Adaptive Threshold Architecture for Spectrum Sensing in Public Safety Radio Channels

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***Abstract*—Cognitive radio make use of spectrum sensing techniques to detect licensed users transmissions and avoid causing interference. The major drawback in current spectrum sensing techniques is the use of static decision thresholds to detect such transmissions, which may be infeasible in public safety radio channels. More precisely, the cognitive radio may find different noise or interference levels when switching among these channels. This can lead to a wrong picture of the channel occupancy status, which in turn can increase the interference caused to licensed users. In this paper we propose an Adaptive Threshold Architecture, which uses machine learning algorithms to dynamically adapt the decision threshold, enabling the detection of licensed users transmissions in public safety radio channels. Results showed that the proposed architecture increased the sensing accuracy up to 2 times, providing results up to 6 times faster when compared to other solutions of the literature.**

I. Introduction

Regulatory agencies usually license the use of radio channels during a long period of time, spread along a large geographical area. These agencies grant to licensed users, such as television broadcasters or mobile network operators, exclusive access to their allocated channels. With most of the useful radio spectrum allocated, it became exceedingly hard to find radio channels to either deploy new wireless services or enhance existing ones. On the other hand, recent measurements stated that some allocated channels are rarely used [1]. This statement led regulatory agencies to propose the Dynamic Spectrum Access (DSA) policy, in which unlicensed radios are allowed to temporarily access underutilized radio channels, with the constraint of not interfering with licensed user's transmissions. In this policy, unlicensed users, usually Cognitive Radios, must analyze a radio channel to evaluate its occupancy status. A channel is "vacant" only if no licensed user is transmitting, otherwise it is "occupied" [2].

The occupancy status of radio channels is evaluated by the Spectrum Sensing (SS). The main techniques for SS are based on the analysis of signal characteristics, such as energy or waveform [2]. Each technique presents different performances regarding accuracy and sensing duration. The accuracy is the ratio between correct channel evaluations and real channel occupancy status [3]. One of the main parameters that influences the accuracy is the Signal-to-Noise Ratio (SNR) of the licensed user at the cognitive radio. Moreover, sensing duration is the time required by the sensing technique to perform an evaluation. Sensing techniques, such as Energy Detection (ED), Waveform Detection (WFD), and Cyclostationary Feature Detection (CFD), usually present low variability in sensing duration, which is influenced by the number of signal samples used and the technique's complexity. Furthermore, these sensing techniques present a trade-off between accuracy and duration [3]. For example, the ED is the fastest technique, but it is also the least accurate, whereas the CFD is a more accurate technique, despite also being one of the slowest [2]. Attempting to balance this trade-off, solutions as cooperative SS and multi-stage architectures were proposed [4], [5], [6].

The use of a static decision threshold to determine the channel occupancy status is the major drawback of current cooperative and multi-stage solutions. A cognitive radio operating with such a limitation may be infeasible in public safety radio channels, *i.e.,* channels used by ambulances, firefighters, and police car communications. More precisely, a cognitive radio may encounter different noise or interference levels when switching among these channels [7]. In addition, these channels are often vacant and become densely occupied during a special situation, *e.g.,* the radio channel allocated for the police is constantly occupied during a football game. In this case, the accuracy may be severely degraded, which in turn can increase the interference caused to licensed users. However, given the importance of communications performed in public safety radio channels, it is of utmost importance to develop a SS solution that achieves a high accuracy in such channels. Machine learning algorithms have been highlighted to properly adjust the decision threshold and increase accuracy [8]. However, at the best of our knowledge, no solution considering the use of machine learning algorithms to adapt the decision threshold has been proposed so far [8].

