Sliding Window Based Detection for Spectrum Sensing in Radar Bands

Dayan A. Guimarães, and Chang H. Lim, *Member, IEEE*

***Abstract*—Recently, radar frequency bands have been drawing much attention as possible candidates for cognitive radio, since their utilization was revealed to be relatively low. One important functionality of a cognitive radio system is the spectrum sensing, which detects the presence of a primary user (PU) signal. The pulse radar signal, which is the PU signal in radar bands, is characterized by its sparsity in the time domain. Exploiting this sparsity, we present a spectrum sensing technique which combines the intermediate detections from multiple small sliding sensing windows of the received radar signal into a final decision. We also show by computer simulation that it can achieve improvement of the sensing performance in comparison with the conventional single-window based spectrum sensing approach.**

***Index Terms*—Cognitive radio, cooperative spectrum sensing, radar, GRCR.**

I. Introduction

THE demand for radio spectrum is explosively growing as a consequence of the emergence of numerous wireless communication systems and services, each one aiming at serving a massive number of users. However, the spectrum scarcity combined with the traditional static spectrum allocation policy places an obstacle to the increasing demand in the near future. In order to address this obstacle, a lot of research efforts have been spent. Among them, the cognitive radio (CR) concept [1] is being considered one of the most promising ones. In short, it is a spectrum sharing technique that allows for a secondary user (SU) to access a frequency band whenever it is not occupied by the primary user (PU), leading to higher spectrum utilization [2], [3].

Recently, radar bands have been attracting much attention as possible candidates for cognitive radio, since they were found to be underutilized and wideband [4]. For instance, the Federal Communications Commission (FCC) has regulated that wireless local area network (WLAN) devices be able to detect radar signals and then switch the wireless network device to another channel to avoid interference with these signals [5]. Thus, the successful operation of cognitive radio in radar bands requires the capability of spectrum sensing [6], which is an essential component of a CR to decide upon the presence or absence of radar signals in a given sensed band.

An immediate approach for radar signal detection is to compare the received signal power for a short time with a predetermined decision threshold. Since this is categorized as an energy detection approach [6][7], it does not exploit the inherent characteristics of a pulse radar signal, and is susceptible to noise power uncertainty. This approach can be refined by applying multiple pulse detection [8] where a single pulse is identified as the change of the received signal power by more than a specific amount in time for both the leading and falling edges. More elaborated detection strategies explores the autocorrelation between pulses in time [9], and the spectral characteristics distinguishing radar signals from noise [10].

Usually, a pulse radar periodically radiates a train of short pulses that tends to be sparse in time. The conventional spectrum sensing techniques are based on applying some detection algorithm to a whole sensing interval, not exploiting this sparsity. Motivated by this fact, in this paper we present an improved spectrum sensing strategy in which the conventional single sensing event during a sensing interval is transformed into multiple short-time detection events by means of a sliding window approach. The multiple sensing results are then combined to yield the final decision upon the occupation of the sensed band. Since there is no requirement for the detectors adopted in this sliding window approach, we have chosen the recently-proposed Gerschgorin radii and centers ratio (GRCR) detector [11], which exhibits the constant false alarm rate (CFAR) property and is robust against nonuniform and dynamical noise and received signal powers. We call the proposed detector the Sliding GRCR.

The remainder of this paper is organized as follows. The system model is given in Section II. The proposed Sliding GRCR approach is described in Section III. Section IV is devoted to the numerical results and discussions. Finally, we end up with some conclusions in Section V.

