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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>
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<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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<tr>
<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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<tr>
<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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<td>NCCFASTICA</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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<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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<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
L, X band RFI

SMAP TA H-pol
1400 MHz

10 GHz GMI
Tb V-pol
(Vertical)

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

To be presented by Adam Schoenwald at the 2017 IEEE International Geoscience and Remote Sensing Symposium, Fort Worth, Texas, July 2017
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]\.

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

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

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

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].

\[
C_K = \frac{q_{2;2} - 2 - |q_{2;0}|^2}{1 + \frac{1}{2} |q_{2;0}|^2}
\]
**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: \( x = As \), observe \( x \).
- \( \hat{s} = Wx \), \( \hat{s} \) is the estimated independent source.

![Diagram of Independent Component Analysis]

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ICA RFI Detection

**ICA Output**

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

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

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

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

**Kurtosis**

**max_{k} \{ \text{ABS}( RSK_k - 3) \}**

**ICA Detector Output**

**Step 1:** Take Kurtosis of each estimated independent component vector

**Step 2:** Select the kurtosis value that deviated the furthest from 3
• 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 ≤ AUC ≤ 1
  – When AUC = 0.5 detector does not work
  – When AUC = 1 the detector works perfectly

ROC curve example, from [8].
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 interfere were not there
Conceptual Signal Model

**Hypothesis Test / Signal Model**

\[ H_0: x[k] = w[k] \]
\[ H_1: x[n] = w[k] + r[k] \]

**Signal-to-Noise Ratio (SNR)**

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

- \( w[k] \sim \mathcal{N}(0, \sigma_w^2) \) = Thermal Noise
- \( r[k] \) = RFI

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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

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

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.

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

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

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

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

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MME Detection Results

Compare detection methods, N=10000, M=4, L=4

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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