2018 GlobalSIP

Polar Feature Based Deep Architectures for Automatic Modulation Classification Considering Channel Impairments

Speaker: Chieh-Fang (Jeff) Teng

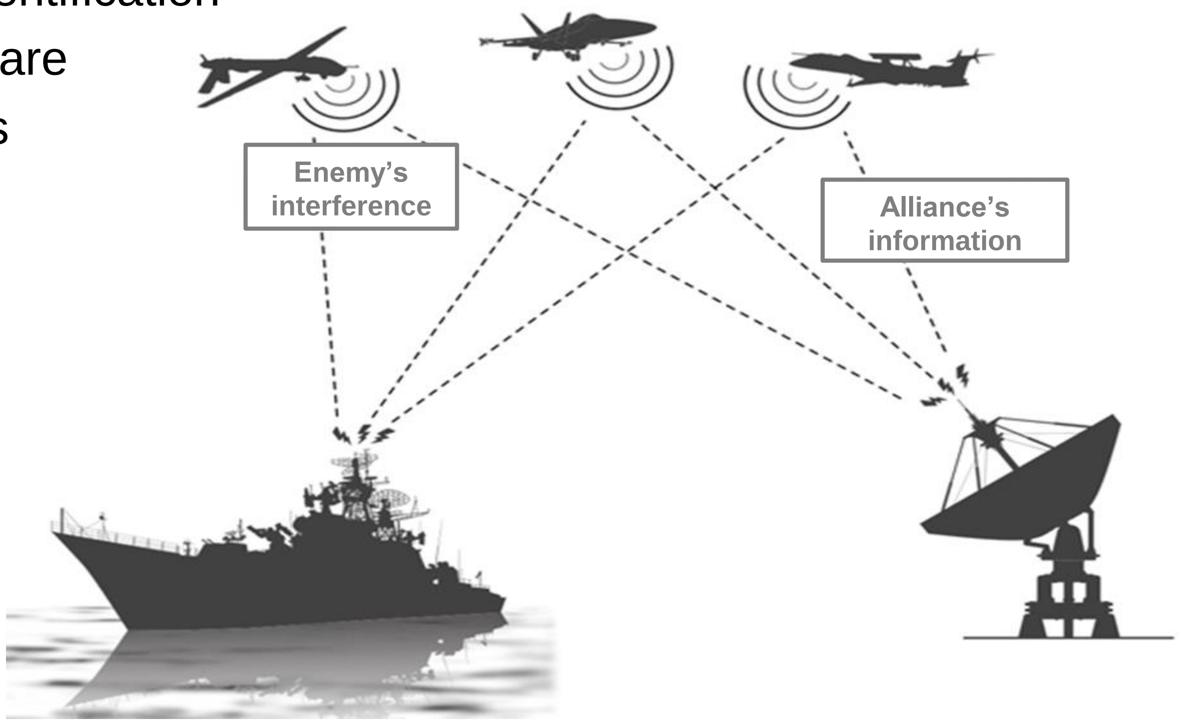
Email: jeff@access.ee.ntu.edu.tw

Advisor: Prof. An-Yeu (Andy) Wu

Date: 2018/11/29

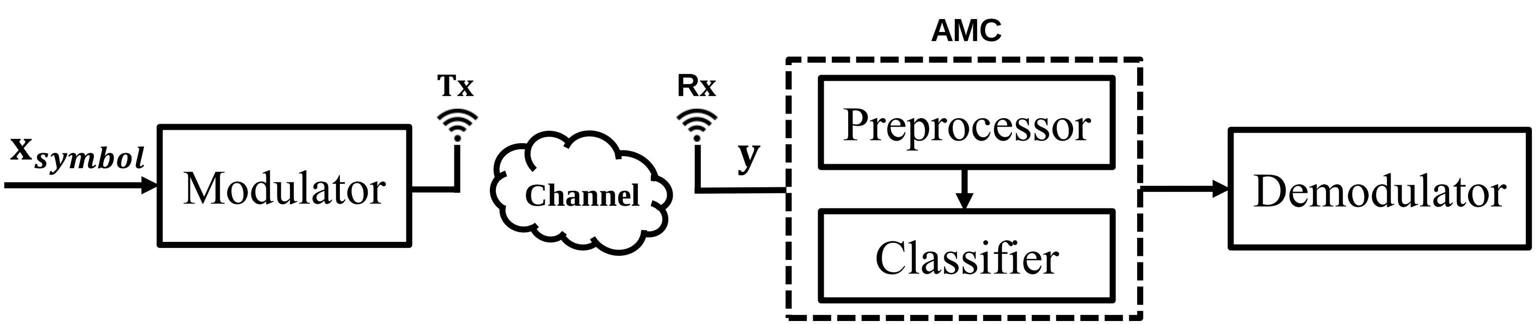
Automatic Modulation Classification (1/3) [1-5]

- Intermediate step between signal detection and demodulation
- Civilian and military applications
- The first time popular: in 2000
  - Interference identification
  - Electronic warfare
  - Threat analysis

