Performance of the Recursive One-Sided Hypothesis Testing Technique under varying Signal to Noise Ratio Conditions in Cognitive Radio

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Abstract— *The Recursive one-sided hypothesis testing technique (ROHT) is one notable example of an Adaptive threshold estimation technique (ATT) for energy detection in Cognitive Radio (CR). It is known to compute accurate threshold values based on the proper choice of its parameter values, namely the coefficient of standard deviation and the stopping criteria. However, determining the performance limits of the ROHT algorithm with regards to its minimum Signal to Noise Ratio (SNR) level remains an unexplored exercise in the literature. Thus, in this paper, a preliminary study of the ROHT algorithm is carried out to examine the effect of varying SNR conditions on the performance limit of the algorithm. The algorithm was evaluated using signals varied from SNR = 10 dB down to 1 dB. It is shown that below the SNR = 3dB margin, the performance of the ROHT may no longer be guaranteed for effective detection performance. Hence the need to improve the performance of the ROHT algorithm for use in CR, using adaptive optimization technique.*

Keywords— Adaptive; Cognitive Radio; Energy Detector; Recursive One-sided Hypothesis Testing; Threshold

1. INTRODUCTION

A cognitive radio (CR) is a wireless communication radio that intelligently senses its Radio Frequency (RF) environment for the presence/absence of Primary User (PU) signals, and uses the vacant channels for opportunistic communication while vacating occupied channels to avoid interference [1], [2]. The concept of CR was first introduced by Joseph Mitola III in 1999 [3], in which he proposed CR for opportunistic communication based on the use of Software Defined Radios (SDRs). CRs are intended to obtain the best available spectrum for communication through the use of cognitive abilities and re-configurability characteristics. In this case, cognitive ability refers to the capacity of the secondary user (SU) to sense radio conditions within its immediate RF environment, while re-configurability infers the ability to adjust its transmission frequency and power, bandwidth and modulation scheme.

Typically, CRs acquire spectra information via the use of Spectrum Sensing (SS) techniques. The use of SS is specified in the IEEE 802.22 draft standard for Wireless Regional Area Network (WRAN) [4], [5]. It specifies several methods for SS namely, the Interference Temperature Detection method, the Matched Filter Detection method, the Cyclostationary Feature Detection method, and the Energy Detection (ED) method. However, the ED is considered the most viable SS technique mainly for its ease of deployment, low computational power, low complexity and its independence of the Primary User (PU) signal waveform [6].

Newer ED designs are required to adapt their respective threshold values in accordance with varying channel conditions. This has led to the design of several adaptive threshold estimation techniques (ATT) in the literature [6]–[9] with the Recursive One-Sided Hypothesis Testing (ROHT) algorithm being one of the most viable algorithms for use in the ED [10], [11]. The ROHT is known for its simplicity, effectiveness and efficiency [10]–[13]. However, determining the performance limits of the ROHT algorithm with regards to its minimum Signal to Noise Ratio (SNR) level remains an unexplored exercise in the literature. This knowledge will enable users to determine particular conditions below which the ROHT's performance may no longer be guaranteed.

Thus, in this paper, we present a preliminary study of the ROHT algorithm to examine the effect of varying SNR levels on its performance limits. It is noted that the ROHT has an SNR limit below which its performance may not be guaranteed for use in the ED. The rest of the paper is structured as follows: Section 2 provides a brief overview of ROHT algorithm, exposition of the ROHT model and its process of operation. Section 4 presented the results and discussion, while the Section 5 provides the conclusion that was drawn.

2. THE SYSTEM MODEL

The detection system under consideration in this work is represented in Figure 1. Typically, we considered the reception of a Radio Frequency (RF) signal emanating in a typical wireless radio environment. These signals are received at the front end of the energy detection system via an antenna designed to operate within a specified frequency range(s), for example, within the VHF/UHF band to detect TV white spaces. The received continuous waveforms, $y(t)$, are passed into the energy estimator block where filtering and analogue to digital conversion takes places. To obtain the frequency domain version of the input signals, the energy estimator block computes the Discrete Fourier Transformation (DFT) of the signal. It then conducts a squaring operation and an averaging function to obtain $Y(n)$.