In this paper we introduce the Adaptive Threshold Architecture (ATA) for SS in public safety radio channels. The main novelty of ATA is to ally machine learning and multi-stage SS to enable the dynamic adaptation of the decision threshold. A prototype was evaluated in an experimental radio environment that emulates the behavior of public safety radio channels. Our proposal was compared with the single-stage version of the ED, WFD, and CFD, and with the traditional two-stage architecture (ED/CFD) proposed by Maleki, Pandharipande and Leus [4]. Furthermore, we evaluated our proposal using two configurations: ED/WFD and ED/CFD. Results showed that ATA increased up to 2 times the accuracy while reducing in 6 times the sensing duration, when compared with the

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architecture of Maleki, Pandharipande, and Leus.

The remainder of this paper is organized as follows. Related work on multi-stage SS is presented in Section II. ATA is detailed in Section III. Performance evaluations are discussed in Section IV. Finally, conclusions and future work are presented in Section V.

II. Related Work

The importance of SS to cognitive radios

SS has been a large topic of research due to its importance in cognitive radios. Current research in SS aims to develop techniques capable of evaluating the radio channel occupancy status with the highest accuracy in the shortest time [1]. However, balancing the existing trade-off between accuracy and sensing duration is challenging. Attempting to achieve this balance, solutions such as cooperative SS and multi-stage architectures were proposed [2], [4].

The goal of cooperative SS is to improve the accuracy by making it more robust against faded signals and the hidden terminal problem [3]. The concept of cooperative SS is to make multiple cognitive radios send their channel evaluations to a common receiver, which in turn combines the evaluations into a final value. However, the increase in the accuracy is limited by many factors, *i.e.,* it might be severely degraded if the majority of radios is configured with a wrong decision threshold [1]. In addition, the operations involved in the cooperation incur in extra sensing duration, delay, and energy consumption when compared to standalone SS [3].

Multi-stage architectures were proposed in the literature to improve the SS of standalone cognitive radios without the need of cooperation. These architectures improve the SS by applying different techniques to each stage, obtaining fast and accurate evaluations regarding the channel occupancy status. Maleki, Pandharipande, and Leus [4] proposed a two-stage architecture that executes the ED in the first stage and the CFD in the second stage. In this architecture, the first stage is always active, whereas the second is activated only when the first stage evaluates the channel as vacant. When this situation occurs, the evaluations of the second stage are considered as correct, even if it contradicts the first stage. The authors showed analytically that combining these two techniques in a hierarchical scheme increases the accuracy when compared to the single-stage solution of both techniques. In addition, the proposed architecture reduced the sensing duration when compared to the single-stage CFD. However, the second stage is frequently activated in environments where the channels are often vacant, increasing the sensing duration. This architecture is used as baseline for other multi-stage architectures proposed in the literature and also in this paper.

Nair, Vinod, and Krishna [5] proposed an algorithm to control the activation of the second stage, aiming to reduce the sensing duration of the architecture proposed by Maleki, Pandharipande, and Leus [4]. This algorithm control the activation of the second stage based on the SNR of the licensed user signal at the cognitive radio. Results obtained showed that the second stage can be disabled without significant accuracy loss when the SNR is above -15.4 dB.

An integration between multi-stage and cooperative approaches was proposed by Liu *et al.* [6]. In such a proposal, each cognitive radio executed a two-stage architecture using an ED with different configurations in each stage. The main contribution of this proposal was to show that multi-stage architectures can be easily extended to cooperative SS. In this sense, we argue that our architecture is also extensible to cooperative SS.

All investigated SS solutions presented results regarding increasing the accuracy and reducing the sensing duration. Nevertheless, these solutions used static decision thresholds in the sensing techniques executed, which is a major drawback for public safety radio channels. We propose an Adaptive Threshold Architecture to overcome this drawback. Our proposal allies a multi-stage solution with machine learning algorithms to dynamically adapt the decision threshold of the first stage. The proposed architecture is better detailed in the next section.

