Unknown Signal Detection in Linear Dynamical System Noise

Gabriel Ford, Timothy Hu, Donald Bucci and Benjamin Foster

Lockheed Martin Advanced Technology Laboratories

Abstract

A machine learning approach to detecting unknown signals in time-correlated noise is presented. A linear dynamical system (LDS) model is trained to represent the background noise via expectation-maximization (EM). The negative log-likelihood (NLL) of test data under the learned background noise LDS is computed via the Kalman filter recursions, and an unknown signal is detected if the NLL exceeds a threshold. The proposed detection scheme is derived as a generalized likelihood ratio test (GLRT) for an unknown deterministic signal in LDS noise. In simple additive white Gaussian noise (AWGN), the proposed scheme reduces to an energy detector. However, experimental results on a wireless software defined radio (SDR) testbed demonstrate that the proposed scheme outperforms energy detection in a time-correlated noise background.

Linear Dynamical System Model for Time-Correlated Noise

The noise background is modeled as a linear time-invariant dynamical system (LDS). Each in-phase and quadrature (I/Q) complex baseband noise sample $n_t = [n_{I,t},\, n_{Q,t}]'$ is drawn according to the following generative process:

$$\begin{aligned} x_{t+1} &= Ax_t + w_t \qquad & w_t &\sim \mathcal{N}(0, Q) \\ n_t &= Cx_t + v_t & v_t &\sim \mathcal{N}(0, R) \\ & & x_1 &\sim \mathcal{N}(\pi_1, V_1) \end{aligned} \tag{1}$$

The LDS model is trained via expectation-maximization (EM).

Generalized Likelihood Ratio Test for Unknown Signal Detection in LDS Noise

Unknown signal detection in LDS noise is formulated as a hypothesis test:

$$\begin{aligned} &\text{(signal absent)} \;\; \mathcal{H}_0 : y_t = n_t \qquad && t = 1, \ldots, T \\ &\text{(signal present)} \;\; \mathcal{H}_1 : y_t = s_t + n_t && t = 1, \ldots, T \end{aligned} \tag{2}$$

where $y_t = [y_{I,t},\, y_{Q,t}]'$ is the received complex baseband data, $s_t = [s_{I,t},\, s_{Q,t}]'$ is an unknown deterministic signal, and n_t is the LDS noise in (1). The generalized likelihood ratio test (GLRT) decides $\mathcal{H}_1$ (signal present) if:

$$\frac{\max_{s_{1:T}} p(y_{1:T};\, s_{1:T}, \mathcal{H}_1)}{p(y_{1:T}; \mathcal{H}_0)} > \gamma. \tag{3}$$

The log-likelihoods $\ln p(y_{1:T}; \mathcal{H}_0)$ and $\ln p(y_{1:T};\, s_{1:T}, \mathcal{H}_1)$ are obtained from the Kalman filter forward recursions:

$$\ln p(y_{1:T}; \mathcal{H}_0) = \sum_{t=1}^{T} l_t = \sum_{t=1}^{T} \ln \mathcal{N}(y_t; Cx_{t|t-1}, S_t) \tag{4}$$

$$\ln p(y_{1:T};\, s_{1:T}, \mathcal{H}_1) = \sum_{t=1}^{T} l_{t;\mathcal{H}_1} = \sum_{t=1}^{T} \ln \mathcal{N}(y_t; Cx_{t|t-1} + s_t, S_t), \tag{5}$$

where $x_{t|t-1}$ is the state predicted mean and S_t is the prediction error covariance. At the MLE $\hat{s}_{1:T}$ of the signal, (5) reduces to a constant w.r.t. the data $y_{1:T}$:

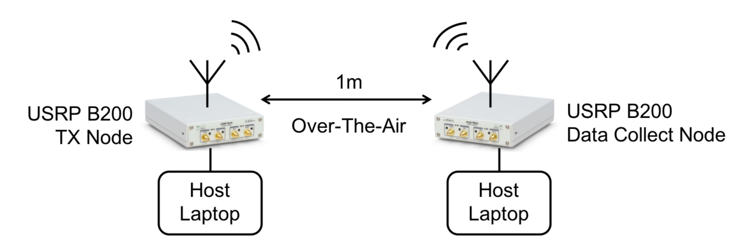
$$\ln \max_{s_{1:T}} p(y_{1:T};\, s_{1:T}, \mathcal{H}_1) = \sum_{t=1}^{T} \left(-\frac{1}{2} \ln |S_t| - \ln 2\pi \right). \tag{6}$$

