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## Acronym List

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
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<tbody>
<tr>
<td>ABS()</td>
<td>Absolute Value</td>
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<tr>
<td>AS&amp;D</td>
<td>ASRC Federal Space and Defense</td>
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<tr>
<td>AUC</td>
<td>Area Under Curve</td>
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<tr>
<td>CERBM</td>
<td>Complex Entropy Rate Bound Minimization</td>
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<tr>
<td>CONUS</td>
<td>Continental United States</td>
</tr>
<tr>
<td>CQAMSYM</td>
<td>Complex Quadrature Amplitude Modulation</td>
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<tr>
<td>CSK</td>
<td>Complex Signal Kurtosis</td>
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<tr>
<td>CW</td>
<td>Continuous Wave</td>
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<tr>
<td>dB</td>
<td>Decibel</td>
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<tr>
<td>DDC</td>
<td>Digital Down Converter</td>
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<tr>
<td>DSP</td>
<td>Digital Signal Processing</td>
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<tr>
<td>DVB-S2</td>
<td>Digital Video Broadcasting - Satellite - Second Generation</td>
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<tr>
<td>ERBM</td>
<td>Entropy Rate Bound Minimization</td>
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<tr>
<td>ESTO</td>
<td>Earth Science Technology Office</td>
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<tr>
<td>FB</td>
<td>Full Band</td>
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<tr>
<td>FPGA</td>
<td>Field Programmable Gate Array</td>
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<tr>
<td>Gbps</td>
<td>Billions of Bits per Second</td>
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<tr>
<td>GMI</td>
<td>GPM Microwave Imager</td>
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<tr>
<td>GPM</td>
<td>Global Precipitation Measurement</td>
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<td>GSFC</td>
<td>Goddard Space Flight Center</td>
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<tr>
<td>H</td>
<td>Horizontal</td>
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<tr>
<td>ICA</td>
<td>Independent Component Analysis</td>
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<tr>
<td>INR</td>
<td>Interference to Noise Ratio</td>
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<td>MME</td>
<td>Maximum Minimum Eigenvalue ratio</td>
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<tr>
<td>MSE</td>
<td>Mean Square Error</td>
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<tr>
<td>NASA</td>
<td>National Aeronautics and Space Administration</td>
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<tr>
<td>NCCFSTICA</td>
<td>Non Circular Complex Fast ICA</td>
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<tr>
<td>PI</td>
<td>Principal Investigator</td>
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<tr>
<td>QPSK</td>
<td>Quadrature Phase Shift Keying</td>
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<td>RADAR</td>
<td>Radio Detection And Ranging</td>
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<tr>
<td>RF</td>
<td>Radio Frequency</td>
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<tr>
<td>RFI</td>
<td>Radio Frequency Interference</td>
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<tr>
<td>ROACH</td>
<td>Reconfigurable Open Architecture Computing Hardware</td>
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<tr>
<td>ROC</td>
<td>Receiver Operating Characteristic</td>
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<td>RRCOS</td>
<td>Root Raise Cosine</td>
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<tr>
<td>RSK</td>
<td>Real Signal Kurtosis</td>
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<tr>
<td>SB</td>
<td>Sub Band</td>
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<tr>
<td>SERDES</td>
<td>Serializer / Deserializer</td>
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<tr>
<td>SMAP</td>
<td>Soil Moisture Active Passive</td>
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<tr>
<td>V</td>
<td>Vertical</td>
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Motivation

• Unmitigated RFI (Radio Frequency Interference) can cause errors in science measurements
  – L- and C-Band: soil moisture measurements over land
  – L-, C- and X-band: ocean salinity, sea surface temperature, wind speed direction
  – K band: water vapor, liquid water

• Approach
  – RF front end development for 18 GHz (K band)
    • These allocations are known to be corrupted by direct broadcast services
  – Digital back end to allow sophisticated RFI detection and mitigation techniques
SMAP TA H-pol
1400 MHz

