



Denoising autoencoder를 이용한 새로운 구조의 채널 denoiser

한소영, 김정현*, 송홍엽
연세대학교, 순천향대학교*

sy.han@yonsei.ac.kr

kimjh@sch.ac.kr

hysong@yonsei.ac.kr

2022.06.23.



목차

I. 서론

- 딥러닝을 적용한 오류정정부호 복호 기법
 - Hyper-Graph-Network Decoder
- Neural network channel denoiser
- Denoising autoencoder

II. 본론

- 제안한 수신기 학습 모델 구조
- 제안한 autoencoder denoiser 구조
- Polar(64,48)의 비트 오류율 및 블록 오류율 성능 비교

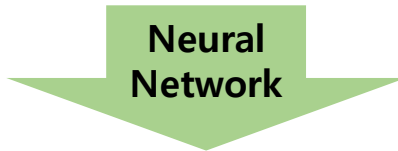
III. 결론

IV. 참고문헌



오류정정부호 복호 기법

- 기존 오류정정부호 복호 기법
 - Belief Propagation(BP)
 - Min-sum algorithm



- 딥러닝을 적용한 오류정정부호 복호 기법

Neural BP decoding [1]

Neural-offset min-sum decoding [2]

Hyper-Graph-Network (HGN) decoder [3] → 제안 모델에 사용

[1] Nachmani, E., Be'ery, Y., and Burshtein, D, "Learning to decode linear codes using deep learning," in Proc. Annu. Allerton Conf. Commun., Control, Comput, Sep. 2016, pp. 341–346.

[2] Lugosch, L., and Gross, W. J. "Neural offset min-sum decoding," in Proc. IEEE Int. Symp. Inf. Theory (ISIT), Jun. 2017, pp. 1361–1365.

[3] Nachmani, E., and Wolf, L. "Hyper-graph-network decoders for block codes," in Proc. Advances in Neural Inform. Proces. Systems (NIPS), 2019, pp. 2329–2339.



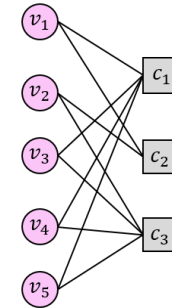
Hyper-Graph-Network (HGN) decoder

▪ HGN decoder [3]

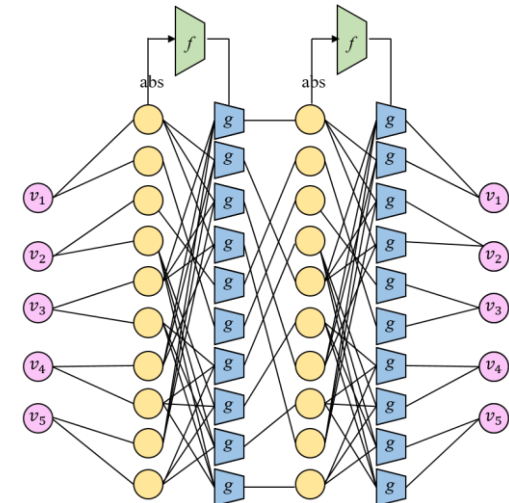
- “hypernetwork” 기법[4] 기반
- Variable 노드를 네트워크 g 로 대체,
그 가중치를 추가적인 네트워크 f 를 사용하여 예측