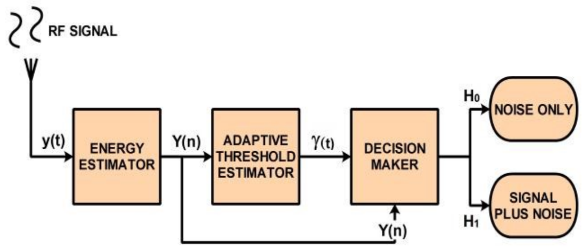

Figure 1: The Energy Detection System

The energy samples, $Y(n)$, are considered to be the test statistic in this case. These samples are passed into the adaptive threshold estimator block to dynamically compute an appropriate threshold value, $\gamma(T)$; which is a function of a certain sensing period, T. The test statistic, $Y(n)$, is compared to γ, to determine the state of the channel. If the channel is vacant ($Y(n)$,< γ), then H_0 is declared implying that the channel contains only noise samples, and if the channel is occupied ($Y(n)$,≥ γ), then H_1 is declared implying the presence of signal plus noise in the channel. These hypothesis are generally defined as:

$$H_0 : Y(n) = W(n), \text{ for } n = 1,2,\ldots,N \quad (1)$$

$$H_1 : Y(n) = X(n) + W(n), \text{ for } n = 1,2,\ldots,N \quad (2)$$

Where n denotes the frequency sample index, N is the total number of frequency samples, $X(n)$ represents the transmitted PU signal, $W(n)$ is modelled as Additive White Gaussian Noise (AWGN), and $Y(n)$ denotes the energy of the received signal at the output of the energy estimator.

3. THE ROHT ALGORITHM

The Recursive One-Sided Hypothesis testing (ROHT) algorithm is considered for use in the adaptive threshold block of Figure 1. We describe in this section the process involved in the ROHT algorithm. The flow chart of the ROHT threshold computation process is presented in Figure 2 [11].

The algorithm begins by initializing the set of signal components within the received energy measurements. It is assumed that the received measurement contains more noise components than signal components and thus the purpose of the ROHT is to disprove this hypothesis. The algorithm then proceeds to set the initial decision threshold which is given as a function of the standard deviation coefficient, $z-value$, the standard deviation, and the mean of the energy samples in the i^{th} iteration. Based on the $z-value$ and the initial threshold, the algorithm assumes that a given percentage of the energy samples on the right hand side of the normal Gaussian distribution belongs to the signal components, while considering other samples to the left hand side of the distribution as noise components. The identified signal portions are discarded and the process repeats. The algorithm comes to a halt once the difference in the standard deviation between two consecutive iterations is less than a specified random positive value given as β. The estimated threshold, the mean and the standard deviation are considered to be the final values for the entire frequency band under consideration at a time. The following pseudo code is presented for the ROHT algorithm [11]:

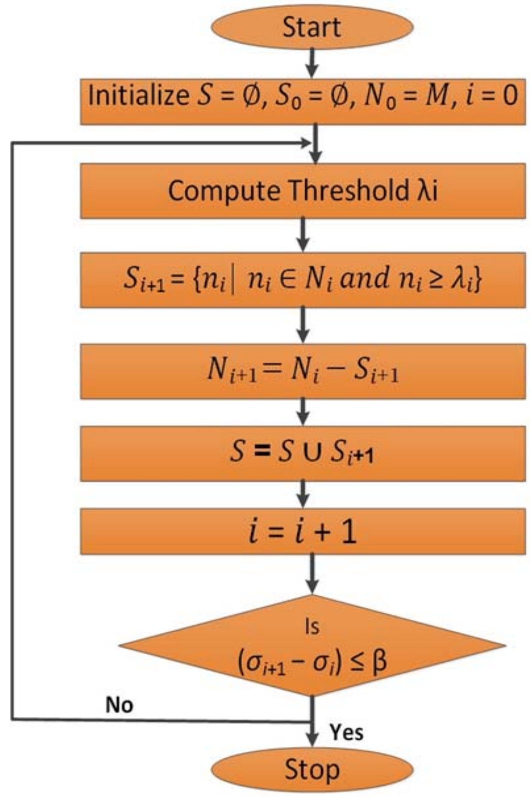

Figure 2: The ROHT Algorithm [11]

