Residual learning denoiser를 적용한 Hyper-Graph-Network 복호기

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오류정정부호 복호기법

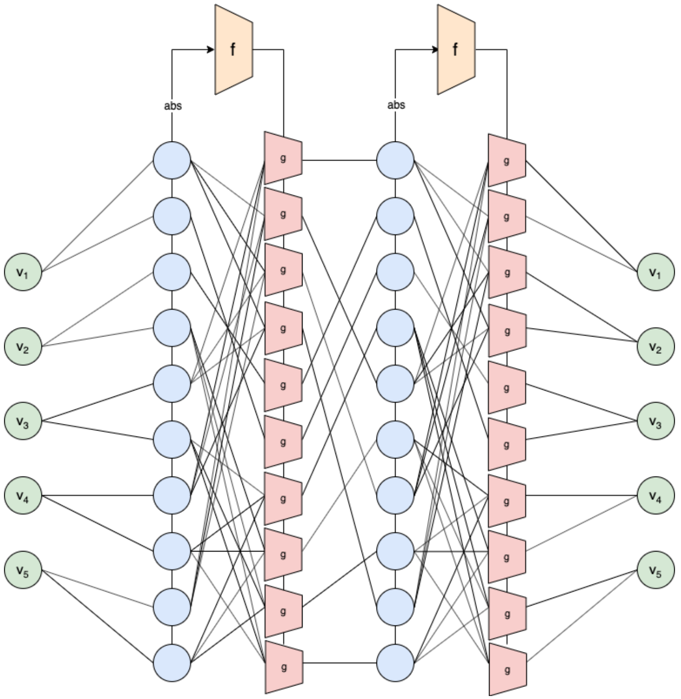
- **오류정정부호 복호기법**
  - Belief Propagation(BP)
  - Min- sum algorithm

Neural Network

- **딥러닝을 활용한 오류정정부호 복호기법**
  - Neural BP decoding [1]
  - Neural-offset min-sum decoding [2]
  - Hyper-Graph-Network decoder [3]

→ 기존 vanilla BP 성능을 능가

→ 충분한 성능을 얻기까지 학습시간이 오래 걸린다는 한계 존재



Trellis graph of
Hyper-graph-network decoder

[1] Eliya Nachmani, 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, pp. 341-346
[2] Lugosch, Loren, and Warren J. Gross. "Neural offset min-sum decoding." 2017 IEEE International Symposium on Information Theory (ISIT). IEEE, 2017, pp. 1361-1365
[3] Eliya Nachmani, and Lior Wolf. "Hyper-graph-network decoders for block codes." Advances in Neural Information Processing Systems, 2019, 32, pp. 2329-2339.

Residual learning

- **Resnet [5]**
  - 이미지 인식 분야에서 처음 제안되어,
    이미지 denoising 효과가 입증된 구조 [6]
  - Deep한 network에서의 성능 degradation을 해결하기 위해 residual(skip)-connection 적용

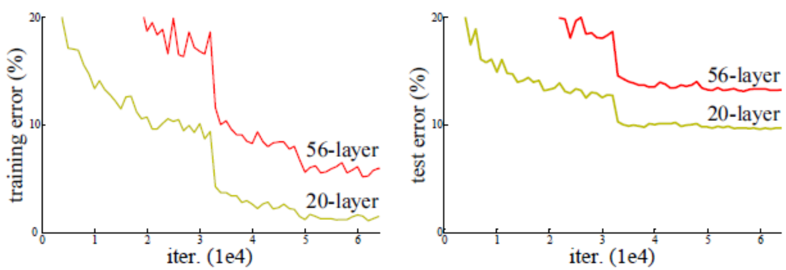


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

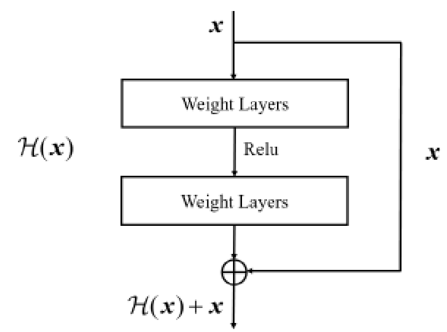


Fig. 4. Diagram of the residual learning block. $\mathcal{H}(x)$ corresponds to the stacked weight layers with Relu non-linearity.