→ 다양한 code family에서 기존 learning-based 복호 성능을 능가

BUT, 충분한 성능을 얻기까지 긴 학습시간 요구



- Tanner graph for a linear block code with $n=5$, $k=2$, $d_v = 2$

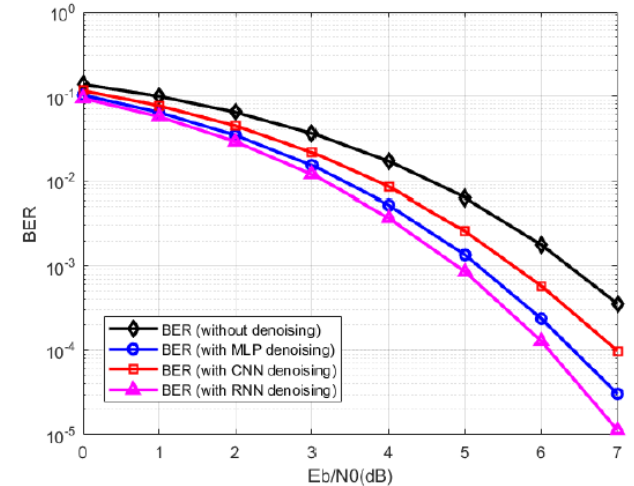


- Trellis graph (two iteration)



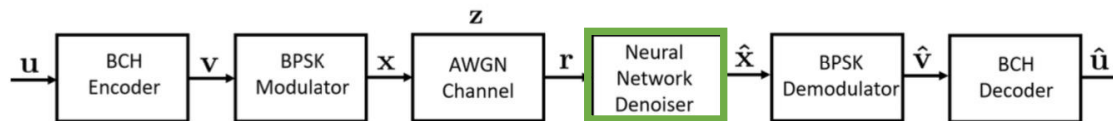
Neural network channel denoiser

- CNN, MLP, RNN 기법을 사용한 neural network (NN) channel denoiser를 제안 [6] - for BCH codes
- CNN, MLP, RNN 의 NN denoiser 모델에 residual connection을 추가하여 향상된 성능을 보임[7] - for Polar codes



(a) BER performance

BCH(15,7,2) BER performance [6]

