An Evaluation of Channel Estimation Method Using Deep Learning for OFDM System

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***Abstract*— In the time- and frequency-variant mobile radio channel such as the Fifth- and Forth-Generation mobile communications systems (5G, 4G), it is very important to estimate the channel coefficients (gains). We propose an estimation method of channel coefficients using a deep learning. The high accuracy of estimation can be evaluated using the deep learning method for super-resolution (SR) Network compared with the conventional method. The estimation of channel gains using orthogonal frequency-division multiplexing (OFDM) can be replaced with the SR problem and applied to the SR Network method. We show that the accuracy of the proposed method is higher than the conventional methods.**

Keywords—CNN, deep learning, SR Network, channel estimation, OFDM

I. Introduction

Recently, 5G and 4G has become the focus of the new generation of communication all over world as an extensive advancement of the existing mobile communication systems based on intensive requirements of market trends to the mobile communication systems. In the time- and frequency-variant (multipath fading channels) mobile radio channels [1], it is very important to estimate the channel coefficients (gains). It is a useful method for channel estimation using deep learning techniques for image processing. In the previous studies [2][3], it is shown that the accuracy of the estimation method is better than the those of the conventional estimation methods. However, these simulations' channel environments are limited; therefore, time- and frequency-variant conditions are not sufficiently validated, which is critical for the actual channel. Fig. 1 shows one of the examples of the fluctuation of channel gains using OFDM. Here, the main parameters that influence the fluctuation are the maximum Doppler frequency (f_d), the channel model, and the delay spread (DS). In the previous studies, each parameter is fixed; however, all the parameters are varying in the actual system. Therefore, the actual channel fluctuation is more complicated. In this case, the training for deep learning is difficult to do it; then, there is a possibility that it may be difficult to estimate the channel. In multipath Rayleigh fading channels, the relation between the received time and signal is shown in Fig. 2 when the signal is transmitted at time $t = 0$. The coefficients h_1, h_2, h_3 show the varying gains, and the attenuations of the received power. The relation of the time and received power is shown by its delay profile (such as TDL-A, TDL-B, and TDL-C) [4]. In each profile, the delay spreads of Urban Micro (UMi) and Urban Macro (UMa) are defined in this study.

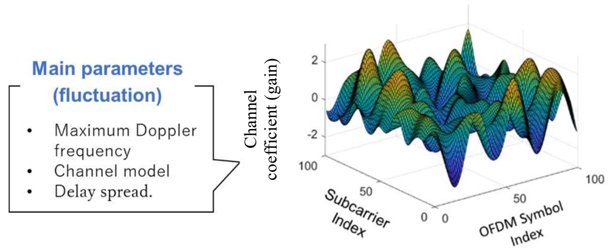


Fig. 1. Fluctuation of channel gains using OFDM

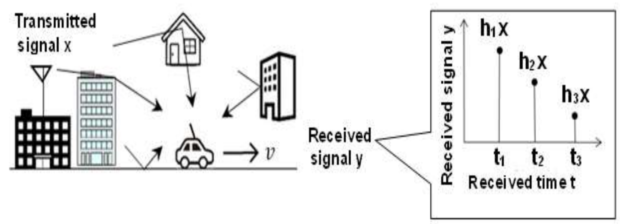


Fig. 2. Multipath Rayleigh fading envirnment

II. Architecture of Conventional and Proposed Method

A. Conventional method

In Fig. 3, the minimum transmission unit of OFDM is decided by the number of subcarriers N_s and time slots N_d which is transmitted OFDM symbols continuously in time. The grid whose size is N_s times N_d indicates the minimum transmission unit size shown in the figure. The transmission signals are assigned to each cell on the grid. Compared the grid with an image form, each grid correspond to each pixel in the image. The channel estimation is carried out per this minimum transmission unit in OFDM system.