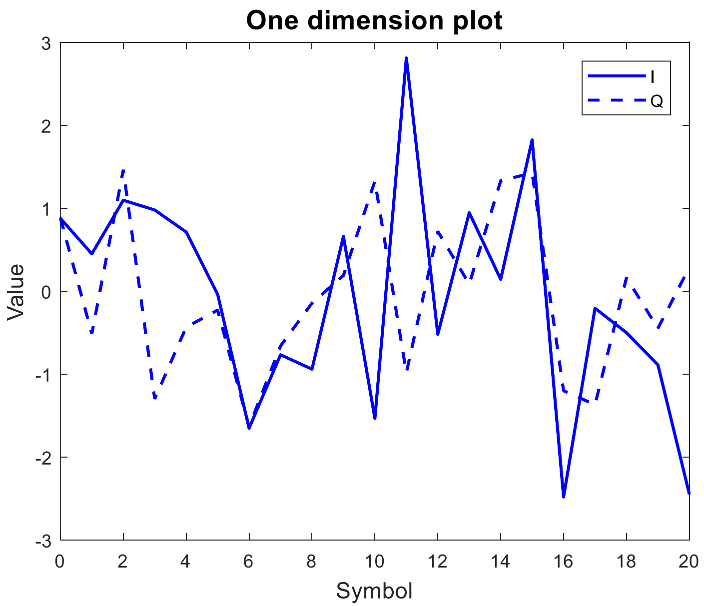


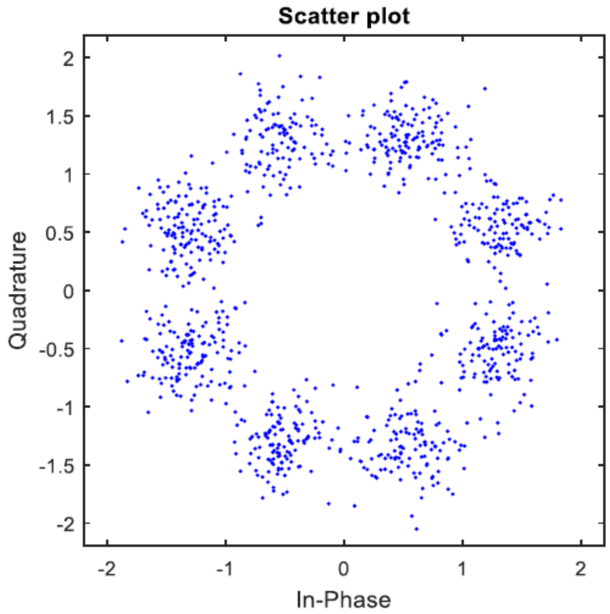
Automatic Modulation Classification (2/3) [1-5]

- Gradually become popular again (second half of 2016 ~ Now)
  - Techniques: Deep learning (DL)
  - Demands: 5G communications
    - Increase traffic demands
    - Reduce the signaling overhead of massive machine type devices
    - Offer different configurations in terms of Quality of Service (QoS)
- **Intelligent modem** by AMC
  - Dynamically switch the rate of data transmission
  - Without handshaking between Tx and Rx → latency & signaling overhead ↓
  - Optimize resource utilization → spectrum management



Automatic Modulation Classification (3/3) [1-6]





- Previous research works on AMC
  - **Likelihood-based approaches**: determine the probability density function and apply hypothesis testing, ex: maximum likelihood
  - **Feature-based approaches**: cumulant, maximum power spectral density, standard deviations amplitude, phase, frequency, …
  - Limited performance in complicated environment, e.g., fading channel

Automatic Modulation Classification [1-12]

- Previous research works on AMC [1-6]
  - Likelihood-based approaches: maximum likelihood
  - Feature-based approaches: cumulant
- Recent approaches [7-12]
  - Machine learning: support vector machine, K-nearest neighbor, genetic programming, …
  - Deep learning: deep neural network, convolutional neural network

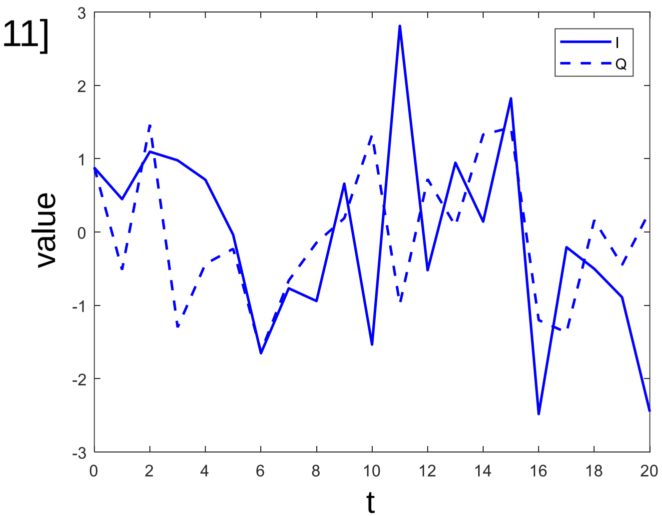
- Calculation of multiple decision thresholds is not convenient