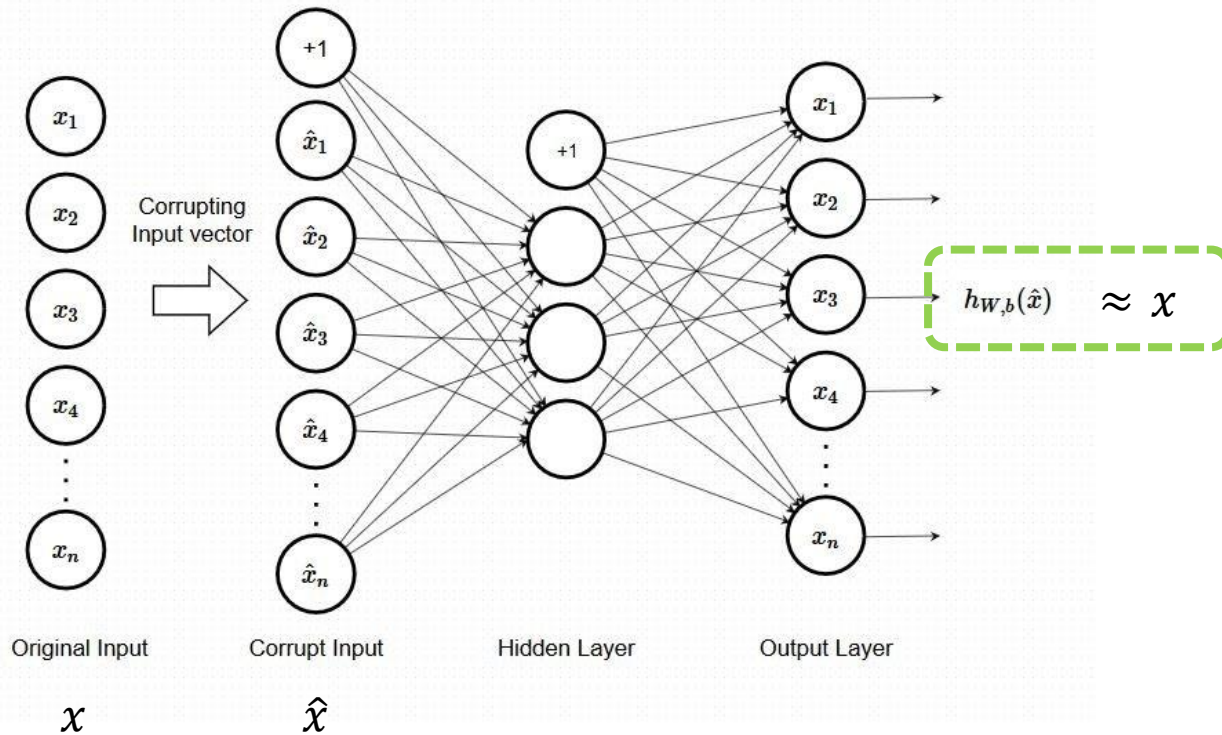


System model of NN denoiser for BCH codes [7]

[6] Zhu, H., Cao, Z., Zhao, Y., and Li, D, "A novel neural network denoiser for BCH codes," in Proc. IEEE/CIC Int. Conf. on Commun. in China (ICCC), Aug. 2020, pp. 272–276.

[7] Zhu, H., Cao, Z., Zhao, Y., and Li, D, "Learning to denoise and decode: A novel residual neural network decoder for polar codes," IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 8725–8738, Aug. 2020.

Denoising Autoencoder

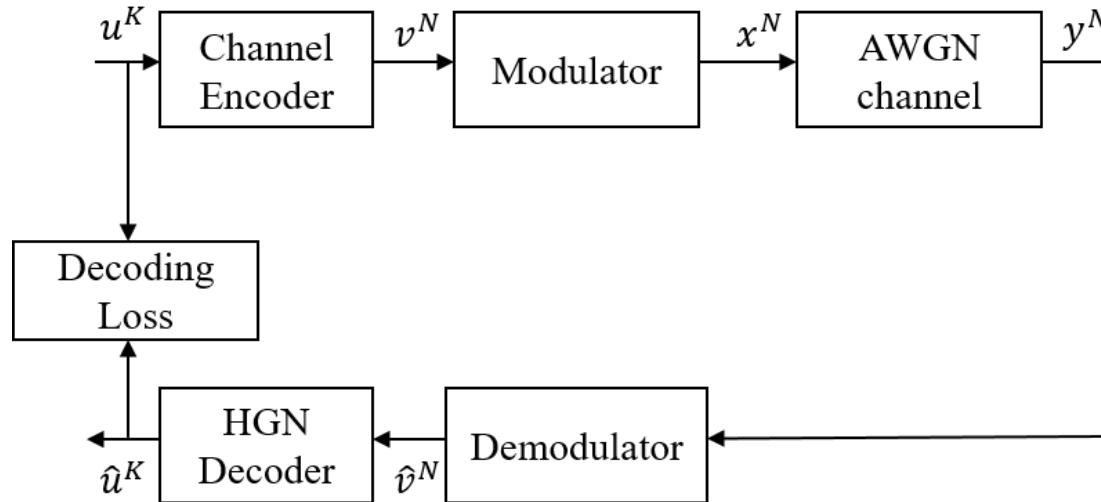


- 압축된 특성을 효과적으로 추출하는 Autoencoder 특성 이용
→ **노이즈 제거에 사용**
- 이미지 잡음 제거, 음성 신호 추출 등 노이즈 제거 분야에서 뛰어난 성능을 보임



Hyper-graph-network 복호기 학습 모델

- 기존 송수신기 모델 [3]



[3] Nachmani, E., and Wolf, L. "Hyper-graph-network decoders for block codes," in Proc. Advances in Neural Inform. Proces. Systems (NIPS), 2019, pp. 2329–2339.

