6G 셀룰러 네트워크를 위한 인공지능: massive MIMO-NOMA 딥러닝 해석

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Artificial Intelligence for Future 6G Cellular Networks: A Deep Learning approach for Massive MIMO NOMA System

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요 약

The upcoming sixth-generation (6G) wireless networks are expected to lay the foundation for intelligent networks powered by isolated artificial intelligence (AI). For this, we assume that 6G wireless networks will operate with automatic on-demand configuration to improve network performance and service types. Non-orthogonal multiple access (NOMA) has received much attention as a major candidate for fifth-generation (5G) mobile communications systems. In this article, authors are exploiting deep learning (DL) approach that suggests that DL is essential to find the optimal sequence of channel gain and signal detection for 6G communication systems.

Ⅰ. 서 론

Data-driven research towards an adaptive and intelligent method has gained the attention of the researchers after the echoes of 6^{th} generation (6G) future wireless networks began to chime. The advents in computing methods from Machine Learning (ML) to Artificial Intelligence (AI) bridged by Deep Learning (DL) approaches have led to the consideration of autonomous management and service classification to reconfigure the demands of future wireless networks. These kinds of data-driven methods show strong potential to realize the ambition of fully developed intelligent 6G wireless communication. In the recent future, the amenity of mass connections, intelligent human-machine interface and huge data traffic, AI seems to be a magic wand that can make the system learn, perform and enhance the operations by exploiting the operational knowledge in the form of data.

A subfield of AI is commonly known as DL and is implemented widely in various engineering streams such as image and video processing, data processing and wireless communication for channel estimation and signal detection [1]. Towards the implementation and fulfil the requirements of 6G network, several kinds of research are ongoing [2]. Among them, Massive Multiple-Input Multiple-Output (mMIMO) and Non-orthogonal Multiple Access (NOMA) systems are believed to have the potential to address the capacity demands and the spectral efficiency of the network respectively. NOMA and mMIMO integrated system if aided with DL methods; can deliver astonishing results due to the ability of deep neural networks to process high dimensional data to enhance the detection performance of the above-mentioned integrated system [3].

This paper examines the ability of downlink mMIMO-NOMA system based on the DL methods for channel estimation for future 6G cellular networks. In the following section, the system model and the ability of AI-driven networks is briefly discussed. Furthermore, the results are provided to give insight into the possible improvements in conventional networks to fulfil the requirements of future communication networks as shown in Figure 1.

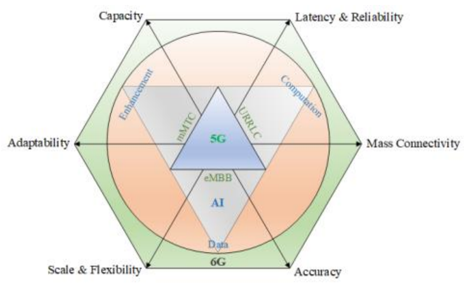

Figure 1: Key requirements and characteristics of 6G

Ⅱ. 본론

Unlike the traditional orthogonal multiple access (OMA) systems, NOMA utilizes power in a non-orthogonal fashion to enhance the spectrum efficiency of the network. Figure 2 shows the basic architecture of the NOMA system. This paper explains the implementation of DL methods in wireless cellular systems to estimate the radio channel quality that is essential for the design of transmitting data.

In the mMIMO-NOMA system, the users are accumulated in a cluster and are served using multiple antennas at the base station (BS) via zero-Forcing (ZF) beamforming technique [4]. Let's assume the total number of users in the system are K, for the i^{th} user the signal can be expressed as y(t):

$$y(t) = \sum_{i=1}^{K} \sqrt{p_i} s_i(t) \tag{1}$$

where p_i is the power coefficient and s_i is the signal of the i^{th} user (i = 1,2,⋯,K). Deep Neural Network (DNN) is a deeper version of a neural network that generally consists of three types of layers: input, hidden, and output. For n layer network, the output of the n^{th} layer y_n can be expressed as:

$$y_n = f(w_n * y_{n-1} + b_n) \tag{2}$$

where w_n is the weight matrix and b_n is the bias vector. For a classic DNN, the activation function is the sigmoid and is limited to [0, 1]. This article adopts a DNN in a mMIMO-NOMA system, the system divides the process of detection into channel estimation, MMSE detection and signal decision. The deep learning method can perform all these procedures as a single process. The matrix for the mMIMO-NOMA signal at the transmitter side can be expressed as:

$$M = (M_1, M_2, \dots, M_L) \tag{3}$$

where M_l is the m^{th} transmission antenna and it can be expressed as:

$$M_l = \sum_{k=1}^{K} \sqrt{P_k M_l^k} \tag{4}$$

NOMA technique strongly depends on the Successive Interference Cancellation (SIC) detection and it needs to be continuous process of decoding, reconstructing, and signal canceling. Allocated power to the users according to the channel gain is (P_1>P_2>⋯>P_K). Figure 2 also presents a DL model for MIMO-NOMA-DL signal detection. Keeping the online block inactive, the offline training will continue in the training state. The input of the DNN system will be the received mMIMO-NOMA signal and the DNN will optimize parameters by considering labelled data as supervised data. After the completion of training process the testing phase will commence. The results are generated when online block access the DNN and offline block is suspended.

Ⅲ. 결론

Figure 3 shows the gain of deep learning method over the conventional channel equalization schemes such as the least square (LS) and minimum mean square error (MMSE).

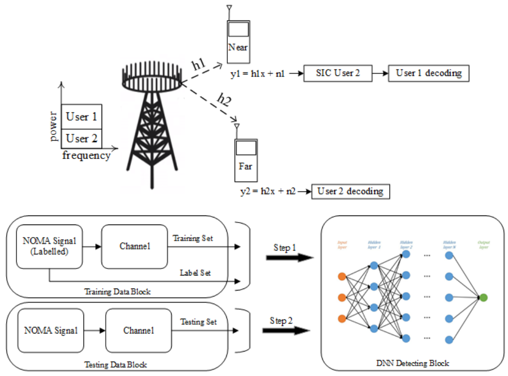

Figure 2: mMIMO-NOMA system model embedded with DL structure

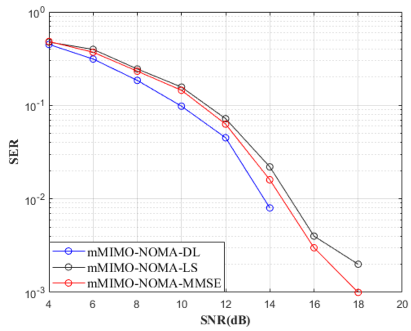

Figure 3: Performance comparison of mMIMO-NOM-DL with different channel estimation schemes

The MMSE inherently leads in the performance comparison with LS, where both the techniques are conventional. Compared to the DL method it is clear from the curves in Figure 3 that DL leads in the performance over LS and MMSE. For the increased signal-to-noise ratio (SNR), the symbol-error-rate (SER) improves systematically. Ths gives intuition that the system's throughput increases if the SER is optimized and hence the spectral efficiency also increases leading to the mass connectivity and high data rate.

In future works, online learning and testing can be considered, also other advanced DL approach can be developed for better signal detection or estimation.

ACKNOWLEDGMENT

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