I. Initialize $S = \emptyset$, $S_0 = \emptyset$, $N_0 = M$, $i = 0$

II. Do

1) λ_{i+1} = z-value $* \sigma_i + \mu_i$
2) $S_{i+1} = \{n_i \mid n_i \in N_i \text{ and } n_i \geq \lambda_i\}$
3) $N_{i+1} = N_i - S_{i+1}$
4) $S = S \cup S_{i+1}$
5) $i = i + 1$

III. Until $(\sigma_{i+1} - \sigma_i) \leq \beta$

4. RESULTS AND DISCUSSION

In this section, we present results from the training and testing phases of the ROHT algorithm. The algorithm was trained with simulated noise only signals to ascertain the algorithm's parameter values. In this case, the false alarm rate is of utmost concern to the CR engineer, so we note that the fixed parameter values cannot be changed during the testing phase, which models a real life deployment scenario. After the training phase, the ROHT algorithm was evaluated based on signal plus noise datasets with varying signal-to-noise (SNR) levels.

4.1. Training with the noise only condition, H_0

To determine the false alarm rate and to show how the ROHT algorithm performed in noise only condition, we simulated a sensed spectra containing N = 250 samples of only Additive White Gaussian Noise (AWGN). A representation of this noise only spectra (a single sweep) is shown in Figure 3. The parameters of the ROHT algorithm were iteratively tuned until we arrived at an effective value of $z - value = 2.5$ and $\beta = 0.5$, respectively. The probability of false alarm of $P_{FA} = 0.04$ achieved for these values were read off the performance curve shown in Figure 4.

4.2. Performance in the signal plus noise condition, H_1

To demonstrate the performance of the ROHT algorithms under different SNR conditions, we simulated an FM signal, and we varied the signal strength relative to a fixed noise level. The SNR was reduced from a high SNR level (SNR = 10dB) to a low SNR level of 1dB. In this work, an SNR of 0dB was not considered because it implies that the signal is totally buried in the noise. It is noted in [12] that sensing below SNR = 0dB is a difficult task for an ED in CR especially when the ED has no knowledge of the noise floor nor the PU's frequency. The threshold estimated by the ROHT algorithm for each SNR condition is presented in Figure 5 and Figures 7—9, while the

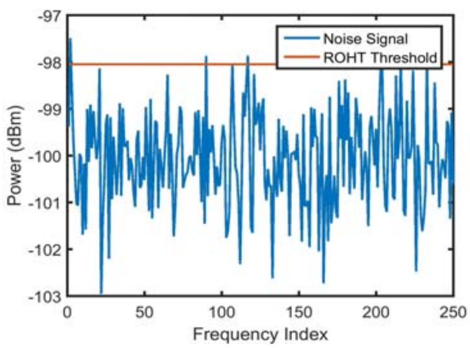

Figure 3: Noise only spectra showing the threshold estimated using the ROHT algorithm

performance curves for the signal plus noise conditions is shown in Figure 6. It is shown in Figure 5 that the estimated threshold effectively detects the signal samples for the SNR = 10 dB condition, while clearly lying above the noise level. Similar characteristics are shown in Figures 7 - 9 for the SNR = 5 dB, SNR = 3 dB and SNR = 1dB conditions, respectively. However, below the SNR = 3dB, particularly at SNR = 1dB, the threshold is shown to miss the very low signal samples,

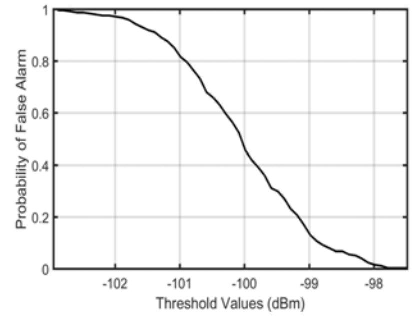

Figure 4: The probability of false alarm computed for the noise only dataset based on a true threshold value of -97 dBm.

