## Joint Neural Network Equalizer and Decoder

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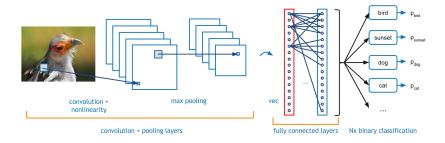
#### Outline

- 1. Motivation
- 2. Problem Formulation
- 3. Proposed CNN Equalizer and DNN Decoder
- 4. Results and Analysis
- 5. Conclusion

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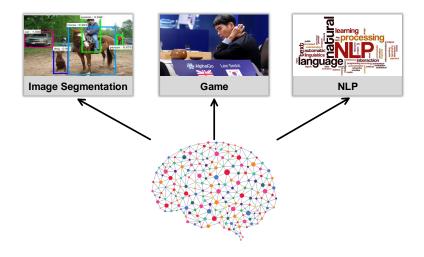
#### **Convolutional Neural Networks**



- Convolution: feature extraction by convolving various filters over input image
- Fully-connected: linear transform over input features
- Pooling and Non-linear: perform down sampling and non-linear function



### **Motivation**

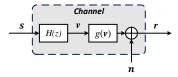




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### **Channel Equalization**



▶ Inter-symbol Interference (ISI) The channel with ISI is modeled as a finite impulse response (FIR) filter h. The signal with ISI is equivalent to the convolution of channel input with the FIR filter as follows:

$$v = s \otimes h$$
.

Nonlinear Distortion and Noise The nonlinearities in the communication system are mainly caused by amplifiers and mixers:

$$r_i = g[v_i] + n_i.$$



### Maximum Likelihood Equalizer

 $\triangleright$  **Estimation** Use training sequence  $s^{\circ}$  to estimate channel coefficients h that maximizes likelihood:

$$\hat{\boldsymbol{h}}_{ML} = \arg \max_{\boldsymbol{h}} p(\boldsymbol{r}^{\circ}|\boldsymbol{s}^{\circ}, \boldsymbol{h}).$$

▶ BCJR Use BCJR algorithm to find codeword that maximizes a posterior probability:

$$p(s_i = s | \mathbf{r}, \hat{\mathbf{h}}_{ML}), i = 1, 2...N.$$

- ▶ Pros & cons:
  - \* Good performance for ISI, but bad for nonlinear distortion
  - \* Require accurate channel state information (CSI)
  - \* Complexity:  $\mathcal{O}(n^2)$



<sup>&</sup>lt;sup>1</sup>[Olmos, Murillo-Fuentes, and Pérez-Cruz, TSP 2010]

#### **SVM** for Nonlinear Distortion

- ▶ Nonlinear Distortion Usually make signal non linearly separable.
- Support Vector Machine Perform nonlinear classification for received signal in high-dimensional feature spaces:

$$f(\mathbf{x}) = \sum_{i \in S} \alpha_i y_i \Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}) + b.$$

- ▶ Pros & cons:
  - \* Improve performance under nonlinear distortion
  - \* Require proper selection of kernel function  $\Phi({m x})$
  - \* Complexity:  $\mathcal{O}(n)$



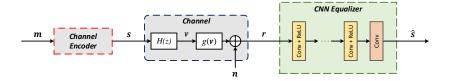
<sup>&</sup>lt;sup>1</sup>[Sebald and Bucklew, *TSP* 2000]

#### **Problems to Solve**

- > A unified framework with high adaptivity
- ▶ Inaccurate CSI or blind CSI
- Channel hard to model
- > Friendly for hardware design
- ▷ .....

#### **Outline**

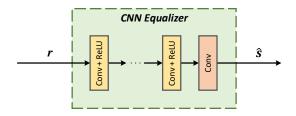
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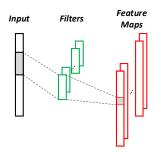
- ▷ Contain trainable filters to cope with various channels.
- ▷ End-to-end parameters training to maximize a posteriori:

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} p(\hat{\boldsymbol{s}} = \boldsymbol{s}^{\circ} | \boldsymbol{r}^{\circ}, \boldsymbol{\theta}).$$





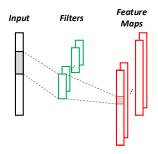
- ▶ Multi-layer fully convolutional network with ReLU activation.
- ▶ The last layer only contains convolution operation.



▶ Fully convolutional neural network with 1-D convolution:

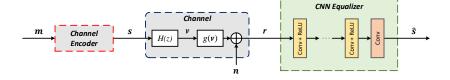
$$\mathbf{y}_{i,j} = \sigma(\sum_{c=1}^{C} \sum_{k=1}^{K} \mathbf{W}_{i,c,k} \mathbf{x}_{c,k+j} + b_i).$$





- $\quad \triangleright \ \, \mathsf{Use} \,\, 1 \times 3 \,\, \mathsf{sized} \,\, \mathsf{filters} \,\, \mathsf{and} \,\, \mathsf{padding} \,\, = \!\! 1.$
- ▷ To keep the signal dimension constant.
- ▷ Avoid information loss.

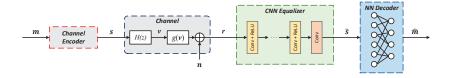




▶ Mean squared error (MSE) loss function:

$$\mathcal{L}(\hat{\boldsymbol{s}}, \boldsymbol{s}) = \frac{1}{N} \sum_{i} |\hat{s}_{i} - s_{i}|^{2}.$$

# **Proposed DNN Decoder**



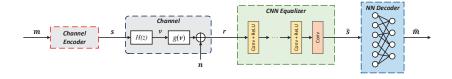
▷ A deep neural network (DNN) polar decoder:

$$\mathbf{y} = \sigma(\mathbf{W}\mathbf{x} + \mathbf{b}).$$

▷ DNN decoder with structure {16, 128, 64, 32, 8}.



