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Comparative Sensitivity Analysis of Energy Detection Techniques for Cognitive Radio Application

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Abstract

With sensitivity being an important factor in spectrum sensing based Cognitive Radio (CR) application; it remains unclear which out of the many existing Energy Detector (ED) techniques provides the best sensitivity performance for CR application. Consequently, this paper reports a study of some known parametric and non-parametric Energy Detector (ED) schemes for Cognitive Radio (CR) application towards providing relevant information. The models studied are the Simple Periodogram (SP), Welch Periodogram (WP), Multi-Taper (MT), Yule-Walker (YW), Burg (BG), and Covariance (CV). Each technique was developed using known mathematical models and appropriate signals were simulated for comparative analysis. However, owing to the limitation of the typical Receiver Operating Characteristic (ROC) curve to infer comparative information, our study proposes a decomposition of the ROCs of each technique into respective detection and false alarm probability curves in comparison with estimated threshold levels to enhance comparative inference. From our findings, it was observed that a detection performance gain of about 50% can be achieved when using parametric techniques over non-parametric methods especially in low SNR conditions. Furthermore, a possible 15dB increase in sensitivity performance can be achieved in narrow than wideband sensing for all techniques. Finally, an increase in sensing time might not necessarily improve detection performance in low SNR conditions provided a low false alarm performance must be maintained.

Keywords: Cognitive Radio, Energy detector, Non-parametric, Parametric, Periodogram, Sensitivity.

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1. Introduction

Cognitive Radio (CR) is proposed to address the current challenge of spectrum underutilization and spectrum scarcity [1-10]. CR refers to a radio device capable of providing dynamic spectrum access to unlicensed Secondary Users (SU) through opportunistic and interference-free use of the licensed Primary User (PU) spectrum. Essentially, a CR device will sense its spectral environment for the presence or absence of PU signals [11]. If PU signal is absent, CR uses the free-band for communication and vacates immediately in the presence of PU signal. This prevents interference to PU while ensuring that allocated spectrum is efficiently utilized [12].

Towards enabling CR, the Energy Detector (ED) has been widely proposed to be the most practical though sub-optimal technique for detecting PU presence or absence [13 – 17]. It is widely considered for its low design complexity, fast sensing periodicity and low cost. However, it performs poorly in low Signal to Noise Ratio (SNR) conditions, hence considered sub-optimal. Consequently, several techniques for the ED have been proposed to improve its performance [18 – 21]. These have been deployed and well documented in the literature [18 – 25]. However, for purpose of CR application, it cannot be categorically stated which ED technique provides the best sensitivity performance and hence suitable for CR application. The quest to fill this gap serves as the motivation for this research.

It is not the focus of this paper to propose any new ED technique or spectral estimation technique but rather to conduct a study on the comparative sensitivity performance of known ED techniques and infer statistical performance levels. Such comparative deductions are conspicuously absent in the literature to the best of the authors' knowledge and its availability can be very useful for CR developers and Engineers during design consideration. In addition, the study proposes an approach to compare the performance of different EDs by disintegrating the known Receiver Operating Characteristic (ROC) curve into respective probability of detection and false alarm statistics against fixed thresholds. This can be seen in the mode of our result presentation. This approach provides better

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details and precise comparative inferences as compared to using the typical ROC. This is because the typical ROC provides no clear information on the values of thresholds used for plotting the curve. Consequently, it becomes difficult to compare techniques across the known ROC space and hence the motivation for our result presentation mode. Furthermore, this work investigates ED performance in as many dimensions as possible including narrow and wideband sensing, long and short sensing time and low and high Signal to Noise Ratio (SNR) conditions.

Thus, we refer to *sensitivity* as the minimum threshold level achievable by each technique below which PU signals cannot be effectively detected without incurring a high probability of false alarm. Consequently, we classified EDs into Parametric and Non-Parametric techniques and specific techniques under each category were developed and simulated. Data was generated per technique, processed using appropriate thresholds and then analyzed. Results were obtained and are discussed in appropriate sections of this paper.

2. An Overview of Different Spectrum Estimation Techniques

This section presents known mathematical models which describe each spectrum estimation technique used in this work. It is noted that the ED is typically realized based on a Power Spectral Estimation (PSE) technique. The major goal of a PSE technique is to estimate the distribution of signal powers over their respective frequencies. This is typically called the Power Spectral Density (PSD). Mathematically, the PSD of a stationary signal x_n is related to its autocorrelation sequence and is given by

$$S_{xx}(f) = \frac{1}{f_s} \sum_{m=-\infty}^{\infty} R_{xx}(m) e^{-j2\pi m f / f_s} \qquad (1)$$

where f denotes the physical frequency in hertz, m the number of lag, f_s the nyquist sampling frequency and R_{xx} the autocorrelation function. To estimate (1), several PSE

