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SUMMARY
OF PhD THESIS

SPECTRUM SENSING ALGORITHMS FOR OPPORTUNISTIC SPECTRUM ACCESS SYSTEM

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Chapter 1: Introduction

The wireless systems and networks are increasing day by day, which is leading to growing demand for the spectral resources to accommodate them for this and as a consequence, resulting in a scarcity of spectrum resources. One technology aimed at overcoming this scarcity is called Cognitive Radio (CR), which offers a groundbreaking solution to this problem. The existing wireless communication networks are regulated by a strategy of fixed allocation of the spectrum, which has been proved inefficient, according to some recent spectral usage investigations. CR achieves maximum spectrum utilization efficiency through opportunistic access to temporarily unused parts of the spectrum.

1.1 Presentation of the field of the doctoral thesis

A lot of focus has been given in recent years to studying frequency spectrum resources, as wireless networking technologies have been developing very fast along with their applications. Given the limitations of the radio spectrum, meeting the demand for greater bandwidth and larger data volumes is a daunting challenge that involves creating technology capable of finding new ways to leverage the available frequency bands.

CR has received growing recognition as a potential effective response to the spectral crowding issue by incorporating the notion of opportunistic spectrum utilisation as one of the key popular innovations for the future generations of wireless communication networks. A key element of CR technology is the spectrum sensing, which allows CRs to identify the spectral gaps. Moreover, one of the emerging trends is to improve the quality of radio spectrum use among Dynamic Spectrum Access (DSA) and Spectrum Sensing (SS). Wireless communications have developed rapidly and although it was conducted in-depth research and development work for more effective technologies, the scarcity of available radio spectrum is considered a key issue for the further development of this field. The focus has been given to the DSA and CR strategies as possible solutions to the problem of spectrum scarcity for the next generation of wireless communication networks, including the Fifth-Generation (5G) [1].

The Federal Communications Commission (FCC) defines a CR as: "a system or a radio that senses its electromagnetic operating environment and can dynamically and separately confirm its radio operating parameters to adjust system operation, like mitigating interference, maximizing throughput, accessing secondary markets and facilitating interoperability" [2]. The 2.4 GHz commercial Industrial Scientific and Medical (ISM) band, owing to its international availability, is a common frequency band suitable for low-cost wireless systems.

One big issue is that users operating in the same radio system can interact significantly with one another. However, there are no appropriate synchronisation or radio-resource management mechanisms for the multitude of networks running in the ISM bands, which contributes to the ineffective use of these frequency bands. To overcome these problems, advanced techniques for CR and signal processing have recently been found. The relocation software-based approach is highly regarded in the latest CR technologies due to its reliability. Under this method, Secondary User (SU) systems receive information about the spectrum supply from a database providing knowledge about the Primary User (PU) operation in the geographic region where the SU is planned to work [3].

One of the CR's key activities is to identify a communication range with no interference. Moreover, spectrum sensing-based techniques are of high importance as a complementary element in database-based CR networks and as a possible future development path, especially in short-range communication. Cooperation and repeated monitoring with another user is required for robust and highly sensitive spectrum sensing due to the changing channel status.

1.2 The purpose of the doctoral thesis

The main purpose of this research is to review and examine some significant techniques for SS and designing improved spectrum detection algorithms, which allow the implementation of efficient CR-based sensors. Cooperative detection introduces one potential option that can make the detection process more accurate. Given the theme of improved SS methods is very broad, the research is limited to focusing on effective non-cooperative detection.

To start with, the ED algorithms and their concepts were studied to ascertain in which direction these needed to be developed. First, the Classical ED (CED) algorithm [4] and some improved performance versions of CED, such as Improved ED (IED) [5] and Three-Event Energy Detection (3EED) [6] algorithms, are investigated. It was noticed that improving the algorithms depended on the measurement of the energy per sensing slot and that increasing the number of the tests, the results improved as well. Moreover, decision threshold adaptation with the value of the noise variance was demonstrated as another significant performance increase method for the CED algorithm in [7]. Starting from this threshold adaptation premise, several adaptive versions of the IED and 3EED algorithms are developed for decreasing the Decision Error Probability (DEP) in the system.

1.3 The content of the doctoral thesis

This thesis is organized as follows.

Chapter 2 contains the presentation of the concept of CR system, along with its components. Spectrum sensing is also explained, as well as general information regarding the energy detection is presented.

In chapter 3, the CED algorithm is presented and its theoretical performance is analyzed. Also, the threshold setting is explained, this being an important parameter configured by the system designer to control the performance of the spectrum sensing. In addition, an adaptive version of this algorithm (named as Adaptive CED (ACED)) is explained and its DEP performance is analyzed theoretically. Moreover, the analytical expression of the adaptive decision threshold is provided for CED.

In chapter 4, an Adaptive threshold IED (AIED) algorithm is proposed and developed. Moreover, the theoretical performance is estimated, and Monte Carlo simulations are run for both algorithms, i.e., ACED and AIED. The results show that the proposed AIED algorithm outperforms ACED in terms of DEP.

Chapter 5 presents a new adaptive version of the 3EED algorithm for SS in CR systems. An analytical expression of the optimum decision threshold is developed for minimizing the DEP of the A3EED algorithm. Using complex simulations, numerical results are obtained, which confirm the derived analytical expressions and demonstrate the enhanced performance of the algorithm.

In chapter 6, a modified amplify and forward cooperative detection algorithm is proposed. Also, a simplified channel model is presented by analyzing theoretically and through simulation the cooperative detection probability of the algorithm, with significant detection gains being found as compared to the non-cooperative case.

Chapter 7 summarizes the results obtained in the research, the original contributions are explained and finally, the perspectives of further development are discussed.

Chapter 2: Cognitive Radio

The cognitive radio technology can be utilized to meet future mobile communication network demand by using complex dynamic source management [8]. Several new abilities, including networking, resiliency, agility and sensing are integrated into CR to allow the spectrum to be used in an efficient way.

2.1 Concepts of cognitive radio technology

There are several new concepts that appeared once with the utilization of the cognitive radio technology as one of the main technologies for the next decade radio systems. In the following subsections some of the key principles underpinning CR technology are explained to facilitate understanding of the subsequently presented subjects.

2.1.1 Primary user and secondary user

In the context of the CR technology, two types of users can be defined, PUs (the licensed users) who are usually granted preferential access to the spectrum and these main users are the original users, which can access their dedicated spectrum unconditionally anytime, anywhere. And the second type of users are SUs (the unlicensed users), who can utilize the spectrum that PUs are licensed to use only when the PU are not actively using the spectrum.