# **Proposed DNN Decoder**

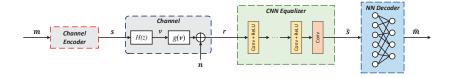


Binary cross entropy (BCE) loss function:

$$\mathcal{L}(\hat{\boldsymbol{m}}, \boldsymbol{m}) = \frac{1}{N} \sum_{i} \hat{m}_{i} \log(m_{i}) + (1 - \hat{m}_{i}) \log(1 - m_{i}).$$



# Joint Training of CNN and DNN



- ▶ The networks can be trained separately or jointly.
- ▶ Total loss of equalization and decoding:

$$\mathcal{L}_{total} = \mathcal{L}(\hat{m{s}}, m{s}) + \mathcal{L}(\hat{m{m}}, m{m}).$$



#### **Outline**

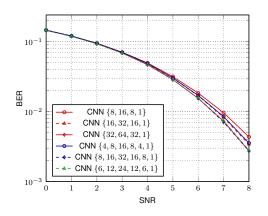
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# **Experiment Details**

- ▷ CNN structure: 6 layers
- $\triangleright$  Learning rate = 0.001
- ▶ Random codewords from SNR 0 dB to 11 dB
- ho Weights initialization:  $\mathcal{N} \sim (\mu = 0, \sigma = 1)$
- **Polar code**: (16,8)



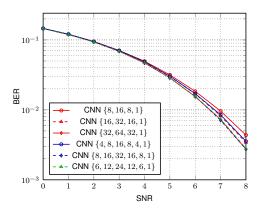
# **Select the Optimal Network Structure**



- ightharpoonup Deeper networks  $\longrightarrow$  Better performance
- ightharpoonup More filters  $\longrightarrow$  Better performance



# **Select the Optimal Network Structure**

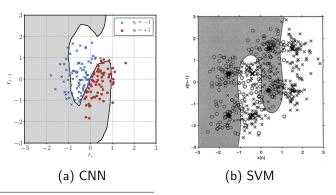


CNN {6, 12, 24, 12, 6, 1} (containing 2257 weights) is close to CNN {32, 64, 32, 1} (containing 12609 weights).



#### **Decision Boundaries**

- ▷ Test under h = [1, 0.5] and  $g(v) = v 0.9v^3$ .
- ▷ CNN has nonlinear decision boundaries similar to SVM.



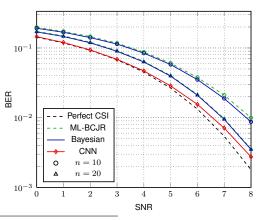
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#### Results on Linear Channel with ISI

▷ Channel coefficients:

$$H(z) = 0.3482 + 8704z^{-1} + 0.3482z^{-2}$$
.



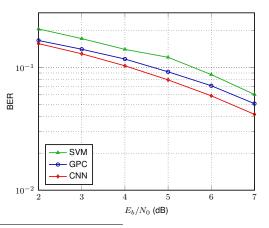
<sup>&</sup>lt;sup>1</sup>[Salamanca, Murillo-Fuentes, and Pérez-Cruz, *ISIT* 2010]



#### Results on Nonlinear Channel with ISI

▶ Nonlinear distortion:

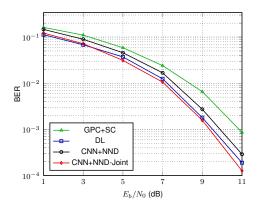
$$|g(v)| = |v| + 0.2|v|^2 - 0.1|v|^3 + 0.5\cos(\pi|v|).$$



<sup>&</sup>lt;sup>1</sup>[Olmos, Murillo-Fuentes, and Pérez-Cruz, *TSP* 2010]



#### Results on Joint DNN-CNN Detector

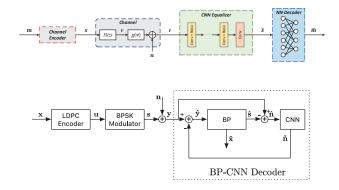


- Do Outperforms GPC+SC.
- $\triangleright$  Only requires about 1/3 parameters compared with DL method.



<sup>&</sup>lt;sup>1</sup>[Ye and Li, VTC-Fall 2017]

### **Analysis**



- ▷ Proposed design: CNN receives channel output.
- ▷ BP-CNN decoder in [5]: CNN receives output of BP decoder.



<sup>&</sup>lt;sup>1</sup>[Liang, Shen, and Wu, JSTSP 2018]

## **Analysis**

- ▶ Robust to different channel conditions.
- $\triangleright$  Computation complexity is about  $\mathcal{O}(n)$  due to the 1-D convolution.
- > Support various sequence lengths without retraining.



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#### **Conclusion**

- A channel equalizer based on CNN
  - Soft-in soft-out equalizer
  - Feasible for long code
- Near optimal performance under various channels
  - No need for accurate CSI
  - Linear complexity:  $\mathcal{O}(n)$
- Friendly to hardware design
  - Regular dataflow
  - Advanced CNN hardware architectures



#### **Future Work**

- Adopt depth-wise separable convolution
  - Prevent information loss
  - Reduce computation complexity
- High order modulation
  - Neural networks on complex domain



#### Reference

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Thanks for Your Attention!

