Multiantenna-Assisted Spectrum Sensing for Cognitive Radio

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INTRODUCTION

What is Cognitive Radio (CR)?

Cognitive Radio is like a smart navigation system that allows public drivers (secondary users) to intelligently find and use these empty private superhighways (primary users' licensed spectrum) without causing any traffic jams or accidents for the owners.

Primary Users (PUs):

The licensed owners of a specific frequency band. They have priority access.

Secondary Users (SUs):

Unlicensed users who want to opportunistically use the band when the PU is not transmitting.

- White Space: A frequency band that is not being used by the PU at a particular time and in a particular location.
- The Goal of CR: To improve the efficiency of radio spectrum usage. Current management assigns exclusive licenses, but studies show that much of this licensed spectrum is underutilized.

What is Spectrum Sensing?

Spectrum sensing is the most fundamental requirement of a Cognitive Radio. It is the process by which the secondary user (SU) listens to the radio environment to determine if a primary user (PU) is present.

PU is absent

The SU can use the frequency band.

PU is present

The SU must vacate the band immediately to avoid causing harmful interference.

For applications like cognitive radios in vehicles, this detection must be extremely fast and accurate, as the vehicle is constantly moving through different radio environments.

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PROBLEM

The Problem: A Hypothesis Test

Mathematically, spectrum sensing is a binary hypothesis testing problem. The SU receives a signal

Hypothesis H0 (Null):

The PU is absent. The received signal is just random background noise

$$H_0 : x(n) = w(n)$$

Hypothesis H1 (Alternative):

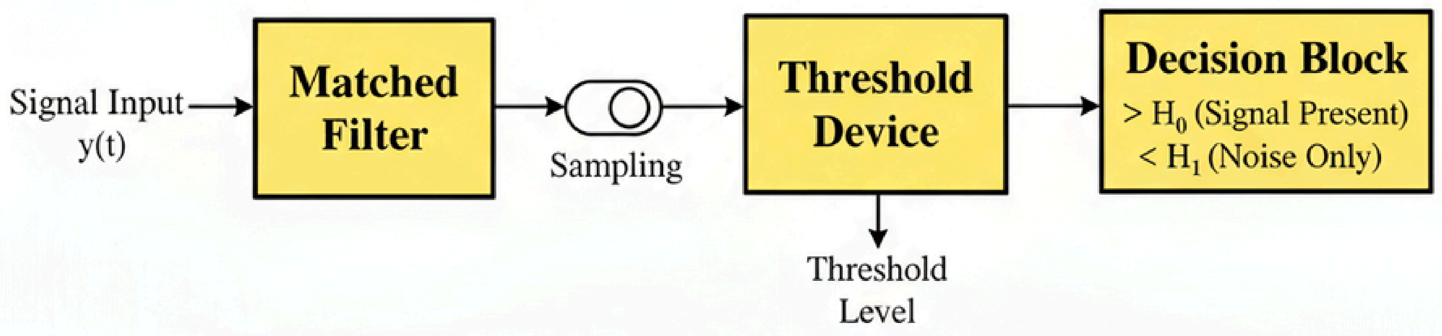
The PU is present. The received signal is the PU's signal, s(n), plus the background noise, w(n)

$$H_1 : x(n) = s(n) + w(n)$$

Common (But Flawed) Sensing Methods

Matched Filter Detection

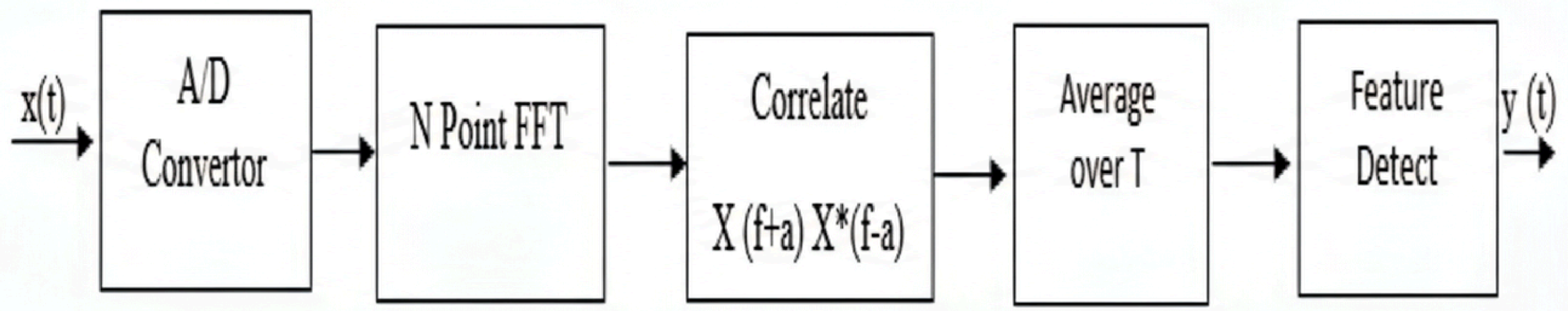
The Method: This is considered the optimal detection method when you have complete information about the signal you're looking for. It works by correlating the incoming signal with a known replica of the primary user's (PU) signal. A high correlation value indicates the presence of the PU.



