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Learning-Based Channel Estimation Method with Non-Orthogonal Pilots for Grant-Free Multiple Access in Massive MIMO Systems

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ABSTRACT

Massive multiple-input and multiple-output (MIMO) systems are efficient technologies that can meet the increasing need for larger user capacities and diverse requirements posed by massive machine-type communications and ultra-reliable low latency communications (URLLCs). In particular, massive MIMO systems that employ grant-free (GF) multiple access have recently been studied, aiming to effectively satisfy the uplink transmission requirements of URLLCs. However, the conventional approach to channel estimation in MIMO systems relies on orthogonal pilot signals, necessitating inter-device synchronization. This limitation causes challenges in the integration of GF multiple access with massive MIMO, due to the inherent difficulty in achieving device synchronization within GF multiple access. To overcome this limitation, we propose a learning-based channel estimation method in massive MIMO systems using non-orthogonal pilots. Numerical results demonstrate that the proposed scheme achieves a bit error rate of less than 10^{-3} for scenarios with 32, 64, and 128 received antennas and 2 devices, as well as scenarios with 128 received antennas and 2 or 3 devices, at signal-to-noise ratio levels above 0 dB. These findings highlight the promising performance of our proposed method.

Key Words : Massive MIMO, Deep learning, grant-free access, low latency, non-orthogonal pilot.

Ⅰ. Introduction

Massive multiple-input multiple-output (MIMO) systems are of significant importance in the 5G physical layer because they allow for the efficient multiplexing of numerous devices using the same time-frequency resources[1]. These technologies are essential for meeting the increasing need for larger user capacities and diverse requirements posed by massive machine-type communications (mMTC) and ultrareliable low-latency communications (URLLC)[2].

Despite the increasing importance of low latency in 5G/6G, most research on massive MIMO continues to focus on improving data rates or increasing the number of concurrent users in mMTC scenarios[3,4]. Consequently, studies have been conducted on pilot designs to accommodate large numbers of users and decoding methods in such scenarios[2,5]. However, research on low-latency techniques that use massive MIMO to satisfy the requirements of URLLC is relatively limited.

Recent studies have explored the integration of grant-free (GF) multiple access with low-latency massive MIMO systems[3,6]. The concept of GF

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multiple access was introduced within the 3GPP RAN WG1 framework[7-9].

In [3], algorithms for GF access that involve the joint detection of device activity and embedded information bits were proposed. In [6], the authors formulated the problem of maximum likelihood device activity detection for GF access, and provided an algorithm based on the coordinate descent method, which has affordable complexity.

To enable GF multiple access in massive MIMO, a pilot design for the channel estimation of GF devices is necessary. In conventional communications, orthogonal pilots are used for channel estimation. However, in massive MIMO systems for mMTC scenarios, the issue of pilot orthogonality arises because of the non-orthogonal pilots caused by pilot overhead [10]. Although discussions on non-orthogonal pilots exist in massive MIMO systems for mMTC, the GF environment demonstrates an even more pronounced non-orthogonality, requiring further research.

This study aims to overcome the channel estimation problem by utilizing non-orthogonal pilots and a learning-based approach. Specifically, a low-latency learning-based non-orthogonal pilot decoder is proposed. By leveraging this technology, online learning becomes feasible as it enables training using available pilots.

Ⅱ. System Model

In wireless communications, when a channel remains relatively stable within a certain range, longer packet lengths can reduce the allocation of resources for channel estimation, thereby leading to more efficient communication. However, longer packet lengths result in an increased waiting time for transmission when packets are generated for devices that are not currently in communication.

This latency issue can be addressed by utilizing GF multiple access for transmission in massive MIMO systems. If the data traffic is not extremely high because of the inherent nature of massive MIMO, the base station (BS) can accommodate additional GF devices even when grant-based (GB) devices are actively transmitting packets.

Figure 1 shows a schematic overview of the proposed communication system. We considered the presence of two device modes: GB and GF devices. GB devices, which do not require low latency, communicate with the BS using channel-estimation techniques based on pilot orthogonality. Additionally, it is assumed that interference from the GB devices is perfectly eliminated using successive interference cancellation (SIC)[11,12].

In such a scenario, conventional massive MIMO systems face a challenge because they cannot estimate the channels of GF devices, resulting in the discarding of packets from both the GB and GF users. However, the characteristic of channel hardening in massive MIMO allows decoding using matched filters based on the knowledge of the channels of only GB devices. Figure 2 demonstrates through simulations that in massive MIMO systems, when the number of users is not high, decoding using channel hardening is sufficiently effective.