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techniques have been proposed and generally categorized into non-parametric and parametric techniques. These are classified differently from other sensing techniques like the Cyclostationary approaches [26 -27] which are not considered in this work. Therefore, for brevity, we present only summaries as follows:

2.1. Non-Parametric PSE

The *Simple Periodogram* (SP) is typically designed to estimate the PSD $S_{xx}(f)$ of a signal $x_L(n)$ of length L [28 - 30] using

$$S_{xx}(f) = \frac{1}{LF_s}\left|\sum_{n=0}^{L-1} x_L(n)e^{-j2\pi fn/F_s}\right|^2 \tag{2}$$

where F_s is the sampling frequency and n denotes the number of signal samples.

The *Welch Periodogram* (WP) [31] presents a tradeoff between variance reduction and improved resolution with respect to SP. The spectral estimate is obtained as the average of different SPs as follows:

$$\hat{S}(f_n) = \frac{1}{K}\sum_{k=1}^{K} I_k(f_n) \tag{3}$$

where K denotes the different segments of a time series and

$$I_k(f_n) = \frac{L}{U}\left|A_k(n)\right|^2 \qquad \forall k = 1, 2, \ldots, K \tag{4}$$

where L is the length of each segment, $A_K(n)$ is the finite FFT of these sequences and U is the average power of the data window used to estimate the SP of each segment. The WP was used in [32 – 35] in Rayleigh fading channels and for OFDM systems with appreciable results recorded therein.

The Multitaper (MT) estimates the PSD $\hat{S}(f)$ of a sequence $x_0, x_1, \ldots, x_{T-1}$ as follows [36]:

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$$\hat{S}(f) = \sum_{k=0}^{K-1} w_k \left| \sum_{t=0}^{T-1} v_t^{(k)} x_t e^{-i2\pi ft} \right|^2 \tag{5}$$

where $v^{(k)} = (v_0^{(k)}, \ldots, v_{T-1}^{(k)})$ for $k = 0, \ldots, K-1$ are K tapers. This estimate is a combination of K eigen spectrum estimates where w_k are the corresponding weights of the individual tapered estimates.

2.2. Parametric PSE

Parametric PSE techniques estimate a signal's PSD by assuming that the signal is an output of a linear system driven by white noise [37]. The PSD of a typical random process using an Autoregressive (AR) model can be obtained as:

$$\hat{S}_{AR}(e^{-jw}) = \frac{s_n^2}{\left| 1 + \sum_{k=1}^{P} a_k e^{-jwk} \right|^2} \tag{6}$$

Consequently, the goal of all PSE parametric techniques is to accurately estimate the values of the model parameters a_k in (6). There are several methods for the model estimation, such as, Yule-walker (YW), Burg (BG) and Covariance (CV) methods. These techniques were studied and designed for comparative studies in this article. However, for further theoretical details on these techniques, interested readers are referred to [29], [38].

3. Method of Simulation and Analysis

In this section, details of parameters used for the simulation and analyses of each PSE technique are described as follows:

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3.1. Noise Data

Additive White Gaussian Noise (AWGN) with zero mean and unit variance was used in our simulation and analysis. The equivalent noise PSD estimate per PSE technique was estimated and used for analyzing the sensitivity performance of each technique. The probability of false alarm P_{FA} was estimated for the case of only noise samples expressed typically as:

$$H_0 : y(n) = w(n) \qquad \forall n = 0, 1, \ldots, N-1 \tag{7}$$

where H_0 denotes the null hypothesis of noise only, $y(n)$ the received CR samples, $w(n)$ the noise samples and N the total number of samples. The model for estimating the P_{FA} of noise samples distributed according to a Gaussian variate $N(2TW, 4TW)$ [39] is:

$$P_{FA} = \frac{1}{\sqrt{8\pi TW}} \int_{V_T}^{\infty} \exp\left[-\frac{(x - 2TW)^2}{8TW} \right] dx \tag{8}$$

$$= \frac{1}{2} erfc\left[\frac{V_T - 2TW}{2\sqrt{2}\sqrt{TW}} \right] \tag{9}$$

where T denotes the observation interval, W the bandwidth under inspection, V_T the threshold and TW the Time-Bandwidth product. For practical purposes, these were appropriately related as follows: TW denoted the total number of samples N (at Nyquist rate), $2TW$ the sample mean $\hat{\mu}$ of noise PSD, 4TW the sample variance $\hat{\sigma}^2$ of noise PSD (the noise power). Hence, (9) can be written as:

$$P_{FA} = \frac{1}{2} erfc\left[\frac{V_T - \hat{\mu}}{\sqrt{2\hat{\sigma}^2}} \right] \tag{10}$$

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3.2. Threshold Selection

An empirical threshold selection method was used in this work. Thus, the choice of respective threshold values to produce the desired P_{FA} was realized using (10) by varying different threshold values V_T over the noise PSD. This was done for each PSE technique examined here and a sample result of this process for the SP is shown in Figure 2.