II. System Model

A. Signal Model

Adapting the model of [11] to the radar signal detection problem, consider a cooperative spectrum sensing scheme in which m cognitive SUs collect mn samples (n samples per SU) of the signal received from a radar transmitter during the sensing interval. At the fusion center (FC) of the secondary network, the received signal matrix $\mathbf{Y} \in \mathbb{C}^{m\times n}$ is given by

$$\mathbf{Y} = \mathbf{h}\mathbf{x}^{\mathrm{T}} + \mathbf{V}, \tag{1}$$

where the superscript T denotes transposition, and $\mathbf{h} = [h_1, h_2, \ldots, h_m]^{\mathrm{T}}$ is the channel vector with h_i representing the complex channel gains between the radar transmitter and the i-th SU receiver, for $i = 1, \ldots, m$. These gains are assumed

D. A. Guimarães is with the National Institute of Telecommunications (Inatel), Santa Rita do Sapucaí, MG, Brazil (e-mail: dayan@inatel.br).

C. H. Lim is with the Department of Electronic Engineering, Pukyong National University, Busan, Republic of Korea (email: chlim@pknu.ac.kr).

Manuscript received April 18, 2018; revised May 02, 2018.

This work was partially supported by Finep (with Funttel resources) Grant 01.14.0231.00, under the Radiocommunications Reference Center (CRR) project of the Inatel, Brazil.

to be constant during the sensing interval, and independent and identically distributed (i.i.d.) between consecutive sensing rounds. The channel vector is modeled as $\mathbf{h} = \mathbf{Ga}$, where $\mathbf{a} \in \mathbb{C}^{m\times 1}$ is the vector whose elements are zero-mean complex Gaussian random variables having unitary second moment to represent flat and slow Rayleigh fading channels. The matrix $\mathbf{G} \in \mathbb{R}^{m\times m}$ is a diagonal gain matrix given by $\mathbf{G} = \mathrm{diag}\left(\sqrt{\mathbf{p}/p_{\mathrm{avg}}}\right)$, with $\mathbf{p} = [p_1, p_2, \ldots, p_m]^{\mathrm{T}}$ being the vector with the received signal power levels in each SU, where $p_{\mathrm{avg}} = \frac{1}{m}\sum_{i=1}^{m} p_i$ is the average received signal power over all SUs. If the overall channel power gain is unitary (without loss of generality), the radar signal is transmitted with a constant power p_{avg}. The matrix $\mathbf{V} \in \mathbb{C}^{m\times n}$ contains independent zero mean complex Gaussian noise samples. To consider the possibility of nonuniform noise variances across the SUs' receivers, the elements in the i-th row of $\mathbf{V}$ have variance σ_i^2, $i = 1, \ldots, m$. Then, denoting the average noise variance as $\sigma_{\mathrm{avg}}^2 = \frac{1}{m}\sum_{i=1}^{m}\sigma_i^2$, the received signal-to-noise ratio, in dB, averaged over all SUs, is $\mathrm{SNR} = 10\log_{10}\left(p_{\mathrm{avg}}/\sigma_{\mathrm{avg}}^2\right)$.

Finally, the vector $\mathbf{x} \in \mathbb{R}^{n\times 1}$ in (1) represents the samples of the radar signal. In practice, a pulse radar signal is formed by a series of short time pulses having duration of about 1-5 microseconds [5]. The time between the start of consecutive pulses is typically on the order of 1 millisecond, yielding a very low duty-cycle waveform. From the perspective of the detector, the received signal from a rotating radar is seen as a series of bursts of pulses. The time from the start of one burst to the start of the next one is typically on the order of 1-10 seconds. That said, in base-band representation the radar signal vector model as seen by the SUs' receivers looks like $\mathbf{x} = [\ldots, v, v, \ldots, v, 0, 0, \ldots, 0, v, v, \ldots, v, 0, 0, \ldots, 0, \ldots]^{\mathrm{T}}$, where v is set according to the desired radar signal power p_{avg} and duty-cycle D, i.e., $v = \sqrt{p_{\mathrm{avg}}/D}$. The number of consecutive vs (i.e., the pulse duration expressed in terms of a number of samples per pulse) and consecutive 0s (i.e., the pulse spacing, also expressed in samples) are set to yield the desired duty-cycle. The number of pulses within the sensing interval is assumed to be a uniform random variable $\mathcal{U} \sim [1, N]$ to represent the asynchronous operation between the radar bursts and the spectrum sensing interval, where N is the number of pulses per burst.