2.2 Cognitive radio structure

CR is a Software Radio (SR) class with extra features and interfaces, including taking decisions, ambient detecting and learning how to achieve the required performance. CR manages the operation of high-level software applications to match a Personal Digital Assistant (PDA) under the software field. To understand the CR structure, we need to examine the software radios and their realistic version of the SDR since they reflect the CR core component.

2.3 Cognitive radio applications

The surrounding adaptability has made CR famous in the communications world. CR offers various advantages in different fields such as governmental, public, military, trade and security.

2.4 Spectrum sensing function

Spectrum sensing is one of the vital functionalities of a cognitive radio taking into consideration the main target for the radio condition. In literature, different spectrum sensing methods are proposed [9] [10]:

- Energy-based sensing.
- Matched filter-based sensing.
- Cyclostationary feature-based sensing.

Distinctive procedures meet different needs, given their favorable circumstances and disadvantages. Energy-based sensing is the most straightforward strategy, the cyclostationary based sensing may require some data about the other client signal qualities and the matched filter-based sensing requires the entire data of the client signal.

Cognitive spectrum sensing thus involves quick and effective strategies for identifying the holes in the spectrum [11]. The sensing method would be smart enough to recognize various contact systems in the medium ambient and to be able to expand the scanning measurements to fill all available spectrum gaps in all possible dimensions.

- **Energy detection**

Energy detection is considered to be the most common signal detection technique because of its simplicity in terms of practical application [12].

In the ED approach, the radio energy of the received signal is measured to decide if a frequency band is occupied or not [13].

- **Matched filter detection**

A matched filter is an ideal sensing strategy as it expands the Signal to Noise Ratio (SNR) of the received signal. The matched filter that can be used in CR has been also referred as coherent detector. This can be considered as the best detecting system if CR knows about PU waveform. It is extremely precise since it maximizes the obtained SNR. The main advantage of matched filter detection is the short sensing time to achieve a good performance, because coherence detection is used [14].

- **Cyclostationary detection**

Cyclostationary detection is a special sensing technique that allows the energy detector to distinguish the PU signal from noise and the interference. Especially, signals of wireless devices generally are modulated and generated following a periodicity. In the event that the signal of the PU shows solid cyclostationary properties, it can be identified at low SNR values. A signal is considered to be cyclostationary (in the wide sense) if its autocorrelation is a periodic function of time *t* with some period. The cyclostationary detection can be performed as presented in [15]. They can be recognized by analyzing the Cyclic Autocorrelation Function (CAF) of received signals, given as:

$$R_y^{(\alpha)}(\tau) = \mathbb{E}\left[y(t+\tau)\, y^*(t-\tau)e^{-j2\pi\alpha t}\right] \tag{1}$$

where α is the cyclic frequency, * stands for complex conjugate and $\mathbb{E}[\cdot]$ denotes expectation. The discrete change of the CAF can then be figured to acquire the Spectral Correlation Function (SCF), additionally called a cyclic spectrum, which is a two-dimensional function in terms of frequency and cyclic frequency. At last, the identification is completed via searching the one-of-a-kind cyclic frequency relating to the peak in the SCF plane.

2.5 Cognitive radio architecture

CR network will run in a specific context, in which the operational range will include licensed and unlicensed frequencies, and licensed frequencies will be assigned to various systems with different networking technologies. Operating in this diverse environment needs a special network infrastructure that can easily adapt, and perform efficiently in such environment.

Chapter 3: Classical Energy Detection and Adaptive Classical Energy Detection Algorithms

3.1 Energy detection

Energy detection is the most prevalent signal location technique because of its basic circuit in a functional application. The standard of energy detector is to discover the energy of the got signal and match that through the limit [16].

3.2 Classical energy detection (CED)

3.2.1 CED Operating principle

The principle of Classical Energy Detection (CED), which is also referred to as radiometric detection, measures the receiving energy on the base range through the observation period and announces the current channel state S_i as occupied (hypothesis H_1) if the measured energy is larger than a correctly set threshold, or otherwise, as inactive (hypothesis H_0) [4].

3.2.2 CED Threshold setting

The process used to determine threshold algorithm resolution is an important aspect because it represents a parameter that is configured by the system designer to control the performance of the spectrum sensing. The threshold λ can be selected for the best trade-off among the probability of detection P_d and the probability of false alarm P_{fa}. However, this needs information about the noise and signal power detected. Though the noise power can be evaluated, the signal power is difficult to guess because it depends on several dissimilar factors like transmission and spread features. Empirically, the threshold is usually selected to satisfy a P_{fa} requirement or target [17], the required threshold λ for the target probability of false alarm given as:

$$\lambda = \left(Q^{-1}\left(P_{fa,target}^{CED}\right)\sqrt{2N} + N\right) \sigma_n^2 \tag{2}$$

3.3 Adaptive classical energy detection (ACED)

CR is considered a smart wireless communication technology to fix the inefficiency of the fixed spectrum assignment policy [18] [19]. The SS is considered as one of the main difficult task in the CR system as it needs a low complexity and high correctness for dynamic spectrum access [20]. The efficiency metric of SS is typically calculated as a trade-off betwixt susceptivity and selectivity and can be measured out by the levels of the false alarm and detection probabilities.

3.3.1 ACED Threshold setting optimization

The trade-off between P_d and P_f is designed to minimize the probability of decision error P_e in the spectrum utilization ratio of PUs α ($0 < \alpha < 1$) and the threshold λ as:

$$\min\left(P_e\ (\lambda)\right) = \min\left\{(1-\alpha)P_f + \alpha(1-P_d\ )\right\} \tag{3}$$

where $(1-P_d)$ denotes the missdetection probability, which suggests that the PU is absent, but in fact, it is present. $\alpha(1-P_d\ )$ determines the probabillity of error decision for PUs being present with spectrum utilization α. Likewise, $(1-\alpha)P_f$ is the probability of decision error for the PU being absent. Thus, the idea is to find an adaptive threshold to minimize the decision error probability. The equation can be written in a simple way as:

$$\lambda^* \approx \frac{2\ \sigma_n^2\ \cdot (1+SNR)}{(2+SNR)}(N \to +\infty) \tag{4}$$

Chapter 4: Improved Energy Detection and Adaptive Improved Energy Detection Algorithms

An Improved Energy Detection (IED) algorithm was proposed, which estimates the average energy over more consecutive sensing slots.

We propose an Adaptive threshold Improved Energy Detection (AIED) algorithm, which requires some a priori knowledge about the Primary User (PU) signal, such as its average duty cycle and SNR. We compared the performance of the AIED algorithm with the ACED algorithm for different SNR and duty cycle values. For the same decision error probability, we demonstrate a detection SNR gain of more than 1 dB of AIED over ACED, in the low SNR regime, for high duty cycle values.

