Modulation Classification of Satellite Communication Signals Using Cumulants and Neural Networks

Presented By: Aaron Smith

Authors: Aaron Smith, Mike Evans, and Joseph Downey
Information and Signal Processing Branch
NASA Glenn Research Center
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
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**

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

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

**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
- $y[n], z[n]$

$E_s$ estimator

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

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\[
\begin{bmatrix}
\hat{E}_s \\
\frac{N_0}{\hat{N}_0} \\
|\hat{C}_{20}\| \\
|\hat{C}_{40}\| \\
|\hat{C}_{41}\| \\
|\hat{C}_{42}\| \\
|\hat{C}_{60}\| \\
|\hat{C}_{61}\| \\
|\hat{C}_{62}\| \\
|\hat{C}_{63}\| \\
|\hat{C}_{80}\|
\end{bmatrix}
\]

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

Each frame: N point sequence in IQ

Cumulants

Constant phase-offset

Frequency-offset

AWGN

Amplifier saturation

\[ z[n] = y^*[n - 1]y[n] \]
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 ~15x more symbols
Frequency Offset

- 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

![Graph showing frequency offset impact on $P_c$]

- $F_{10k, z}$
- $F_{80k, z}$
- $F_{1k, y}$
- $F_{2.5k, y}$
- $F_{5k, y}$
- $F_{10k, y}$
- $F_{20k, y}$
- $F_{40k, y}$
- $F_{80k, y}$

Parameters:
- $f_0T$ on the x-axis
- $P_c$ on the y-axis
• 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 $E_s/N_0$.

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

Left: $y[n]$

Right: $z[n]$

$P_{e_{\alpha}}$
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