B. GRCR Detector

At the FC, the sample covariance matrix of the received signal is computed as $\mathbf{R} = \frac{1}{n}\mathbf{Y}\mathbf{Y}^{\dagger}$, where $\dagger$ denotes the complex conjugate and transpose. The Gerschgorin radii and centers ratio (GRCR) test statistic defined in [11] is

$$T_{\mathrm{GRCR}} = \frac{\sum_{i=1}^{m}\sum_{j=1, j\neq i}^{m}\left|r_{ij}\right|}{\sum_{i=1}^{m} r_{ii}}, \tag{2}$$

where r_{ij} is the element in the i-th row and j-th column of $\mathbf{R}$, for $i, j = 1, \ldots, m$.

The performance metrics often used to assess the spectrum sensing performance are the probability of detection and the probability of false alarm, respectively defined as $P_{\mathrm{d}} = \Pr(\text{decision} = \mathcal{H}_1|\mathcal{H}_1)$ and $P_{\mathrm{fa}} = \Pr(\text{decision} = \mathcal{H}_1|\mathcal{H}_0)$, where $\mathcal{H}_1$ and $\mathcal{H}_0$ are the hypotheses of the presence (i.e. $\mathbf{Y} = \mathbf{h}\mathbf{x}^{\mathrm{T}} + \mathbf{V}$) and absence (i.e. $\mathbf{Y} = \mathbf{V}$) of the radar signal, respectively, and $\Pr(\cdot)$ is the probability of the underlying event. Notice that the absence of the radar signal might be declared if no radar signal is being transmitted or if the sensing interval falls in between radar signal bursts.

III. Proposed Sliding GRCR Approach

The motivation behind the Sliding GRCR approach goes as follows: for the succesful detection of a pulse radar signal, it could be better to adopt a divide-and-conquer strategy in which the whole sensing interval (single sensing round) is split into multiple smaller sensing windows (multiple sensing rounds), since the signal has a small duty-cycle. By doing so, the large pulse energy can be captured in one of the sensing rounds, affected by a noise energy smaller than the one present in the whole sensing interval. However, a simple partition of the sensing interval into adjacent windows may be ineffective, since a pulse might not entirely fall into a given window due to its random position, reducing the detection capability. A more effective approach is to slide a sensing window through the whole sensing interval as an attempt to hit the radar pulse with higher probability. An intermediate decision on the presence or absence of the radar signal is then made for each step of the sliding window. When the window reaches the end of the sensing interval, a logic operation is made among the intermediate decisions to yield the final global decision. In principle, this sliding window approach can be combined with any detection technique, but it can benefit from the low complexity and the CFAR property of the GRCR test statistic devised in [11]. The name Sliding GRCR was given to the resulting spectrum sensing technique due to the application of the GRCR to the approach just described.

Figure 1 illustrates the operation of the proposed Sliding GRCR spectrum sensing with some hypothetical numerical values. In this figure, a single radar burst with N pulses (3 in this example) during the sensing interval is shown. The beginning of the first pulse is a random variable, since the radar burst and the sensing interval are not synchronous to each other. Each pulse lasts an interval corresponding to W_{p} samples (20 in this example). The sliding window has a size of S_{w} samples and moves through the sensing interval (600 samples in this example) in steps of size S_{s} samples.