The Flaw: Its major drawback is the need for perfect a priori knowledge of the PU's signal, including details like modulation type, pulse shaping, and precise timing. In a cognitive radio scenario, a secondary user (SU) rarely has this information, making the matched filter impractical for most real-world applications.

Cyclostationary Feature Detection

The Method: This technique exploits the fact that man-made communication signals have hidden periodicities in their statistical properties (like mean and autocorrelation) due to processes like modulation and carrier frequencies. These repeating patterns, or "cyclic frequencies," are not present in random noise. By searching for these specific signatures, this method can reliably distinguish a signal from noise.



The Flaw: This method has two main disadvantages. First, it requires prior knowledge of the PU's cyclic frequencies, which may not be available to the SU. Second, it is computationally very complex and demanding, which makes it difficult to implement in real-time systems.

Energy Detector (ED)

The Method: This is the simplest and most common approach because it doesn't require any information about the PU's signal. It operates by measuring the total energy of the received signal within a specific frequency band over a certain period. If this measured energy exceeds a predetermined threshold, the detector declares that a PU is present.

The Flaw: The ED's biggest weakness is its high sensitivity to uncertainty about the noise power. The detection threshold is set based on an estimate of the background noise. However, in practice, noise levels can fluctuate due to factors like temperature changes or radio interference. If the actual noise power is even slightly different from the estimate, the ED's performance degrades significantly, leading to either missed detections of the PU or frequent false alarms.

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PROPOSED SOLUTION

Proposed Solution

The Maximum Likelihood Estimate (MLE) of the unknown parameters is used to obtain the test statistic, which serves as the Generalized Likelihood Ratio Test (GLRT) detector for the hypothesis testing framework.

We will compare the performance of the GLRT detector with the following spectrum sensing methods:

- Energy Detector (ED)
- Energy Detector with Uncertainty (ED-U)
- Autocorrelation-based Geometric Mean (AGM), defined as -

$$T_{AGM} = \frac{\frac{1}{M}\sum_{m=1}^{M}\hat{\lambda}m}{\left(\prod m = 1^{M}\hat{\lambda}m\right)^{1/M}} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma AGM$$

- Maximum-Minimum Eigenvalue (MME), defined as -

$$T_{MME} = \frac{\hat{\lambda}_1}{\hat{\lambda}M} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma MME$$

Signal Model

$$H_0 : x[n] = w[n]$$
$$H_1 : x[n] = s[n] + w[n]$$

$$n = 0, 1, \ldots\ldots N-1$$

$x[n] \rightarrow M \times 1$ baseband equivalent of the received signal

$$w[n] \rightarrow CN\left(0, {\sigma_w}^2 I_M\right)$$
$$s[n] = h \times d[n]$$

d[n] are the symbols sent by the primary user

h is a *M x* 1 matrix which are the channel coefficients

Under H_0 the noise variance ${\sigma_w}^2$ is unknown

Under H_1 the noise variance ${\sigma_w}^2$ and filter coefficient matrix h are unknown