Substituting (4) and (6) in (3), the GLRT decides $\mathcal{H}_1$ (signal present) if:

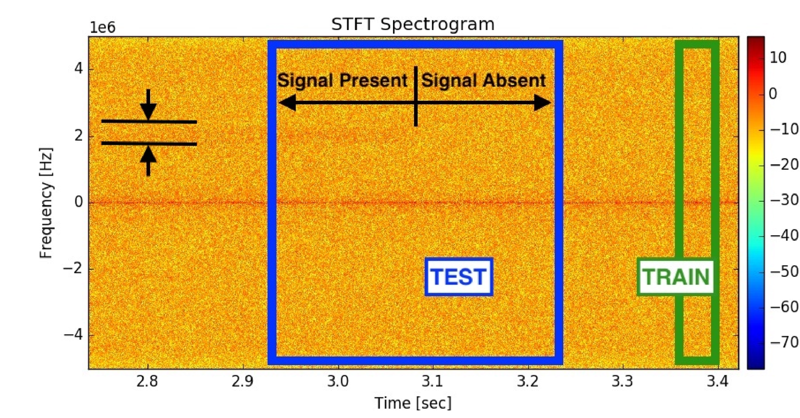
$$-\sum_{t=1}^{T} l_t > \gamma'. \tag{7}$$

Thus the test statistic reduces to the negative log-likelihood (NLL) of the received data $y_{1:T}$ under the LDS noise model (1).

Experimental Demonstration



(a) Experimental testbed setup. The TX node transmits a 500 kHz bandwidth QPSK signal in the 1.2 GHz UHF band. The data collect node receives 10 MHz RF bandwidth including the transmit channel and downconverts it to complex baseband.



(b) Spectrogram of the received complex baseband data. The QPSK signal centered at 2MHz baseband (faintly visible) serves as the unknown signal of interest. An LDS model is trained on the background noise and the detection procedure is evaluated on the test region.

Figure 1: Experimental demonstration on an over-the-air software defined radio testbed.

