1. introduction

With recent development of deep learning, It has shown great achievements in other areas. Therefore, it is also applied to physical layer communication research such as channel coding, MIMO(Multi Input Multi Output). Deep learning is applied to communication research for the following reasons: First, the goal of communication is that receiver must receive the message accurately, but noise is added when the message passes through the channel, so that the receiver may not receive the message. To improve this, there is a process called encoding and decoding in the classical communication domain. The first reason is to apply deep learning technology with decoding to achieve better performance. Second, Popular decoding method, known as Belief Propagation Algorithm (BPA) or the other name Sum Product Algorithm (SPA), has good performance, but it consists of many multiplication operation. Therefore, the longer the length of the message used as input value, the more complicated calculation is. To improve complexity problem, there is a solution called min-sum algorithm (MSA). In min-sum algorithm, complexity problem was improved, but performance loss degradation occurred. To properly adjust trade-off relationship of performance and complexity, there are two algorithm. First, normalized min-sum algorithm(NMSA) that multiplies correction factor value, which is a constant value, from check node update process. Second, offset min-sum algorithm(OMSA) that adds or subtracts correction factor value from check node update process. The reason for use of deep learning is that it wants to improve performance more than before by incorporating deep learning into existing communication system.

<related work>

Recently, many researchers have been actively researching deep learning into channel coding. Nachmani, channel coding's prior researcher, used deep learning in decoding process, and by setting different wieght values at the edges connecting check nodes(CN) and variable nodes(VN), performance was improved by reducing effect of small cycles in tanner graph during decoding process, and it is very meaningful in that it used deep learning for first time [1]. In [2], Lugosch did a study about OMS. It was used to obtain 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 low complexity. This algorithm is called neural offset min-sum(NOMS). In the case of [3], which conducted a similar research, neural normalized min-sum(NNMS) was proposed using an optimized correction factor by deep learning. And Wang suggested another way. In order to improve the complexity problem, he used shared method that uses the same correction factor value for each iteration, unlike recent one that used different correction factor values for each iteration and node. This algorithm is called Shared Neural NMS(SNNMS). Researches mentioned used deep learning for optimizing correction factor. However, there is a study focusing on deep learning architecture. Deep Learning has several architectures such as Deep Neural Network(DNN), Convolutional Neural Network(CNN), and Recurrent Neural Networks(RNN) and so on. In [4], it is a research using 'RNN'. It is called a 'circular neural network' and is a deep learning architecture that utilizes past data for learning through concept of recurrent. In other words, it is an algorithm that utilizes not only current inputs but also past data for learning. And, these research is remarkable. Because it was first study to incorporate 'RNN' into decoding process, and showed similar performance to previous study using fewer parameters. However, 'RNN' has two limitations. To be specific, input vectors are entered sequentially to enable sequential data processing, but 'parallelization operation' is not possible. And derivative value of tanh, activation function of RNN, is used, there is a disadvantage that back propagation information is rarely transferred because vanishing gradient occurs.

The way that I came up with to solve these problems is using Long Short Term Memory (LSTM). And proposed method used concept of relaxation [5], and purpose of proposed method is to determine how much to use previous data. In order to show performance excellence of 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. Then, Using 'sionna' [6], a tensorflow open-source library recently published by nvdia research group, 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.

<reference>

[1] Nachmani, Eliya, Yair Be'ery, and David Burshtein. "Learning to decode linear codes using deep learning."2016 54th Annual Allerton Conference on Communication, Control, and Computing (Allerton). IEEE, 2016.

[2] Lugosch, Loren, and Warren J. Gross. "Neural offset min-sum decoding." 2017 IEEE International Symposium on Information Theory (ISIT). IEEE, 2017.

[3] Wang, Qing, et al. "A model-driven deep learning method for normalized min-sum LDPC decoding." 2020 IEEE International Conference on Communications Workshops (ICC Workshops). IEEE, 2020.

[4] Nachmani, Eliya, et al. "RNN decoding of linear block codes."*arXiv preprint arXiv:1702.07560*(2017).

[5] Nachmani, Eliya, et al. "Deep learning methods for improved decoding of linear codes." IEEE Journal of Selected Topics in Signal Processing 12.1 (2018): 119-131.

[6] Hoydis, Jakob, et al. "Sionna: An Open-Source Library for Next-Generation Physical Layer Research." arXiv preprint arXiv:2203.11854 (2022).