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

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

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

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

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

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

SNR estimator

Cumulant estimators

Neural Network

$r(t)$

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

\( \hat{E}_s \)
\( \frac{N_0}{C_{20}} \)
\( |C_{40}| \)
\( |C_{41}| \)
\( |C_{42}| \)
\( |C_{60}| \)
\( |C_{61}| \)
\( |C_{62}| \)
\( |C_{63}| \)
\( |C_{80}| \)

argmax

\( \hat{\Omega}_i \)
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

\[
\begin{align*}
\{y[n]\}_{n=1}^{N} \\
N &= \{1k, 2.5k, 5k, 10k\}
\end{align*}
\]

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

For similar classification performance, classification based on \{z[n]\} required ~15x more symbols
• Frequency offset 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

\[ \Omega_i = 32 \text{ APSK} \]

\[ \{z[n]\} \text{ w/o DVB-S2} \]

\[ \{z[n]\} \text{ w/ DVB-S2} \]
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: $z[n]$

Diagram showing $P_{c,n}$ as a function of $\frac{E_s}{N_0}$ [dB] for different modulation schemes:
- 16 APSK
- 32 APSK
- 2 PSK
- 4 PSK
- 8 PSK
- 16 QAM
- 64 QAM
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