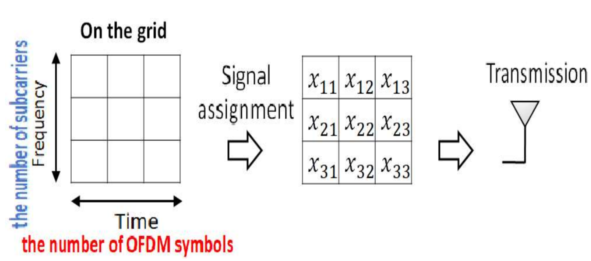


Fig. 3. Minimum transmission unit of OFDM

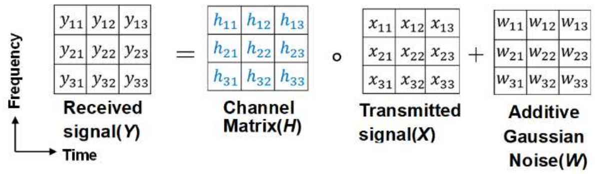


Fig. 4. A relational expression for the transmitted and received signals

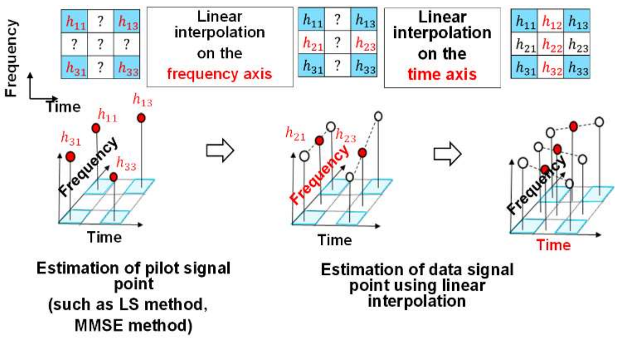


Fig. 5. Conventional channel estimation method

The transmitted OFDM signals are affected by multipath propagation channels. A relational expression for the transmitted and received signals is shown in the Fig. 4, $\circ$ represents the Hadamard product (element-wise product), and $\boldsymbol{X}$, $\boldsymbol{Y}$, $\boldsymbol{H}$, $\boldsymbol{W}$ are defined. Here, $\boldsymbol{W}$ and $\boldsymbol{H}$ represent white Gaussian noise (AWGN) and channel matrices respectively. We estimate the channel matrix $\boldsymbol{H}$ using the pilot signals. The part of the transmitted signals are pilot signals that are known between the transmitter and receiver. The receiver estimates the channel gains for all transmitted signals on the grid using the pilot signals. The pilot signals are arranged in lattice pattern. The method of estimation of channel matrix using the pilot signals is shown in Fig. 5. The receiver estimates the channel gains at the position of the pilot signals using such as least square (LS) and minimum mean square error (MMSE) estimation method. The estimation error of channel gains occurs due to the noise depending on the receiver and channel. The MMSE method can estimate the channel gain with high accuracy that reduces the influence of noise; however, the method needs the value of the noise power and channel correlation matrix as the prior knowledge. Because of this, the method is not practical. On the other hand, it is not necessary to use the prior knowledge when using the LS method; therefore, the method is practical. However, the result of estimation directly involves in the influence of the noise. The channel gains at the data signal points are estimated by linear interpolation method. In the linear interpolation, all the data (channel gains) are interpolated between the pilot signals. The interpolations are performed along the frequency- and time-axis in turn.

The relation between the transmitted and received pilot signals is shown in Eq. (1), where $\boldsymbol{X}_p, \boldsymbol{Y}_p, \boldsymbol{H}_p, \boldsymbol{W}_p \in \mathbb{C}^{N_{ps} \times N_{pd}}$ are the transmitted and received pilot signals, the channel gains and the Gaussian noises at the pilot signals, and N_{ps}, N_{pd} are the number of the pilot signals along the frequency- and time-domain axis, respectively.

$$\boldsymbol{Y}_p = \boldsymbol{H}_p \circ \boldsymbol{X}_p + \boldsymbol{W}_p \tag{1}$$

The estimated value $\widehat{\boldsymbol{H}}_p^{LS}$ of $\boldsymbol{H}_p$ using LS estimation is shown in Eq. (2) [5]. In Eq. (2), the column vectors of $\boldsymbol{X}_p, \boldsymbol{Y}_p, \boldsymbol{H}_p, \boldsymbol{W}_p, \widehat{\boldsymbol{H}}_p^{LS}$ are $\boldsymbol{x}_p(t), \boldsymbol{y}_p(t), \boldsymbol{h}_p(t), \boldsymbol{w}_p(t), \widehat{\boldsymbol{h}}_p^{LS}(t)$ $(t = 1, \dots, N_{pd})$, respectively.