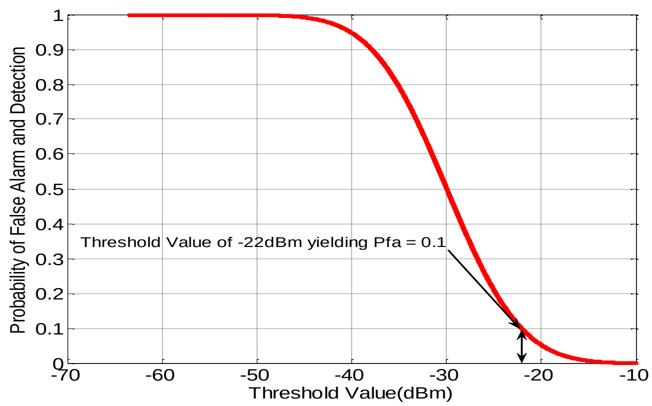

Figure 2: Probability of False Alarm for Different Threshold Values (in dBm). Result shown is for AWGN of zero mean, unit variance using the PD technique.

This result was used to determine the datum threshold value of *-22dBm* used to realize $P_{FA} = 0.1$. This same process was used for each technique and for subsequent analysis.

3.3. Signal Data

Deterministic PU signals with measurable energy content embedded in AWGN were used for comparative analysis. To achieve the most basic comparative platform, and to avoid factors such as phase from influencing one technique over the other, the model for a simple unmodulated carrier signal in discrete time was used as follows

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$$s(nT) = A\sin(2\pi f_c nT) \quad \forall n = 0,1,\ldots,N-1 \tag{11}$$

where A denotes the maximum amplitude, f_c the carrier frequency, N the total number of samples and T the sampling time. The performance of each ED was investigated for both narrow and wideband sensing as follows:

For sparse wideband sensing: Two PU signals with equal amplitudes A_1 and A_2 were varied to achieve low and high SNR conditions with respect to AWGN; each had frequencies $f_{c1} = 500Hz; f_{c2} = 2000Hz$ respectively in a sensing span of 4KHz as shown in Figure 3 using the SP technique. It is noted that this dataset was generated for each ED technique examined here. We note that this sparsely dense spectrum (Figure 3) was simulated to represent obtainable real-life sensing scenarios with wideband frequency occupancy of about 10% at threshold of *-15dBm*. Also, though low frequencies were used here, such low frequencies could easily fit for typical low baseband frequencies or down sampled versions of the high frequency signal; therefore, the concept is adaptable for higher frequency bands.

For narrowband sensing: A typical PU signal of bandwidth $W = 60Hz$ was simulated for a 100Hz narrowband sweep as shown in Figure 4. This sample result is shown for the SP technique; however, same process was applied to other techniques examined here. For analysis, the hypothesis testing for the case of signal plus noise generally expressed as

$$H_1 : y(n) = s(n) + w(n) \tag{12}$$

where H_1 denotes the alternative hypothesis was used. Simulations were conducted for each PSE technique and estimates of the respective Probability of Detection P_D were obtained using [39]:

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$$P_D = \frac{1}{2} erfc\left[\frac{V_T - 2TW - \lambda}{2\sqrt{2}\sqrt{TW + \lambda}}\right] \tag{13}$$

where λ denotes the Signal to Noise Ratio (SNR) estimated using each respective technique.

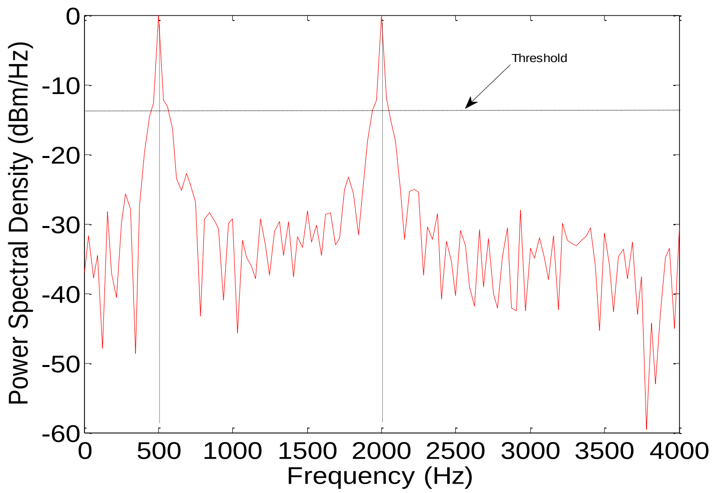

Figure 3: Simulated Wideband Spectrum Sensing of Two low Frequency PU signals at 500Hz and 2KHz in AWGN