PDF and MLE

$$p(\mathbf{x}(n)|H_0, \sigma_w^2) = \frac{1}{(\pi\sigma_w^2)^M} \exp\left(-\frac{\mathbf{x}(n)^H \mathbf{x}(n)}{\sigma_w^2}\right)$$

$$p(\mathbf{x}(n)|H_1, \sigma_w^2, \mathbf{h}) = \frac{1}{\pi^M |\mathbf{h}\mathbf{h}^H + \sigma_w^2 \mathbf{I}_M|} \exp\left(-\mathbf{x}(n)^H \left(\mathbf{h}\mathbf{h}^H + \sigma_w^2 \mathbf{I}_M\right)^{-1} \mathbf{x}(n)\right)$$

$$\hat{\sigma}^2_{w,H_0} = \frac{1}{M} \sum_{m=1}^{M} \hat{\lambda}_m$$

$$\hat{\sigma}^2_{w,H_1} = \frac{1}{M-1} \sum_{m=2}^{M} \hat{\lambda}_m$$

$$\hat{\mathbf{h}}_{ML} = \left(\hat{\lambda}_1 - \frac{1}{M-1} \sum_{m=2}^{M} \hat{\lambda}_m\right)^{1/2} \mathbf{u}_1$$

GLRT Test Statistic

$$T_{GLR} = \frac{\hat{\lambda}_1}{\sum_{m=1}^{M} \hat{\lambda}_m} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_{GLR}$$