제안한 수신기 학습 모델

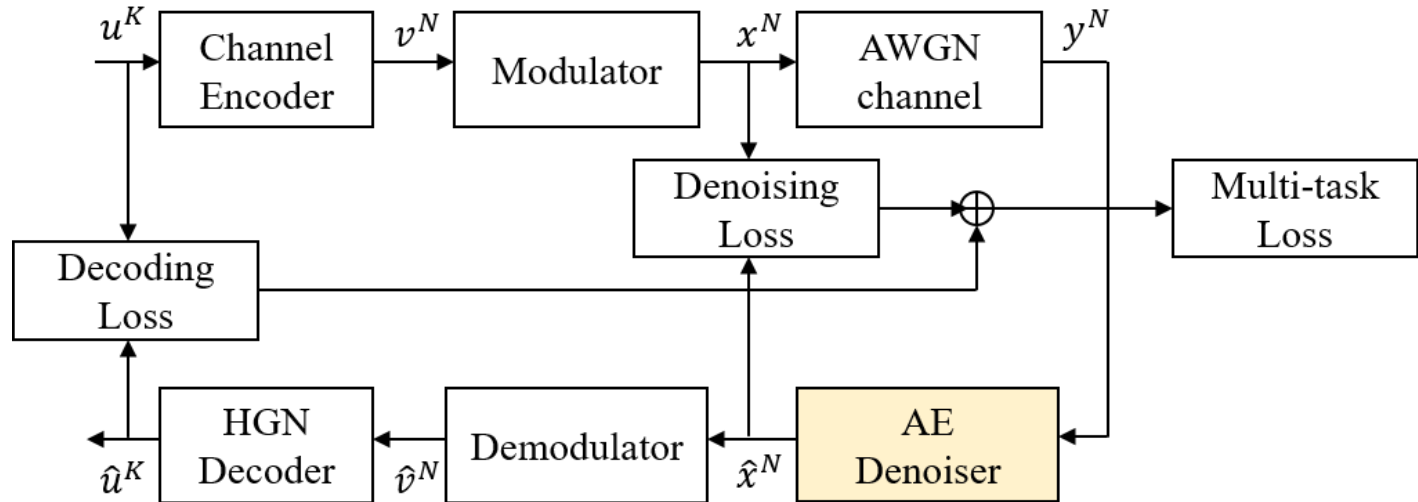


그림 1. 제안한 수신기 학습 모델 구조

▪ Multi-task Loss (L) [7]

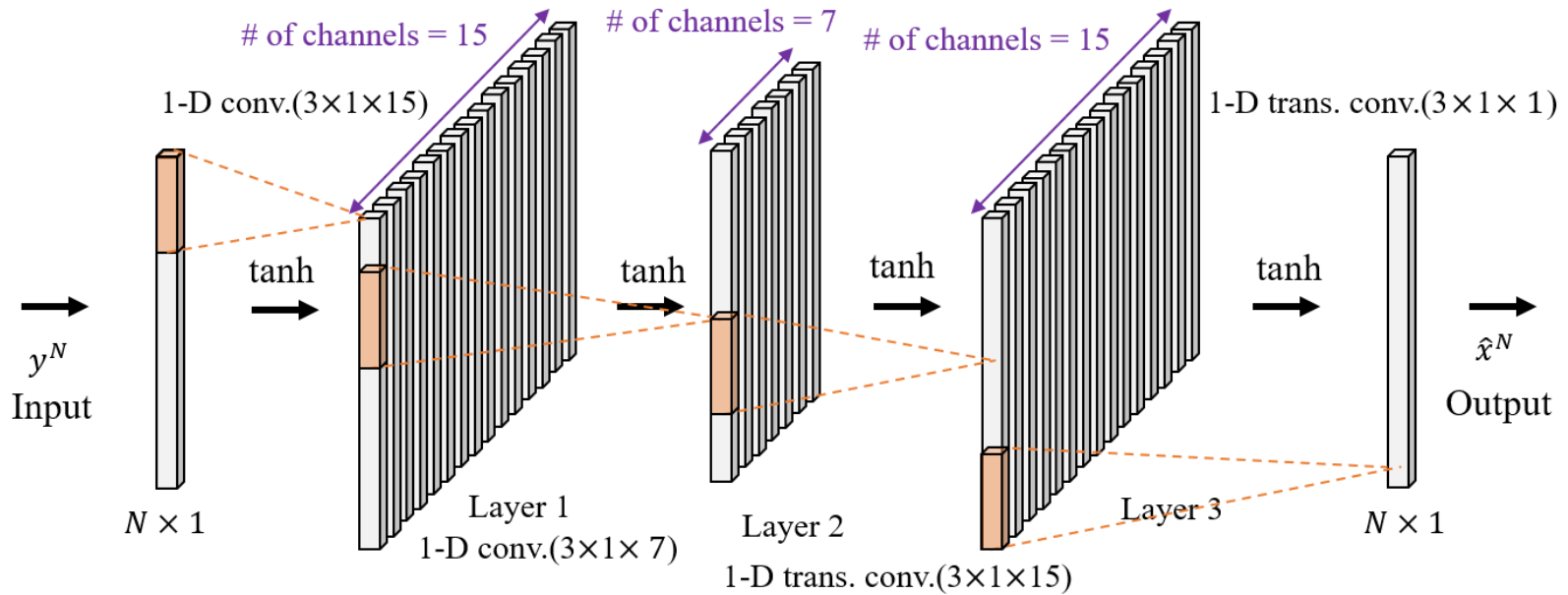
- $L = w_1 L_{Denoise} + w_2 L_{Decode}$ (1)