$\boxed{H(x)+x \approx y}$

[5] He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016, pp. 770-778
[6] Zhang, Kai, et al. "Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising." IEEE transactions on image processing 26.7, 2017, pp. 3142-3155

Residual learning 기법을 활용한 복호기

- **Denoiser를 적용한 NN 복호기**
  - BCH 부호[7]와 Polar 부호[8] 각각에서 NN 복호기보다 향상된 성능을 보임
  - NN denoiser 구조로 MLP, CNN, RNN 사용

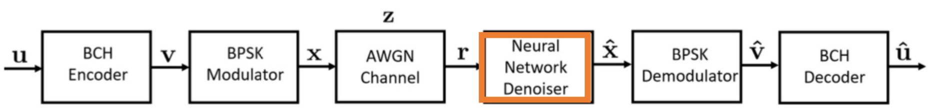
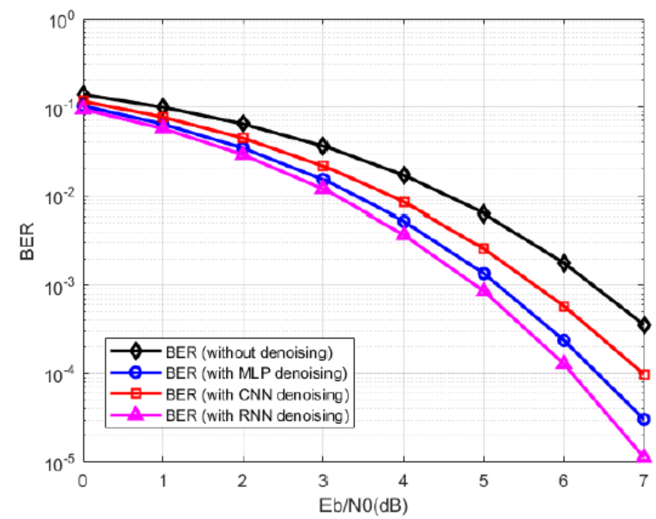


Fig. 1: The system model of the proposed neural network denoiser for BCH codes.

BCH(15,7,2)



(a) BER performance

[7] Zhu, Hongfei, et al. "A Novel Neural Network Denoiser for BCH Codes." 2020 IEEE/CIC International Conference on Communications in China (ICCC). IEEE, 2020, pp. 272-276
[8] Zhu, Hongfei, et al. "Learning to denoise and decode: A novel residual neural network decoder for polar codes." IEEE Transactions on Vehicular Technology 69.8 (2020), pp. 8725-8738.

