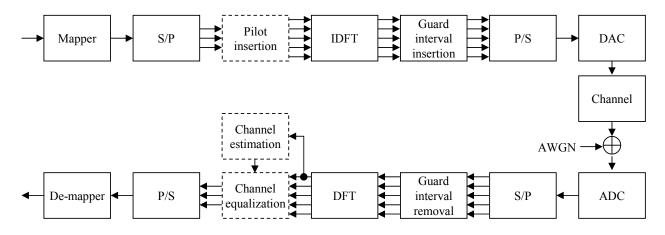


Fig.1. Illustration of OFDM based wireless communication system. The dashed boxes can be skipped when no channel correction is performed.

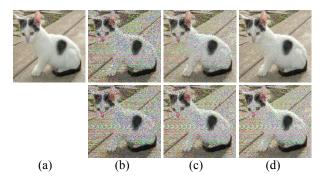


Fig. 2. Example cat image from the dataset. (a) is an original image. (b)-(d) are the recovered images with channel correction (top) and without channel correction (bottom) for $E_b/N_0 \in \{0, 5, 10\}$, respectively. Image appearance improves significantly with channel correction from left to right.

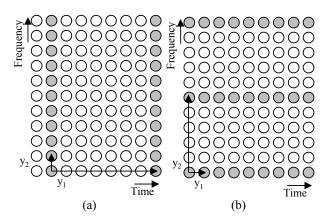


Fig. 3. Pilots arrangement for channel estimation in OFDM system. (a) block-type pilots arrangement (b) comb-type pilots arrangement.

Finally, the parallel data is converted to serial data stream and the binary data is recovered in the de-mapping block. In order to recover the original image, the binary data is first converted to decimal form and reshaped to meet the original image dimensions. Fig. 2. shows example images transmitted using an OFDM system.

B. Pilot-based Channel Estimation Methods

In wireless communication systems, channel estimation is performed to infer knowledge about the Channel Impulse Response (CIR) [2], [4]. For this purpose, a channel estimator (data-aided) exploits information that is known both to a transmitter and receiver. On the receiver side, a channel estimator compares the received sequence of bits with the known ones and get an estimation of the CIR, which is then used by equalizers to mitigate signal distortions. The two basic types of pilot-based channel estimations in OFDM systems are block-type and comb-type pilots as shown in Fig. 3. Both techniques are based on positions where the pilots appear. In the block-type pilot channel estimation, pilots are inserted into all OFDM subcarriers within a specified period in time. In order to ensure validity of the channel estimates, between two consecutive pilot symbols, the interval must be shorter than the channel coherence time. The block-type method could be effective against selective frequency fading as all frequencies are covered. However, they are more sensitive to fast fading

channel and causes complete loss of estimated channel parameters. On the other hand, in comb-type pilot channel estimation, pilots are inserted into certain OFDM subcarriers and are continuously transmitted. In this case, the spacing of pilot subcarriers should be significantly less than the channel coherence bandwidth. Unlike block-type arrangement, the comb-type pilot estimation works better with fast fading channels. In this work, we have considered comb-type pilot arrangement with linear interpolation for channel estimation and provided its description here.

Several approaches have been proposed for comb-type pilot channel estimation. Among them, one of the popular methods is frequency-domain interpolation. The frequencydomain interpolation methods up sample the channel frequency responses at pilot subcarriers and then apply an interpolation technique to estimate the CIR at data subcarriers. An efficient interpolation method is required in comb-type pilot based channel estimation to estimate channel at data subcarriers by using the channel information of pilot sub-carrier. Various interpolation techniques can be used such as, linear interpolation. Gaussian interpolation, cubic spline interpolation etc. The linear interpolation make use of two adjacent pilots to estimate the frequency response of data subcarriers between two pilots. For k data carrier the channel estimation $H_{e}(k)$ is given by

$$H_e(k) = \frac{1}{L} \Big(H_p(m+1) - H_p(m) \Big) + H_p(m), \tag{9}$$

where L is the number of carriers per pilot signals, and H_p is the frequency response of the channel at pilot signals.