$$\begin{aligned} \widehat{\boldsymbol{h}}_p^{LS}(t) &= \underset{\widehat{\boldsymbol{h}}_p}{\operatorname{argmin}} \left\| \boldsymbol{y}_p(t) - \widehat{\boldsymbol{h}}_p(t) \circ \boldsymbol{x}_p(t) \right\|_2^2 \\ &= \boldsymbol{y}_p(t) \circ (\, \boldsymbol{x}_p(t)\,)^{\circ -1} \\ &= \boldsymbol{h}_p(t) + \boldsymbol{w}_p(t) \circ (\, \boldsymbol{x}_p(t)\,)^{\circ -1}, \end{aligned} \tag{2}$$

where $\| \; \|_2$ and $(\cdot)^{\circ -1}$ operator mean Euclidean norm and the inverse of each matrix element, respectively. In Eq. (2), the results of estimation are affected by the noise vector of $\boldsymbol{w}_p$.

Linear minimum mean square error (LMMSE) estimation [6] reduces the effect of noise; therefore, the estimation accuracy is higher than that of LS estimation. The column vectors $\widehat{\boldsymbol{h}}_p^{LMMSE}(t)$ $(t = 1, \dots, N_{pd})$ of the estimation values $\widehat{\boldsymbol{H}}_p^{LMMSE}$ of $\boldsymbol{H}_p$ are shown in Eq. (3) [6].

$$\widehat{\boldsymbol{h}}_p^{LMMSE}(t) = \boldsymbol{R}_{h_p,h_p} \left(\boldsymbol{R}_{h_p,h_p} + \mathrm{E}\left(\boldsymbol{x}_p \boldsymbol{x}_p^H\right)^{-1} \sigma^2 \boldsymbol{I} \right)^{-1} \widehat{\boldsymbol{h}}_p^{LS}(t), \tag{3}$$

where $\boldsymbol{R}_{h_p,h_p}$ is the autocorrelation matrix of $\boldsymbol{h}_p$, $\mathrm{E}\,(\boldsymbol{x})$ means the expected value of $\boldsymbol{x}$, σ^2 is the noise power, it shows $\boldsymbol{R}_{h_p,h_p} = \mathrm{E}(\boldsymbol{h}_p \boldsymbol{h}_p^H)$, and $\boldsymbol{h}_p^H$ is the complex conjugate transposition of $\boldsymbol{h}_p$ and $\boldsymbol{I}$ is the unit matrix. The calculation of $\left(\boldsymbol{x}_p \boldsymbol{x}_p^H\right)^{-1}$ when each $\boldsymbol{x}_p$ changes, which is needed when using MMSE; on the other hand, it takes the expected value of $\mathrm{E}\left(\boldsymbol{x}_p \boldsymbol{x}_p^H\right)^{-1}$ when using LMMSE. In this study, there are cases where $\boldsymbol{R}_{h_p,h_p}$ is completely known as an ideal LMMSE estimation and $\boldsymbol{R}_{h_p,h_p}$ is estimated by the received signals as a practical LMMSE. In the practical LMMSE estimation, the simulations are carried out 20 times under the same conditions (parameters: channel model, velocity of terminal (v), delay spread (*DS*), and signal-to-noise ratio (SNR)) before the evaluation for the accuracy of the channel estimation. In each simulation, the estimation values $\widehat{\boldsymbol{R}}_{h_p,h_p} = \mathrm{E}\,(\widehat{\boldsymbol{h}}_p^{LS} \widehat{\boldsymbol{h}}_p^{LS^H})$ of $\boldsymbol{R}_{h_p,h_p}$ are calculated after calculation of $\widehat{\boldsymbol{h}}_p^{LS}$ by using Eq. (2); and then, the estimated $\boldsymbol{R}_{h_p,h_p}$ $[\widehat{\boldsymbol{R}}_{h_p,h_p} = \mathrm{E}\,(\widehat{\boldsymbol{h}}_p^{LS} \widehat{\boldsymbol{h}}_p^{LS^H})]$ can be used in Eq. (3).