Figure 2 shows a bit error rate (BER) with respect to the number of users when decoding using matched

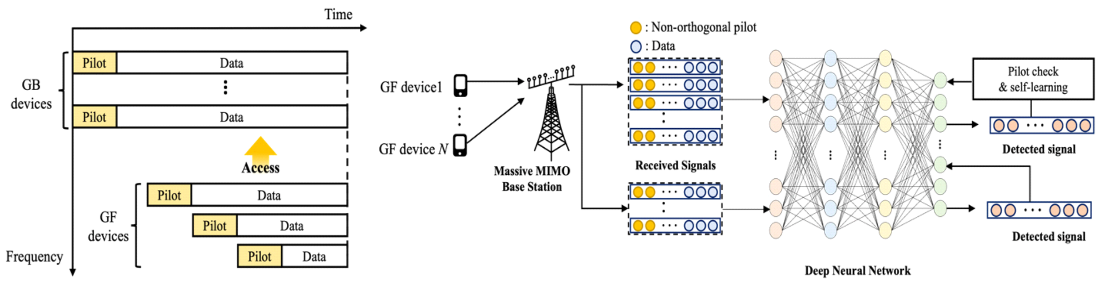

Fig. 1. Schematic overview of the learning-based channel estimation model for GF multiple access.

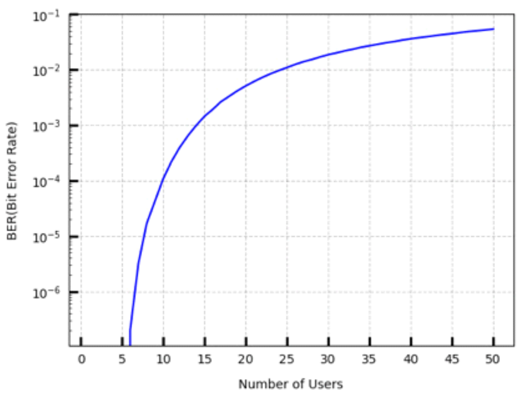

Fig. 2. BER for the number of concurrent users in massive MIMO with matched filtering decoding.

filters, assuming perfect knowledge of the channel information to decode the device. This scenario considered a signal-to-noise ratio (SNR) of 10 dB and M= 128. The results, as illustrated in Fig. 2, indicate that up to 13 GF users exhibit a BER of a GB user below 10^{-3}, indicating that they achieve a BER close to 0 when channel coding is applied.

2.1 Massive MIMO received signal

This study focused on an uplink communication scenario between a single BS equipped with M antennas and N single-antenna devices using GF multiple access. We consider the channel between the device and BS to follow a Rayleigh fading channel. Additionally, we assumed the presence of additive white Gaussian noise (AWGN). Let us denote the received signal of the t-th orthogonal frequency-division multiplexing (OFDM) symbol $\mathbf{y}_t \in \mathbb{C}^{M\times 1}$ as

$$\mathbf{y}_t = \sum_{i=1}^{N} \mathbf{h}_i s_{t,i} + \mathbf{z}_t, \quad (1)$$

where $\mathbf{h}_i \in \mathbb{C}^{M\times 1}$ is the channel vector between i-th device and the BS, $s_{t,i}$ is the t-th OFDM symbol of the i-th device, and $\mathbf{z}_t \in \mathbb{C}^{M\times 1}$ represents a zero-mean independent and identically distributed (i.i.d.) AWGN of the t-th OFDM symbol.

In wireless communication, the frame structure is defined such that the lengths of the pilots cannot be extended arbitrarily. For example, in the frame structure of LTE, one time slot consists of seven OFDM symbols, one subframe consists of two time slots, and one frame consists of 10 subframes. Therefore, one frame, which corresponds to a 10-ms packet, is composed of 140 OFDM symbols[13]. Therefore, if the number of OFDM symbols in one packet is denoted as N_s, the number of pilots, N_p, is defined as $N_p := \lfloor N_s \times p \rfloor$, where p represents the overhead value.

In this scenario, we transmit 140 OFDM symbols, of which p = 11 symbols are designated as pilot signals. We employed quadrature phase-shift keying (QPSK) as the modulation scheme.