4.1 Improved energy detection (IED) algorithm

4.1.1 IED Threshold setting

The simple threshold or it also called fixed threshold of IED scheme was suggested in [5] to expose if the signal of the PU is present or not in the environment of an AWGN with a defined SNR. In every detecting slot i, with the PU's E_i energy test in the present slot (the one test present in CED), The IED method performs two more tests in a row, the first measures the average energy calculated in the last L detecting slots and the other examine is to measure the energy in the earlier slot E_{i-1}.

4.2 Adaptive threshold IED algorithm

In [7], an adaptive threshold method was proposed to improve the performances of the CED algorithm. Let us consider a PU transmission model with an average number of B consecutive busy slots followed by a number of T-B idle slots. This optimization problem can be defined as:

$$\lambda_{\text{opt}}(\alpha, SNR) = \arg\min_{\lambda} P_e{}^{ED}\ (\lambda, \alpha, SNR) \tag{5}$$

for ACED, an exact expression of the optimum threshold value is derived in [7]. Unfortunately, for the adaptive threshold IED algorithm an exact expression of the optimum threshold cannot be determined. However, using the expressions of P_d^{IED} and P_f^{IED} determined in [5], we can determine the optimum threshold using the minimization problem from (5).

4.2.1 Theoretical and simulation results

Here, we analyze the performances of the ACED and AIED in terms of decision error probability, denoted as P_e. For the AIED algorithm, we considered the following values of the parameters: L = 3 and $M \in \{1, 2, 3\}$.

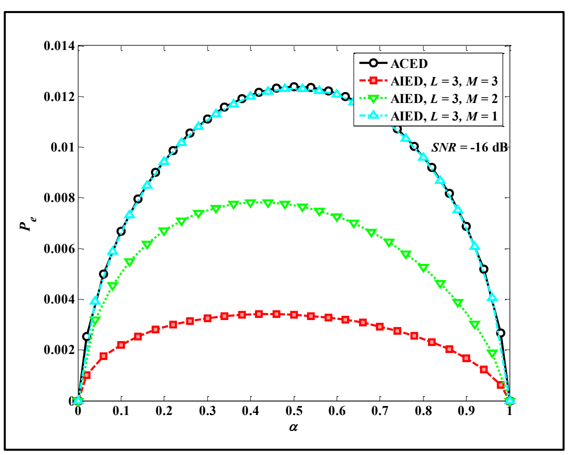

Fig. 1 *Error probability as a function of α (SNR = -16 dB).*

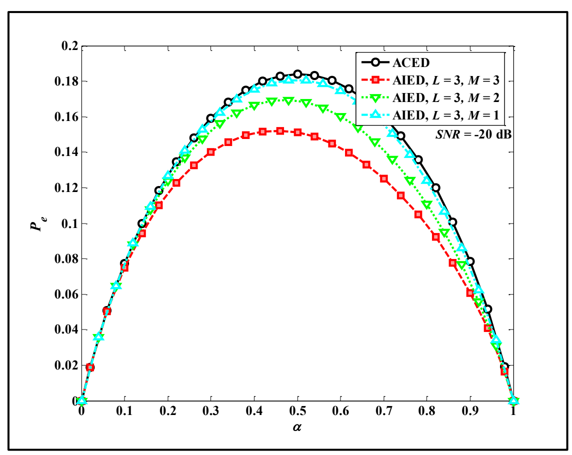

Fig. 2 *Error probability as a function of α (SNR = -20 dB).*

However, for M = 2, the maximum P_e value for AIED is obtained at α = 0.43. Finally, for M = 3, the maximum P_e value for AIED is obtained at α = 0.44. In Figure 2, we represented a similar plot as in Figure 1, P_e (α) for SNR = -20 dB. In this case, the maximum P_e value for AIED is obtained at α = 0.5 for M = 1, at α = 0.47 for M = 2, and at α = 0.45 for M = 3. Comparing the results in Figure 2 with the ones from Figure 1, we notice that, when SNR decreases, the gap between maximum P_e values for ACED and AEID is increasing (for the same value of M).

We represented in Figure 3 the values P_e SNR for different values of α = ct. As noticed in Figures 1 and 2, due to the even symmetry of the ACED P_e (α) plots around $\alpha \cong$ 0.5, the maximum values of P_e are obtained for duty cycle α value around 0.5, while the minimum values of P_e are obtained for $\alpha \leq 0.1$ and $\alpha \geq 0.9$ (for any value of SNR). We have to mention that, in Figure 3, we represented both the theoretical and the simulation P_e plots for ACED and AIED algorithms, considering the three representative values $\alpha \in$ {0.1, 0.5, and 0.9}. For AIED, we considered the best parameter values, $M = L = 3$.