B. Proposed method

The estimation of channel gains using OFDM can be replaced with the super-resolution problem and applied to the SR Network method [7]. This summary is shown in Fig. 6. First, the estimation values $\widehat{\boldsymbol{H}}_p^{LS}$ of channel gains at the pilot signal positions can be obtained. The values are input into the SR Network as the low-resolution images. The output signals of the high-resolution images are the estimation values $\widehat{\boldsymbol{H}}$ of channel gains for all the transmitted signals on the grid. The channels matrix complex values are processed, divided into the real and imaginary parts. Using the deep learning model to increase the number of pixels in an image, the adequate interpolation for channel estimation can be done.

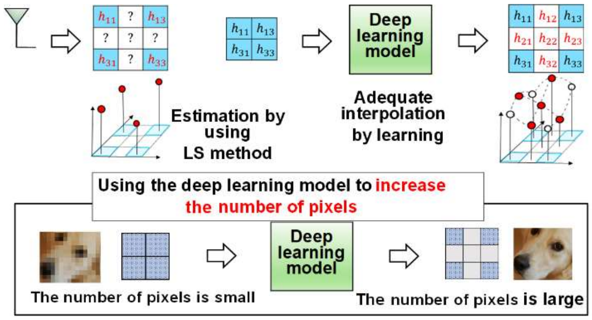


Fig. 6. Estimation method using deep learning

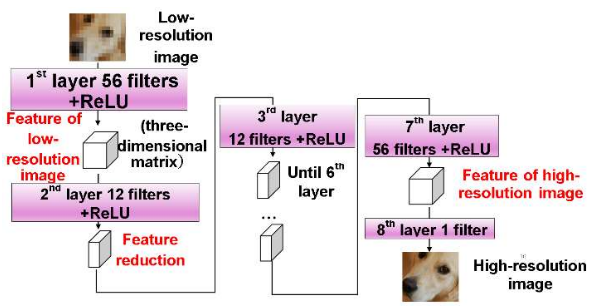


Fig. 7. Structure of deep learning model (8 layers convolutional neural network(CNN))

The structure of SR Network used in this study is based on "fast super resolution CNN" (FSRCNN) [7] which exhibits high super-resolution performance. This structure is composed of 8 layers CNN and can change low resolution images to high resolution ones. The last layer is "the transposed convolution layer." This layer does not use the activation function. The other layers are normal configurations of CNN involved in the activation ReLu functions, as shown in Fig.7. When using SR Network learning, the loss function L is shown in Eq. (4). The optimization parameters are updated (weight of convolutional layer, bias) to minimize L. Here, $\| \|_F$, $\boldsymbol{H}$, $\widehat{\boldsymbol{H}}$ mean Frobenius norm, the correct data, and the outputted data from SR Network for the input data $\widehat{\boldsymbol{H}}_p^{LS}$, respectively. The sets of $\widehat{\boldsymbol{H}}_p^{LS}$ and $\boldsymbol{H}$ are learning data sets. The number of data sets is 25,600. The number of repeated datasets (epoch) is 50. In addition, the calculation of L and the parameters update are calculated per mini-batch. Each mini-batch size of the data sets is 128.

$$L = \frac{1}{2}\left\|\boldsymbol{H} - \widehat{\boldsymbol{H}}\right\|_F^2 \tag{4}$$

The method of gradient descent can be used for optimization. In Eqs. (5) and (6), the number of times of learning is t and the gradient $\partial L/\partial\theta_t$ is calculated and updated; moreover, $\alpha > 0$ is the learning ratio. It is important to adjust the update quantity of α and $\partial L/\partial\theta_t$ until the parameters are converged. In this study, we use the method of adaptive moment estimation (Adam) to attain the optimum converged characteristics. The updating equations are shown in Eq. (6).

$$\theta_{t+1} = \theta_t - \alpha\frac{\partial L}{\partial\theta_t} \tag{5}$$

$$\begin{gathered}\theta_{t+1} = \theta_t - \frac{\alpha}{\sqrt{v_t} + \epsilon}m_t \\ m_t = \beta_1 m_{t-1} + (1-\beta_1)\frac{\partial L}{\partial\theta_t} \\ v_t = \beta_2 v_{t-1} + (1-\beta_2)\left(\frac{\partial L}{\partial\theta_t}\right)^2 \\ v_{t=0} = 0, m_{t=0} = 0\end{gathered} \tag{6}$$