Here $\hat{\lambda}_i$ s are the eigenvalues of the sample covariance matrix R_x

$$H_0 : R_x = R_w$$

$$H_1 : R_x = R_s + R_w$$

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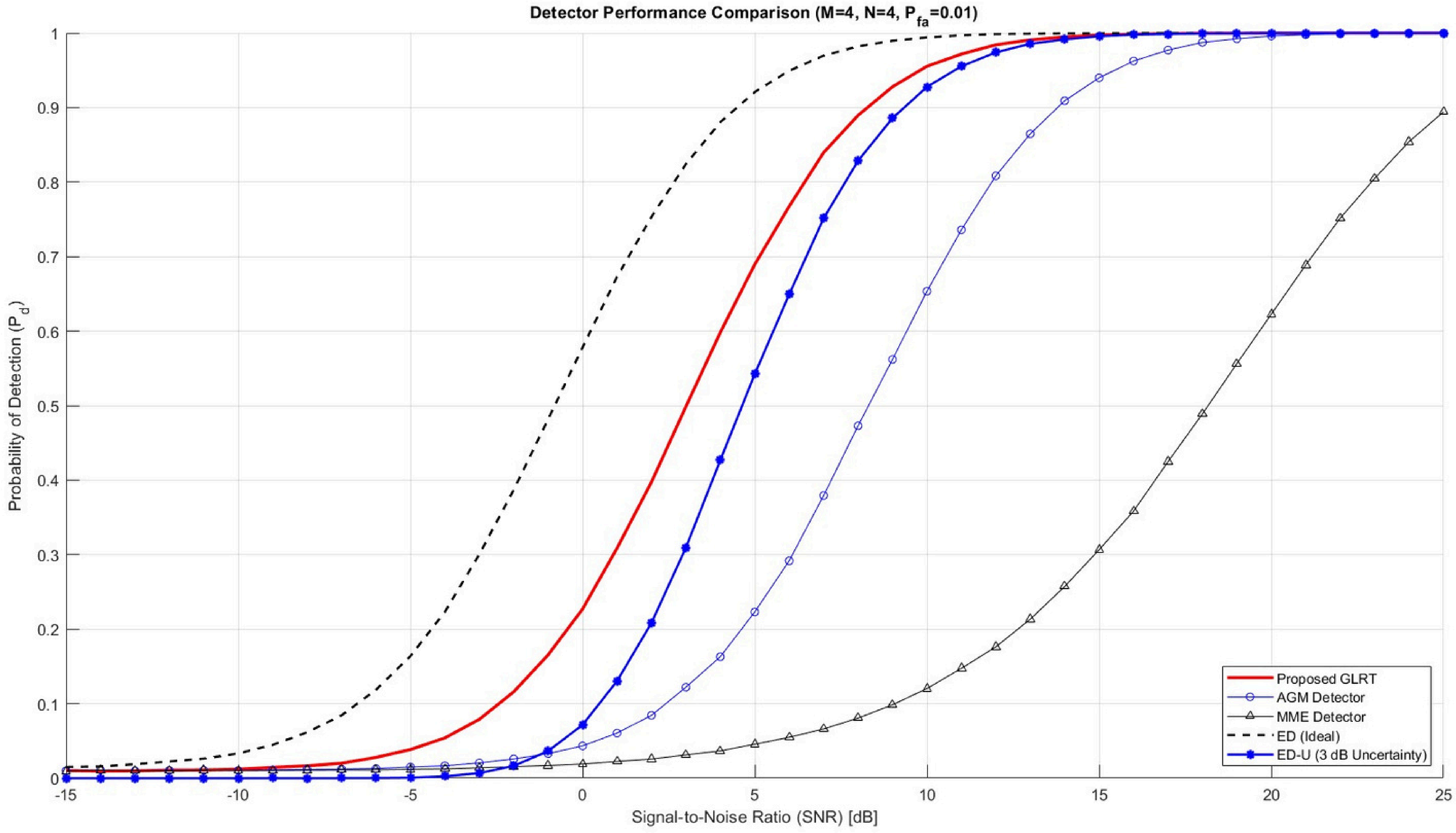
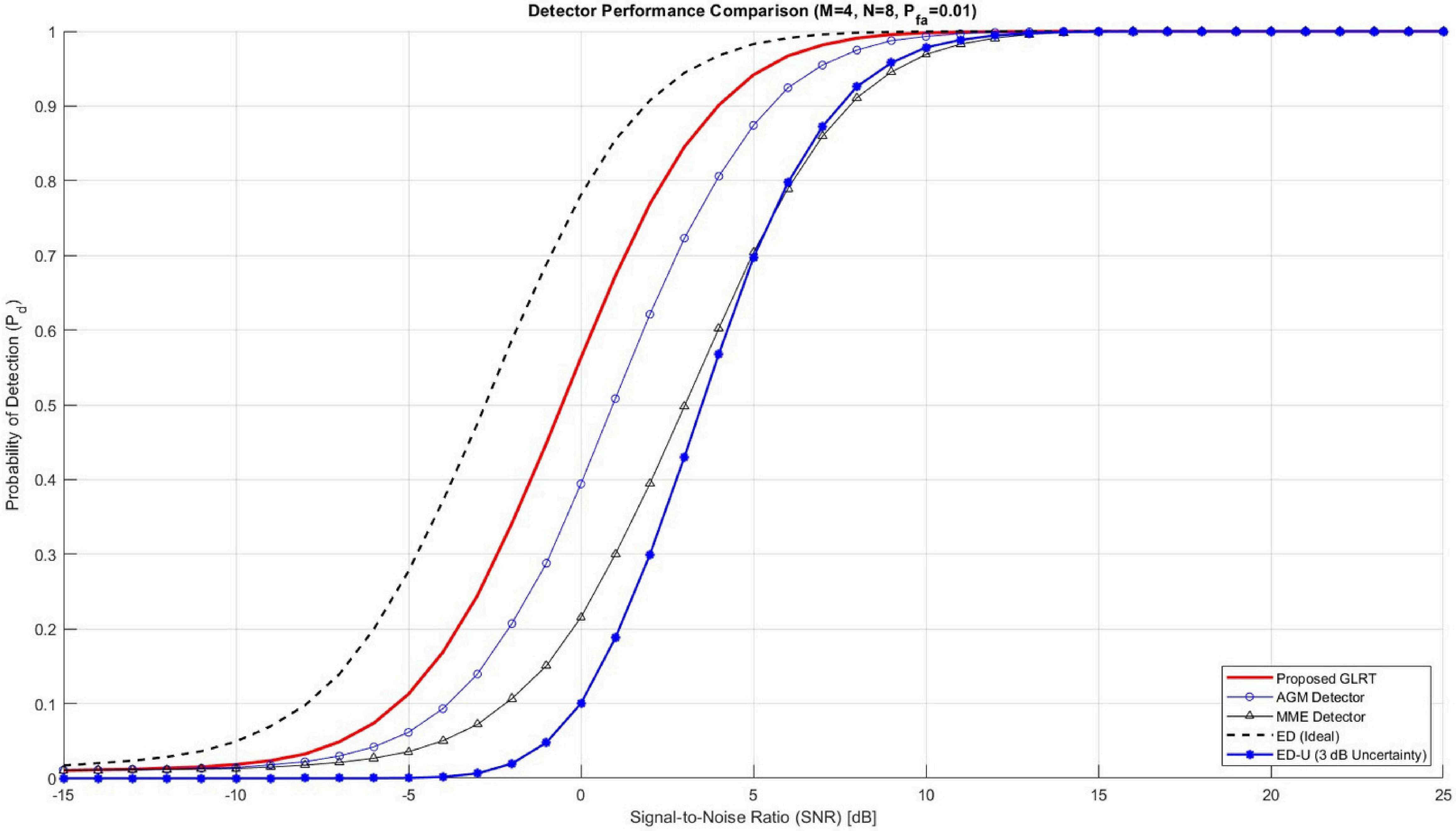
Simulations/
Future Improvements