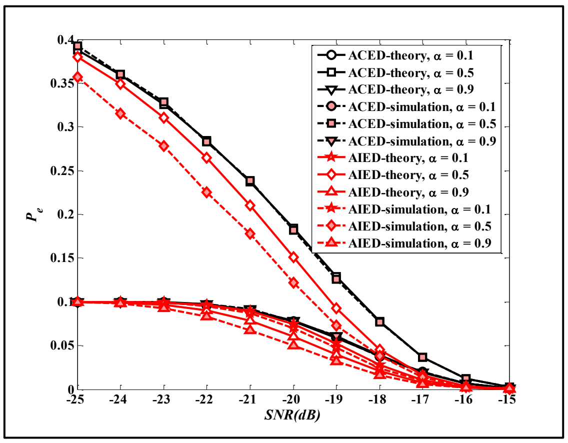

Fig. 3 *Error probability as a function of SNR.*

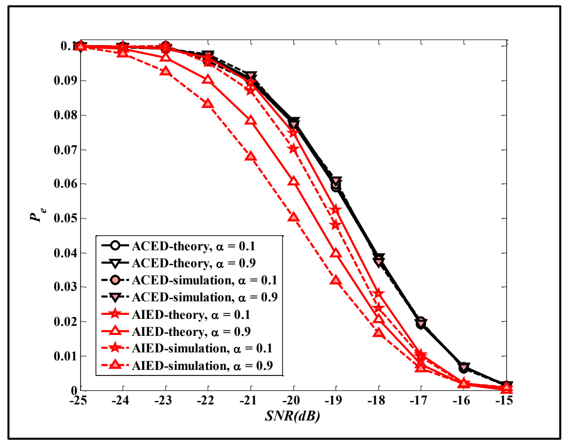

Fig. 4 *Error probability as a function of SNR for α ∈{0.1, 0.9}.*

Notice that, for ACED, the simulation plots match perfectly the theoretical plots [7]. On the other hand, the simulation P_e plots for AIED do not approximate accurately the theoretical results. This is explained by the fact that the decision threshold is not estimated accurately for IED [5]. However, the decision threshold is chosen to set an upper bound for the performances of the IED algorithm. Hence, all P_e simulation results depicted in Figure 3 for AIED are lower than the theoretically determined results. Analyzing the results from Figure 3, we can see that, in the range of $SNR \in$ [-24, -17] dB, the AIED offers a detection SNR gain over ACED of more than 1dB for the same value of $\alpha \geq 0.5$. For a better view, we present in Figure 4 only the P_e plots for $\alpha \in$ {0.1, 0.9}. In Figure 4 one can notice that for α = 0.9 the AIED provides an SNR gain over ACED of more than 1 dB in the middle of the considered SNR range (for SNR $\in$ [-21, -19] dB). Also, for α = 0.1 the AIED provides a lower *SNR* gain as compared to ACED of more than 0.6 dB in the upper section of the considered *SNR* range (for SNR $\in$ [-17, -15] dB). It is also interesting to notice that for lower values of $\alpha < 0.5$ the AIED P_e performance improvement over ACED is lower than in the higher range of $\alpha \geq 0.5$. This asymmetry was also noticed in skewed AIED plots from Figures 1 and 2.

The analysis of the decision error probability, for the proposed AIED algorithm, as compared to the adaptive classical ED ACED algorithm, revealed that the first one provides a detection SNR gain over the second one. However, the detection of SNR gain depends on the PU duty cycle values. Hence, the AIED performs best for busy PU networks, duty cycles higher than 50%.

Chapter 5: Three-Event Energy Detection and Adaptive Three-Event Energy Detection Algorithms

The Three-Event Energy Detection (3EED) algorithm for spectrum sensing is considered for which an accurate approximation of the optimal decision threshold that minimizes the decision error probability is found using Newton's method with forced convergence in one iteration. The proposed algorithm is analyzed and illustrated with numerical results obtained from simulations that closely match the theoretical results and show that it outperforms the conventional ED algorithm for spectrum sensing.

5.1 Simple three-event energy detection (3EED) algorithm

The simple (or fixed threshold) 3EED algorithm was proposed to detect the PU signal presence in CR network affected by AWGN, which is specified by a certain SNR [6]. In each sensing slot i, first test the energy E_i from the current slot (CED algorithm performs only this test). If this E_i test fails, then, 3EED performs a second test in the previous slot E_{i-1}, If and only if the E_{i-1} test failed also, 3EED will run a third test in the next slot E_{i+1}. Both additional tests in 3EED, as compared to CED, allow the SU to detect more accurately the PU signal presence in case of temporary energy drops or the PU signal absence [6].

The decision threshold λ is determined based on a desired performance level that is specified in terms of a target probability of false alarm value P_{fa} as it is usually the case with constant false alarm rate detectors [6].

$$\lambda = \left[Q^{-1}\left(1 + \sqrt[3]{P_{fa} - 1}\right)\sqrt{2N} + N\right] \sigma_n^2 \qquad (6)$$

5.2 Adaptive threshold three-event energy detection (A3EED) algorithm

We propose a novel Adaptive Threshold Three Event Energy Detection (A3EED) algorithm that minimizes the decision error probability for given SNR and primary user signal's average duty cycle values. Comparing the decision performance of these algorithms, for low SNR values, we prove a decision SNR gain of more than 1 dB of A3EED over the ACED. We presented the fixed threshold approach for an ED algorithm. An adaptive decision threshold was shown to provide better detection performances. The decision threshold will be set to minimize the P_e^{3EED} value. Therefore, this optimization problem is defined by [7] [21]:

$$\lambda_{\text{opt}}(\alpha, SNR) = \arg\min_{\lambda} P_e^{\,3EED}\,(\lambda, \alpha, SNR) \qquad (7)$$

where λ_{opt} represents the optimal threshold.

5.2.1 Theoretical and simulation results

The performances of the ACED and A3EED algorithms are analyzed in terms of decision error probability P_e. Therefore, we compare, for both algorithms, the theoretical values of P_e estimated with the Monte Carlo simulations results. In Figure 5, for an SNR value of -16 dB, the theoretical values of P_e. For ACED and A3EED have been plotted, as a function of the duty cycle α. Each value of α, the optimum decision threshold value is determined so that the minimum P_e value is reached. By analyzing the results from Figure 5, we notice that A3EED outperforms ACED, for any value of α.

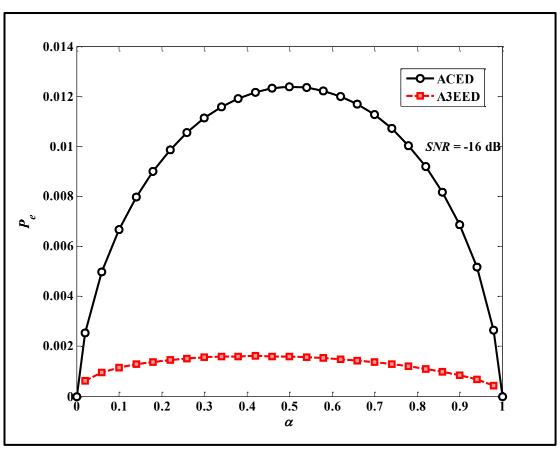

Fig. 5 *Error probability as a function of α (SNR = -16 dB).*

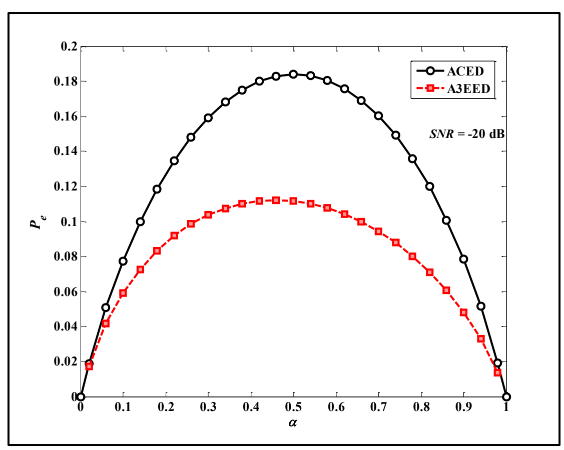

Fig. 6 *Error probability as a function of α (SNR = -20 dB).*

Also, it can be noticed that the maximum P_e value for ACED is obtained at α = 0.5 [7], while for A3EED is obtained at a lower value of α = 0.42. This difference between the maxima of ACED and A3EED P_e plots proves that A3EED performs better in the region of large values for the duty cycle or performs asymmetrically in terms of α values. Following the same procedure, the P_e plots can be obtained for any SNR value between -25 dB and -15 dB. Similarly, in Figure 6, we represented P_e (α), for SNR = -20 dB. In this case, the maximum P_e value for A3EED is reached at α = 0.46. Comparing the results from Figures 5 and 6, we notice that the difference between maximum P_e values for ACED and A3EED is increasing when SNR decreases. In fact, when SNR decreases, then P_e increases, for the same α value.