The number of samples collected by each SU, n, the number of radar pulses per burst, N, the radar pulse width, W_{p}, and the radar signal duty-cycle, D, are related via

$$n = \frac{W_{\mathrm{p}}N}{D}. \tag{3}$$

Depending on the sliding window size S_{w}, the number of steps $S_{\mathrm{n}} \in \mathbb{N}_+$, which is the total number of sensing rounds during the whole sensing interval, is given by

$$S_{\mathrm{n}} = \frac{n - S_{\mathrm{w}}}{S_{\mathrm{s}}} + 1. \tag{4}$$

In each sensing round, the GRCR test statistic (2) is formed from a sample covariance matrix $\mathbf{R}$ computed from a received signal matrix $\mathbf{Y}$ similar to (1), but of order $m \times S_{\mathrm{w}}$ instead of $m \times n$. The final global decision is reached via the logic OR operation among the intermediate decisions made in all

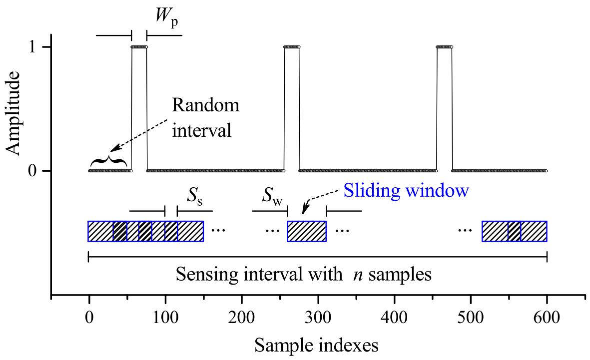

Fig. 1. Radar burst with $N = 3$ pulses, pulse width $W_p = 20$ samples, and duty-cycle $D = 10\%$. The whole sensing interval corresponds to n samples, S_s is the step size and S_w is the window size.

rounds, which is equivalent to say that the decision will be made in favor of the presence of the radar signal if $\max\{T_{\text{GRCR}}(1), T_{\text{GRCR}}(2), \ldots, T_{\text{GRCR}}(S_n)\} > \gamma$, where γ is the decision threshold.

The computational complexity of calculating a sample covariance matrix from a received signal matrix $\mathbf{Y}$ of order $m \times S_w$ is $O(S_w m^2)$. Then, the complexity of the Sliding GRCR is $O(S_n S_w m^2)$ due to the repeated sensing rounds. It can be noticed from (4) that $S_n S_w \geq n$. Since the complexity of the original GRCR is $O(nm^2)$ [11], the Sliding GRCR will exhibit a complexity greater than or equal to the original GRCR, with the equality holding when the step size is equal to the window size, i.e., $S_s = S_w$. Notice that the energy consumption due to the existence of multiple sensing windows is related to the computational burden at the FC. The multiplicity of windows do not affect both the energy spent for sensing at each SU, and the energy due to the transmission over the report channel.

The proposed Sliding GRCR approach has its parameters fully configurable to allow for a trade-off between the spectrum sensing performance and overall sensing speed. For instance, if the window size S_w fits the pulse width W_p, the maximum pulse energy is captured, improving the sensing performance. Moreover, if the step size is $S_s = 1$, the chance of hitting a radar pulse is maximized at the expense of a large number of sensing rounds and, thus, a large processing time.

Finally, it is worth emphasizing that the average SNR of the configuration according to the system model described in Section II, i.e. $\text{SNR} = 10\log_{10}\left(p_{\text{avg}}/\sigma^2_{\text{avg}}\right)$, will be higher than the actual SNR due to the random number of radar pulses seen by the SUs during the sensing interval. It can be shown that the actual SNR can be well approximated by

$$\text{SNR} \approx 10\log_{10}\left[\frac{(N+1)p_{\text{avg}}}{2N\sigma^2_{\text{avg}}}\right]. \tag{5}$$

The reason why (5) is not exact is that, based on the model depicted in Fig. 1, a radar pulse can be partially included in the sensing interval.