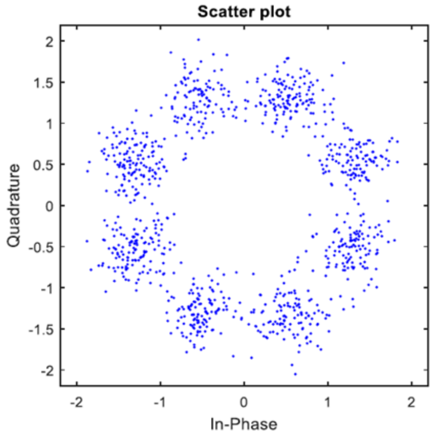
  ➔ learn the appropriate thresholds automatically
- Need high dimension of the feature set

  ➔ replace simplified analytic features to high-level features

AMC Using Convolutional Neural Network

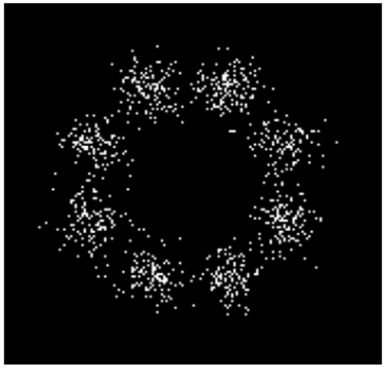
- 1-dimension convolutional neural network [10-11]
  - Split signal into I-Q two dimension
  - Training data: received modulation signal
- 2-dimension convolutional neural network [12]
  - Convert to image patterns
  - Grid-like images
  - Fix the image resolution 227*227





Complex samples

Data conversion

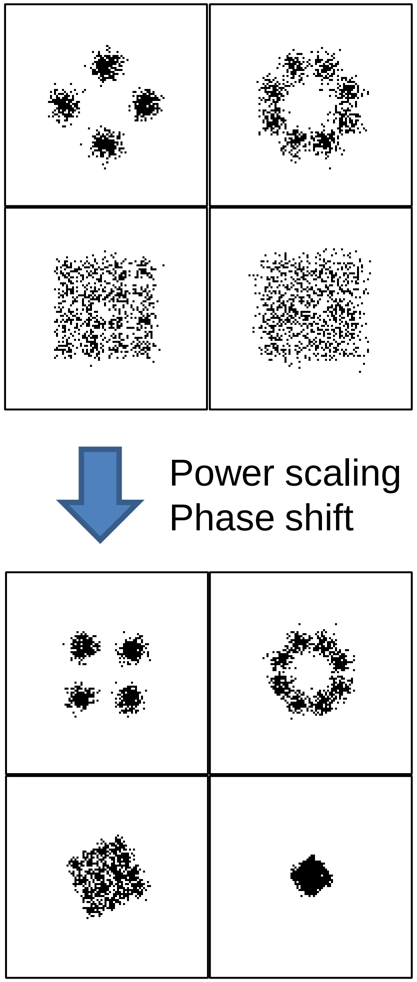


Images

Input data for 2D CNN model

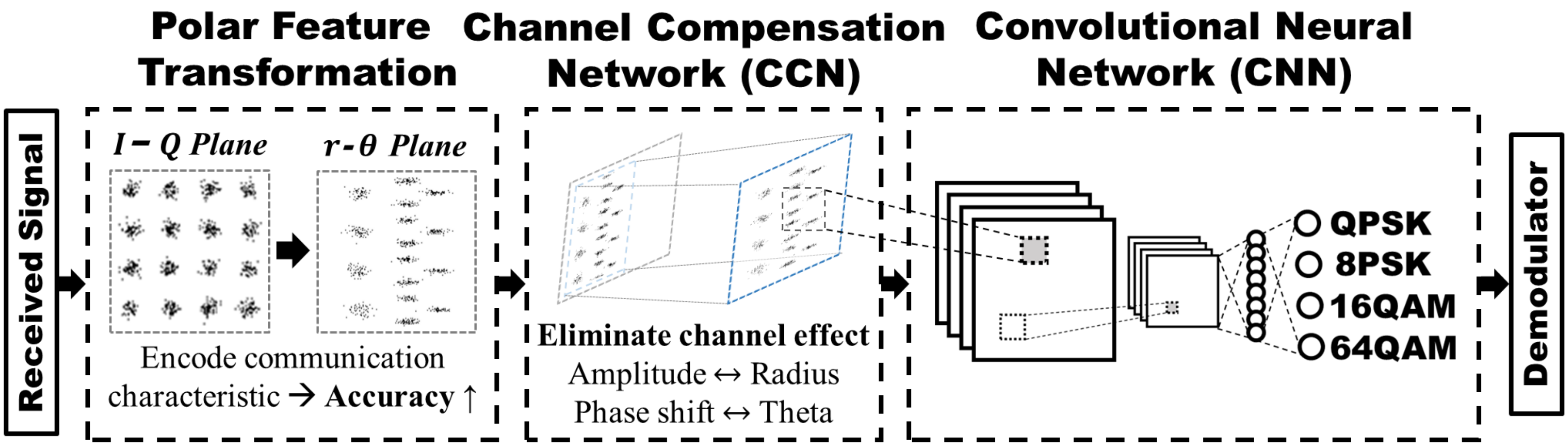
Motivation & Goal

- Directly transform and learn on I-Q domain may loss sense of communication
  - Value of I-Q has correlation
  - Try to encode communication characteristic



