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AN OPTIMAL THRESHOLD ADAPTATION OF ENERGY DETECTOR IN COGNITIVE RADIO FOR SMART CITIES APPLICATIONS

Rade Božović⁷; Goran Keković⁸

Abstract

A smart city is a technological modern concept of interconnection between different devices with mission to collect and post-process different data type. Based on that gained information, efficiency of different services across the city, such as security, energy consumption, safety is optimized and improved, what significantly raise quality of living of their citizens. The concept implies integration of advanced information and communication technologies. Lack of radio spectrum is one of the main challenges for wireless networks performance due to coverage and capacity issues. Cognitive radio technology enables efficient usage of radio spectrum. In order to avoid or minimize interference spectrum sensing function is of a crucial importance for cognitive radio operations. Due to its low implementation complexity, non-coherent energy detector, which is based on comparison of the detected signal energy with the decision threshold, represents a good choice for spectrum sensing. In this paper closed-form solution for energy detector threshold adaptation in cognitive radio is described.

Keywords: *advanced smart communications, cognitive radio, energy detector, spectrum sensing, threshold adaptation.*

Introduction

One of the definitions of smart cities is that it is a collection of entities (humans and machines) in an urban area that is always connected, fully aware, auto-managed, self-secure, adaptive, and well-informed, [1], [2]. It will change perspective of how we live, work, and connect, and it should provide services to efficiently manage the increased population of cities, the resources and optimize energy consumption. To enable such services, it is necessary to handle and drive a lot of data collected form wide-scale deployed networks of sensors and smart objects. These advances will improve the quality of citizens' lives while addressing

⁷ Rade Božović, 1983, Ph.D. E. E., Assistant Professor, Faculty of information technology, Alfa BK University, rade.bozovic@alfa.edu.rs <https://orcid.org/0000-0002-8580-714X>

⁸ Goran Keković, 1967, Ph.D. E. E., Assistant Professor, Faculty of information technology, Alfa BK University, goran.kekovic@alfa.edu.rs <https://orcid.org/0000-0003-1429-0582>



important tasks such as real-time tracking, traffic congestion, security, safety, authenticity, and availability of classified information to decision makers, [3].

All these innovative applications and technologies are backboned by wireless networks that power it all and enable the sharing of data and information across systems. It is obviously how the performance of smart cities depends on the wireless spectrum [3].

To make some city be smart, a very representative communications infrastructure is required in order to connect and to network different smart objects, humans and sensors. For any smart city the first step is to implement robust, reliable and highspeed wireless network. These are the backbone of all the potential smart city applications. Within cities, various wireless signal types and standards are used, such as Wi-Fi, 3G/4G/LTE/5G, Bluetooth, NFC, GPS, and others. 5G wireless and other future standards is critical to run applications that rely in a big measure on high bandwidth and low latency connections, while dedicated short-range communications (DSRC) may become a key standard for enabling fully autonomous vehicles [4], [5].

With so many different signal types in such a dense and complex environment, establishing reliable connections and avoiding RF interference will be extremely challenging for smart city designers. Many of the applications mentioned above depend on real-time data sharing and continuous connectivity, meaning any disruption can cause serious problems. In the case of traffic signals or utility grids, a loss in connectivity could bring the entire city to a standstill [3], [5].

With the rapid increase in the number of wireless devices, applications and services, and the constant user's demands for higher data throughputs, the problem of limited radio resources and frequency spectrum distribution is increasingly coming to the fore. From smartphones to smart homes, from self-driving cars to industrial IoT devices, the need for a reliable and high-speed wireless network has never been more crucial. By 2025, it is estimated that there will be over 75 billion IoT devices, all requiring wireless connectivity. Over 80% of mobile traffic is expected to be carried by wireless networks by 2025, [6].

As technology continues to advance and more devices join the Internet of Things (IoT), the current spectrum allocation model is not feasible. It is evident that the user licensing policy, the principle of fixed frequency spectrum allocation, cannot meet all modern challenges. In addition, the conducted measurements showed that already assigned frequency bands are used by licensed systems only in a certain percentage of time and in a certain percentage of locations. Therefore, there are parts of the already allocated spectrum that are only partially occupied or mostly free.