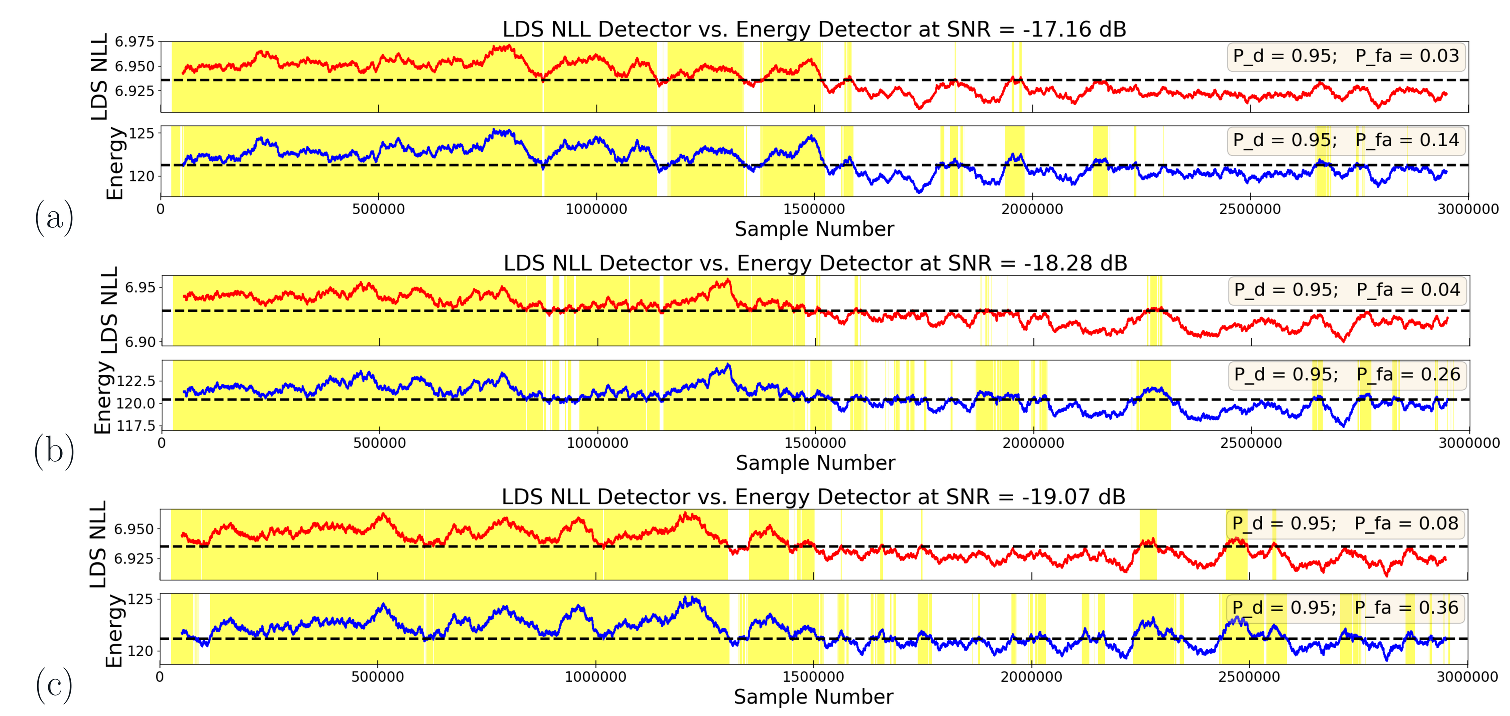
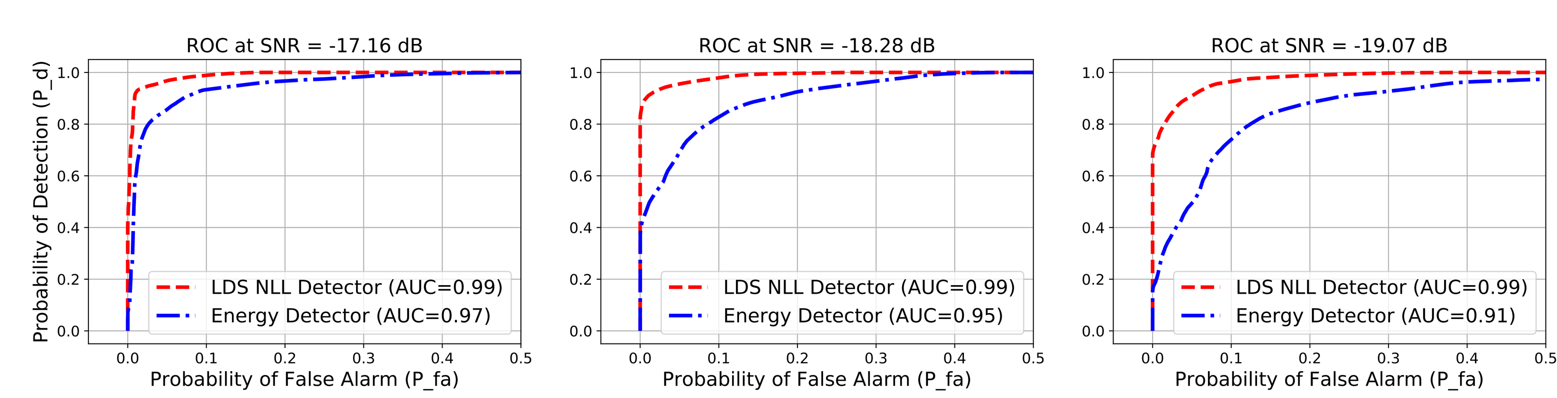


Figure 2: Detector test statistics for three repetitions of the experiment with progressively decreasing transmitted signal powers. SNR is defined relative to the *total* noise power across the entire receiver bandwidth, including the dominant LO leakage noise at DC. The energy detector exhibits substantially higher false alarm rates relative to the LDS NLL detector.



