Spectral Sensing for Wireless Communication Monitoring

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1 Spectral Sensing

- Signal Detection
- Signal Classification
- Channel-State Estimation
- Decision Making
- Monitoring and System Management

1.1 Signal Detection

- Data Collection and Assembly:
  - Signal Reception Arrangement
  - Sampling and ADC Conversion
  - Data Storage
- Signal Conditioning
  - Data cleaning and anomaly detection
  - Narrowband Filtering and demodulation
  - Wideband Signal Decimation
- Energy calculation
  - Power Estimation and frequency scanning
  - Noise (SNR) Estimation
  - Thresholding

1.1.1 Data Collection and Assembly

Acquisition, down/sampling, storage, and preparation of sample sets holding primary information.

- Enhanced signal reception
  - Diversity Antennas for reducing the impact of fading and shadowing: spatial diversity (using multiple antennas at different locations), polarization diversity (utilizing antennas with different polarization orientations), frequency diversity, and pattern diversity (employing antennas with different radiation patterns).
  - Enhanced Detection Sensitivity: By combining signals from multiple antennas, diversity combining techniques such as selection diversity, maximal ratio combining (MRC), or equal gain combining (EGC) can be employed to improve the detection sensitivity of spectrum sensing.
  - Multisensor Sensor Synchronization. Implementing diversity antennas adds complexity to the cognitive radio system, including hardware requirements and signal processing algorithms.
- Sampling and ADC conversion

Nyquist sampling

Oversampling to improve resolution

Data Compression and Undersampling to feed NN estimators: sigma-delta modulation

Trade-offs between ADC performance parameters (including cost, power consumption, and size) evaluated based on the specific requirements and constraints of the cognitive radio system.

- Data Storage

  Real-time analysis

  Off-line training and validation

  Data Retention Policies dictated by regulatory requirements, operational needs, or privacy considerations.

  Data anonymization or encryption to protect sensitive information and ensure compliance with privacy regulations.

  Data storage infrastructure for spectrum sensing applications may include local storage on cognitive radio devices, networked storage systems, or cloud-based storage solutions.

1.1.2 Signal Conditioning

- Data cleaning and anomaly detection
- Narrow-band Filtering and demodulation

  Narrow-band band pass filtering and adaptive filtering to isolate specific signals or frequency bands of interest while suppressing noise and interference, improving the signal-to-noise ratio (SNR) of the desired signals.

  Demodulation involves extracting the original information carried by modulated signals, such as voice, data, or multimedia content.
- Wideband Signal Decimation

  Channelization, filter banks, and multichannel sensing

  Software-defined filters: Filtering implementation on software-defined radio (SDR) platforms (processing power, flexibility, cost, and power consumption).

1.1.3 Signal Presence Detection

$$\begin{aligned}
\text{Channel Model :}\quad & \boldsymbol{y} = \boldsymbol{x} + \boldsymbol{\eta}, \\
& \boldsymbol{y} = [y_0, y_1, \ldots, y_{K-1}]^\top,\ \boldsymbol{x} = [x_0, x_1, \ldots, x_{K-1}]^\top \\
\text{Hypothesis :}\quad & \\
\text{Signal Absence },H_0 \longrightarrow \alpha = 0 :\quad & y_k = \eta_k, \\
\text{Signal Presence}, H_1 \longrightarrow \alpha = 1 :\quad & y_k = \alpha x_k + \eta_k; \quad \forall k \in [0, K-1]
\end{aligned}$$

where x_i is a given signal with known shape, η_k is White Gaussian Noise having a known variance σ_η^2, and $\alpha{\in}\{0,1\}$ is the unknown constant to be estimated.