- Only consider AWGN channel is not practical
  - Power scaling and phase shift
  - Severely degrade the performance

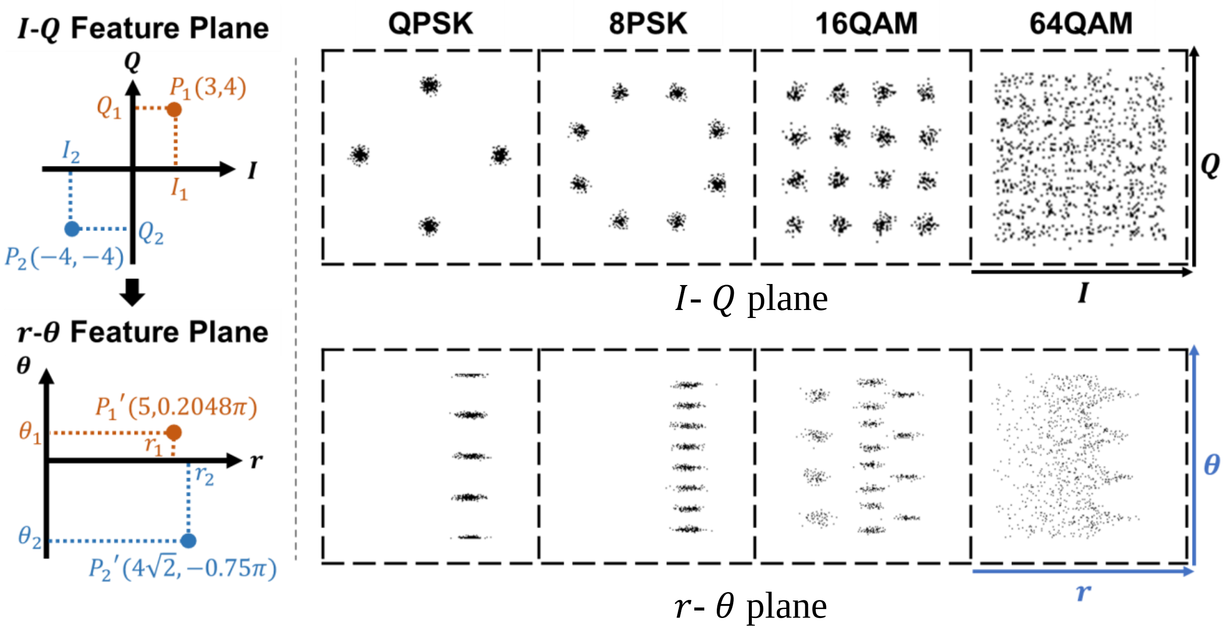
Proposed Deep Architecture for AMC



- Polar feature transformation
  - Transform the received symbols from I-Q to r-θ domain
  - Encode communication characteristic
- Channel compensation network (CCN)
  - Inspired by spatial transformer network [9]
  - Compensate for the distorted received signals