The values of recommended variables are $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, and $\epsilon = 10^{-8}$ For the initial parameters $\theta_{t=0}$ of the CNN, the weights are initialized using the Glorot initialization method [8], and the biases are set to zero. In the case that the learning ratio is constant, it takes a lot of time until the optimum value and the value exceeds the optimum one (it also takes a lot of time to attain the value) when it is small and large, respectively. To avoid this problem, gradient $\partial L/\partial\theta_t$ is replaced with m_t in Eq. (5) using Adam method. m_t is decided by the past and current gradient values. The value is far away from the optimum value and close to the value when m_t is large and small, respectively.

III. Simulation Conditions and Results

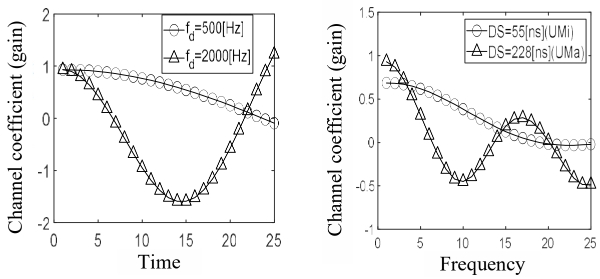
In this study, we randomly vary the velocity of terminal (v), delay spread (DS), channel model, and SNR (randomly only during training) to conduct simulations and verify the effectiveness of the SR Network. The simulation conditions are shown in Table. 1. v is randomly determined between 0 and 60 km/h. The delay spread and channel model are randomly determined according to the 3rd Generation Partnership Project (3GPP) standard, as shown in Table 1. The SNR during training is randomly selected between 0 and 30 dB, and during testing, evaluations are performed for each SNR. The conditions other than SNR are the same during both training and testing. The values of the maximum Doppler frequency f_d (related to v) and DS indicate channel variation. As an example, the Fig. 8 shows the channel variation when f_d and DS are varied. Fig. 8(a) shows the time variation of the channel in TDL-A (DS = 55 ns) for $f_d = 500$ Hz($v \approx 11$ km/h) and $f_d = 2000$ Hz($v \approx 43$ km/h), when carrier frequency is 50 GHz. Fig. 8(b) shows the frequency variation of the channel gain in TDL-A.

The pilot signal placement follows the 3GPP 5G standard. The simulations are performed with two types of pilot signal placements, as shown in the Fig. 9. In this study, we refer to the case with fewer pilot signals as Type A and the case with more pilot signals as Type B.

The simulation results are shown in Fig. 9 (single input and single output environment). Using a lot of pilot signals, the accuracy of linear interpolation is high; therefore, the mean square error (MSE) characteristics of Type B (use a lot of pilot signals) are better than that. Considering of both Type A and B's results, the accuracy of the estimation of the channel gains using the deep learning method in the case that SNR are 0 to 30 dB is superior to those of LS estimation and practical LMMSE. In the case that SNR is

TABLE I. SIMULATION CONDITIONS

Number of subcarriers (N_s)	240
Number of time slots (N_d)	14
Subcarrier interval	60 kHz
Carrier frequency	50 GHz
Velocity of terminal (v)	0~60 km/h
Delay spread (DS)	55 ns (UMi) 228 ns (UMa)
Channel model	TDL-A, B, C
SNR	0~30 dB



(a) effect of maximum Doppler frequency (f_d) (b) effect of delay spread(DS)

Fig. 8. Fluctuation of channel gains

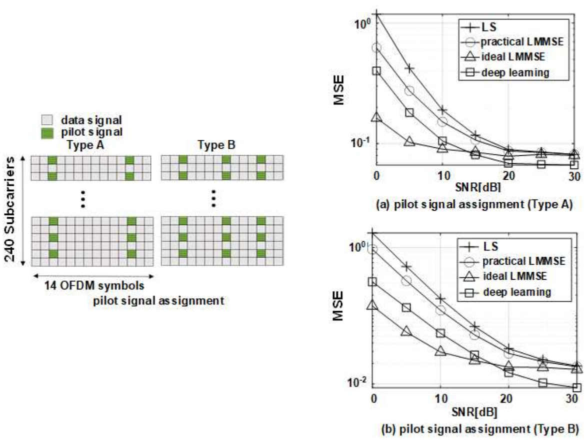


Fig. 9. MSE characteristics and pilot signal assignments

higher than 15 dB, the accuracy using the deep learning method is higher than that of ideal LMMSE. It was supposed that the learning for SR Network was difficult to carry out in various conditions; however, the high accuracy of estimation can be evaluated using the deep learning method for SR Network (FSRCNN [7]) compared with the conventional methods.