The current radio spectrum licensing policy has led to a phenomenon that could be described as - high occupancy and low utilization. Static spectrum allocation causes the appearance of empty bands within the allocated part of the spectrum, the so-called. spectrum holes. A spectrum hole represents a frequency range within the range assigned to a licensed user who is not using it at a given time and a given location. That is why it is necessary to introduce innovative technologies that would contribute to a more efficient exploitation of the available spectrum, which is a limited natural resource [7].

Energy detection-based spectrum sensing for cognitive radio network

Cognitive radio is one of the technologies for dynamic spectrum management, i.e. for opportunistic access to licensed spectrum by unlicensed users, under predefined conditions and restrictions. Based on one of popular definitions, cognitive radio (CR) is an intelligent wireless communication system that is aware of its



ambient environment. This CR will learn from the environment and adapt its internal states to statistical variations in the existing RF stimuli by adjusting the transmission parameters (frequency band, modulation type and transmit power) in real-time in accordance with statistical variations of its radio environment. Sensing function and ability to promptly modify its transmission parameters are unique features and challenges of cognitive radio implementation, [8].

In cognitive radio terminology, licensed users are called primary users, PU (Primary Users), while unlicensed users are classified as secondary users, SU (Secondary Users) or cognitive users, CR (Cognitive Radio). A mandatory requirement for secondary users is that their presence in the licensed part of the spectrum must not degrade the performance of primary users. More precisely, the interference generated by secondary users to primary users must be minimized [9].

Various methods have been proposed for spectrum sensing in CR, which include matched filter, cyclostationary detection, and energy detection. Matched filter and cyclostationary detection are coherent detection techniques, with better detection performance than non-coherent energy detection. However, coherent detectors require a priori knowledge about the signal of the primary users (PU). Matched filter is the optimal detection technique since it maximizes the signal to noise ratio (SNR), but requires demodulation parameters of the PU signal. Cyclostationary detector can detect very weak signals on the basis of their cyclic features, but information about the cyclic characteristics is needed. Non-coherent energy detector [8] is based on comparison of the detected signal energy with the decision threshold. This method does not require any knowledge about the PU signal, and has low implementation complexity compared to matched filter and cyclostationary detection. In addition, the energy detection can provide lower sensing time than the other methods (in the high SNR environments) and can be applied for wideband sensing.

On the other hand, the energy detector has many disadvantages such as high sensitivity of the threshold level to variations of the noise level, high sensing time in the low SNR environments, it cannot distinguish primary and secondary user signals as well as signals and noise, and cannot detect spread spectrum signals. Despite the numerous drawbacks, energy detection is the most popular and the most studied technique among all spectrum sensing methods, [9],[10].

The most important process that affects performance of energy detectors is the threshold selection. Exact closed-form expression for the optimal detection threshold for different receiver diversity systems was derived in [11]. Also, many algorithms use a fixed decision threshold to distinguish PU signals from the noise. However, in practical systems, the noise power fluctuates due to the temperature changes, ambient interference, and it is difficult to guarantee the detection probability and the false alarm probability with the fixed threshold setting.

In order to achieve better performance and to improve reliability of detection, CR as environment-aware system should dynamically adapt the decision threshold according to the changes in the environment. Iterative gradient-based algorithm for threshold adaptation is often impractical, since it requires an initial estimate to ensure global convergence. Also, iterative approach can be computationally inefficient. On the other hand, closed-form solution provides optimal decision threshold in a single step and does not require initial estimate values, resulting in a lower spectrum sensing time. Also, closed-form solution is more efficient from the viewpoint of arithmetical operations, computational efficiency, which improves general performance of the cognitive radio spectrum sensing process [10]. As radio environment is challenging and dense, and with so many different signals in air interface, to do reliable spectrum sensing, even for wideband. with lower sensing time is of high importance for smart city applications. The aim is to receive reliable information as soon as possible and then to use available spectrum for smart city needs. This



motivated the work presented in this paper, which studies energy-based spectrum sensing in dynamic scenarios, and proposes a closed-form solution for the sensing threshold adaptation, assuming that the noise power is known at the cognitive user.

The paper is organized as follows: system model and general problem description are presented in the next section, followed by threshold determination and analysis of closed-form solution. Then, simulation results are shown and the end the main conclusion of the work is given.