Simulations



https://github.com/Git-Silk/GLRT-for-Spectrum-Sensing-in-Cognitive-Radio

Simulations



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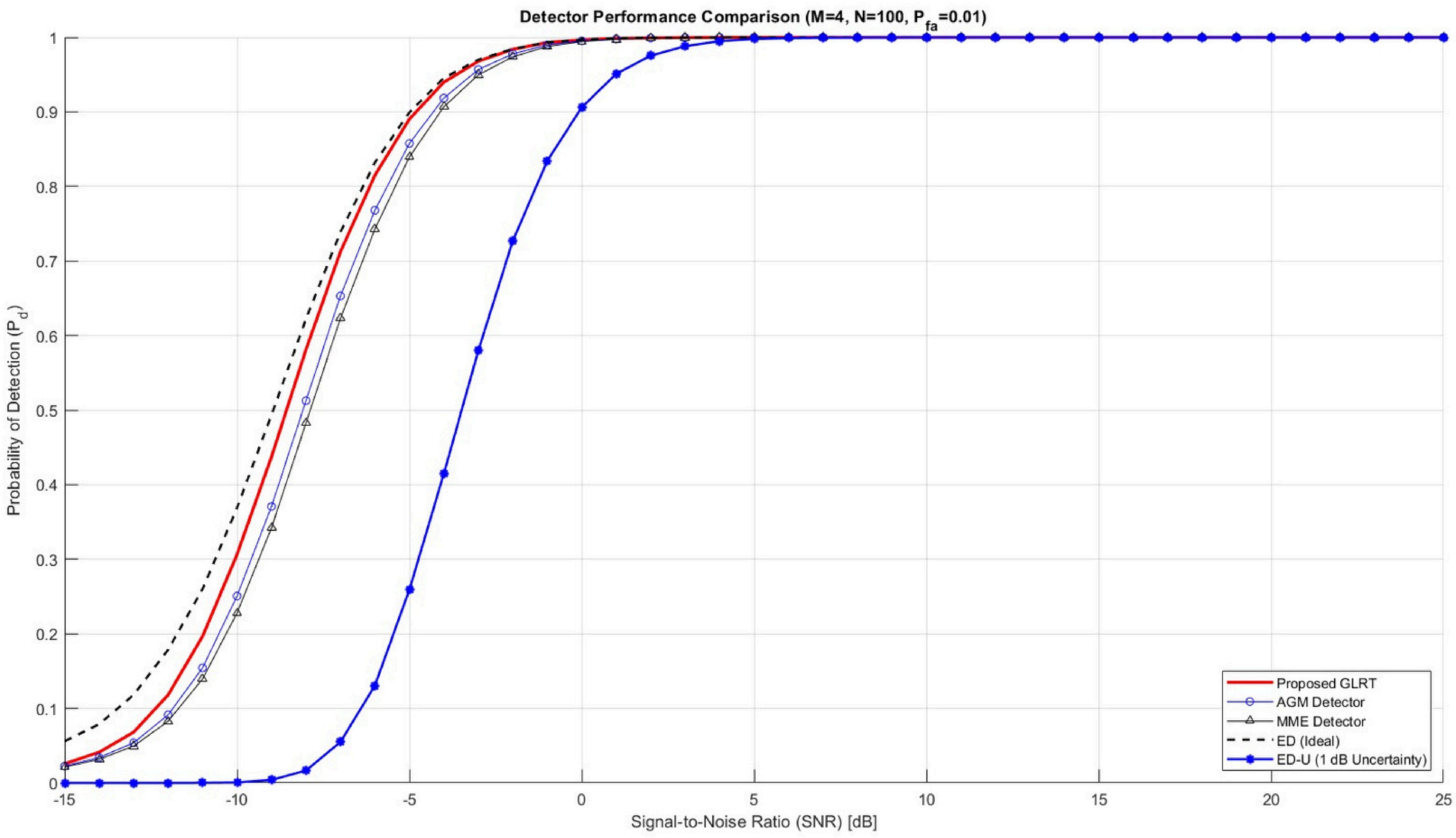