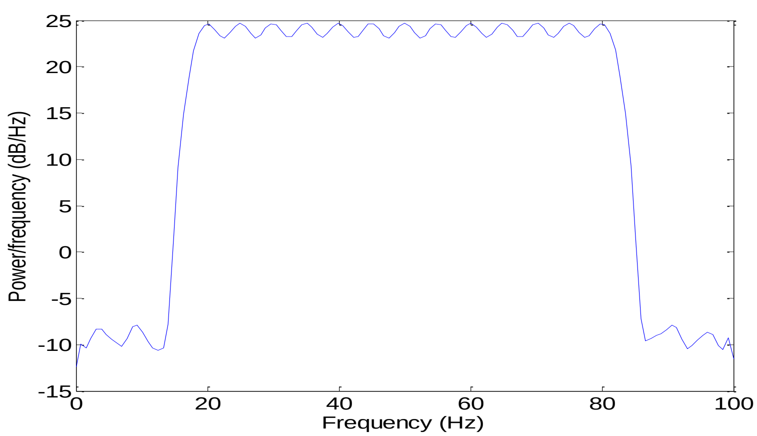

Figure 4: Narrowband Spectrum Sensing of a 60Hz Bandwidth Signal in AWGN

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3.4. Normalization:

For comparative analysis, the SNR of each technique was tuned empirically using (14) to achieve 1dB and 10dB for low and high SNR conditions respectively. Tuning was achieved by adding a gain factor $G(dB)$ to the measured SNR as follows:

$$SNR(dB) = 10\log(Ps/\ Pn) + G(dB) \tag{14}$$

where P_s denotes the PU signal power and P_n the noise power (variance). The values of $G(dB)$ used for each technique are provided in Table 1.

Table I: Different Values of Gain Factor $G(dB)$ used for SNR Normalization per ED Technique.

ED Technique	$G(dB)$
Simple Periodogram	-7
Welch Periodogram	-5.5
Multitaper	-5
Yule-Walker	0
Burg	0
Covariance	0

3.5. Summary of Simulation Approach

The simulation steps used are as follows:

Step one: Time domain samples of noise were generated using the random number generator in Matlab, while signals were generated as described in Section 3.3.

Step two: The PSDs of these signals were generated for SP, WP, MT and parametric techniques using (2), (3), (5) and (6) respectively.

Step three: The P_{FA} and P_D were estimated using (9) and (13) respectively along with the threshold estimation process of Section 3.2.

Step four: Sensitivity analysis was achieved by decomposing the Receiver Operating Characteristics (ROC) curve into its respective P_D and P_{FA} curves and comparing with the corresponding threshold estimates.

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4. Results for Non-Parametric Techniques

4.1. Simple Periodogram (SP)

Several results were obtained using the SP technique, however, for graphical clarity; results are presented for sampled cases of low and high time-bandwidth products in both low and high SNR conditions for short and long sensing times. Figure 5 presents results obtained in low SNR condition for narrow and wideband sensing in short and long sensing times. As observed for the 1dB SNR level, the P_D and P_{FA} curves were shifted apart by an average of 1dB across the dynamic range of the signal. This indicated a very low SNR level such that little could differentiate the detection and false alarm performance. Furthermore, by increasing the sample number, i.e., longer sensing time in narrow or wideband sensing, an increase of only about 5% in detection performance was recorded for the low SNR case. However, by using the minimum sensitivity threshold level of *-22dBm* (yielding a $P_{FA} = 0.1$), little or no difference was observed for an increase in sensing time. This implied that in low SNR condition, an increase in sensing time might not necessarily contribute significantly to improving detection performance as long as a low P_{FA} level must be maintained.

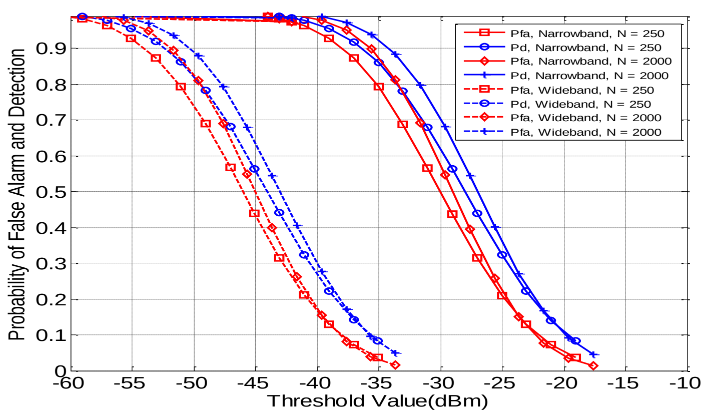

Figure 5: Sensitivity Plot for Low SNR = 1dB using the SP technique for Narrow and Wideband Sensing in short and long sensing times