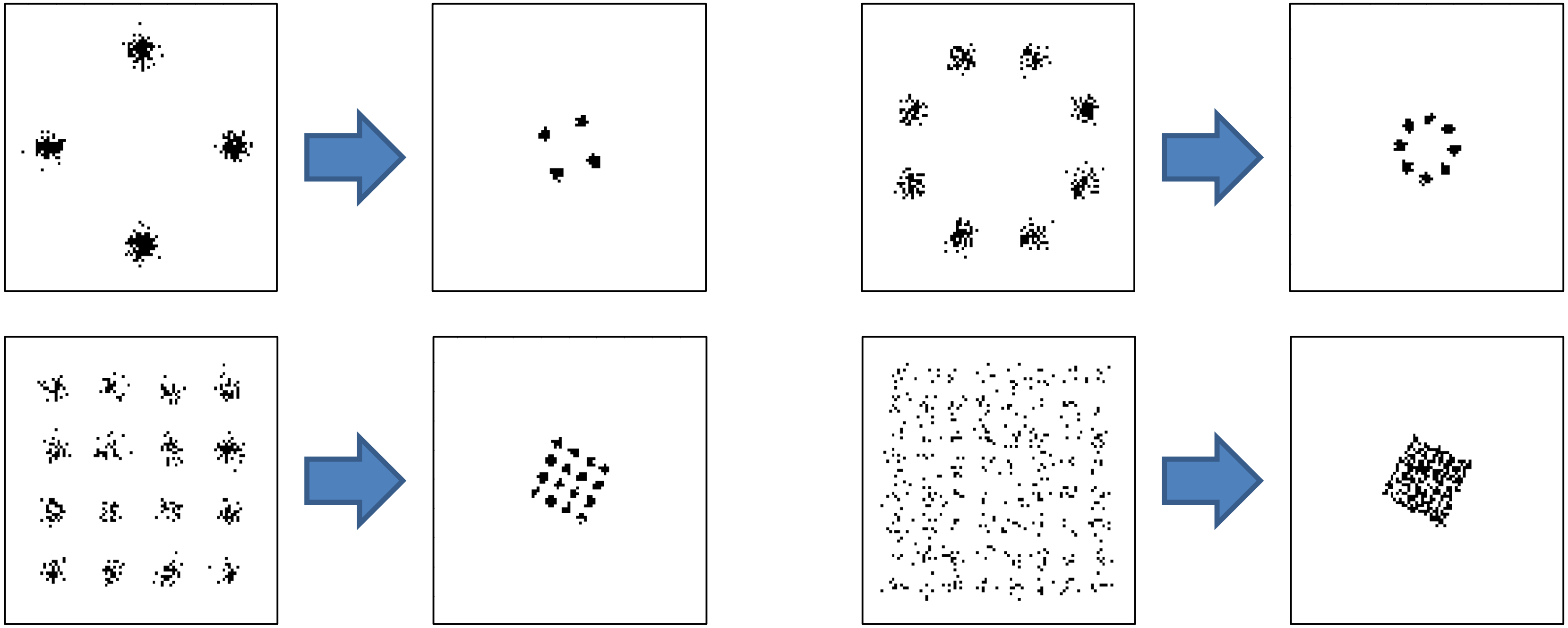
Proposed Polar Feature Transformation

- Encode specific relation between I & Q
- $radius[n] = \sqrt{I[n]^2 + Q[n]^2}$
- $theta[n] = arctan(\frac{Q[n]}{I[n]})$
- Make the system more robust to channel fading



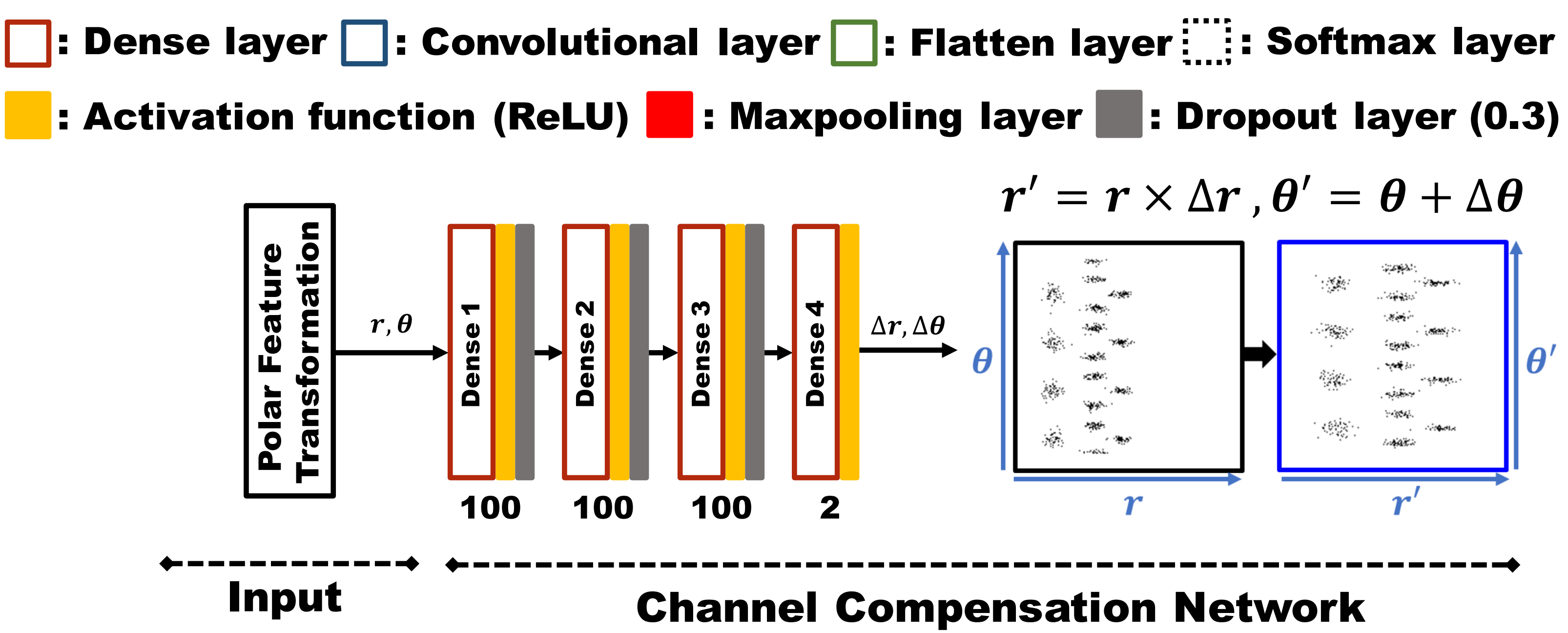
Realistic Environment: Channel Fading

- Besides to AWGN, received symbols suffer from channel imperfection effects
  - Power scaling and phase shift