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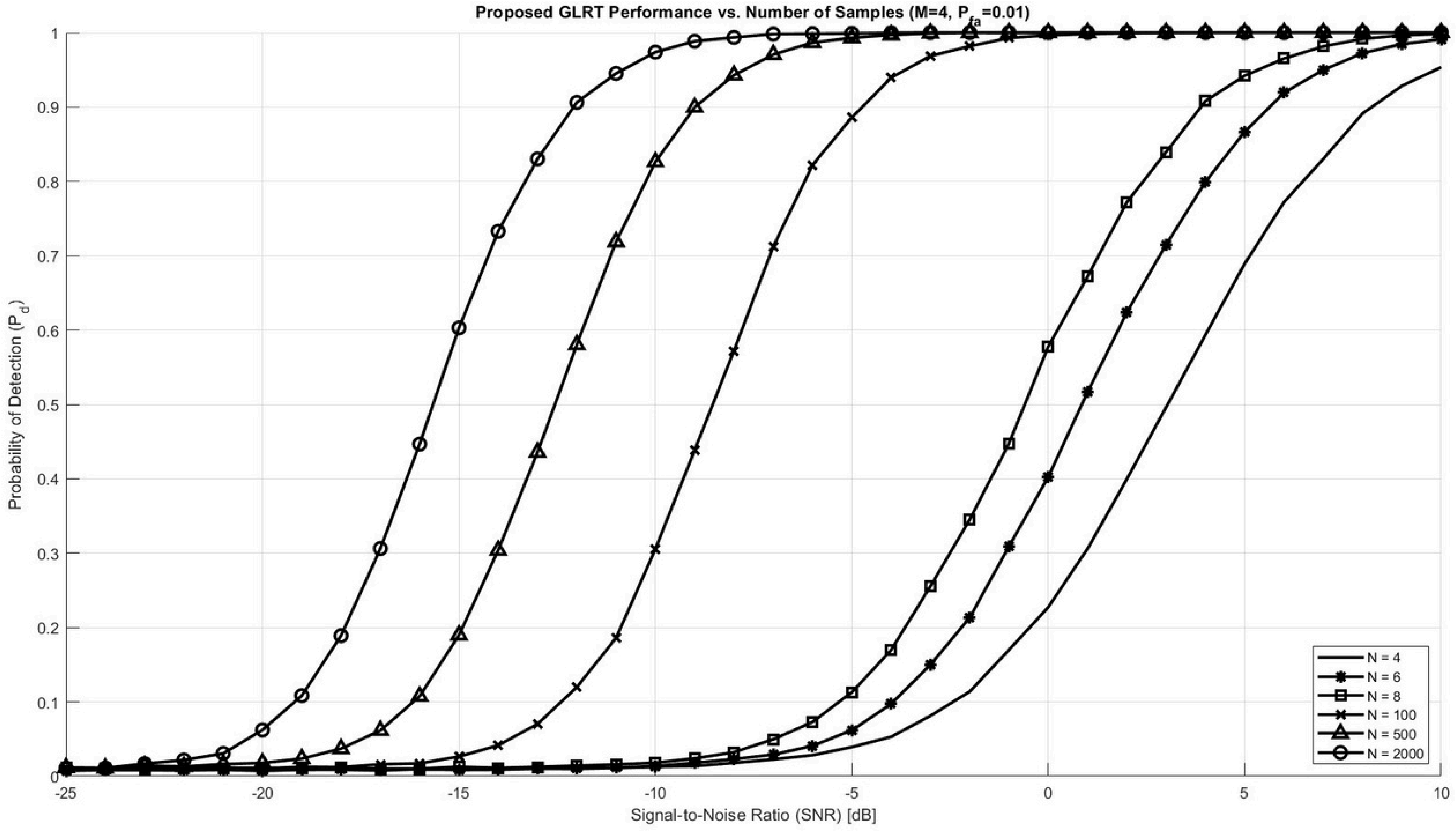

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Future Improvements

1. We could try to extend the same model for multiple PUs
2. Consider coloured noise instead of white noise

https://github.com/Git-Silk/GLRT-for-Spectrum-Sensing-in-Cognitive-Radio

Thank You

Aryaman | Uday