System model

Environment with the PU as an M-quadrature amplitude modulation (16-QAM) signal is considered. Transmitted signals are passed through the channel with additive white Gaussian noise (AWGN), assuming variance is known in advance. From the detected input signal (N number of samples), CR estimates variances of the PU signal. According to the estimated parameters, CR determines the threshold level and performs test statistic for spectrum sensing. The system model is schematically described in the block diagram of Fig. 1.

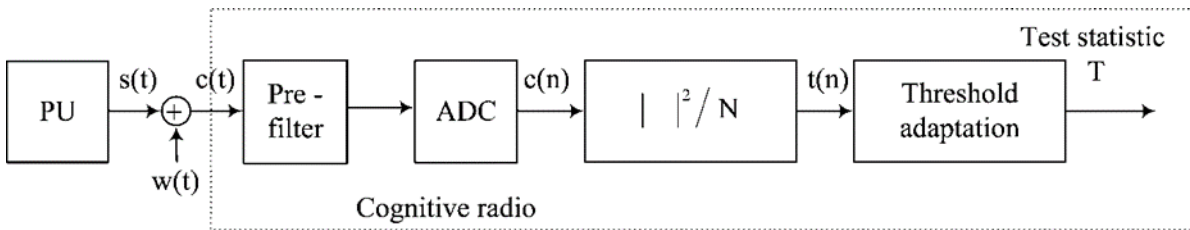


Fig. 1. System model

After the CR processing along with the analog to digital conversion (ADC), the received signal $c(n)$ can be expressed as

$$c(n) = s(n) + \omega(n), \quad (1)$$

with $s(n)$ being the active radio signal generated by the PU and $\omega(n)$ the AWGN, with zero mean and variance $\sigma_{\omega}^2(n)$. Signal $s(n)$ can be considered as a Gaussian random process, with variance $\sigma_s^2(n)$ [12].

Test statistic for the energy detector is implemented as the time average of the received signal energy

$$t(n) = \frac{1}{N} \sum_{i=n-N}^n |c(i)|^2, \quad (2)$$

with $t(n)$ as an average power of the received CR signal at the time instant n . Binary hypothesis is performed at any given time instant n in order to estimate occupancy of the frequency band, where H_0 and H_1 denote hypothesis of the absence and the presence of the PU signal, respectively, as formulated by

$$H_0: c(n) = \omega(n), \quad (3)$$



$$H_1: c(n) = s(n) + \omega(n). \quad (4)$$

The decision rule is given by

$$t(n) \underset{H_0}{\overset{H_1}{\gtrless}} \gamma(n), \quad (5)$$

where $\gamma(n)$ is the decision threshold determined at the time instant n . Performance of the spectrum sensing can be evaluated through the probability of detection of active PU, P_d , and the probability of false alarm for presence of active PU, P_{fa} , which is given in the terms of Q function [12] as

$$P_d(\gamma(n)) = P_r(t(n) > \gamma(n)|H_1) = Q\left(\sqrt{\frac{N}{2}} \frac{\gamma(n) - (\sigma_\omega^2(n) + \sigma_s^2(n))}{\sigma_\omega^2(n) + \sigma_s^2(n)}\right), \quad (6)$$

$$P_{fa}(\gamma(n)) = P_r(t(n) < \gamma(n)|H_0) = Q\left(\sqrt{\frac{N}{2}} \frac{\gamma(n) - \sigma_\omega^2(n)}{\sigma_\omega^2(n)}\right). \quad (7)$$

Based on equations (6) and (7), performance of the spectrum sensing at any time instant n highly depends on the threshold value ($\gamma(n)$). Higher P_d means less harmful interference to PU and less P_{fa} means less missed transmission opportunities and therefore better spectrum utilization. Large value of P_d and small value of P_{fa} are the design goals. Improving one of these performance indicators implies degradation of the other one, so a trade-off between these two parameters is determined by $\gamma(n)$. To optimize the spectrum sensing process, both P_d and P_{fa} should be considered, and they are combined into a single criterion - spectrum sensing error (SSE), $\varepsilon(\gamma(n))$ [13] as

$$\varepsilon(\gamma(n)) = \alpha P_{fa}(\gamma(n)) + (1 - \alpha) (1 - P_d(\gamma(n))). \quad (8)$$

The goal is to minimize SSE in order to improve performance of the energy-based spectrum sensing in dynamic scenarios. Parameter α is using for weighted probability of detection and probability of false alarm. In this paper, we propose a closed-form solution for the optimal decision threshold $\gamma(n)$ and a dynamic adaptation to time variation of the PU signal and noise, causing the system to respond to the changes in the environment [10].

