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Channel Estimation for OFDM Systems Using an Improved SRGAN Architecture

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ABSTRACT

It is important to accurately estimate channel values in orthogonal frequency division multiplexing systems. In the channel estimation (CE), the channel values in the positions of pilot signals can be regarded as low-resolution images, therefore deep learning (DL)-based super-resolution (SR) algorithms can be applied to estimate all the channel values. The existing DL-based CE algorithm with the SR generative adversarial network (SRGAN) achieves good performance and we further improved the neural network architecture, enhancing the CE accuracy with lower complexity.

Key Words : Channel estimation, Deep learning, Neural network, SRGAN

Ⅰ. Introduction

In wireless communication systems, the received signal is distorted by channel effects and noise, so estimating channel characteristics is essential for signal reconstruction. Conventional channel estimation (CE) methods such as least square (LS) and minimum mean squared error (MMSE) exploit pilot signals at predefined positions. The LS estimation uses only the received signal and pilot signals, which results in low complexity but is sensitive to noise. The MMSE estimation utilizes 2D channel statistics and noise variance to provide better performance but with high complexity.

Recently, deep learning (DL)-based approaches have gained significant attention in wireless communications. A DL-based CE was introduced in the multipath fading channel using the pilot signal and the received signal as inputs[1]. Another DL-based CE pipeline, denoted as ChannelNet, was proposed, which combines super resolution convolutional neural network (SRCNN) and denoising CNN (DnCNN)[2]. CE methods based on NN with residual block (RB)[3] and residual in residual dense block (RRDB)[4] were proposed. To reduce the difficulty of CE, the NN with progressive upsampling structure[5] was proposed. Additionally, a CE algorithm based on SR generative adversarial networks (SRGAN)[6] was introduced. A CE algorithm applying enhanced SRGAN (ESRGAN)[7] was also developed.

The GAN-based algorithms make the channel distribution more similar to the actual channel through the discriminator. Inspired by this, we modified the generator structure, applying the RRDB instead of RBs. Simplifying the dense block, we achieve a good performance with only two RRDBs. As a result, the proposed NN shows better CE accuracy even with lower computational complexity, compared to the ideal MMSE.

Ⅱ. ChannelNet- and SRGAN-based CE

DL-based CE considers the channel as a 2D image

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in the time-frequency grid. It is assumed that pilot signals can be regarded as low-resolution (LR) images, and the entire estimated channel is considered high-resolution (HR) images. Thus SR algorithms can be used to estimate the channel.

The ChannelNet-based CE[2] integrates SRCNN and DnCNN in a sequential manner. It takes the LS-estimated vector as input, and performs interpolation. Then interpolated channels are input to SRCNN and DnCNN, sequentially. SRCNN has powerful image resolution capability while DnCNN effectively removes noise. The output is estimated and denoised channel. However, ChannelNet-based CE has several issues: (1) It has high complexity caused by the direct adoption of the DnCNN. (2) The real and imaginary parts of the complex channel are processed as separate images, ignoring their correlations. (3) The two-stage channel estimation process is trained separately.

The SRGAN-based CE effectively leverages the adversarial learning approach to refine CE[6]. It consists of a generator and a discriminator. The generator takes the LS-estimated and interpolated channel as input and estimates the channel, while the discriminator learns to distinguish between the estimated channel and the true channel. The goal of GAN-based CE is to develop a generator that accurately estimates $\hat{H}$ from H_p by ensuring that the $\hat{H}$ closely matches the true channel distribution.

