Modulation Classification of Satellite Communication Signals Using Cumulants and Neural Networks

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Objective
• Correctly predict the transmitted modulation scheme

Applications
• Automatic receiver reconfiguration
  - Reduce transmission overhead due to modulation coordination
• Interference Mitigation
  - Identify and respond to interferers uniquely
• Spectrum Management
  - Automate violation notification process
Requirements

Classify typical satellite communication signals

- $\Omega = \{\text{BPSK, QPSK, 8-PSK, 16-APSK, 32-APSK, 16-QAM, 64-QAM}\}$

Evaluate performance with

- Various capture lengths
- AWGN, -5 to 20 dB
- Es/No approximation errors < 5 dB
- Phase and frequency offsets
- Nonlinear amplifier drive levels
- DVB-S2 pilots and headers

Assume

- Coarse carrier frequency estimation
- Symbol timing recovery
- Zero ISI, matched pulse shape filters
Cumulants
- Effective at differentiating modulation order
- Well documented in literature

Neural Networks
- Universal function approximator
- Showed increased accuracy over decision tree and SVM

Cumulant Generation

\[ S = \{s[n], \ldots, s[n], s^*[n], \ldots, s^*[n]\} \]

\[ C_{pq}(S) = \sum_{\pi} (-1)^{|\pi|-1} (|\pi| - 1)! \prod_{B \in \pi} E \left[ \prod_{i \in B} S_i \right] \]
Simulation Diagram

Preprocessing
- Coarse carrier removal
- Timing recovery
- Normalization
- \( y[n], z[n] \)

\[ r(t) \]

SNR estimator
\[ \{y[n]\}_{n=0}^{N-1} \]

Cumulant estimators
\[ \{y[n]\}_{n=0}^{N-1} \text{ or } \{z[n]\}_{n=0}^{N-1} \]

\[ \begin{bmatrix} \hat{E}_s \\ N_0 \\ |C_{20}| \\ |C_{40}| \\ |C_{41}| \\ |C_{42}| \\ |C_{60}| \\ |C_{61}| \\ |C_{62}| \\ |\bar{C}_{63}| \\ |C_{80}| \end{bmatrix} \]

Neural Network
\[ \hat{\Omega}_i \]

\[ x[n] = \text{symbols of } \Omega_i \]
\[ g[n] = \text{Gaussian noise} \]
\[ y[n] = Ae^{j(2\pi f_0 n T + \phi)} x[n] + g[n] \]
\[ z[n] = y[n] y^*[n-1] \]
Neural Network Architecture

Feed-Forward Multilayer Perceptron Network

Optimizer: Adaptive Moment Estimation (Adam)

Layer 0
Dense
(10,40)
tanh

Layer 1
Dense
(40,40)
tanh

Layer 2
Dense
(40,40)
tanh

Layer 3
Dense
(40,7)
softmax
What does the Neural Net see?

Each frame: N point sequence in IQ

Cumulants

Constant phase-offset

Frequency-offset

AWGN

Amplifier saturation

\[ z[n] = y[n - 1]y[n] \]

\[ y[n] \]
Vector Length Analysis

Feature vector generated from

\[ \{y[n]\}_{n=1}^{N} \]
\[ N = \{1k, 2.5k, 5k, 10k\} \]

\[ \{z[n]\}_{n=1}^{N} \]
\[ N = \{10k, 20k, 40k, 80k\} \]

For similar classification performance, classification based on \{z[n]\} required \sim 15x more symbols
• Frequency offset imposes upper bound on $y[n]$ sequence length
• $z[n]$ converts fixed frequency offset into fixed phase offset
• Cumulant magnitudes are not impacted by constant phase offset
Es/No Approximation Error

- Neural net requires SNR estimation
- Imperfect estimation of SNR will degrade performance
- Most sensitive to error at low Es/No
- $y[n]$ and $z[n]$ exhibit similar responses to Es/No error
- Results provide accuracy requirements for SNR estimator
Nonlinear Amplifier

- Previous results in literature did not account for nonlinear amplification
- Amplifier simulated using Saleh model using coefficients from operational TWTA
- PSK – only one ring, not impacted by amplifier
- Classification of higher order modulations experienced significant degradation at levels where a user could expect to operate
- Additional input features needed to train neural network over this dimension
Previous research has not measured impact of pilots/headers on classifier performance.

DVB-S2 physical layer extends alphabet of received symbols, due to inclusion of headers/pilots.

Unable to classify 16 APSK using $z[n]$ at 20 dB $Es/No$.

Classifier performance degradation due to DVB-S2 framing was < 5% in most cases.

IQ constellations of 32 APSK with and without DVB-S2 physical layer.
Next Steps and Conclusions

Next Steps

• Investigate additional features
• Implement a SNR approximation algorithm
• Classify modulation types in lab
• Add timing acquisition and carrier removal
• Classify live signals

Conclusions

• Created modulation classifier using cumulants and a neural network
• Evaluated performance over
  – Capture length
  – AWGN
  – Constant frequency and phase offset
• Extended previous work in field to include analysis over
  – SNR approximation error
  – Nonlinear amplifier distortion
  – DVB-S2 physical layer effects
Questions?
Classification by Modulation

Left: \( y[n] \)
Right: \( z[n] \)
Left: $y[n]$
Right: $z[n]$
DVB-S2 Pilots and Headers, Cont.

Probability of classifying modulation type with DVB-S2 headers (H) and pilots (P)

\( \frac{E_s}{N_0} = 20 \text{ dB} \)

\( z[n] \) signal type