In Figure 7, the values P_e SNR have been represented to study the dependence on SNR of the performances of ACED and A3EED, for different values of α = ct. As observed already in Figures 5 and 6, due to the even symmetry of the P_e (α) plots, the minimum values of P_e are obtained for $\alpha \leq 0.1$ and $\alpha \geq 0.9$ and the maximum values of P_e are obtained for duty cycle α value around 0.5 (for any value of SNR). Moreover, in Figure 7, we considered three representative values $\alpha \in$ {0.1, 0.5, and 0.9} and we represented graphically both the theoretical and the simulation P_e values. One can easily notice that both for ACED and A3EED, the simulation plots match perfectly the theoretical plots [7] [6] [22]. This matching is explained by the fact that the optimum decision threshold is estimated accurately for the adaptive algorithms. Finally, analyzing the results from Figure 7, we can see that, for an SNR $\in$ [-24, -17] dB, A3EED offers a detection SNR gain over ACED of more than 1.3 dB, for the same value of $\alpha \geq 0.5$. In order to emphasize the detection SNR gain of A3EED over ACED, we present in Figure 8 only the P_e plots for $\alpha \in$ {0.1, 0.9}. Hence, it can be noticed that A3EED provides an SNR gain over ACED of about 1 dB in the middle of the considered SNR range (for SNR $\in$ [-22, -18] dB) for α = 0.1.

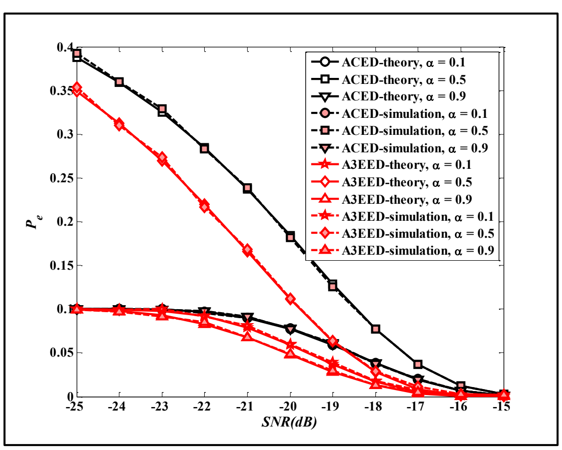

Fig. 7 *Error probability as a function of SNR.*

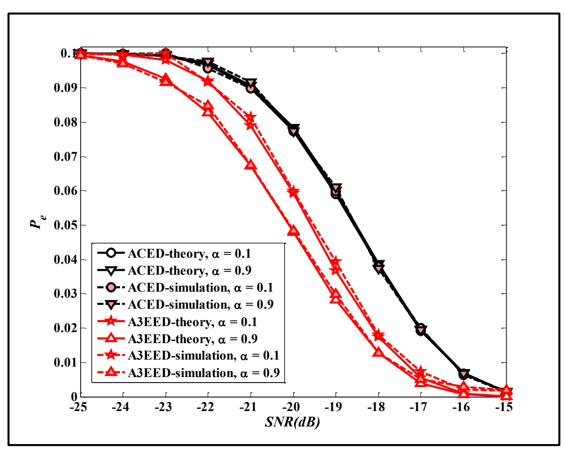

Fig. 8 *Error probability as a function of SNR for α ∈{0.1, 0.9}.*

Also, for α = 0.9 and in the same SNR range, A3EED provides a larger SNR gain over ACED, of about 1.5 dB. We presented and analyzed a novel adaptive threshold 3EED algorithm. Both theoretical and simulation results demonstrate that A3EED offers a decision SNR gain over ACED of more than 1 dB. It was also showed that the value of this SNR gain depends on the duty cycle of PU.

5.2.2 Three-event energy detection with adaptive threshold for spectrum sensing in cognitive radio systems on the convexity of the decision error probability

We present a new adaptive ED algorithm with adaptive sensing threshold for spectrum sensing, which is based on the 3EED algorithm [6] but in which the sensing threshold is adapted similar to [7], to optimize the decision error probability DEP, which is a weighted sum of the probabilities of missed detection and false alarm [7] [23].

We note that, obtaining an accurate analytical expression for the optimal threshold is elusive as the expressions involved in finding the sensing threshold do not have closed-form expressions and require approximations. However, for more efficient algorithms than CED, regularly having more complex expressions for DEP, the optimization equation is not analytically solvable. Therefore, we aim at extending the method from [7] to a more complex and efficient ED algorithm, such as 3EED [6]. Under the Gaussian approximation, the DEP for any ED algorithm can be written as an expression based on several Q-function terms.

First, we have to prove that DEP is a convex function in the threshold value and then, we propose the use of a numerical method, such as the Newton's method [24], to iteratively determine the root of the analytically unsolvable optimization equation. However, the main drawback of iterative methods is the increased operating time, which is a critical issue for the spectrum sensing algorithms. In order to overcome this problem, we propose a transformation of the optimization function, such that the Newton's method for the transformed function converges faster. Finally, we derive an analytical approximate expression of the adaptive threshold for 3EED by using a fast convergence numerical method. Moreover, we consider that this method can be generalized for most if not all ED-based spectrum sensing algorithms.

A closed-form expression for the optimal detection threshold is derived using Newton's method with a novel approach that reduces the number of iterations to a single one by changing the monotonicity of the optimization function, and an adaptive 3EED algorithm is formally stated and analyzed. We propose an adaptive version of the three-event energy detection algorithm published in [6] [22]. We compare the performance of the proposed algorithm with the ACED algorithm [25] for different scenarios and discuss the obtained results.

5.2.2.1 Simulations and numerical results

We present numerical results obtained from simulations that support the proposed approach for one-step threshold calculation and illustrate the performance of the 3EED algorithm with adaptive threshold. The parameter values used in the simulations are the number of samples in a sensing slot N = 65537, the SNR (γ) is between -25 dB and -15 dB, and T = 500 slots. The signal transmitted by the PU is implemented using Binary Phase Shift Keying (BPSK) modulation, and 2500 sensing slots were considered in each transmission sequence in all simulations.