→ L 을 최소화하는 방향으로 jointly 학습

[7] Zhu, H., Cao, Z., Zhao, Y., and Li, D, "Learning to denoise and decode: A novel residual neural network decoder for polar codes," IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 8725–8738, Aug. 2020.



Denoising autoencoder channel denoiser



- Encoding part
 - 2개의 1D-convolutional layer
 - 채널 개수 : 15, 7
- Decoding part
 - 2개의 1D-transposed convolutional layer
 - 채널 개수 : 15, 1
- Filter size : 3×1

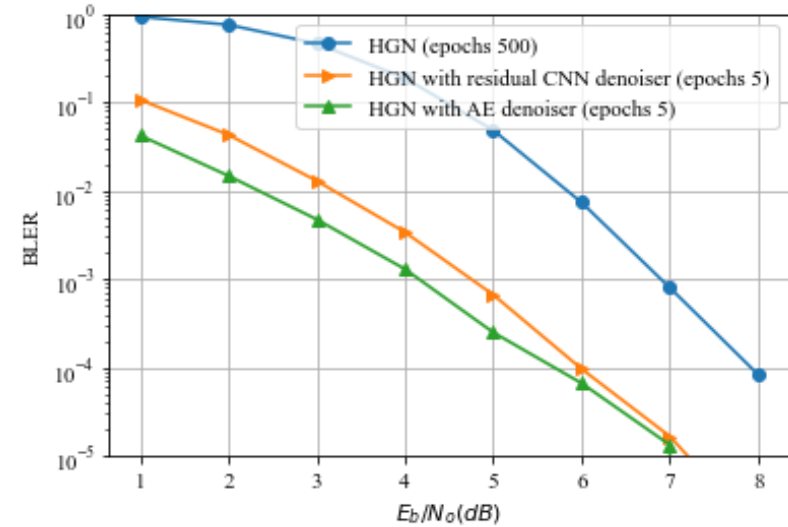
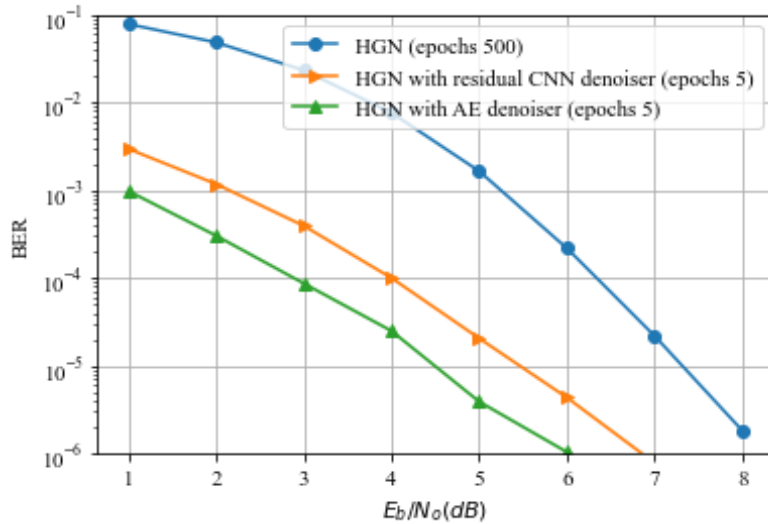