In Fig. 10, the exact channel gains (relative values) (Fig. 10(a)) and the results of estimation for channel gains (relative values) (Fig. 10(b)(c)(d)) are shown and we compare among them. The pilot signal assignment, channel model, SNR, terminal speed, and delay spread are Type B, TDL-A, 0 dB, 60 km/h, and 55 ns, respectively. Prior information is not needed when using the LS estimation (Fig. 10(b)); therefore, the accuracy of estimation is the lowest of all methods. Because of this, the results are affected by noise; therefore, the channel correlation matrix and value of noise power are needed when using the ideal LMMSE estimation (Fig. 10(c)). The results of channel estimation are high because it reduces the impact of noise. The accuracy of the proposed method using the deep learning is high (Fig. 10(d)).

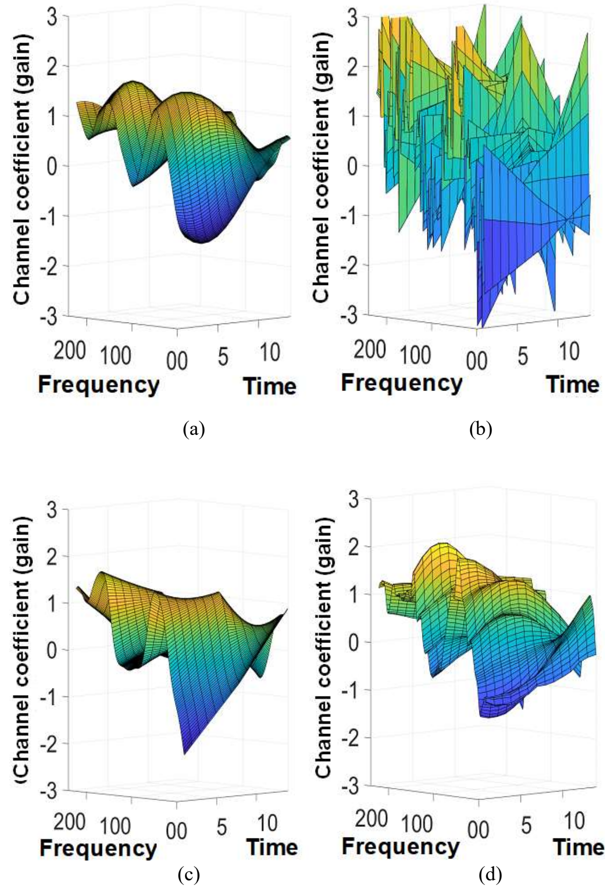


Fig. 10. Exact channel gains (a) and the results of estimation for channel gains ((b) LS method, (c)ideal LMMSE method, (d)deep learning method) .

IV. CONCLUSIONS AND FUTURE WORKS

As for SR Network, the accuracy of the interpolation is better than those of the LS and ideal LMMSE. The effect of noise depending on the input signals which are the channel estimation values at the pilot signals obtained by LS method into the SR Network can be solved. First, using the LMMSE method instead of the LS method is useful. This is because the accuracy using the LMMSE method is better than that. Second, a deep learning network using a denoising network composed of CNN for noise elimination after the process of SR Network is useful. Third, the improvement of SR Network because this model was developed in 2016. After the development, a lot of high-accuracy models were developed. We can apply them to the model to improve the estimation accuracy (for example, it can be improved for the accuracy when reducing the number of pilot signals such as using Type A). In addition, using the measurement of actual environment is useful for evaluation. Specifically, we will get the channels' information using radio wave propagation analysis by the ray trace method and it helps evaluations.

ACKNOWLEDGMENT

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