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Further simulation results for wideband sensing revealed that to achieve $P_{FA} = 0.1$, the SP technique must achieve a sensitivity level of *-36dBm* leading to a 15dB difference in sensitivity level required to achieve same sensing performance with narrowband sensing. This implied that sensitivity requirements can be more demanding in sparse wideband sensing than narrowband, hence making narrowband sensing a better option for CR sensing. In Figure 6, results are presented for the case of high SNR (10dB) for both narrow and wideband sensing. It was observed that the same 15dB difference in sensitivity levels was maintained between narrow and wideband sensing, hence providing a hint that SNR might not necessarily affect the performance gain between narrow and wideband sensing. Furthermore, for a datum threshold of *-22dBm* to achieve $P_{FA} = 0.1$ in narrowband sensing, an 80% increase in P_D was achieved over the low SNR condition. This implied that for high SNR condition, a $P_D = 0.9$ at $P_{FA} = 0.1$ is achievable.

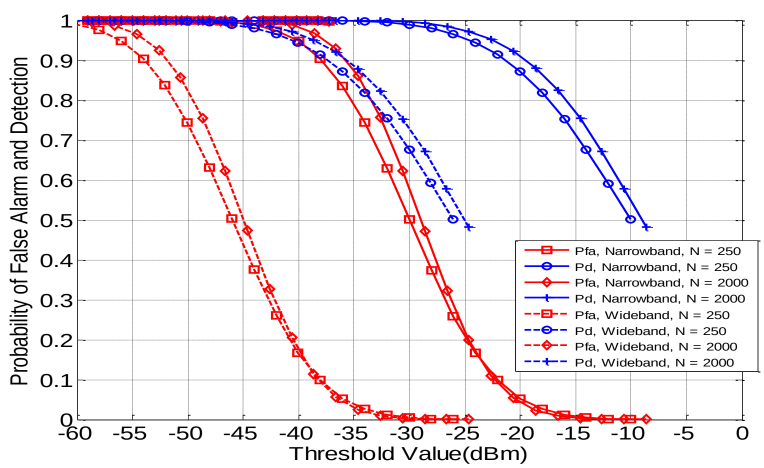

Figure 6: Sensitivity Plot for High SNR = 10dB using the SP technique for Narrow and Wideband Sensing in short and long sensing times

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Also, only about a 5% increase in P_D was achieved by increasing the sensing time by a factor of 10. However, this result still confirmed the known claim that longer observation time results in better detection performance [39]. Also, by using a low P_{FA} = 0.1 in wideband sensing, a detection performance drop of about 80% was recorded over the low SNR condition. However, it can be observed that at the reference threshold of -22dBm, detection probability in wideband sensing will be below 0.5; hence further confirming that sensitivity demands is less in narrow than wideband irrespective of the SNR condition.

4.2. Welch Periodogram

Results for Welch Periodogram (WP) of 50% window length and number of overlap $D = 10$ are presented here with parameter values selected to ensure accurate PSD estimation. Figure 7 describes the case of low SNR for both N = 250 and 2000 in narrow and wideband sensing. Similar performance differences were observed for the WP as obtained in the SP; however, a strange observation was recorded for the case of increase in sensing time which resulted in a drop in detection performance. Further inspection of the estimated spectrum revealed quite an increase in the estimated variance hence corrupting the PU signal level. This was identified as a possible reason for this anomaly. In comparing narrow and wideband sensing at P_{FA} = 0.1, same 15dB difference in sensitivity level was recorded.

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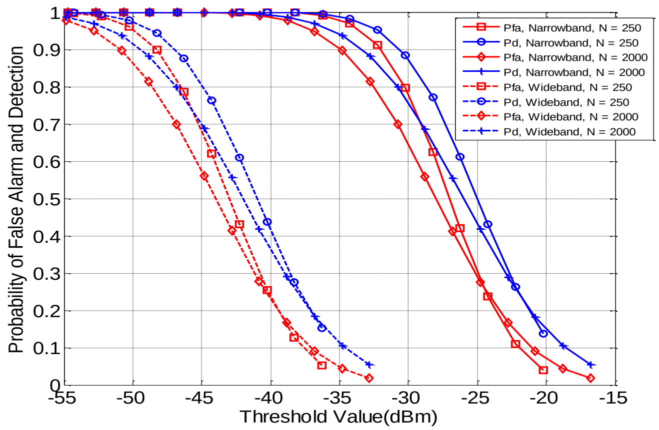

Figure 7: Sensitivity Plot for Low SNR = 1dB using the WP technique for Narrow and Wideband Sensing in both short and long sensing times

With respect to CR design complexities; this indicated that less sensitivity demand is needed for narrow than wideband sensing even for the WP technique. Figure 8 presents results of corresponding investigation of WP in high SNR conditions. By using the datum threshold of -22dBm to achieve stipulated $P_{FA} = 0.1$ for narrowband, a 5% increase in detection performance was recorded when sensing time was increased by a factor of 10. However, a detection probability of 0.98 was recorded for WP as compared to the 0.95 recorded in SP for the best sensing conditions and sensitivity demands. This provided a slightly better performance of the WP over the SP technique.