2.2 Massive MIMO matched filter

In a massive MIMO scenario, when using matched filtering for decoding, it is possible to decode the data if the channel information of the desired device is known, even in the absence of the channel information for other devices. Let us assume that we aim to decode the tth OFDM symbol of the nth device. In this case, symbol decoding can be performed as follows:

$$\mathbf{f}_n^{\mathrm{H}} \mathbf{y}_t = \sum_{i=1}^{N} \mathbf{f}_n^{\mathrm{H}} \mathbf{h}_i s_{t,i} + \mathbf{f}_n^{\mathrm{H}} \mathbf{z}_t, \quad (2)$$

where $\mathbf{f}_n$ is the estimated channel vector of the n-th device.

If the value of M is sufficiently large, the term $\mathbf{f}_n^{\mathrm{H}} \mathbf{h}_i$ can be approximated as zero for I $\neq n$[14]. Therefore, equation (2) can be approximated as follows:

$$\mathbf{f}_n^{\mathrm{H}} \mathbf{y}_t \approx \mathbf{f}_n^{\mathrm{H}} \mathbf{h}_n s_{t,n} + \mathbf{f}_n^{\mathrm{H}} \mathbf{z}_t. \quad (3)$$

Hence, it is possible to decode the signal without requiring channel information from other devices.

Ⅲ. Learning-based Channel Estimation Model

In this study, a learning-based channel estimation method using non-orthogonal pilots is proposed. Unlike conventional orthogonal pilots, the proposed method employs random QPSK symbols as pilots, thereby enabling asynchronous transmission among devices. The proposed model employs a

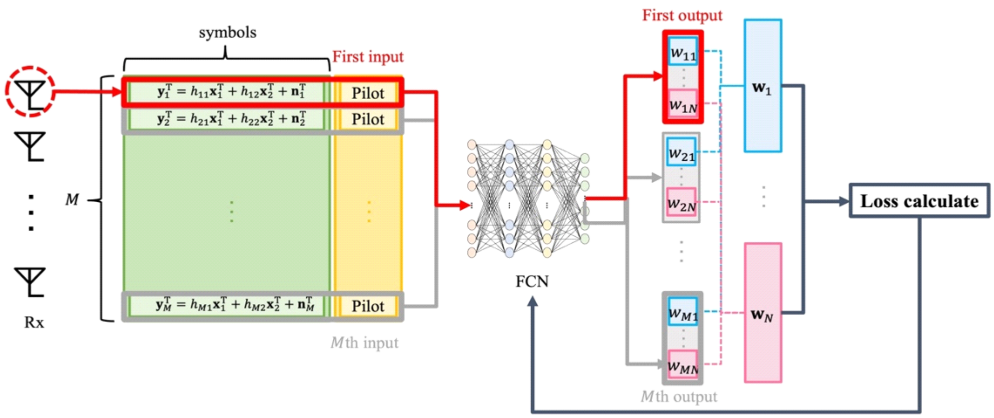

Fig. 3. Structure of the learning-based channel estimation model.

semisupervised learning approach that relies solely on pilot information for channel estimation. Importantly, our model does not rely on transmitted data for learning, thus allowing continuous learning during ongoing communication.

In the scenario depicted in Fig. 1, the devices communicate with a multiantenna BS, where pilots are inserted before data transmission. To enable pilot-based channel estimation without pilot synchronization, we utilized random QPSK symbols as pilots. By inputting the received signals from each antenna and the corresponding pilots into the proposed neural network, the channel information can be obtained and used to detect the original data.

Figure 3 illustrates the structure of the proposed model, which comprises a fully connected network consisting of four hidden layers. The input signals in the model are complex values, whereas the weights of the neural network are real values[15]. Therefore, it is necessary to separate the input data into real and imaginary components.

Instead of using all received signals as input data, we utilized the real and imaginary parts of the received signals from each antenna and the corresponding pilots. This approach helps to prevent the input data size from increasing proportionally with the number of antennas received. In addition, it helps to mitigate overfitting issues.

Each output data point represents the channel information of an individual antenna. By collecting the channel information from M antennas, we can obtain the channel information vectors of each device, $\mathbf{w}_1, \mathbf{w}_2, \cdots \mathbf{w}_N$. The pilots can be estimated using these channel information vectors. The mean square error (MSE) between the pilots and estimated pilots was used as the loss function. The loss formula is given by:

$$Loss = \frac{1}{Np}\sum_{i=1}^{N}\sum_{t=1}^{p}\left(\mathbf{w}_i^{\mathrm{H}}\mathbf{y}_t - s_{t,i}\right)^2. \qquad (4)$$

The loss is updated after M iterations of the model execution. As the loss approaches zero, the phases of $\mathbf{w}_1, \mathbf{w}_2, \cdots \mathbf{w}_N$ converge to the phase of the channel vector in the massive MIMO system.

