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

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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

\[ x_{symbol} \xrightarrow{} \text{Modulator} \xrightarrow{} \text{Channel} \xrightarrow{} y \xrightarrow{} \text{Preprocessor} \xrightarrow{} \text{Classifier} \xrightarrow{} \text{Demodulator} \]
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-dimensional convolutional neural network \([10-11]\)
  - Split signal into \(I-Q\) two dimension
  - Training data: received modulation signal
- 2-dimensional convolutional neural network \([12]\)
  - Convert to image patterns
  - Grid-like images
  - Fix the image resolution 227*227

[Diagram showing data conversion and complex samples to images for input into a 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

Power scaling
Phase shift
Proposed Deep Architecture for AMC

- Polar feature transformation
  - Transform the received symbols from $I$-$Q$ to $r$-$\theta$ 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 $I$ & $Q$
- $radius[n] = \sqrt{I[n]^2 + Q[n]^2}$
- $theta[n] = \arctan\left(\frac{Q[n]}{I[n]}\right)$
- Make the system more robust to channel fading
Realistic Environment: Channel Fading

- Besides 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
  - \(r' = r \times \Delta r\)
  - \(\theta' = \theta + \Delta \theta\)

\[r' = r \times \Delta r, \theta' = \theta + \Delta \theta\]
Deep Architecture with Channel Compensation Network

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

![Diagram of CNN Architecture and Channel Compensation Network]

\[ r' = r \times \Delta r, \quad \theta' = \theta + \Delta \theta \]
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

<table>
<thead>
<tr>
<th>Different AMC Approach</th>
<th>Training Time with GPU (s)</th>
<th>Inference Time with CPU (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image-based 2D CNN [12]</td>
<td>52.9556 (1x)</td>
<td>9.31e-04</td>
</tr>
<tr>
<td>Proposed polar-based 2D CNN</td>
<td>27.5152 (0.52x)</td>
<td>9.31e-04</td>
</tr>
</tbody>
</table>

- Proposed polar feature transformation reduces the training overhead about 48% compared to image-based approach.
- Learning in $r$-$\theta$ domain has **better performance** and **faster convergence speed**.
- The inference time is short enough for real time applications.
Simulation Results – Under Channel Fading

- 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%

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setups</th>
</tr>
</thead>
<tbody>
<tr>
<td>Modulation type</td>
<td>QPSK, 8PSK, 16QAM, 64QAM</td>
</tr>
<tr>
<td>SNR</td>
<td>-4 ~ 12</td>
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<tr>
<td>Total training images</td>
<td>20000</td>
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<tr>
<td>Total testing images</td>
<td>4000</td>
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<tr>
<td>Symbol length</td>
<td>1000</td>
</tr>
<tr>
<td>Power scaling</td>
<td>0.2 ~ 1</td>
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<tr>
<td>Phase shift</td>
<td>$-\pi \sim \pi$</td>
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</tbody>
</table>
Conclusion

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

- Learning in $r$-$\theta$ 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)


The end

Thank you for your listening
Appendix
AMC Using High-order Cumulant [6]

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

<table>
<thead>
<tr>
<th></th>
<th>$C_{20}$</th>
<th>$C_{21}$</th>
<th>$C_{40}$</th>
<th>$C_{41}$</th>
<th>$C_{42}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-PAM</td>
<td>1.0000</td>
<td>1.0000</td>
<td>-2.0000</td>
<td>-2.0000</td>
<td>-2.0000</td>
</tr>
<tr>
<td>4-PAM</td>
<td>1.0000</td>
<td>1.0000</td>
<td>-1.3600</td>
<td>-1.3600</td>
<td>-1.3600</td>
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<tr>
<td>8-PAM</td>
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<td>1.0000</td>
<td>-1.2381</td>
<td>-1.2381</td>
<td>-1.2381</td>
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<td>-2.0000</td>
<td>-2.0000</td>
<td>-2.0000</td>
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<tr>
<td>QPSK</td>
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<td>1.0000</td>
<td>1.0000</td>
<td>0.0000</td>
<td>-1.0000</td>
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<tr>
<td>8-PSK</td>
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<td>0.0000</td>
<td>0.0000</td>
<td>-1.0000</td>
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<tr>
<td>4-QAM</td>
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<td>1.0000</td>
<td>1.0000</td>
<td>0.0000</td>
<td>-1.0000</td>
</tr>
<tr>
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<td>1.0000</td>
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<td>0.0000</td>
<td>-0.6800</td>
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<tr>
<td>64-QAM</td>
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<td>1.0000</td>
<td>-0.6191</td>
<td>0.0000</td>
<td>-0.6191</td>
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Difficult for classification!