$$\begin{aligned}
& \text{Maximum Likelihood (ML) ratio} \\
\Lambda(\boldsymbol{y}|\hat{\alpha}) &= \frac{P(\boldsymbol{y}|\hat{\alpha})}{P(\boldsymbol{y})} > \gamma - \text{threshold} \\
P(\boldsymbol{y}|\hat{\alpha}) &= \frac{1}{(2\pi\sigma_\eta^2)^{K/2}} \exp\left(-\frac{1}{2\sigma_\eta^2}\big(\boldsymbol{y} - \alpha\boldsymbol{x}\big)^\top\big(\boldsymbol{y} - \alpha\boldsymbol{x}\big)\right) \\
P(\boldsymbol{y}) &= \frac{1}{(2\pi\sigma_\eta^2)^{K/2}} \exp\left(-\frac{1}{2\sigma_\eta^2}\boldsymbol{y}^\top\boldsymbol{y}\right)
\end{aligned}$$

The estimation of $\hat{\alpha}$ the ML rule is as follows:

$$\begin{aligned} \frac{\partial}{\partial \alpha} \Lambda(\boldsymbol{y}|\hat{\alpha}) &= 0 \\ \frac{\partial}{\partial \alpha} \ln P(\boldsymbol{y}|\hat{\alpha}) &= 0 \\ \frac{\partial}{\partial \alpha}(\boldsymbol{y}^2 - 2\alpha \boldsymbol{x}\boldsymbol{y} + \alpha^2 \boldsymbol{y}^2) &= 0 \\ -2\boldsymbol{x}\boldsymbol{y} + \alpha \boldsymbol{y}^2 &= 0 \end{aligned}$$

So, the optimal value yields the estimation value for $\hat{\alpha}$:

$$\begin{aligned} \hat{\alpha} &= \frac{\boldsymbol{y}^\top \boldsymbol{x}}{\boldsymbol{x}^\top \boldsymbol{x}} \\ &= \frac{1}{\|\boldsymbol{x}\|} \boldsymbol{y}^\top \boldsymbol{x} \end{aligned}$$

$$\hat{\alpha} = \frac{\sum_{\forall k \in K} y_k x_k}{\sum_{\forall k \in K} x_k^2}$$

Now, we calculate the log of ML inequality, $\Lambda(\boldsymbol{y}|\hat{\alpha}) > \gamma$:

$$-\frac{1}{2\sigma_\eta^2}\sum_{\forall k \in K}(-2\hat{\alpha}x_k y_k + \hat{\alpha}^2 \boldsymbol{x}^2) > \ln\gamma$$

Replacing α by its estimate of $\hat{\alpha}$:

$$-\frac{1}{2\sigma_\eta^2}\left(-2\hat{\alpha}\hat{\alpha}\sum_{\forall k \in K} x_k^2 + \hat{\alpha}^2\sum_{\forall k \in K} x_k^2\right) > \ln\gamma$$

Therefore, each hypothesis H_i about the signal holds, as below:

$$\hat{\alpha}^2 \underset{H_0}{\overset{H_1}{\gtrless}} \frac{2\sigma_\eta^2 \ln\gamma}{\sum_{\forall k \in K} x_k^2}$$

$$\sum_{\forall k \in K} x_k^2 y_k^2 \underset{H_0}{\overset{H_1}{\gtrless}} 2\sigma_\eta^2 \ln\gamma$$

$$\left|\sum_{\forall k \in K} x_k y_k\right| \underset{H_0}{\overset{H_1}{\gtrless}} \sqrt{2\sigma_\eta^2 \ln\gamma},\ \boldsymbol{x} \text{ is not available practically!}$$

Energy calculation. By the law of large numbers (that is, making $K_\alpha \to \infty$), we have:

$$\begin{aligned} &\mathcal{N}(\mu_1, \sigma_\eta) + \mathcal{N}(\mu_2, \sigma_\eta) \longrightarrow \mathcal{N}((\mu_1 + \mu_2)/2, \sigma_\eta) \\ \Rightarrow\ &\mathcal{N}(0, \sigma_\eta) + \mathcal{N}(\mu_2, \sigma_\eta) = \mathcal{N}(\mu_2/2, \sigma_\eta) \end{aligned}$$

$$\text{therefore,} \quad \hat{\alpha} \simeq 2 \sum_{\forall k \in K_\alpha} y_k$$

