

1. Introduction ~~There are two reasons why deep learning is used.~~

With its recent development ~~of deep learning~~, deep learning ~~It~~ has shown great achievements ~~in when applied to other areas outside the computer science domain~~. Therefore, ~~it deep learning is has~~ also been applied to physical layer communication research such as channel coding and, MIMO(Multi Input Multi Output) antenna technology. There are two reasons why deep learning is used in communication systems. Deep learning is has recently been applied to communication research for the following two main reasons: Pperformance improvement and ,Reduced complexity reduction. TheBased upon the first reason, is to apply deep learning technology with decoding is applied to communication systems with decoding to achieve better performance. Before the integration of deep learning, First, the goal of communication is that receiver must receive the message accurately, but noise, which is added when the a message passes through the a channel, can so that prevent the receiver may not from receiving the message. To improve this, there is a process called encoding and decoding in the classical communication domain. ThereThe first reason is to apply deep learning technology with decoding to achieve better performance. Second is, a pPopular decoding method, known as the Belief Propagation Algorithm (BPA), or the otheralso named the Sum Product Algorithm (SPA). This algorithm, has good performance, but it consists ofis composed of many multiplication operations. Therefore, the longer the length of the message used as an input value, the more complicated calculation is. At thatIn such circumstances time, the second reason to use deep learning, is reducing complexity is important. To improve this complexitysolve this complexity problem, there is a solution called the min-sum algorithm (MSA). In this, this min-sum algorithm, the complexity problem was improved, but performance loss degradation occurred. To properly adjust this trade-off relationship of between performance and complexity, there are two algorithms:- 1.First, The a nNormalized min-sum algorithm (NMSA) that multiplies correction factor value, which is a constant value, from the check node update process. 2.-Second, The an oOffset min-sum algorithm (OMSA) that adds or subtracts correction factor value from check node update process. By incorporating deep learning in this way into existing communication systems, the correction factor is optimized. Remarkably, rResults from the use of these algorithms showed better performance than MSA and improved complexity than BPA, respectively. This is a remarkable pointcan be. The reason for use of deep learning these systems is that it wants to improve performance can be further improved. more than before by incorporating deep learning into existing communication system.

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메모 포함[NP1]: Is this an example?

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메모 포함[c2]: NMSA, OMSA is method, so I think i...

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메모 포함[NP3]: If you wanted to you could shorter...

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서식 있음: 글꼴 색: 빨강

서식 있음: 글꼴 색: 텍스트 1

<related work>

Recently, many researchers have been actively researching methods to incorporate deep learning into channel coding. A formative study, by Nachmani, channel coding's prior researcher, used deep learning in the decoding process, and by By setting different weight values at the edges connecting check nodes(CN) and variable nodes(VN), [1] improved performance was improved by reducing the effect of small cycles in tanner graphs during the decoding process, and it is very meaningful in that it used deep learning for first time [1]. In [2], unlike deep learning's application applied to BPA, Lugosch applied it to OMS (did a study about OMS Deep Learning). The OMS algorithm was used to obtain OMS's optimized correction factor value. More computations result in more complexity, more load, higher hardware devices temperatures, and permanent performance degradation. Therefore, to improve this, complexity is one of the problems that hardware must solve. Particularly, OMS is an algorithm consisting of addition and subtraction, not a more complex multiplication calculation, a complex calculation, 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). In the case of [3], which conducted a similar research where a, neural normalized min-sum (NNMS) was proposed using an optimized correction factor by through deep learning. And Alternatively, Wang et. al suggested another a different way method. In order to improve the complexity problem, he they used a sharing shared method that uses the same correction factor value for each iteration, unlike recent one studies that used different correction factor values for each iteration and node. This algorithm is called a Shared Neural NMS (SNNMS).

The aforementioned R Researches mentioned used deep learning for 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) and so on. In [4], it is a seminal research work using RNN. It is called a 'circular neural network', and This RNN is a deep learning architecture that utilizes past data for learning through the concept of a recurrent. In other words, it is an algorithm that utilizes not only current inputs but also past data for learning. Remarkably, And, this research is remarkable. Because this was first study to incorporate RNN into the decoding process, and showed similar performance to previous prior studies using fewer parameters. Subsequently, researcher improved performance by incorporating "relaxation" into the RNN architecture in [5]. The Purpose of using this relaxation concept was to determine how much previous data to use. Notably, this method optimized the decoder relaxation factor through deep learning as opposed to the previous method, brute force simulation.

메모 포함[NP4]: Instead of just listing, compare these works. What was done better, or worse or was improved upon.

메모 포함[NP5]: Use a reporting verb instead of "did a study"

메모 포함[NP6R5]: E.g. Lugosch examined the application of an OMS algorithm on a

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메모 포함[NP7]: Good.

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메모 포함[NP8]: "for an algorithm to hardware". The meaning of this phrase is unclear.

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메모 포함[c9]: [4] : use RNN architecture -> [5] : use RNN + relaxation.

메모 포함[NP10R9]: Got it.

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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. And 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.

And Also, the s-S-emiconductor company 'NVIDIA' recently announced an open source simulator 'sSionna' [6] to help research 5G communication using deep learning. In channel coding, there are many methods to compare performance, and I used Bit Error Rate (BER), which is number of bits that have errors in the process of being transmitted to the number of bits received. And it will be shown that performance is better when using our proposed method than when using RNN, 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.

메모 포함[c11]: Proposed method -> our method

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메모 포함[NP12]: Past tense used since this is referencing paper [5].

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메모 포함[NP13]: Run on sentence.

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메모 포함[NP14]: Run on sentence.

메모 포함[NP15]: In general, better. But I still want you to close with a summary the potential outcomes or applications of your work.

메모 포함[NP16R15]: However, you can submit this as is (after the changes I've made in this iteration of the writing).

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서식 있음: 글꼴: (영어) Helvetica, (한글) 굴림, 12 pt, 글꼴 색: 텍스트 1

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서식 있음: 글꼴: 굴림, 글꼴 색: 빨강

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