IV. Numerical Results

A typical tool for analyzing P_d and P_{fa} simultaneously is the receiver operating characteristic (ROC) curve, which trades P_{fa} versus P_d by varying the decision threshold γ. The results

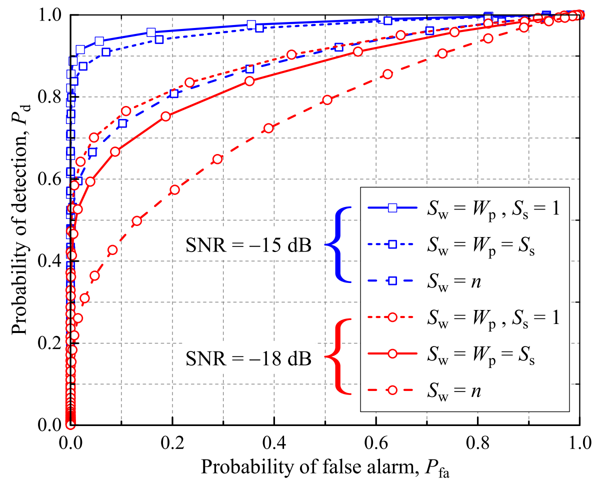

Fig. 2. Performances of the Sliding GRCR ($S_w = W_p$) and the original GRCR ($S_w = n$) for detecting a radar signal under different SNR and S_s values, for $m = 5$, $n = 2400$, $W_p = 30$, $D = 5\%$, and $N = 4$.

shown hereafter are given in terms of ROC curves obtained from 20000 Monte Carlos events in which the received signal matrix $\mathbf{Y}$ is generated under the $\mathcal{H}_1$ and $\mathcal{H}_0$ hypotheses.

We assumed $m = 5$ SUs and a radar signal with duty-cycle $D = 5\%$, with a maximum of $N = 4$ pulses per burst during the sensing interval under the $\mathcal{H}_1$ hypothesis. The random interval shown in Fig. 1 was made uniformly distributed in $[0, n - W_p - 1]$ samples, meaning that at least a single entire pulse is present during the whole sensing interval under $\mathcal{H}_1$.

To consider a scenario of practical significance, nonuniform noise variances and nonuniform received powers were assumed. In each sensing, they were independently drawn from a uniform distribution such as $\sigma_i^2 \sim \mathcal{U}[0.05\sigma^2_{\text{avg}}, 1.95\sigma^2_{\text{avg}}]$ and $p_i \sim \mathcal{U}[0.05p_{\text{avg}}, 1.95p_{\text{avg}}]$, respectively.

Figure 2 shows the performance of the Sliding GRCR for a radar pulse width $W_p = 30$ samples, window size $S_w = 30$ samples, and window step sizes $S_s = 1$ ($S_n = 2371$ sensing rounds) and $S_s = W_p = 30$ ($S_n = 80$ sensing rounds), under different SNR values, for $n = 2400$ samples collected by each SU. The corresponding performances of the original GRCR ($S_w = n$, $S_n = 1$) are also shown. From this figure it can be readily noticed that the Sliding GRCR outperforms the original GRCR for any SNR. Notice from (4) that, with $S_s = S_w$, then $S_n S_w = n$, meaning that the complexity of the Sliding GRCR is equal to the complexity of the GRCR. In the case of $S_s = 1$, the largest performance gain over the original GRCR is attained, at the expense of a higher computational complexity.

In Figure 3, the SNR is kept fixed at −15 dB, and the window size S_w is varied, again for $m = 5$, $n = 2400$, $W_p = 30$, $D = 5\%$, $N = 4$, and $S_s = W_p = 30$. This figure illustrates that the performance improves as the window size decreases from $S_w = n = 2400$ to $S_w = W_p = 30$. In this case, the performance is traded against the number of sensing rounds S_n, but the computational complexity remains unchanged.