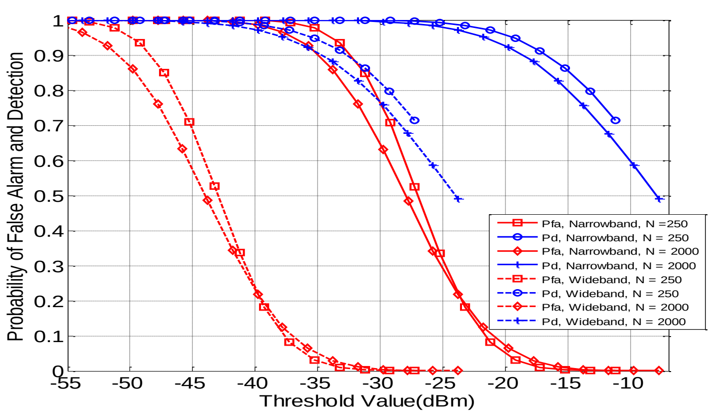

Figure 8: Sensitivity Plot for High SNR = 10dB using the WP Technique for Narrow and Wideband Sensing in Short and Long Sensing Times

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4.3. Multi-Taper

Figure 9 presents results of MT for narrow and wideband sensing in low SNR for short and long sensing times. At $P_{FA} = 0.1$, using the -22dBm threshold value, a detection performance of $P_D = 0.3$ was recorded as compared to the $P_D = 0.25$ of WP for similar condition. However, similar conclusions were reached for the MT approach as obtained in both SP and WP.

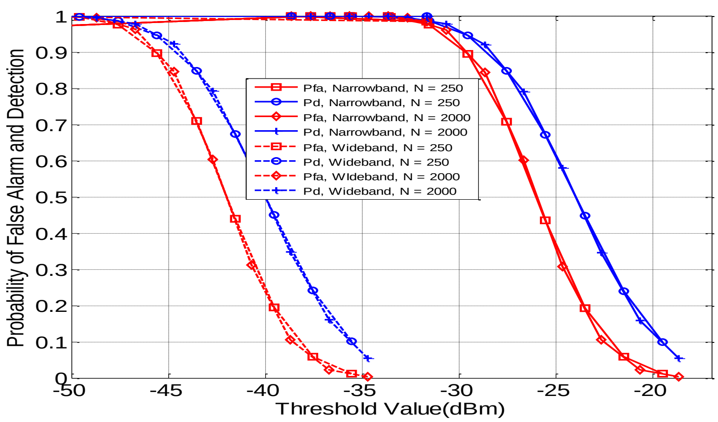

Figure 9: Sensitivity Plot for Low SNR = 1dB using the MT technique for Narrow and Wideband Sensing in Short and Long Sensing Times

In Figure 10, consideration was given to the high SNR condition and the following were observed:

1. There was little recorded difference in both detection and false alarm performance for an increase in sensing time. This implied that the MT technique is also little affected by a corresponding increase in sensing time at low SNR.
2. A $P_D = 0.99$ was recorded as the highest performance for the MT technique at $P_{FA} = 0.1$ for high SNR conditions in both long and short sensing time. This presented a better performance than the WP and SP technique especially in short sensing time conditions.

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3. The same 15dB sensitivity difference was recorded for the MT technique between narrow and wideband sensing. However, the constraint in dynamic range was responsible for the inability to explore the detection performance in wideband sensing to threshold ranges of -22dBm.