Figures 9 and 10 show the values of the optimal sensing threshold λ_{otp} that minimizes the DEP, as a function of α the spectrum utilization ratio, for SNR values of -25 dB and -20 dB corresponding to the proposed approach. We note that the values of the sensing threshold obtained using the proposed approach closely match those obtained using the (brute-force) approach [26] for values of α between 0.2 and 0.7, in particular for α around 0.5 and support the application of the numerical approach for threshold calculation with minimal overhead. We also note that, according to studies performed on GSM channels [27] or in the industrial, ISM bands [28], this is the range of values for the spectrum utilization ratio α that is of practical interest for SU access to licensed spectrum.

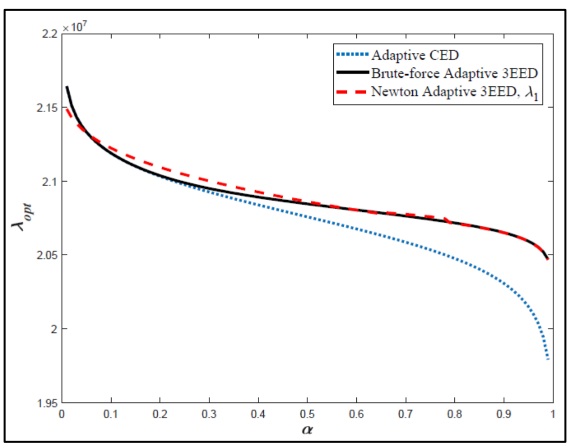

Fig. 9 *Optimum threshold as a function of α for SNR = -25dB.*

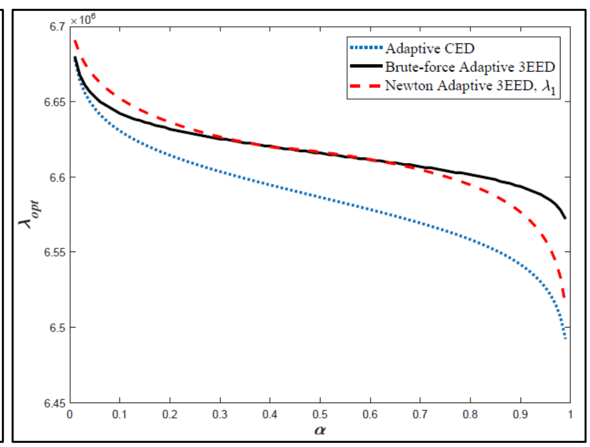

Fig. 10 *Optimum threshold as a function of α for SNR = -20dB.*

Figures 11, 12 and 13 show the values of the DEP P_e as a function of the SNR γ for different values of the spectrum utilization ratio α for the proposed 3EED algorithm with adaptive threshold as well as for the adaptive CED algorithm in [7]. Based on the plots shown in Figures 11, 12 and 13 we first note that the values of the DEP obtained through Monte Carlo simulations closely match the analytical values of the DEP for the proposed 3EED algorithm with adaptive threshold or by the corresponding DEP expression in [7], for all SNR and α values. We also note that the proposed 3EED algorithm with adaptive threshold outperforms the adaptive CED algorithm in cases of practical interest corresponding to spectrum utilization ratios above 0.2 and below 0.7, with maximum gain of the proposed algorithm in terms of the DEP of about 1 dB achieved for α around 0.5. Furthermore, for both the proposed 3EED algorithm with adaptive threshold and the adaptive CED algorithm, the value of the DEP becomes less sensitive to changes in the spectrum utilization ratio α as the SNR values increase.

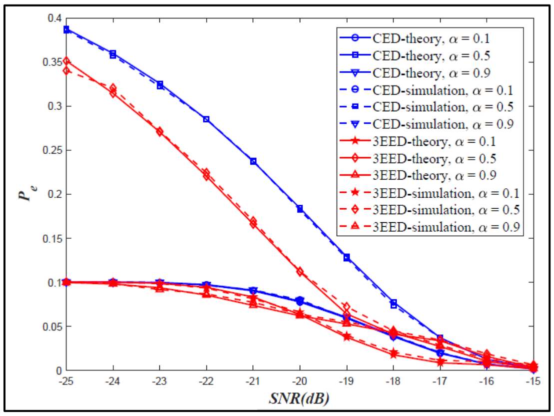

Fig. 11 *Error probability as a function of SNR for α ∈{0.1, 0.5, 0.9}.*

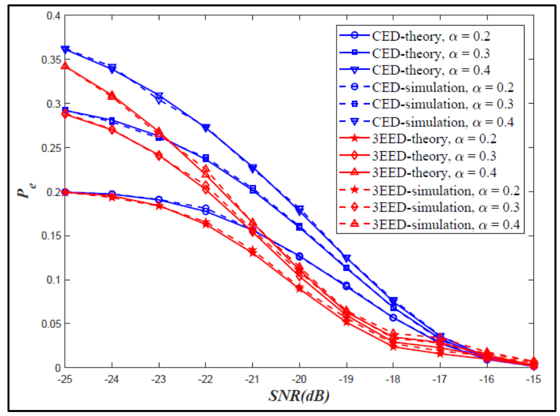

Fig. 12 *Error probability as a function of SNR for α ∈{0.2, 0.3, 0.4}.*

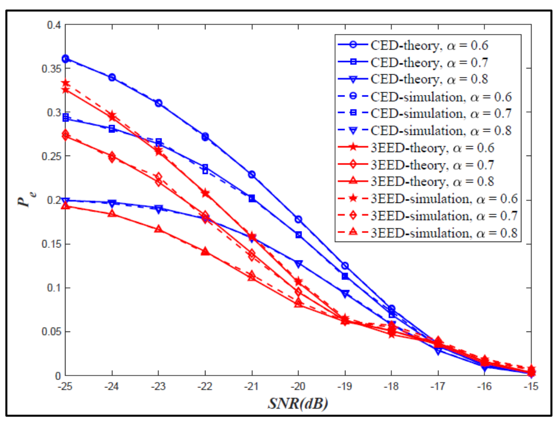

Fig. 13 *Error probability as a function of SNR for α ∈{0.6, 0.7, 0.8}.*

Figures 14 and 15 shows the dependence of the DEP on the spectrum utilization ratio α for two different SNR values $\gamma = -23$ dB and $\gamma = -20$ dB. As it can be observed, the DEP decreases with increasing SNR for both the proposed 3EED algorithm with adaptive threshold and the adaptive CED algorithm. Furthermore, the proposed algorithm outperforms the adaptive CED one for all values of the spectrum utilization ratio α. We note that, for each value of α the corresponding DEP values are minimum since the optimal sensing threshold is used for that α.