Residual learning denoiser를 적용한 Hyper-Graph-Network 복호기

▪ **제안 모델**

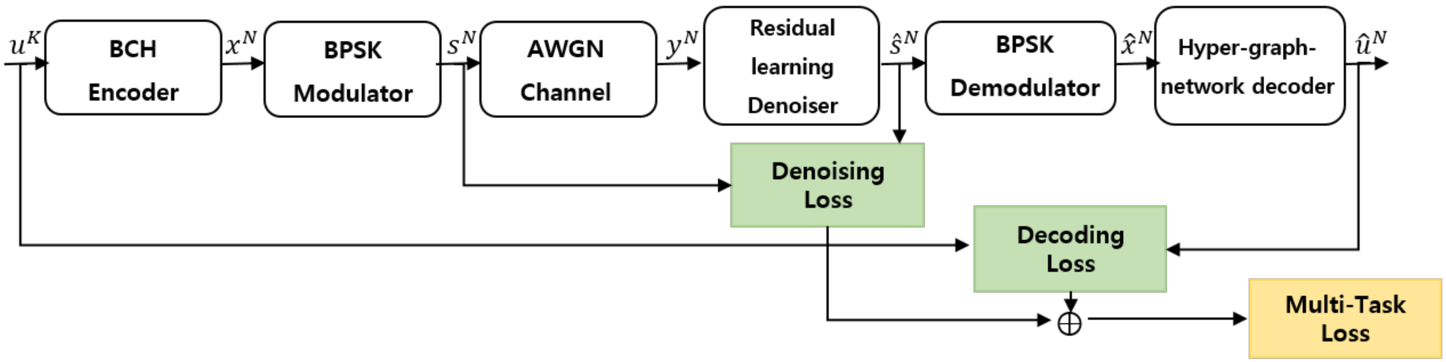
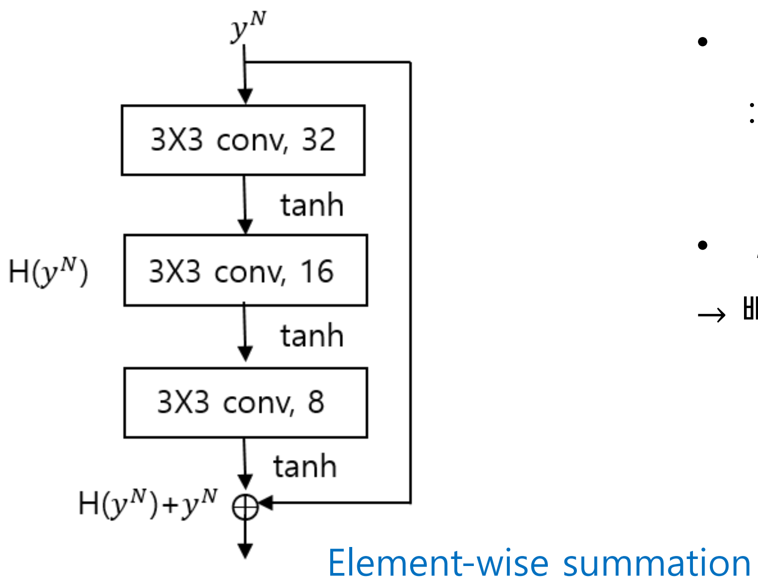


그림 1. 제안한 BCH 부호의 수신기 학습 모델 구조

Residual learning denoiser를 적용한 Hyper-Graph-Network 복호기

- **Residual learning denoiser 구조**



- Shortcut connection

  : $\hat{\boldsymbol{s}}^{\boldsymbol{N}} \approx \boldsymbol{s}^{\boldsymbol{N}}$

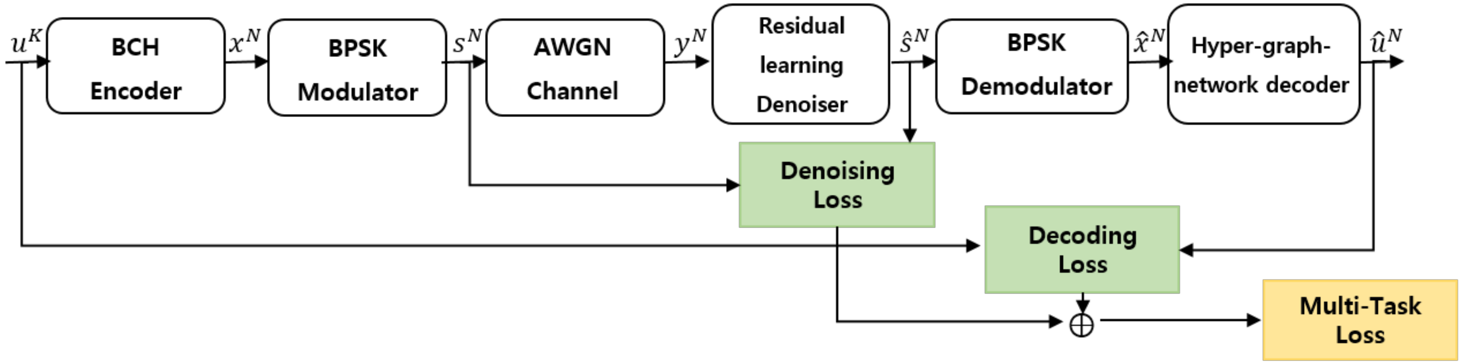
- $\hat{\boldsymbol{s}}^{\boldsymbol{N}}$ 의 label 인 $\boldsymbol{s}^{\boldsymbol{N}}$의 값을 -1,1로 정확히 알고있음