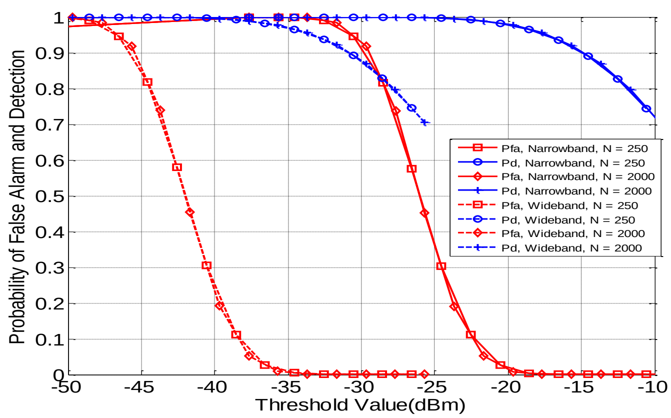

Figure 10: Sensitivity Plot for High SNR = 10dB using the MT Technique for Narrow and Wideband Sensing in Short and Long Sensing Times

5. Results for Parametric Techniques

Simulations were conducted for parametric based PSE techniques using the Yule-Walker (YW), Burg (BG) and Covariance (CV) methods. Results obtained for these techniques indicated a very close performance level and hence a single result was sufficient to describe the performance of all three techniques. Same simulation conditions were used for the YW, BG and CV as obtained in the non-parametric techniques. Figure 11 presents the case for low SNR in narrow and wideband sensing for both small and large sample numbers for YW, BG and CV.

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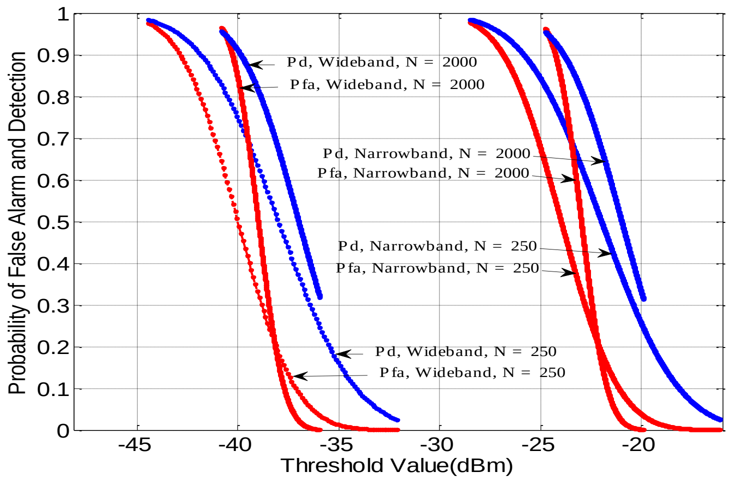

Figure 11: Sensitivity Plot for Low SNR = 1dB using the YW, BG and CV Technique for Narrow and Wideband Sensing in Short and Long Sensing Times

Once again, a 15dB sensitivity difference was recorded between narrow and wideband sensing conditions. However, a very interesting finding at low SNR indicated that for $P_{FA} = 0.1$, a corresponding $P_D = 0.6$ was recorded for the YW, BG and CV technique as compared to the highest $P_D = 0.3$ achieved in the non-parametric MT technique.

This clearly indicated a 50% increase in detection performance in low SNR for parametric techniques over non-parametric techniques. By considering the case of high SNR in Figure 12 the following observations were made:

1. For $P_{FA} = 0.1$ in narrowband sensing, a detection probability of 0.9999 was achieved for both long and short sensing time. Furthermore, a 2% increase in detection performance was recorded for an increase in sensing time only at higher threshold values.
2. A 15dB difference in sensitivity levels was yet recorded between narrow and wideband sensing conditions. This was not different from results obtained in the non-parametric techniques.

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3. A higher detection performance of $P_D = 0.7$ was recorded for wideband sensing at threshold of -22dBm as compared to below 0.5 recorded for the best non-parametric performer. These results revealed a better performance in using the parametric techniques over the non-parametric particularly in terms of sensitivity gain.

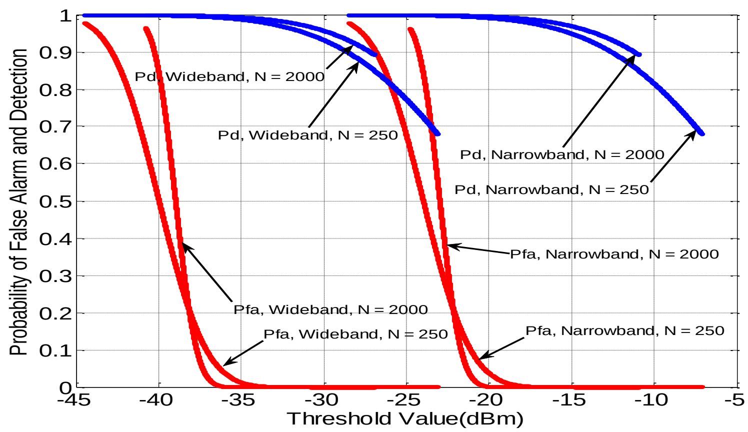

Figure 12: Sensitivity Plot for High SNR = 10dB using the YW, BG and CV Technique for Narrow and Wideband Sensing in Short and Long Sensing Times