SMAP TA H-pol filtered

SMAP (Soil Moisture Active Passive) algorithms developed previously under ESTO (Earth Science Technology Office)

10 GHz GMI Tb V-pol (Vertical)

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The 18 GHz Channel sees significant RFI from surface reflections around CONUS (Continental United States) and Hawaii.
Real Signal Kurtosis (RSK)

Given a complex baseband signal \( z(n) = I(n) + jQ(n) \), the fourth standardized moment is computed independently for both the real and imaginary vectors, I and Q, as was used in SMAP[3].

\[
\text{RSK}_I = \frac{\mathbb{E}[(I-\mathbb{E}[I])^4]}{\left(\mathbb{E}[(I-\mathbb{E}[I])]\right)^2} - 3, \quad \text{RSK}_Q = \frac{\mathbb{E}[(Q-\mathbb{E}[Q])^4]}{\left(\mathbb{E}[(Q-\mathbb{E}[Q])]\right)^2} - 3
\]

The test statistic, RSK [2,3] (Real Signal Kurtosis), is then defined as

\[
\text{RSK} = \frac{|\text{RSK}_I| + |\text{RSK}_Q|}{2}
\]
Complex Signal Kurtosis

Complex signal kurtosis (CSK) [4,5] is used to improve ability of the digital radiometer to detect RFI. It makes use of additional information in complex signals.

Given a complex baseband signal $z(n) = I(n) + jQ(n)$, moments $\alpha_{\ell,m}$ of $z(n)$ are defined as

$$\alpha_{\ell,m} = \mathbb{E}[(z - \mathbb{E}[z])^{\ell}(z - \mathbb{E}[z])^{*m}], \quad \ell, m \in \mathbb{R} \geq 0$$

With $\sigma^2 = \alpha_{1,1}$, Standardized moments $q_{\ell,m}$ can then be found as

$$q_{\ell,m} = \frac{\alpha_{\ell,m}}{\sigma^{\ell+m}}$$

Leading to the CSK (Complex Signal Kurtosis) RFI test statistic used [4].

$$C_K = \frac{q_{2;2} - 2 - |q_{2;0}|^2}{1 + \frac{1}{2}|q_{2;0}|^2}$$

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Independent Component Analysis

- ICA [6] uses higher order statistics to perform blind source separation
- This suggests it may be useful for separating RFI from Gaussian noise in the radiometry context, studied in [7].
- We assume noise and RFI are statistically independent sources, mixing is linear, sources are non Gaussian
- Mixture model: \( \mathbf{x} = \mathbf{A}\mathbf{s} \), observe \( \mathbf{x} \)
- \( \hat{\mathbf{s}} = \mathbf{W}\mathbf{x} \), \( \hat{\mathbf{s}} \) is the estimated independent source
ICA RFI Detection

Step 1: Take Kurtosis of each estimated independent component vector

Step 2: Select the kurtosis value that deviated the furthest from 3

\[ \text{ICA Output} \]

\[ s_0[0] \quad s_0[1] \quad \ldots \quad s_0[N-1] \]

\[ s_1[0] \quad s_1[1] \quad \ldots \quad s_1[N-1] \]

\[ s_2[0] \quad s_2[1] \quad \ldots \quad s_2[N-1] \]

\[ s_3[0] \quad s_3[1] \quad \ldots \quad s_3[N-1] \]

\[ \text{Kurtosis} \]

\[ \text{RSK}_0 \]

\[ \text{RSK}_1 \]

\[ \text{RSK}_2 \]

\[ \text{RSK}_3 \]

\[ \max_k \{ \text{ABS}(\text{RSK}_k - 3) \} \]

ICA Detector Output

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ROC Curves and AUC

- Each point on an ROC curve can be represented by the set \{FAR, PD\}
  - \{False alarm Rate, Probability of Detection\}
- ROC curves will generate from (0,0) to (1,1) by varying the threshold
- Poor detectors are close to the 1:1 line
- Better detectors show higher PD and smaller FAR
- **Figure of Merit = Area Under Curve (AUC)**
  - \(0.5 \leq \text{AUC} \leq 1\)
  - When AUC = 0.5 detector does not work
  - When AUC = 1 the detector works perfectly

ROC curve example, from [8].