→ 빠른 학습!

$$\boxed{\mathbf{H}(\boldsymbol{y}^{\boldsymbol{N}})+\boldsymbol{y}^{\boldsymbol{N}} \approx \boldsymbol{s}^{\boldsymbol{N}}}$$

Residual learning denoiser를 적용한 Hyper-Graph-Network 복호기

- **Multi-task Loss (L)**
  - $L = w_1 L_{Denoise} + w_2 L_{Decode}$ (1)
  - Denoising loss와 decoding loss를 더하여 최종 loss로 지정하고 jointly 학습



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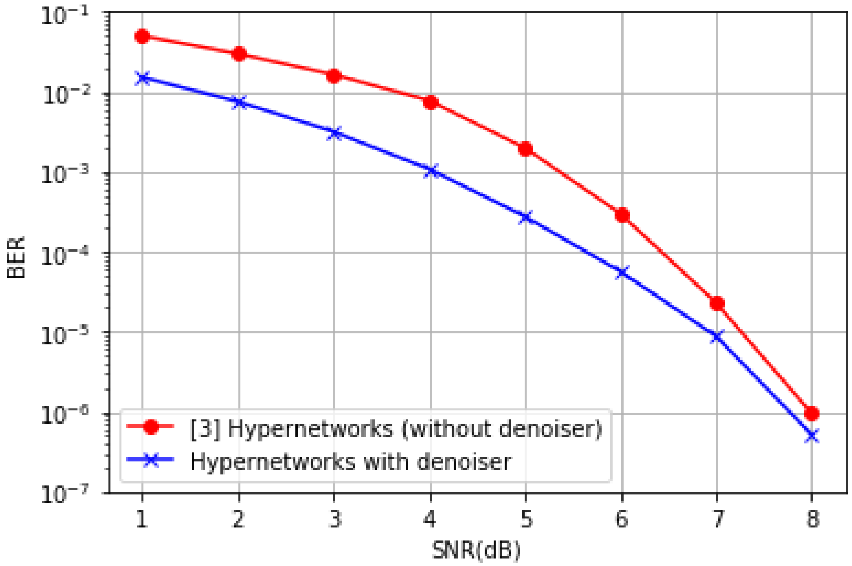
수신기 학습에 사용된 하이퍼 파라미터

파라미터	설정값
Denoiser 블록	3층 2D-CNN, 필터크기=3 채널개수 =32, 16, 8
배치 크기	256
손실함수	Mean squared error(MSE)
최적화 방법	Gradient Descent, 학습률 = 0.0001
에포크 수	25

(63,51) BCH 의 비트 오류율 성능 비교



- **실험 환경**
  - 학습 : zero-codeword에 노이즈를 더해 진행
  - 테스트 : generator matrix로 codeword를 생성하고 노이즈를 더해 실험
- **실험 결과**
  - 제안 기법이 기존 HGN 복호기보다 모든 영역에서 우수
  - BER 10^{-4}를 기준으로 약 1dB 의 SNR 개선
  - 낮은 SNR에서는 보다 큰 차이를 보여줌

결론

- Residual learning denoiser를 적용한 HGN 복호기의 성능향상을 실험을 통해 확인
  - Denoising에 효과적인 Resnet 구조 + multi-task loss 적용
- Future work
  - MLP, RNN 혹은 새로운 구조의 신경망을 residual learning denoiser에 적용
  - 긴 길이를 갖는 다양한 code family에 적용

    학습의 복잡도 ↓, 성능↑

참고문헌

[1] Eliya Nachmani, 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, pp. 341-346

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