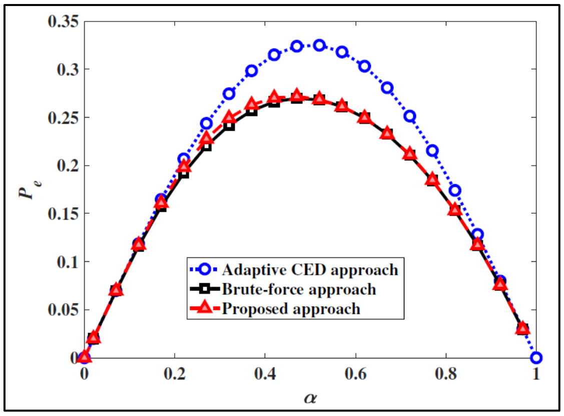

Fig. 14 Error probability as a function of α (SNR = -23).

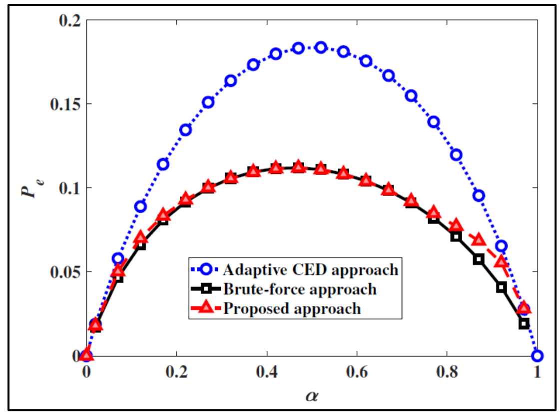

Fig. 15 Error probability as a function of α (SNR = -20).

A new ED algorithm for spectrum sensing in CR systems is presented. The proposed algorithm employs an adaptive sensing threshold that is optimized to minimize the DEP and has minimal overhead, since the value of the optimal threshold is found through a one-step iterative method. Numerical results obtained from simulations are presented to illustrate the performance of the proposed algorithm and to compare it to the adaptive CED algorithm. The results show that the proposed algorithm outperforms the CED algorithm for spectrum sensing, resulting in lower values for the DEP for all values of the spectral utilization ratio that are of practical interest for CR systems providing SU access to licensed spectrum.

Chapter 6: Cooperative Spectrum Sensing Methods

Spectrum sensing is a core feature of cognitive radio to avoid unnecessary interaction with authorized users and to define the available frequency for increasing the usage of the spectrum. Invisible PU issue that occurs while the PU is not detected by the sensing station could be solved, and cooperative sensing can greatly decrease the sensing time [29]. The greatest difficulty of Cooperative Spectrum Sensing (CSS) would be that it needs the development of an effective network for information sharing among CRs.

6.1 AF cooperative spectrum sensing using three secondary users for cognitive radio

In the CR networks, SUs has to detect the presence of the PUs in a fast and accurate manner and vacate the channel for the PUs. For a cooperative CR scenario, the SUs in a specific area can collaborate for enhancing the PU's detection. We extend the AF cooperative detection algorithm by increasing the number of collaborating SUs from two to three [30]

[31]. Therefore, there are more situations for which the cooperation detection outperforms the non-cooperative scenario. We analyze the ED probability of the cooperative algorithm both theoretically and using simulations.

In order to facilitate the analysis, we propose a simple power-low path loss channel model that relates the distance between users to the channel gain. Therefore, in a typical cooperative scenario, we demonstrate a detection probability increase between 7.7% and 15.6% as compared to the non-cooperative scenario.

6.2 Cooperative detection using three secondary users

In CR systems, the SUs transmit when the licensed PUs are idle. In cooperative CR, the SUs exchange information about PUs to enhance the PUs' detection. Let us assume a CR environment where three SUs, denoted as S_1, S_2, and S_3 operate in a TDMA frame to send data to a common receiver for detecting a PU denoted by P, as shown in Figure 6.3.

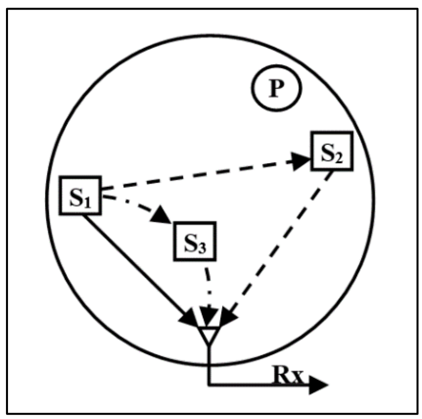

Fig. 16 *Cooperation in cognitive networks.*

When the PU starts to transmit, the three SUs must stop transmitting as fast as possible. Here, the aspect of interest for us is the SU's detection probability, which decreases with the distance to P for instance, if one of the SUs (S1) is at a large distance with respect to P, the signal received by S1 from the licensed user is weak, making hard for S1 to detect its presence. Therefore, cooperation between the non-licensed users can increase the detection probability for the weaker user, improving in this way the global detection in the CR network. We consider this cooperation, considering S2 and S3 as the relays of S1, where all three users S1, S2, and S3 are SUs. The three cognitive users transmit data to a common receiver, in a certain frequency band, as shown in Figure 6.3.

A TDMA transmission model is used and the signals are transmitted successively, using an AF protocol. This system is an extension of the system proposed in [32] by increasing the number of cooperative SUs from two to three.

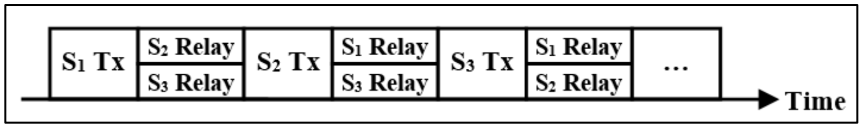

Fig. 17 *TDMA frame for the SUs relay protocol.*

Let us assume that the TDMA transmission occurs as follows: in the first time slot, S_1 transmits and S_2 and S_3 listen; in the second time slot, S_2 and S_3 relay the information received in the previous time slot. We have to note that the additional SU relay, as compared to the system in [32], will not increase the detection time, because both relays operate simultaneously. However, it is expected from the additional SU relay to improve the detection of PU. Besides the 3 SUs, there is a PU that has a greater priority to occupy the channel. At this moment, the most essential action is detecting accurately this licensed user. We proposed a modified AF cooperative detection algorithm, by increasing the number of relaying SUs from one to two. Also, we proposed a simplified channel model, which relates the channel gains to the distances between SUs and PU. We analyzed theoretically and by simulation, the cooperative detection probability of the algorithm and significant detection gains were found as compared to the non-cooperative case.