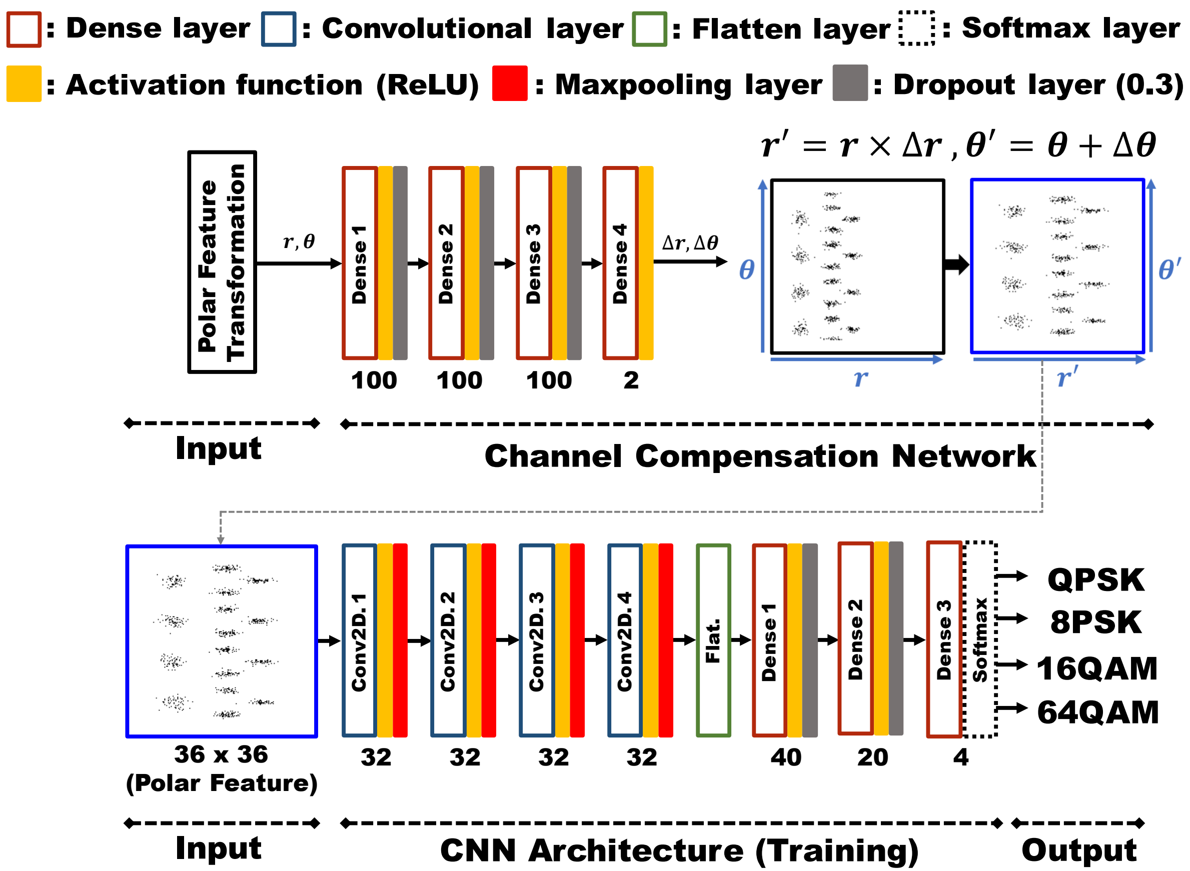
Proposed Channel Compensation Network

- Inspired by spatial transformer network from Google DeepMind [13]
- Learn the inverse channel parameters and reconstruct signals
  - $r' = r \times \Delta r$
  - $\theta' = \theta + \Delta\theta$