6. General Implications of Study

Summary of key observations are presented in Table II and it is worth noting that SA in this work was done with respect to AWGN of zero mean and unit variance for all investigated techniques. All techniques were subjected to identical simulation conditions and numerical details of threshold levels. Table III presents a fuzzy descriptive assessment of each technique for easy comprehension and it can be easily observed that all parametric techniques performed considerably better than non-parametric techniques even in low SNR with a 30% increase in detection performance for both short and long sensing times. A close comparative performance was observed for the parametric techniques with little to separate them. For non-parametric techniques, the SP performed least in all investigated scenarios with MT comparatively better than SP and WP in all scenarios. Hence, for CR application, it was concluded that the parametric techniques provide better sensitivity levels

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and detection performances especially in low SNR and fast sensing conditions for model order $P = 30$.

Table II: Detection Performance recorded at Sensitivity Level of -22dBm for Narrowband and – 37dBm for Wideband to achieve $P_{FA} = 0.1$ in all respective conditions. (Simulations were conducted for each Technique using the same input PU signals embedded in zero mean, unit variance AWGN)

	NARROWBAND SENSING (-22dBm)				WIDEBAND SENSING (-37dBm)			
	LOW SNR		HIGH SNR		LOW SNR		HIGH SNR	
	SS	LS	SS	LS	SS	LS	SS	LS
SIMPLE PERIODOGRAM	0.2	0.2	0.9	0.95	0.2	0.2	0.9	0.95
WELCH	0.25	0.25	0.95	0.98	0.2	0.2	0.95	0.97
MULTI-TAPER	0.3	0.3	0.99	0.99	0.3	0.3	0.99	0.99
YULE-WALKER, BURG, COVARIANCE	0.5	0.6	» 1.00	» 1.00	0.5	0.6	» 1.00	» 1.00

*SS = SHORT SENSING; LS = LONG SENSING; HIGH SNR = 10dB, LOW SNR = 1dB

Table III: Fuzzy Assessment of Detection Performance with respect to sensitivity levels of Each Energy Detector Technique

	NARROWBAND SENSING (-22dBm)				WIDEBAND SENSING (-37dBm)			
	LOW SNR		HIGH SNR		LOW SNR		HIGH SNR	
	SS	LS	SS	LS	SS	LS	SS	LS
SIMPLE PERIODOGRAM	Very Poor	Very Poor	Very Good	Very Good	Very Poor	Very Poor	Very Good	Very Good
WELCH	Very Poor	Very Poor	Very Good	Excellent	Very Poor	Very Poor	Very Good	Excellent
MULTI-TAPER	Very Poor	Very Poor	Excellent	Excellent	Very Poor	Very Poor	Excellent	Excellent
YULE-WALKER, BURG, COVARIANCE	Poor	Poor	Excellent	Excellent	Poor	Poor	Excellent	Excellent

Very Poor: $P_D < 0.5$ **Poor**: 0.5 £ $P_D < 0.7$ **Good**: 0.7 £ $P_D < 0.9$ **Very Good**: 0.9 £ P_D £ 0.95

Excellent: $P_D > 0.95$

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Conclusion

With a need for more information on the most suitable ED technique for Cognitive Radio (CR) application with respect to sensitivity levels, simulations of several techniques including SP, Welch Periodogram (WP), Multi-Taper (MT), Yule-Walker (YW), Burg (BG) and Covariance (CV) has been conducted and results thoroughly analyzed in this paper. Sensitivity analysis was achieved by decomposing the Receiver Operating Characteristic into probability of detection and false alarm curves and comparing with respective threshold values. Outcomes of this investigation provide several interesting and instructive highlights as follows: firstly, a constant 15dB difference in sensitivity levels was observed between narrow and sparse wideband sensing. This implied higher sensitivity demand on the CR device to ensure a high detection performance for sparse wideband sensing as compared to narrowband. Consequently, it was easily concluded that simultaneously using a CR device for both narrow and wideband sensing might prove challenging. Secondly, detection performance was improved by only about 5% for a corresponding increase in sensing time by a factor of 10. However, in low SNR conditions and in maintaining $P_{FA} = 0.1$, little or no difference is gained by increasing the sensing time. If any gain must be made in detection performance, a corresponding increase in false alarm must be incurred. Thirdly, parametric techniques provide about 50% increase in detection performance over non-parametric techniques at low SNR and fast sensing conditions. These conditions seem to be the focus of improvement in ED for CR application. Hence, parametric techniques could provide the necessary performance gain needed for ED techniques in such conditions. Fourthly, it was easily and obviously concluded that all ED techniques provide considerable high detection performance in high SNR and long sensing conditions. Finally, it is noted that consideration was not given to design complexities in this work and though parametric techniques performed better for model order $P = 30$, much remains unknown about the degree of their engineering design complexities for such high model order choices.

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