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
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

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

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

Preprocessing
- Coarse carrier removal
- Timing recovery
- Normalization
- $y[n], z[n]$

SNR estimator

Cumulant estimators

Neural Network

$r(t)$

Preprocessing block:
- Coarse carrier removal
- Timing recovery
- Normalization
- $y[n], z[n]$

SNR estimator:

Cumulant estimators:

Neural Network:

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

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

\[\hat{\Omega}_i\]
What does the Neural Net see?

Each frame: N point sequence in IQ

Cumulants

Constant phase-offset

Frequency-offset

AWGN

Amplifier saturation

\[ z[n] = y^*[n-1]y[n] \]
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
• 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
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 $\mathrm{Es/No}$.

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)

$\frac{E_s}{N_0} = 20 \text{ dB}$

$z[n]$ signal type