- AUC = 1
- AUC = 0.5
AUC Results - ICA Performance - CW

More ICA results in [7], generally a marginal improvement in detection is seen.

Various ICA algorithms are tested [9,10,11,12,13,14,15,16,17]. No ICA pre-processing is done on ‘direct’ data sets.

RSK = Real Signal Kurtosis
CSK = Complex Signal Kurtosis
Eigenvalue Approach

• Two objectives:
  – Detection: Identify power measurements that have been contaminated with interference
    • The Minimum Maximum Eigenvalue (MME) approach, adapted from the cognitive radio context [10], is applied here for RFI detection in passive remote sensing.
  – Excision: Accurately guess what the power measurement would have been if the interference were not there
Hypothesis Test / Signal Model

\[ \mathcal{H}_0: x[k] = w[k] \]
\[ \mathcal{H}_1: x[n] = w[k] + r[k] \]

\[ SNR = \frac{P_s}{\sigma_w^2} \quad P_s = \mathbb{E}[(r[k])^2] \]

\[ w[k] \sim \mathcal{N}(0, \sigma_w^2) = \text{Thermal Noise} \]
\[ r[k] = \text{RFI} \]
Measure the Sample Covariance  
(Oversampled)

Given our sampled signal $x$,

\[
x_i(n) \equiv x[nM + i - 1] \quad i = 1, 2, \ldots, M
\]

\[
x(n) \equiv [x_1(n), x_2(n), \ldots x_M(n)]^T
\]

\[
\hat{x}(n) \equiv [x^T(n), x^T(n - 1), \ldots x^T(n - L + 1)]^T
\]

\[
R_x = \mathbb{E}[\hat{x}(n)\hat{x}^H(n)]
\]

\[
R_x(N_s) \equiv \frac{1}{N_s} \sum_{n=L-1}^{L-2+N_s} \hat{x}(n)\hat{x}^H(n)
\]

The Eigenvalues of the covariance matrix are found

\[
\lambda_1 > \lambda_2 > \cdots > \lambda_{ML}
\]

The test statistic is then formed as

\[
T_\lambda = \frac{\lambda_{\text{max}}}{\lambda_{\text{min}}}
\]
Eigenvalue Noise Power Estimate

Scale the minimum eigenvalue of the covariance matrix to estimate the variance of the Gaussian thermal noise. The limiting distributions from [19] help derive the scaling factor.

\[ \mathbf{R_x} \rightarrow \lambda_1 > \lambda_2 > \ldots \geq \lambda_{ML} \]

\[ \lim_{N_s \rightarrow \infty} \lambda_{min} = \sigma^2 (1 - \sqrt{y})^2 \]

\[ \lim_{N_s \rightarrow \infty} \lambda_{max} = \sigma^2 (1 + \sqrt{y})^2 \]

\[ \tilde{\sigma_w^2} = \lambda_{min} \frac{N_s}{(\sqrt{N_s} - \sqrt{ML})} \]
Wideband RFI – 5 QPSK Channels

All 5 QPSK Channels

Combined QPSK
MME Detection Results

Eigenvalue Detection method greatly outperforms all other methods tested (Kurtosis[2,3] and Spectral Kurtosis[20])
RFI Excision Performance

Sample Variance Compared to Eigenvalue Variance Estimate

Eigenvalue Variance Estimate outperforms sample variance at interference levels of -14db INR and greater.

Eigenvalue variance estimate accuracy depends on the complexity of the RFI
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