Ⅲ. CE with improved SRGAN

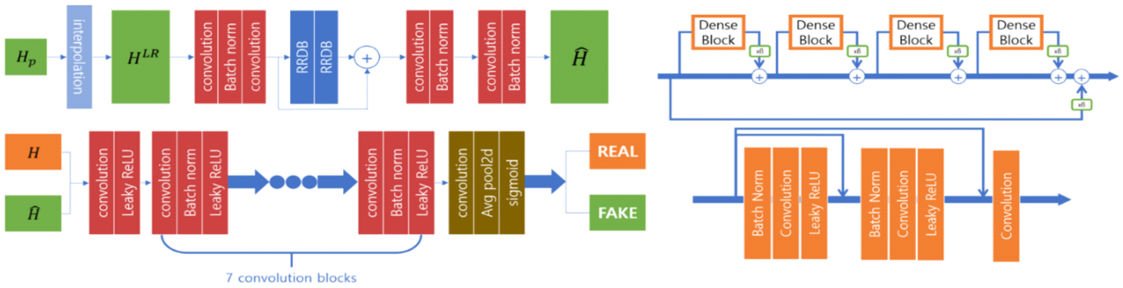
To improve the performance of CE, we modify the structure of the generator in the SRGAN-based CE. Specifically, we replace the traditional RBs with RRDBs. As shown in Fig. 1 (b), the RRDB structure consists of four dense blocks connected through residual links. Due to the numerous residual connections, the proposed model makes training step stable even with its deep structure and achieves strong performance with only two RRDBs.

Furthermore, following the approach[8], we employ residual scaling factor β, multiplying residual connections by a value between 0 and 1, to facilitate training of deep networks. We also use smaller initialization, as residual architectures tend to train more easily when initial parameters are small.

The dense blocks in the RRDB, used by the original ESRGAN for image processing, consist of five convolution layers and four activation functions. However, to reduce complexity, we modify this structure as shown in the bottom of Fig. 1 (b). Additionally, we decrease the number of filters compared to those proposed[6], resulting in low computational complexity of generator. The proposed overall network architecture is illustrated in Fig. 1 (a).

Ⅳ. Simulation Results

In this section, we show a mean square error (MSE) performance across different signal-to-noise ratio (SNR) ranges. We utilize a Veh-A channel in a single-antenna scenario. Each frame of the channel consists of 72 subcarriers and 14 time slots, with a carrier frequency of 2.1 GHz, a bandwidth of 1.6 MHz, and a user equipment (UE) speed of 50 km/h. Out of a



(a) Network structure (b) Residual in Residual Dense Block

Fig. 1. Proposed Network Structure (a) overall improved SRGAN-based structure, and (b) RRDB structure.

total of 40,000 datasets, 60% are used for training, 10% for validation, and 30% for testing. Interpolation method is rbf[9]. The learning rates for training the generator and discriminator networks are set to 0.001, with a batch size of 128 and 150 epochs, and we employ the Adam optimizer.

As shown in Fig. 2, the proposed CE structure consistently outperforms other DL-based CE across all SNR levels. Its performance is comparable to that of ideal MMSE, even surpasses the ideal MMSE at the SNR levels above 15dB. Given that the ideal MMSE assumes perfect channel state information (CSI) conditions but it is not practical, the performance of the proposed structure demonstrates reliable CE for practical wireless communication systems with lower complexity than SRGAN-based CE, using more residual links and reducing the number and the size of convolution filters. The complexity of the generator is demonstrated in Table 1.

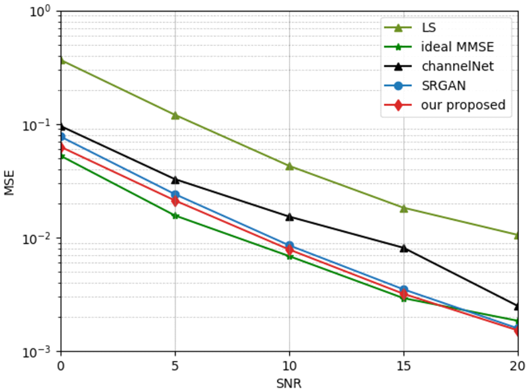


Fig. 2. MSE performance of the all CE algorithms

Table 1. Complexity of Generator in SRGAN-Based and Proposed Model

	SRGAN	Proposed
Parameters	24.55K★	17.36K
FLOPs	476.1K	K

★ 1K = 1,000

V. Conclusions

In this letter, we propose a structure by modifying the generator in the SRGAN-based CE algorithm, achieving superior performance with lower complexity. The model demonstrated performance comparable to ideal MMSE, even which is under CSI conditions.

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