1. introduction There are two reasons why deep learning is used.

With its recent development, deep learning has shown great achievements when applied to areas outside the computer science domain. Therefore, deep learning has also been applied to physical layer communication research such as channel coding and antenna technology. There are two reasons why deep learning is used to communication system.: Performance improvement, Reduced complexity. The primary goal of communication is that the receiver must receive the message accurately, but noise is added when a message passes through a channel, possibly preventing the receiver from receiving the message. To improve this, there is a process called encoding and decoding in the classical communication domain. There is a popular decoding method, known as the Belief Propagation Algorithm (BPA), also named the Sum Product Algorithm (SPA). This algorithm has good performance, but it is composed of many multiplication operations. Therefore, the longer the length of the message used as an input value, the more complicated calculation is. At that time, second reason to use deep learning is reducing complexity. To solve this problem, there is a solution called the min-sum algorithm (MSA). In min-sum algorithm, the complexity problem was improved, but performance loss degradation occurred. To properly adjust this trade-off relationship between performance and complexity, there are two algorithms: 1. a normalized min-sum algorithm (NMSA) that multiplies correction factor value, which is a constant value, from the check node update process. 2. an offset min-sum algorithm(OMSA) that adds or subtracts correction factor value from check node update process. By incorporating deep learning into existing communication systems, correction factor is optimized. As a result, Complexity is improved compared to BPA, and performance is improved compared to MSA.

<related work>

Recently, many researchers have been actively researching methods to incorporate deep learning into channel coding. A formative study, by Nachmani, used deep learning in the decoding process. By setting different weight values at the edges connecting check nodes(CN) and variable nodes(VN), [1] improved performance by reducing the effect of small cycles in tanner graphs during the decoding process [1]. In [2], unlike deep learning applied to BPA, Lugosch applied it to OMS. Deep Learning was used to obtain OMS’s optimized correction factor value. Particularly, OMS is an algorithm consisting of addition and subtraction, not multiplication, so it is a suitable method for an algorithm to hardware because of its low complexity. This algorithm is called a neural offset min-sum (NOMS). [3] conducted similar research where a neural normalized min-sum (NNMS) was proposed using an optimized correction factor through deep learning. Alternatively, Wang suggested another method. In order to improve the complexity problem, he used a sharing method that uses the same correction factor value for each iteration, unlike recent studies that used different correction factor values for each iteration and node. This algorithm is called a Shared Neural NMS (SNNMS).

Aforementioned research used deep learning to optimizing correction factor. However, there is a study focusing on refining the deep learning architecture for this application. Deep Learning has several architectures such as Deep Neural Network (DNN), Convolutional Neural Network(CNN), and Recurrent Neural Networks(RNN). [4] is a seminal work using ‘RNN’ called a ‘circular neural network’. This RNN utilizes past data for learning through concept of a recurrent. In other words, it is an algorithm that utilizes not only current inputs but also past data for learning. Remarkably, this first study to incorporate ‘RNN’ into the decoding process showed similar performance to prior studies using fewer parameters. However, this ‘RNN’ based method has two limitations. To be specific, input vectors are entered sequentially to enable sequential data processing, but ‘parallelization operation’ is not possible. The derivative value of tanh, activation function of RNN, is used in this case. However, there is a disadvantage that back propagation information is rarely transferred because a vanishing gradient occurs. To solve these problems, proposed method is using Long Short Term Memory (LSTM) along with the concept of relaxation [5]. Then, LSTM is a special case of ‘RNN’ and purpose of using relaxation concept is to determine how much previous data to use. And It is noteworthy that this method optimized decoder relaxation factor through deep learning rather than previous method, brute force simulation. In order to show excellent performance from our proposed method, simulations were conducted in BCH code, which is a high density parity check code (HDPC) and low density parity check code (LDPC) with different lengths. And Semiconductor company ‘NVIDIA’ recently announced an open source ‘sionna’ [6] to help research 5G communication using deep learning. Using 'sionna', I compared performance through simulation of Bit Error Rate (BER), which is number of bits that have errors in the process of being transmitted to the number of bits received.

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