수신기 학습에 사용된 하이퍼 파라미터

파라미터	설정값
배치 크기	500
손실함수	Mean squared error(MSE)
최적화 방법	Adam optimizer, 학습률 = 10^{-5}
에포크 수	5



Polar (64,48) BER, BLER 성능 비교



■ 실험 환경

- 학습 : zero-codeword에 노이즈를 더해 진행
- 테스트 : generator matrix로 codeword를 생성하고 노이즈를 더해 실험

■ 실험 결과

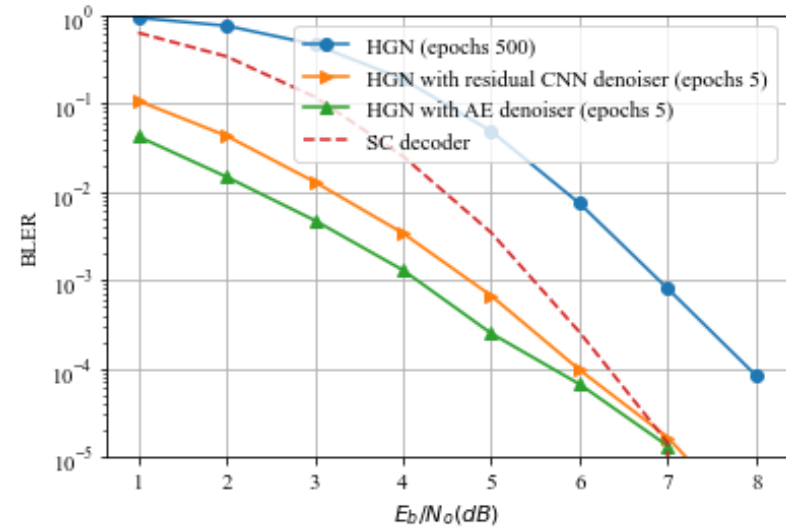
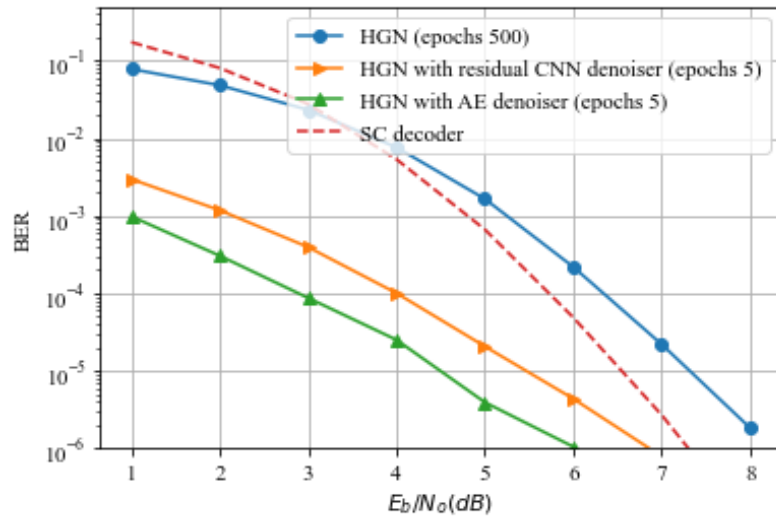
- 제안 기법이 residual CNN denoiser[7]를 접목한 HGN 복호기[3]보다 모든 SNR 영역에서 좋음
- 제안 기법이 denoiser 없는 HGN 복호기[3] 대비 1%의 에포크 만으로 향상된 성능을 보임
→ BER 10^{-4} 기준으로 약 3.5dB 개선, BLER 10^{-3} 기준으로 약 3dB 개선

[3] Nachmani, E., and Wolf, L. "Hyper-graph-network decoders for block codes," in Proc. Advances in Neural Inform. Proces. Systems (NIPS), 2019, pp. 2329–2339.