Figure 4 is similar to Fig. 3, but now the pulse width was reduced to $W_p = 5$, which in practice is equivalent to a reduction in the received signal sampling rate. The other system parameters are $m = 5$, $n = 400$, $D = 5\%$, $N = 4$,

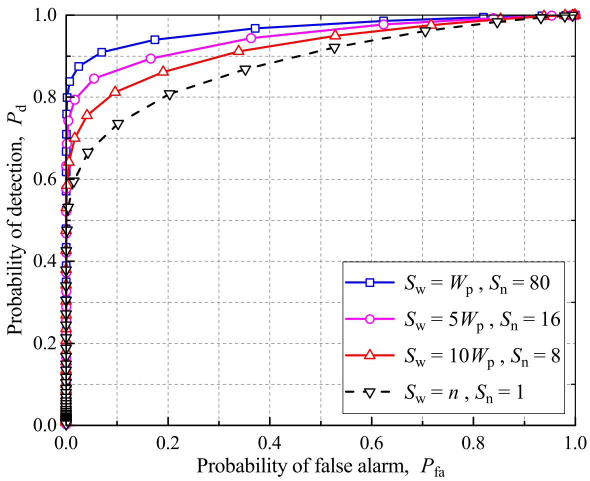

Fig. 3. Performances of the Sliding GRCR and the original GRCR ($S_w = n$, $S_n = 1$) for detecting a radar signal under different values of the window size S_w, for $m = 5$, $n = 2400$, $W_p = 30$, $D = 5\%$, $N = 4$, and SNR = −15 dB.

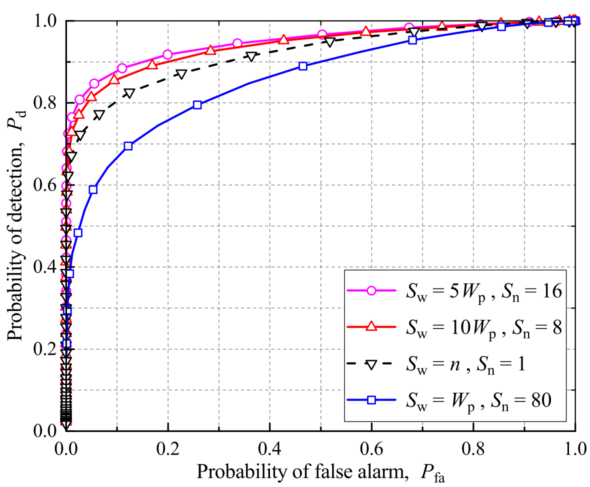

Fig. 4. Performances of the Sliding GRCR and the original GRCR ($S_w = n$, $S_n = 1$) for detecting a radar signal under different values of the window size S_w, for $m = 5$, $n = 400$, $W_p = 5$, $D = 5\%$, $N = 4$, and SNR = −10 dB.

and SNR = −10 dB. One can see that the reduction of the window size has brought improvements up to $S_w = 5W_p = 25$. However, the sensing performance for the case of $S_w = W_p = 5$ became even worse than the single-round sensing made by the original GRCR. This behavior is due to the poor sample covariance matrix estimation when S_w is small, because the order of $\mathbf{Y}$ is $m \times S_w$.

Even when the sampling rate is small, causing the reduction of the number of samples during the pulse existence, it is still possible to recover the monotonic performance improvement of the Sliding GRCR as the window size approaches the pulse width. Figure 5 exemplifies this situation. The difference from Fig. 4 is that the number of SUs has been increased from $m = 5$ to $m = 30$. Then, if the number of samples obtained from a radar pulse is small, increasing the number of SUs in cooperation may reestablish the desired behavior of the sliding spectrum sensing approach.

