Modulation Classification of Satellite Communication Signals Using Cumulants and Neural Networks

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Automatic Modulation Classification

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
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
Classification Method

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

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

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

Features
- Probability Density Function
- Spectral Statistics
- Fourier-wavelet
- Cumulants
- Autocorrelation
- Raw IQ
- Centroids

Classifiers
- Decision Tree
- Neural Network
- SVM
- Catalog Comparison
- KNN
Preprocessing

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

SNR estimator

Cumulant estimators

Neural Network

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

Feed-Forward Multilayer Perceptron Network

- Layer 0: Dense (10,40), tanh
- Layer 1: Dense (40,40), tanh
- Layer 2: Dense (40,40), tanh
- Layer 3: Dense (40,7), softmax

Optimizer: Adaptive Moment Estimation (Adam)

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

\(\Omega_i\)
What does the Neural Net see?

Each frame: N point sequence in IQ

Cumulants

Constant phase-offset

Frequency-offset

AWGN

Amplifier saturation

\[ y[n] \]

\[ z[n] = y^*[n - 1]y[n] \]
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
DVB-S2 Pilots and Headers

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: $z[n]$
Cumulant Magnitudes

Left: $y[n]$
Right: $z[n]$
Probability of classifying modulation type with DVB-S2 headers (H) and pilots (P)

Es/No = 20 dB

z[n] signal type