[7] Zhu, H., Cao, Z., Zhao, Y., and Li, D, "Learning to denoise and decode: A novel residual neural network decoder for polar codes," IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 8725–8738, Aug. 2020.



Polar (64,48) BER, BLER 성능 비교



■ 실험 환경

- 학습 : zero-codeword에 노이즈를 더해 진행
- 테스트 : generator matrix로 codeword를 생성하고 노이즈를 더해 실험

■ 실험 결과

- 제안 기법이 residual CNN denoiser[7]를 접목한 HGN 복호기[3]보다 모든 SNR 영역에서 좋음
- 제안 기법이 denoiser 없는 HGN 복호기[3] 대비 1%의 에포크 만으로 향상된 성능을 보임
→ BER 10^{-4} 기준으로 약 3.5dB 개선, BLER 10^{-3} 기준으로 약 3dB 개선

[3] Nachmani, E., and Wolf, L. "Hyper-graph-network decoders for block codes," in Proc. Advances in Neural Inform. Proces. Systems (NIPS), 2019, pp. 2329–2339.

[7] Zhu, H., Cao, Z., Zhao, Y., and Li, D, "Learning to denoise and decode: A novel residual neural network decoder for polar codes," IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 8725–8738, Aug. 2020.



결론

- Denoising autoencoder를 적용한 HGN 복호기의 성능향상을 실험을 통해 확인
 - Epoch : 500 → 5

- Future work
 - 여러 길이의 다양한 부호에 적용하여 제안 모델 성능 검증
 - 본 모델의 추가적인 구조 개선
 - 복잡도↓, 성능↑



참고문헌

- [1] Nachmani, E., Be'ery, Y., and Burshtein, D, "Learning to decode linear codes using deep learning," in Proc. Annu. Allerton Conf. Commun., Control, Comput, Sep. 2016, pp. 341–346.

- [2] Lugosch, L., and Gross, W. J. "Neural offset min-sum decoding," in Proc. IEEE Int. Symp. Inf. Theory (ISIT), Jun. 2017, pp. 1361–1365.

- [3] Nachmani, E., and Wolf, L. "Hyper-graph-network decoders for block codes," in Proc. Advances in Neural Inform. Proces. Systems (NIPS), 2019, pp. 2329–2339.

- [4] Ha, D., Dai, A., and Le, Q. V. "Hypernetworks," arXiv preprint arXiv:1609.09106, 2016.

- [5] Zhang, K., Zuo, W., Chen, Y., Meng, D., and Zhang, L. "Beyond a gaussian denoiser: residual learning of deep CNN for image denoising." IEEE transactions on image processing, vol. 26, no. 7, pp. 3142-3155, 2017.

- [6] Zhu, H., Cao, Z., Zhao, Y., and Li, D, "A novel neural network denoiser for BCH codes," in Proc. IEEE/CIC Int. Conf. on Commun. in China (ICCC), Aug. 2020, pp. 272–276.

- [7] Zhu, H., Cao, Z., Zhao, Y., and Li, D, "Learning to denoise and decode: A novel residual neural network decoder for polar codes," IEEE Trans. Veh. Technol., vol. 69, no. 8, pp. 8725–8738, Aug. 2020.

- [8] Vincent, P., Larochelle, H., Bengio, Y., and Manzagol, P. A. "Extracting and composing robust features with denoising autoencoders," in Proc. Int. Conf. Mach. Learn. (ICML), Mar. 2008, pp. 1096–1103.