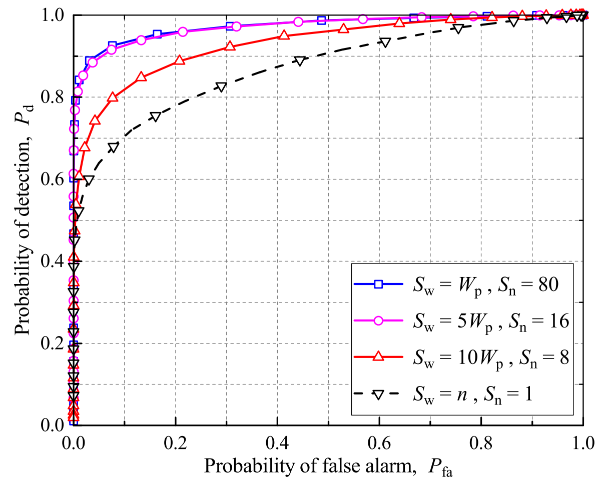

Fig. 5. Performances of the Sliding GRCR and the original GRCR ($S_w = n$, $S_n = 1$) for detecting a radar signal under different values of the window size S_w, for $m = 30$, $n = 400$, $W_p = 5$, $D = 5\%$, $N = 4$, and SNR = −17 dB.

V. Conclusion

Exploiting the temporal sparsity of a pulse radar signal, we presented a novel spectrum sensing technique that combines intermediate detections from multiple small sliding sensing windows into a final global decision. Simulation unveiled that the sliding window approach can provide significant performance improvement over the conventional single-window spectrum sensing. Moreover, it can be combined with any spectrum sensing scheme, and is flexible by allowing full control over the spectrum sensing performance and computational burden. If the SUs are equipped with multiple antennas, the Sliding GRCR can be performed in each SU for local decision, allowing for the implementation of a decision fusion strategy.

References

[1] J. Mitola and J. G. Q. Maguire, "Cognitive radio: making software radios more personal", *IEEE Commun. Mag.*, vol. 6, no. 4, pp. 13-18, Aug. 1999

[2] G. Ding et al., "On the limits of predictability in real-world radio spectrum state dynamics: from entropy theory to 5G spectrum sharing," in IEEE Communications Magazine, vol. 53, no. 7, pp. 178-183, July 2015.

[3] X. Kang, Y. C. Liang, H. K. Garg and L. Zhang, "Sensing-Based Spectrum Sharing in Cognitive Radio Networks," in IEEE Transactions on Vehicular Technology, vol. 58, no. 8, pp. 4649-4654, Oct. 2009.

[4] F. Paisana, N. Marchetti, and L. A. DaSilva "Radar, TV and Cellular Bands: Which Spectrum Access Techniques for Which Bands?", *IEEE Comm. Survey & Tutorials*, vol. 16, no. 3, pp. 1193-1219, 2014

[5] S. Tsai, C. Huang, and S. Yin, "Method and device for robust signal detection in wireless communications," Feb. 7 2008, US Patent App. 11/498,432. [Online]. Available: https://www.google.com.br/patents/US20080031386

[6] T. Yucek and H. Arslan, "A survey of spectrum sensing algorithms for cognitive radio application", *IEEE Communication Survey & Tutorials*, vol. 11, no. 1, pp. 116-130, 2009

[7] M. Wen and L. Hanwen, "Radar detection for 802.11a systems in 5 GHz", *International Conference on Wireless Communications, Networking and Mobile Computing*, vol. 1, pp. 512-514, Sept. 2005

[8] V. Hayes, "Report of IEEE 802 Radio Regulatory Group relating to DFS and JPT5G proposal", *IEEE 802.RR-02/018Ad2*, Jan. 2002

[9] J. Sydor, and S. Chow, "Draft Canadian analysis for BWAS and RADAR", *IEEE 802.RR-02/039r0*, Mar. 2002

[10] W. McFarland, C. Zeng, and D. Dhamdhere, "Radar detection and dynamic frequency selection for wireless local area networks", *USA: 6,697,013 B2*, Feb. 2004

[11] D. A. Guimarães, "Robust test statistic for cooperative spectrum sensing based on the Gerschgorin circle theorem," *IEEE Access*, vol. 6, pp. 2445-2456, 2017.