Chapter 7: Conclusion

In this thesis, we present the CR system in general. Also, we study the spectrum sensing function in detail together with the energy detection algorithm.
We have proposed several different methods to develop the performance of the ED algorithm.

7.1 Obtained results

In Chapter 1, we have presented a general introduction about the CR method and we have mentioned the scope of the thesis, which is to design improved spectrum sensing algorithms that can allow the implementation of CR.

In Chapter 2, we have provided a detailed explanation about the CR methods and its concepts and it was described how this algorithm is working. We also clarified the functions of the spectrum sensing.

In Chapter 3, we have presented the theoretical performance of the classical energy detection algorithm, together with the threshold setting. It was studied also in detail the adaptive version of this algorithm and its performance. The scenario for both algorithms was described as well.

In Chapter 4 an adaptive threshold IED algorithm was proposed and developed and we have estimated a theoretical performance by using Monte Carlo simulations for both algorithms. The results were compared with the classical version of this algorithm. The study of the probability of decision error, for the proposed (AIED) algorithm compared to the adaptive classical ED ACED algorithm, demonstrated that the first algorithm offers an SNR gain over the second algorithm.

In Chapter 5 it is presented a new energy detection algorithm for spectrum sensing in CR systems. In this algorithm it was proposed a threshold which has been developed to decrease the decision error probability. The results obtained using the simulations were used to highlight the efficiency of the proposed algorithm.

In Chapter 6 we have provided theoretical information about the cooperative spectrum sensing methods. Also, the system that used two cooperative secondary users was presented. A simplified channel model which relates the channel improvements to the distances between secondary and primary users was proposed. By increasing the number of relaying secondary users from one to two, a modified AF cooperative detection algorithm was proposed as well.

7.2 Original contributions

In this section the main original contributions of the research are being presented, together with the articles in which these were published.

[1] Proposal for an adaptive threshold IED algorithm that required some knowledge about the primary user signal.

Comparison of the AIED performance algorithm with the Adaptive Classical ED algorithm for different SNR and duty cycle values. Taking into consideration the same decision error probability, it was demonstrated a detection SNR gain of more than 1 dB of AIED over ACED, in the low SNR regime, for high duty cycle values.

[2] Proposal of a new Adaptive threshold 3EED (A3EED) algorithm which reduces the decision error probability for a certain Signal-to-Noise Ratio (SNR) and Primary User (PU) signal's average duty cycle values. The comparison of the decision performance showed that A3EED outperform ACED with a SNR gain of more than 1 dB.

[3] The review of some aspects related to New Radio physical layer, such as frequency bands, radio technologies. Proposal in the context of an ongoing research project of an initial design for a spectrum occupancy evaluation system.

[4] The extension of Amplify and Forward (AF) cooperative detection algorithm by increasing the number of collaborating secondary users from two to three and the proposal of a simple power-law path loss channel model that relates the distance between users to the channel gain. As a result, it was proven a detection probability increase between 7.7% and 15.6% for a typical cooperative scenario by comparing it to a non-cooperative scenario.

[5] The proposal of a novel ED algorithm with an adaptive sensing threshold. The suggested algorithm is evaluated and demonstrated with numerical results obtained from

simulations closely resembling the theoretical results and demonstrating that it is outperforming the traditional spectrum sensing algorithm ED (CED).

We have minimized the decision error probability (DEP) of the three-event ED (3EED) algorithm for spectrum sensing by using Newton's method with forced convergence in one iteration.

[6] A comparison between four different SDR platforms from a Radio Frequency front end receives a performance perspective. A theoretical calculation of the noise figure for the receive side of the RF front end of each of the platforms was performed. For the USRP N210 with the WBX RF daughterboard we obtained the lowest NF from all the platforms, therefore it is recommended as an optimal solution for spectrum sensing applications.

[7] Introduction of a novel AF cooperative detection scheme which utilizes three secondary users, with two secondary users performing a sequential relaying and proposal of a trigonometric method in order to decrease the channel gain variables from three to two, which helps to simplify the threshold approximation in the detection algorithm.

7.3 List of published works

[1] Mahmood J. A. Al Sammarraie, A. Marțian, C. Vlădeanu, "Adaptive IED Spectrum Sensing Algorithm for Different Duty Cycle Values," in International Conference on Communications (COMM), Bucharest, Romania, June 2018. [ISI Proceedings]

[2] Mahmood J. A. Al Sammarraie, A. Marțian, C. Vlădeanu, "A Modified 3EED Spectrum Sensing Algorithm Using an Adaptive Decision Threshold," in 2018 International Symposium on Electronics and Telecommunications (ISETC), Timișoara, Romania, November 2018. [ISI Proceedings]

[3] A. Marțian, C. Vlădeanu, Mahmood J. A. Al Sammarraie, "On the Introduction of 5G Networks in Romania A novel architecture for spectrum occupancy evaluation," in International Conference on Digital Telecommunications (ICDT), Valencia, Spain, March 2019. [ISI Proceedings]

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[5] A. Marțian, Mahmood J. A. Al Sammarraie, C. Vlădeanu, Dimitrie C. Popescu, "Three-Event Energy Detection with Adaptive Threshold for Spectrum Sensing in Cognitive Radio Systems," in MDPI sensors journal, June 2020. [ISI-Q1, IF 3.275]

[6] A. Marțian, Florin L. Chiper, Omer M. Kh. Al-Dulaimi, Mahmood J. A. Al Sammarraie, C. Vlădeanu, Ion Marghescu, "Comparative Analysis of Software Defined Radio Platforms for Spectrum Sensing Applications," in International Conference on Communications (COMM), Bucharest, Romania, June 2020. [ISI Proceedings]

[7] Omer M. Kh. Al-Dulaimi, Mahmood J. A. Al Sammarraie, C. Vlădeanu, A. Marțian, Dimitrie C. Popescu, "Cooperative Spectrum Sensing for Three Secondary Users with Sequential Relaying for Cognitive Radio," in International Conference on Communications (COMM), Bucharest, Romania, June 2020. [ISI Proceedings]

7.4 Perspectives of future work

As future research, one proposal would be to implement the adaptive 3EED algorithm in a real software-defined architecture of a SU system and to generalize the adaptive threshold estimation method, using Newton's method, for any ED algorithm. The intention is to implement and validate the proposed algorithm using SDR platforms from the USRP family. A focus should be dedicated to the optimization of the expressions which are being used in the algorithm to estimate the decision threshold for minimizing the computational complexity and the sensing time. One direction of future research can be the extending of the adaptive threshold analysis to other energy detection algorithms.

Another direction of future research can be the analysis of the agility gain of the AF algorithm and to extent this analysis for more relaying secondary users.

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