Detection of a zero-mean Gaussian signal and known variance:

$$\begin{aligned} H_0 : &\quad y_k = \eta_k, \quad \eta_k \sim \mathcal{N}_\eta(0, \sigma_\eta) \\ H_1 : &\quad y_k = \alpha x_k + x_k; \quad x_k \sim \mathcal{N}_x(0, \sigma_x) \\ &\quad \text{s.t.: } \sigma_x^2 > \sigma_\eta^2, \text{ high SNR condition} \end{aligned}$$

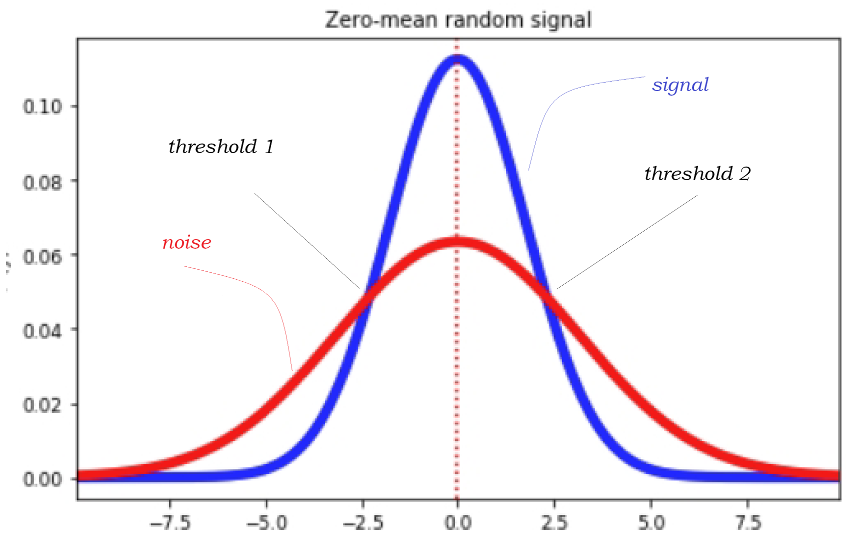
Therefore, it holds that:

$$\begin{aligned} &\sigma_y^2 = \sigma_a^2 + \sigma_\eta^2, \\ \Rightarrow\ &\Lambda(y|\hat{\alpha}) = \frac{P(y|\hat{\alpha})}{P(y|0)} = \frac{\mathcal{N}_y(0, \sigma_y)}{\mathcal{N}_\eta(0, \sigma_\eta)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma \end{aligned}$$

From ML rule, after some simplifications, we have:

$$\sum_{\forall k \in K} y_k^2 \left(\frac{1}{\sigma_\eta^2} - \frac{1}{\sigma_y^2}\right) = K \ln(\sigma_y^2/\sigma_\eta^2 + \gamma)$$

$$\begin{aligned} \sum_{\forall k \in K} y_k^2 &= K m_{2y} \\ &= \left(\frac{1}{\sigma_\eta^2} - \frac{1}{\sigma_y^2}\right)^{-1} K \ln(\sigma_y^2/\sigma_\eta^2 + \gamma) \end{aligned}$$



Gaussian signal plus noise with high SNR

$$\begin{aligned} m_{2y} &= \left(\frac{1}{\sigma_\eta^2} - \frac{1}{\sigma_y^2}\right)^{-1} \ln(\sigma_y^2/\sigma_\eta^2), \qquad \text{making } \gamma = 1 \\ &\simeq \sigma_\eta^2 \ln(\sigma_y^2/\sigma_\eta^2), \;\; \sigma_y^2/\sigma_\eta^2 \gg 1 \end{aligned}$$