III. RESULTS AND DISCUSSION

This section presents our simulation analysis. The experiments were carried out to analyze robustness of deep learning (DL) model's inferencing on transmitted images. For this purpose, two OFDM systems were implemented for image communication. First OFDM system was implemented with channel correction (withCC) and second without channel correction (withOCC). For the channel correction, pilot based estimation was used as discussed in Section II.B. The simulation parameters are given in Table 1. The efficiency of the systems are being considered in terms of bit error rate (BER) and image quality metrics, such as peak signal-to-noise ratio (PSNR) and perception-based image quality evaluator (PIQUE which sometimes also refer to as PIQE) [6]. In all of our experiments, $E_b/N_0 \in \{0, 1, 2, \dots, 10\}$ and the DL model used is EfficientNetV2 proposed in [7].

For visual analysis, an example image from the dataset is shown in Fig. 2. Fig.2. (a) is the original image and (b)-(d) are the recovered images after it is transmitted over proposed OFDM communication systems for $E_b/N_0 \in \{0, 5, 10\}$. Fig. 2. (b) - (d) top row shows the recovered images with channel corrections and bottom row shows the images without channel corrections. Based on visual inspection, images recovered

TABLE I. Simulation parameters of the image communication system.

Parameters	Values
Modulation technique	16 QAM
Cyclic Prefix (CP) length	16 samples
Subcarriers	64
Transform	DFT
Channel model	Multipath + AWGN
Pilots	8
Equalization	Zero Forcing (ZF) equalizer

with correction has better appearance as with higher E_b/N_0 . On the other hand, when no channel correction is used, visually the noise patterns appear same in all images with a slight reduction in its intensity. For better understanding, we have quantified the image quality in the following sub-section.

A. Image Quality Analysis

Bit Error Rate (BER) is a standard performance evaluation metric in wireless communication system to evaluate quality of a reconstructed signal on a receiver side. For proposed OFDM based image communication systems, namely withCC and withoutCC, BER (%) analysis is shown in Fig. 4. The BER value for an image is obtained by taking average of OFDM data sub-carriers. The BER presented in Fig. 4. is the mean across all the images in test dataset. The BER of both systems improves with higher E_b/N_0 . For $E_b/N_0=10$, there is up to 17% and 9% BER reduction compared to $E_b/N_0=0$ for withCC and withoutCC systems, respectively. However, such higher E_b/N_0 is not feasible in practice. When comparing the BER of the two systems, withCC has better signal quality than withoutCC system, due to the channel correction.

The BER measure does not provide any information about perceptual quality of recovered images. Therefore, in analysis we have considered peak signal-to-noise ratio (PSNR) to quantify quality of the images. PSNR is a well-known matric used in image communication system. It is a full-reference image quality measure that compares a received image with an original transmitted image. The higher PSNR value indicates better quality of the received image. The recovered image quality in terms of PSNR for proposed OFDM systems is shown in Fig.5 (a). The PSNR values are the mean across all the images in test dataset. Similar to BER, the PSNR value also improves with higher E_b/N₀. In withCC system, there is a significant difference between the PSNR values for each E_b/N_0 as compared to without CC. The PSNR value increases up to 11 dB and 3 dB for withCC and withoutCC systems. respectively. Overall, withCC system is able to retain higher quality images than its counterpart.

The full-reference image quality measures such as PSNR, requires a reference image with no distortion to calculate an objective quality score. However, when images are outsourced for cloud computations, original images are not available on the clouds; therefore, in such situation noreference image quality can be used. In our analysis, we have used Perception-based Image QUality Evaluator (PIQUE). PIQUE is a perception-based evaluation matric that uses arbitrary distortion for image quality measurement in natural images. PIQUE value is in the range of [0 to 100], and the score is interpreted in steps of twenties, for example, 0 to 20 means excellent and 81 to 100 means bad quality of the image. The measure of statistical features in terms of PIQUE of the proposed systems is shown in Fig.5 (b). The values are the mean across all the images in test dataset. In general, when natural images datasets are constructed, conditions under which the images are acquired may differ, which sometimes result in image distortions. Therefore, Fig. 5 (b). also shows quality of the original images, which is used as a baseline to compare other methods with it. Following the same trend as PSNR, PIQUE score improves with higher E_b/N_0 for both systems. For the given range of Eb/No, PIQUE is improved up to 15 and 6 for withCC and withoutCC systems, respectively. The withCC system achieves PIQUE same as original image after 7 dB whereas, withoutCC system does not reach closer to the original images throughout the experiments. In addition,

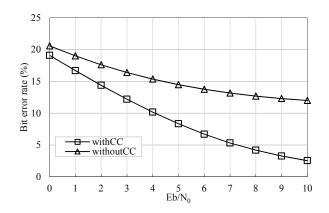


Fig. 4. Bit error rate analysis with respect to various E_b/N_0 values for OFDM system with channel correction (withCC) and without channel correction (withoutCC).