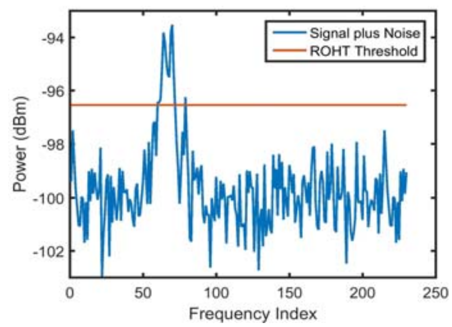

Figure 5: Signal plus noise spectra at SNR = 10dB showing the threshold estimated by the ROHT algorithm

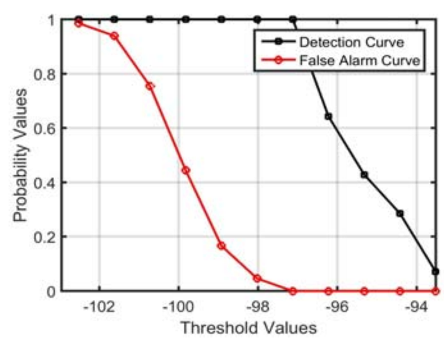

Figure 6: Performance for the Signal plus Noise dataset for (SNR=10dB to 1dB)

nevertheless maintaining a good false alarm rate by ly-ing above the noise level. This preliminary results indicate that the ROHT algorithm estimates effective thresh-old values only until the SNR = 3dB condition, below which the detection performance of the algorithm may no longer be guaranteed to meet the IEEE 802.22 re-quirement given in [5].

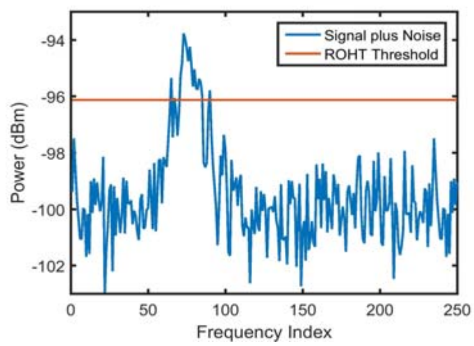

Figure 7: Signal plus Noise spectra at SNR = 5 dB showing the threshold estimated by the ROHT algorithm

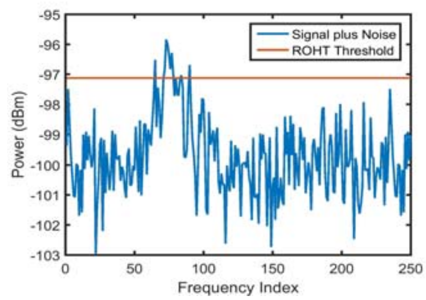

Figure 8: Signal plus Noise Spectra at SNR = 3 dB showing the threshold estimated by the ROHT algorithm

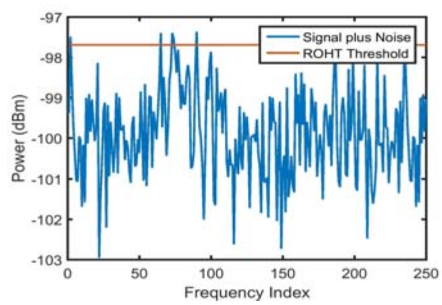

Figure 9: Signal plus Noise spectra at SNR = 1dB showing the threshold estimated by the ROHT algorithm

5. CONCLUSION

The ROHT algorithm has been presented and evaluated under different SNR conditions ranging from SNR = 10 dB down to SNR = 1 dB. The results obtained indicate that the performance of the ROHT algorithm may not be guaranteed below the SNR = 3 dB. These results will be valuable in the design of effective adaptive energy detection systems for spectrum sensing in CR. Further research will be carried out to develop automatic and optimized methods for improving the performance of the ROHT algorithm in low SNR conditions.

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