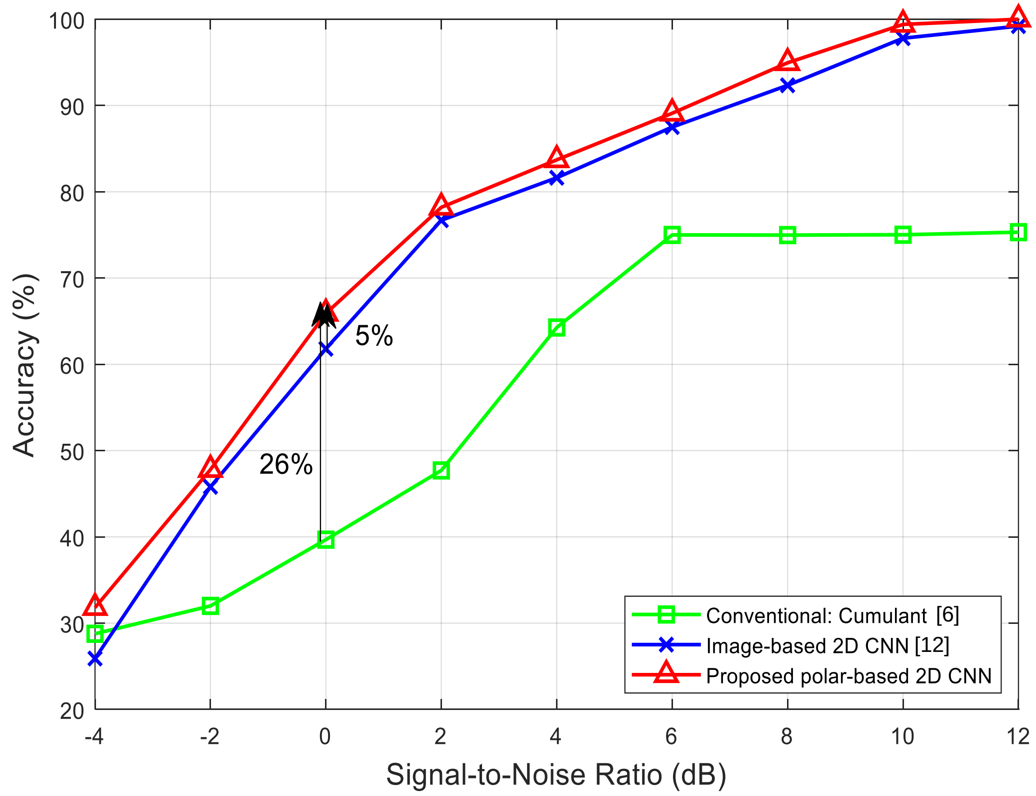
Deep Architecture with Channel Compensation Network

- The reconstructed signal is as input for the concatenated CNN model
- Loss function: categorical cross-entropy



Simulation Results – w/o Channel Fading

Parameter	Setups
Modulation type	QPSK 8PSK 16QAM 64QAM
SNR	-4 ~ 12
Total training images	20000
Total testing images	4000
Symbol length	1000



- Proposed polar feature based approach improves 5% and 26% recognition accuracy than image-based and cumulants approach when SNR equals to 0dB

Run Time of Different Approach

Different AMC Approach	Training Time with GPU (s)	Inference Time with CPU (s)
Image-based 2D CNN [12]	52.9556 (1x)	9.31e-04
Proposed polar-based 2D CNN	27.5152 (0.52x)	9.31e-04

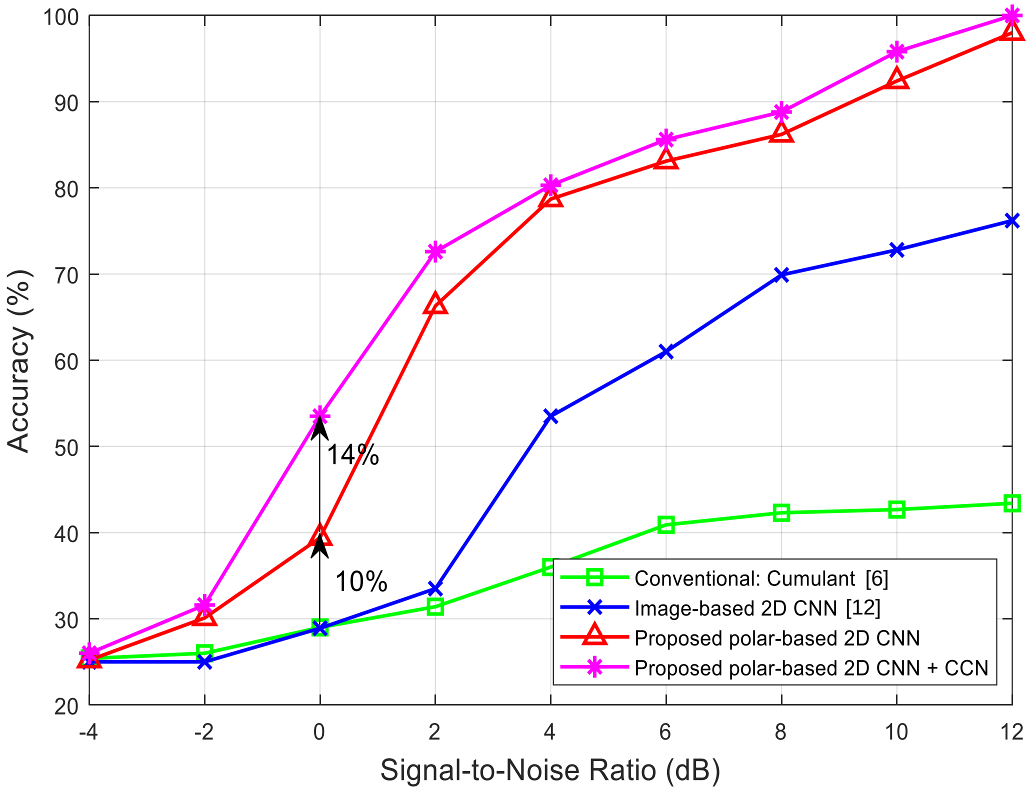
- Proposed polar feature transformation reduces the training overhead about 48% compared to image-based approach