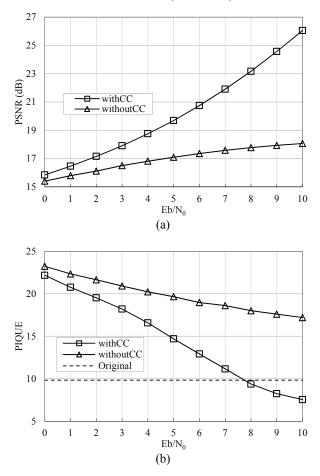


Fig. 5. Recovered image quality analysis for OFDM image communication system with channel correction (withCC) and without channel correction (withoutCC). (a) image quality in terms of PSNR and (b) PIQUE measures.

for excellent quality of images, $E_b/N_0 \ge 3$ should be used when OFDM system has channel correction and $E_b/N_0 \ge 5$ should be used when there is no channel correction. For withCC systems' $E_b/N_0 \ge 8$ the recovered images have surpassed quality of the original pristine images. The reason is that PIQUE measure is designed for simple distortions resulted from image compression and additive noises, and not

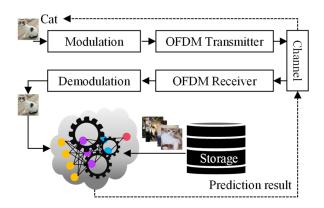


Fig. 6. OFDM based image communication system to enable cloud-based deep learning computations.

for the case when images have complexed distortions occurred during communication.

B. Deep Learning Model Analysis

The main objective of this study is to analyze performance of a trained Deep Learning (DL) model on reconstructed images in system with channel correction (withCC) and without channel correction (withoutCC). In the experiments, we have considered a scenario where a user wants to use thirdparty trained model for binary classification task as shown in Fig. 6. For this purpose, the model was first trained from scratch and evaluated on images locally available on the thirdparty server. Therefore, the images had no noise or distortion whatsoever. The dataset used was Kaggle Dogs vs. Cats dataset [8], which consists of 25K color images uniformly distributed between the two classes. All images were resized to a same dimension of 224×224 to meet the model input size requirements. The dataset split was 80%, 10% and 10% for training, validation and testing, respectively. For inferencing, 50 images were randomly selected from the test dataset. The model was trained for 60 epochs with stochastic gradient descent (SGD), various regularization techniques like early stopping, reduce learning rate, and dropout layers were used to avoid over-fitting. The model achieved 96.40% training accuracy and 92% testing accuracy.

The DL model performance of proposed systems in terms of classification accuracy on received distorted images is shown in Fig.7. The accuracy corresponds to the mean across all the images in test dataset. In higher E_b/N_0 regions, model performance on images recovered with channel correction is same as that on the original images while when images are recovered without channel correction, the accuracy dropped by 6%. When no correction is applied, highest accuracy for minimum $E_b/N_0 = 8$ dB achieved is 86%. In lower E_b/N_0 regions, the model accuracy reduces around 10% on average for both systems. In addition, the model performance shows overlapping pattern in that region and for 3dB it has performed better on images recovered without correction.

The analysis presented in Section III. A. have shown a direct relation between the E_b/N_0 and recovered image quality that is, higher the E_b/N_0 better the image quality. However, this is not a case for the model performance. The reason is that DL models are unstable to any perturbations on natural images [9]. Therefore, it can be seen in Fig. 7. that model responds randomly to different levels of distortion.

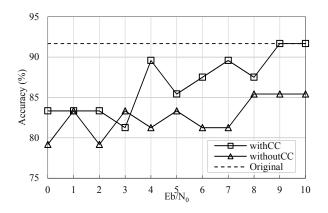


Fig. 7. Model performance on images recovered with correction (withCC) and without correction (withoutCC).

IV. CONCLUSION

In this study, we have analyzed performance of a deep learning (DL) model on images transmitted over OFDM wireless communication system. Specifically, we have considered two scenarios: images recovery with channel correction and without channel correction. The main objective was to eliminate the additional computational cost incurred by the channel estimation in wireless communication systems. The analysis has shown that for smaller E_b/N_0 values, the DL accuracy remains almost the same in both systems.

In future, we are interested in improving accuracy of the DL model by performing training on distorted images.

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