PU signal $s(n)$ and the noise signal $\omega(n)$ are uncorrelated, thus PU signal variance $\sigma_s^2(n)$ can be estimated based on the calculated variance of CR signal $\sigma_c^2(n)$ as

$$\sigma_s^2(n) = \sigma_c^2(n) - \sigma_\omega^2(n) \quad (9)$$



Threshold determination and dynamic adaptation

Function of the SSE, specified by (8), is strictly convex function of the threshold $\gamma(n)$, for given value of α [14]. Next, let $\frac{\partial \varepsilon(\gamma(n))}{\partial \gamma(n)} = 0$ and according to equations (6), (7) and (8) a quadratic equation for the decision threshold is obtained

$$\frac{2\sigma_{\omega}^2(n) + \sigma_s^2(n)}{\sigma_{\omega}^2(n)(\sigma_{\omega}^2(n) + \sigma_s^2(n))} \gamma^2(n) - 2\gamma(n) - \frac{4\sigma_{\omega}^2(n)(\sigma_{\omega}^2(n) + \sigma_s^2(n))}{N\sigma_s^2(n)} \ln\left(\frac{\alpha(\sigma_{\omega}^2(n) + \sigma_s^2(n))}{(1-\alpha)\sigma_s^2(n)}\right) = 0. \quad (10)$$

Let us define $S(n) = \sigma_s^2(n)/\sigma_{\omega}^2(n)$ as a signal to noise ratio (SNR). Solving the quadratic equation (10), two normalized solutions are obtained as

$$\frac{\gamma_{1/2}(n)}{\sigma_c^2(n)} = \frac{1 \pm \sqrt{1 + \frac{4}{N} \frac{(2+S(n))}{S(n)} \ln\left(\frac{\alpha}{1-\alpha}(1+S(n))\right)}}{2+S(n)} \quad (11)$$

Determined decision threshold must be a real number, non-negative, and larger than the estimated noise variance. Accordingly, discriminant of equation (11) must be non-negative. If the discriminant in equation (11) is in the range [0,1], two solutions for the decision threshold are obtained. Decision threshold must be positive, so in the case that the discriminant in equation (11) is larger than 1, only one solution for the decision threshold is possible. If the sensing time in the process of spectrum sensing is predefined, the design goal for the CR, which is expressed through the weighting factor α , must be adjusted to the environmental conditions.

Having in mind satisfaction of the requested conditions for the decision threshold and analysing equation (11), it is determined that weighting factor α must satisfy [10]

$$\alpha > 1/(2 + S(n)) \quad (12)$$

at any time instant n . In this case, determined normalized decision threshold $\gamma(n)$ as a solution of equation (11) is unique, and it is given by

$$\gamma(n)/\sigma_c^2(n) = \frac{1 + \sqrt{1 + \frac{4}{N} \frac{(2+S(n))}{S(n)} \ln\left(\frac{\alpha}{1-\alpha}(1+S(n))\right)}}{2+S(n)} \quad (13)$$

In all the other cases, the design goal (weighting factor α) should be modified and adjusted to its dynamic environment according to (12).

Finally, the proposed algorithm for the threshold determination and adaptation of the energy detector based spectrum sensing is described below:



Algorithm: Threshold adaptation algorithm for the energy detector-based spectrum sensing

- 1: Calculate the average energy of the received CR signal using (2).
- 2: Calculate the variance of the detected signal $\sigma_c^2(n)$
- 3: Estimate the PU signal power $\sigma_s^2(n)$ from equation (9).
- 4: Verify that assumed weighting factor satisfies equation (12).
- 5: If yes, the optimal threshold value $\gamma(n)$ is determined according to equation (13). If no, the design goal must be modified and adjusted; get back to step 4.

The number of samples used by CR, N , directly impacts the spectrum sensing time, which is directly connected to the spectrum usage efficiency of CRs, as well. The algorithm order of complexity of with respect of the number samples N is obtained as $O(N)$, which indicates efficient implementation. It is important to note that the closed form solution always leads to the threshold value in a finite number of steps, in contrast to iterative procedures [10], [14].