➔ learning in r-θ domain has better performance and faster convergence speed

- The inference time is short enough for real time applications

Simulation Results – Under Channel Fading

Parameter	Setups
Modulation type	QPSK 8PSK 16QAM 64QAM
SNR	-4 ~ 12
Total training images	20000
Total testing images	4000
Symbol length	1000
Power scaling	**0.2 ~ 1**
Phase shift	$-\pi \sim \pi$



- Polar feature based approach is more robust and more resistant to channel distortion ➔ 10% better than I-Q based
- CCN can compensate the channel distortion and improve the recognition by 14%

Conclusion

- Automatic modulation classification is attractive in 5G communications for realizing intelligent receiver

- Learning in r-θ domain can improve recognition accuracy with faster convergence speed
- Channel compensation network (CCN) can compensate for the channel imperfection before learning and prediction
- Proposed approach is far more robust and more resistant under channel effect

Reference (1/2)

[1] Jondral, Friedrich K. "Software-defined radio: basics and evolution to cognitive radio." EURASIP journal on wireless communications and networking 2005.3 (2005): 275-283.

[2] Nolan, Keith E., et al. "Modulation scheme classification for 4G software radio wireless networks." Proc. IASTED. 2002.

[3] Haykin, Simon. "Cognitive radio: brain-empowered wireless communications." IEEE journal on selected areas in communications 23.2 (2005): 201-220.

[4] Sun, Hongjian, et al. "Wideband spectrum sensing for cognitive radio networks: a survey." IEEE Wireless Communications 20.2 (2013): 74-81.

[5] Dobre, Octavia A., et al. "Survey of automatic modulation classification techniques: classical approaches and new trends." IET communications 1.2 (2007): 137-156.

[6] Swami, A. and Sadler, B. M. “Hierarchical Digital Modulation Classification Using Cumulants,” IEEE Transactions on Communications, 48 (3), 416–429, 2000.

[7] Cheol-Sun Park, Won Jang, Sun-Phil Nah. and Dae Young Kim, “Automatic Modulation Recognition using Support Vector Machine in Software Radio Applications,” in Proc. 9th IEEE ICACT, Feb. 2007, pp. 9-12

Reference (2/2)

[8] X. Zhou, Y. Wu, B. Yang, “Signal Classification Method Based on Support Vector Machine and High-Order Cumulants,” Sicintific research, Wireless Sensor Networks, No. 2, pp. 48-52, Nov. 2009.

[9] M. W. Aslam, Z. Zhu, A. K. Nandi, “Automatic Modulation Classification Using Combination of Genetic Programming and KNN,” IEEE Transactions on wireless communications, vol.11, no.8, pp.2742-2750, Aug. 2012.

[10] O’Shea, Timothy J., Johnathan Corgan, and T. Charles Clancy, “Convolutional radio modulation recognition networks,” International Conference on Engineering Applications of Neural Networks. Springer International Publishing, 2016.

[11] Nathan E. West and Timothy J. O’Shea, “Deep architectures for modulation recognition,” In 2017 IEEE International Conference on Dynamic Spectrum Access Networks, March 2017.

[12] Peng, Shengliang, et al., “Modulation classification using convolutional Neural Network based deep learning model,” 26th Wireless and Optical Communication Conference (WOCC), 2017 26th. IEEE, 2017.

[13] Jaderberg, Max, Karen Simonyan, and Andrew Zisserman. “Spatial transformer networks,” Advances in Neural Information Processing Systems. 2015.

The end

Thank you for your listening

Appendix

AMC Using High-order Cumulant [6]

- Fourth-order cumulant of the complex-valued signal
  - $\hat{C}_{20} = \frac{1}{N}\sum_{n=1}^{N} r^2[n]$, $\hat{C}_{21} = \frac{1}{N}\sum_{n=1}^{N} |r[n]|^2$
  - $\hat{C}_{40} = \frac{1}{N}\sum_{n=1}^{N} r^4[n] - 3\hat{C}_{20}$
  - $\hat{C}_{41} = \frac{1}{N}\sum_{n=1}^{N} r^3[n]r^*[n] - 3\hat{C}_{20}\hat{C}_{21}$
  - $\hat{C}_{42} = \frac{1}{N}\sum_{n=1}^{N} |r[n]|^4 - \left|\hat{C}_{20}\right|^2 - 2\hat{C}_{21}^2$

	C_{20}	C_{21}	C_{40}	C_{41}	C_{42}
2-PAM	1.0000	1.0000	−2.0000	−2.0000	−2.0000
4-PAM	1.0000	1.0000	−1.3600	−1.3600	−1.3600
8-PAM	1.0000	1.0000	−1.2381	−1.2381	−1.2381
BPSK	1.0000	1.0000	−2.0000	−2.0000	−2.0000
QPSK	0.0000	1.0000	1.0000	0.0000	−1.0000
8-PSK	0.0000	1.0000	0.0000	0.0000	−1.0000
4-QAM	0.0000	1.0000	1.0000	0.0000	−1.0000
16-QAM	0.0000	1.0000	−0.6800	0.0000	−0.6800
64-QAM	0.0000	1.0000	−0.6191	0.0000	−0.6191

Difficult for classification!