Ⅳ. Simulation Results

In [2], the system model used 10% pilot overhead involving 140 transmitted symbols, of which 14 were pilot symbols. We evaluated the performance of the proposed model using 8% pilot overhead, which was lower than the 10% previously used.

In this experiment, we transmitted 140 OFDM symbols, of which 11 symbols were allocated to pilots and 129 symbols to data transmission. The modulation scheme employed was QPSK. Notably, our model is flexible and can be used with other fixed constellations.

As depicted in Fig. 4, we performed simulations of the proposed model with a fixed number of devices (N= 2) while varying the number of received antennas

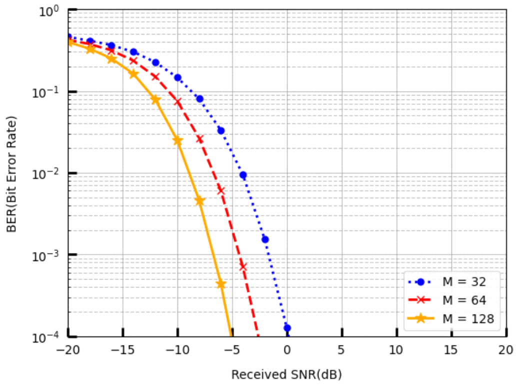

Fig. 4. BER for three different numbers of received antennas with $N = 2$ ($M = 32$, 64, 128).

and SNR. For SNR values above 0 dB, the BER remained below 10^{-3}across all three scenarios, with M = 32, 64, 128.

In Fig. 5, the BER graph is plotted with a fixed value of $M = 128$ and varying numbers of devices $N = 2, 3, 4$. The results indicate that the BER remains below 10^{-3} for both scenarios with $N = 2$, 3.

Figure 6 depicts the BER against epochs for the scenario with $N = 2$, M = 64, 128 and SNR values of -5 and 0 dB. As the number of epochs increases, the BER decreases.

When the proposed model is used for channel estimation, the training time does not affect the latency because a pre-trained model is employed. However, the inference time of the model affects latency.

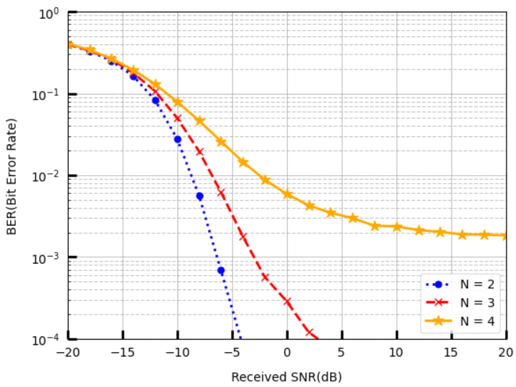

Fig. 5. BER for three different numbers of devices with $M = 128$($N = 2$, 3, 4).

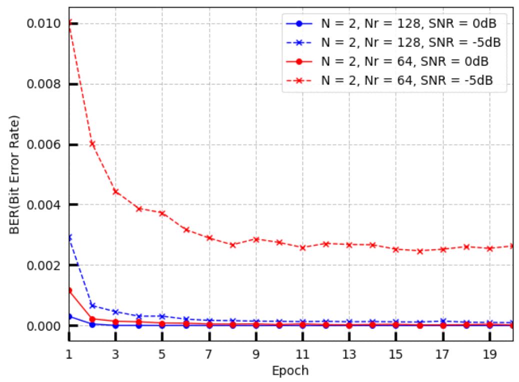

Fig. 6. BER versus epoch for various SNR values and the number of received antennas with $N = 2$.

Ⅴ. Conclusions

In this study, we introduced a learning-based channel estimation method for massive MIMO systems using nonorthogonal pilots. Although existing simulation studies often assume that channels are independent; in reality, there is a correlation between the channels. By employing a learning-based channel estimation model, we anticipate that such correlations can be learned to enhance the channel estimation accuracy. Although this study did not consider channel correlations, it demonstrated the feasibility of utilizing Deep Neural Networks (DNN) for channel estimation. Moreover, this study indicated the potential for the future development of learning models that incorporate channel correlation. The proposed model allows GF multiple access because it utilizes non-orthogonal pilots, eliminating the need for pilot synchronization. Furthermore, we demonstrated the feasibility of learning-based channel estimation. Because the proposed model follows a semisupervised learning approach, it can be further enhanced by incorporating online learning capabilities.

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