Simulation results:

Evaluation of the proposed dynamic spectrum sensing algorithm is performed by 1 200 Monte-Carlo simulations. Array of 1 000 16-QAM symbols [15], which are considered as the PU signals, were generated and passed through the channel with AWGN only. The AWGN has known SNR features, and PU variance should be estimated by the CR. Weighting factor $\alpha = 0,5$ represent design goal in this example.

Fig. 2 illustrates the dynamic adaptation of the decision threshold for various levels of SNR.

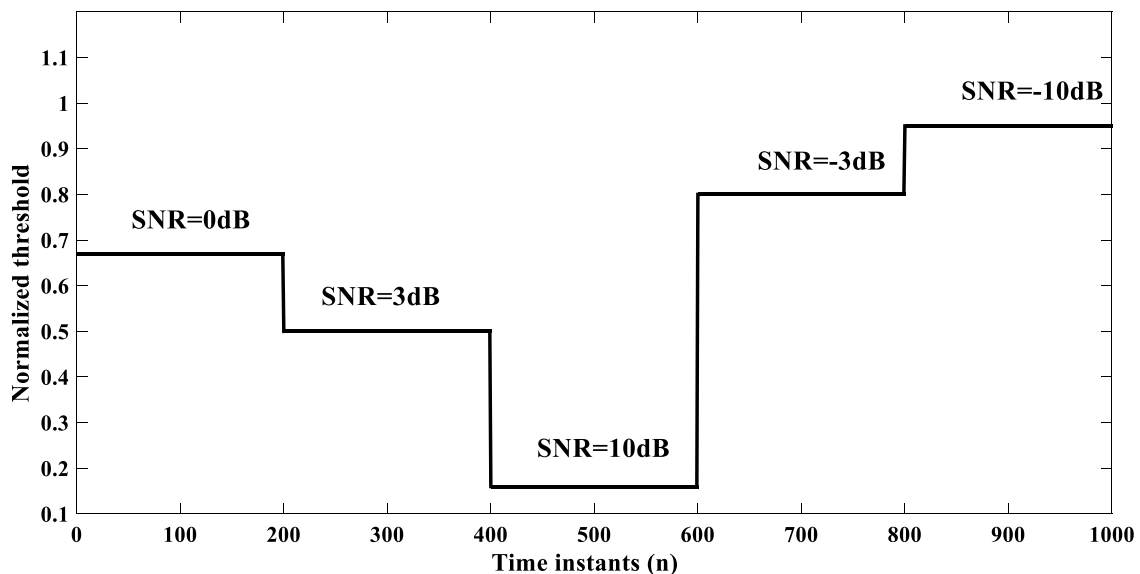


Fig. 2 Normalized threshold adaptation in various SNR, 16-QAM PU signals, AWGN channel



From Figure 2, the normalized decision threshold value is obviously dynamically changing according to (13), depending on the SNR value in the radio environment. The first 200 simulated PU signals (array of 16-QAM symbols) were exposed to AWGN, with $SNR = 0dB$. For the next 200 simulations, SNR was increased for 3dB, then for the next 600 (200 each) simulation SNR was 10dB, -3dB and -10dB, respectively. It should be noted that the value of the decision threshold is lower for higher SNR and vice versa. For each simulation, weighting factor α satisfied (12).

Conclusion

Smart cities concept is reshaping the way how we live, work and network. Deploying and maintenance of required wireless networks, standing behind smart cities, is a big challenge and it is bringing a lot of issues. One of the biggest is the lack of radio spectrum, so advance and innovative approach of spectrum sharing is required to answer all the challenges.

Cognitive radio technology enables efficient usage of radio spectrum in an opportunistic way. In order to avoid or minimize interference spectrum sensing function is of a crucial importance for cognitive radio operations. Due to its low implementation complexity, non-coherent energy detector, which is based on comparison of the detected signal energy with the decision threshold, represents a good choice for spectrum sensing.

In this paper, an algorithm for the decision threshold determination and adaptation in energy-based spectrum sensing in cognitive radio is proposed. The closed-form solution for the optimal decision threshold is proposed and analyzed. Simulation results confirmed effectiveness of the proposed method for optimizing the sensing threshold as well as the capability for dynamic adaptation according to the changes in the operating environment. Also, order of complexity of the algorithm indicates efficient implementation. Future research should focus on more realistic working conditions, considering not only AWGN channel, but real-world channels (fading effects), and unknown noise variance.

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