(a) (b) (c)

Figure 3: Receiver operating characteristics (ROCs) for three repetitions of the experiment with progressively decreasing transmitted signal powers. The performance improvement of the LDS NLL detector relative to the energy detector becomes more pronounced as the SNR decreases.

Online LDS NLL Detection Procedure

We compute a moving average of the NLL over a sliding window of length T and detections are declared sample-by-sample:

$$\bar{\delta}_{t,T} = -\frac{1}{T} \sum_{k=t-T+1}^{t} l_k \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \tau \qquad t = 1, 2, \ldots \tag{8}$$

Probability of false alarm is related to the detection threshold τ and the window length T:

$$P_{FA} = \Pr\left[\bar{\delta}_{t,T} > \tau \,|\, \mathcal{H}_0\right] = Q_{\chi^2_{Td_y}} \left(2T\tau - \sum_{k=t-T+1}^{t} \left(\ln |S_k| + d_y \ln 2\pi \right) \right), \tag{9}$$

where $Q_{\chi^2_{Td_y}}$ is the right-tail distribution of a chi-squared random variable with Td_y dof.

Experimental Testbed

The testbed in Fig. 1a includes an Ettus Research Universal Software Radio Peripheral (USRP) B200 Software Defined Radio (SDR) acting as a transmitter (TX) node and a second B200 SDR serving as the receiver and data collection node. The TX node transmits a Quadrature Phase Shift Keying (QPSK) modulated signal over a 500 kHz channel bandwidth in the 1.2 GHz UHF frequency band. The receiver node captures 10 MHz RF bandwidth including the transmit channel and downconverts it to complex baseband, generating I/Q data at a 10 MHz sampling rate. The I/Q data are input to our detection framework running on the receiver node host laptop. Fig. 1b shows a short-time Fourier transform (STFT) spectrogram of the received complex baseband data, with the QPSK signal centered at 2 MHz baseband (faintly visible in the spectrogram). In addition to the wideband noise background, there is a strong narrowband, time-correlated noise component at DC primarily due to receiver local oscillator (LO) leakage.

Results

An LDS noise model is trained (50 EM iterations) on 20,000 data samples (0.02 sec) representing the background noise in the absence of the signal of interest taken from the training region indicated in Fig. 1b. The detection procedure is evaluated on 3E6 data samples (0.3 sec) from the test region in Fig. 1b. The signal of interest is present in the first 1.5E6 of these samples (0.15 sec). We present results for three runs of the same experiment with progressively decreasing transmitted signal powers.

The top time series plots (in red) in Figs. 2a - 2c show the moving average NLL (8) of the test data under the LDS noise model, which serves as the detector test statistic (window length $T = 5\text{E}5$ samples $= 0.05$ sec). Detections are declared on a per-sample basis if the moving average NLL exceeds the threshold (detections are indicated in yellow). The resulting probability of correct detection and false alarm are estimated as the relative frequency of detections per sample in the 'signal present' and 'signal absent' regions, respectively. The lower time series plots (in blue) in Figs. 2a - 2c show the energy detector test statistic computed using the same window length.

Figs. 3a - 3c show the receiver operating characteristics (ROCs) generated by varying the detection threshold, for both the LDS NLL and energy detectors. The LDS NLL detector shows substantial improvement over the energy detector in all cases, with the improvement in performance becoming more pronounced as the SNR decreases.

Conclusion

A machine learning approach to detecting unknown signals in time-correlated noise was presented and compared to the standard energy detector. In the proposed approach, an LDS is used to represent the background noise. The time-varying hidden state captures correlation in the noise process. The LDS model parameters are learned from the data via expectation-maximization. The negative log-likelihood of newly received data under the learned background noise LDS is monitored and an unknown signal detection is declared if the NLL deviates significantly.

This approach was shown to reduce to the standard energy detector when the background noise is simple AWGN. However, experimental results on an over-the-air wireless radio testbed demonstrated that the proposed approach substantially outperforms energy detection in more complicated time-correlated noise. Furthermore, the proposed approach retains the principal advantages of energy detection in that it requires no prior knowledge of the characteristics of the signal or the background noise, and is computationally efficient.