III. Adaptive Threshold Architecture

The proposed architecture is composed of the radio frequency front-end, the *Sensing Component*, and the *Machine Learning Component*, as can be seen in Fig. 1. The front-end provides the radio signal received to the *Sensing Component*. We provide more details on the *Sensing Component* and the *Machine Learning Component* in Subsection III-A and III-B, respectively. In addition, Subsection III-C details ATA's operation.

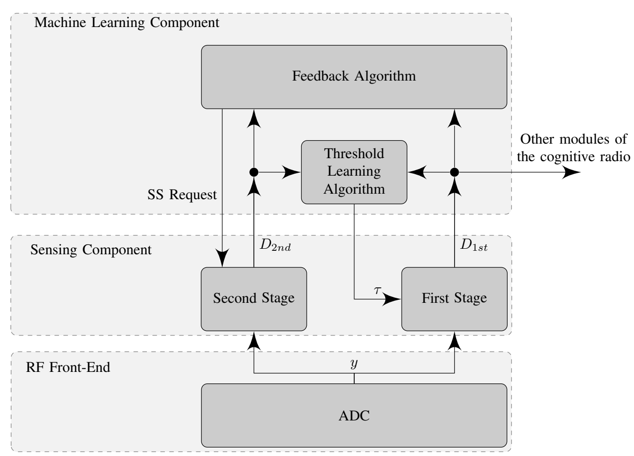


Fig. 1. Proposed Architecture

A. Sensing Component

The *Sensing Component* performs the operations required to evaluate whether the sensed channel is occupied or vacant. ATA employs two SS techniques to achieve a high accuracy while maintaining a low sensing duration. We refer to the two SS techniques as *First Stage* and *Second Stage*, following the standard naming convention for multi-stage architectures.

The *First Stage* is always active, *i.e.,* it provides results regarding the channel occupancy status without interruptions. The inputs for this stage are the received radio signal (y) from the *RF Front-End* and the decision threshold (τ) from the *Machine Learning Component*. The output is the channel occupancy status (D_{1st}), which is sent to the *Threshold Learning Algorithm*, to the *Feedback Algorithm*, and to modules that will use it to select which vacant radio channel should be accessed, *e.g.,* the "spectrum decision" function of cognitive radios.

The *Second Stage* enables the adaptation of the decision threshold τ used by the *First Stage*. The inputs for the *Second Stage* are the radio signal y and the *SS Request*. With the purpose of reducing the sensing duration of ATA, this stage is activated only when the *SS Request* is received. The output is the evaluation indicating the presence or absence of licensed users (D_{2nd}), which is sent to the *Threshold Learning Algorithm* and to the *Feedback Algorithm*.

The selection of which SS technique will be executed in each stage depends on both the accuracy and the sensing duration required by the cognitive radio. Although any SS technique could be used, to obtain the best performance from ATA, a faster technique should be used in the *First Stage*, *e.g.,* ED, and a more accurate technique in the *Second Stage*, *e.g.,* WFD or CFD. This is recommended because the *First Stage* is always active, whereas the *Second Stage* is activated only when the *SS Request* is received.

B. Machine Learning Component

The *Machine Learning Component* is the main novelty presented in ATA and it is composed of two algorithms: a *Threshold Learning Algorithm* and a *Feedback Algorithm*. The former is responsible for adapting the value of the decision threshold τ such that D_{1st} becomes equal to D_{2nd}. This adaptation can be performed using different machine learning algorithms, *e.g.,* bayesian learning [9], Q-learning [10] or State-Reward-State-Action (SARSA). We highlight that the machine learning algorithm plays a major role in ATA. For example, ATA may need to met different requirements, such as interference minimization, access opportunities maximization, or user identification [8]. Different learning algorithms might be best suited for each one of these requirements. However, the study of which algorithm is better for each requirement is outside the scope of this article.

The learning algorithm proposed by Gong *et al.* [9] is based in the bayesian learning process and was used in the prototype of ATA. We present the main operations of such proposal in Algorithm 1. The learning occurs by associating a risk factor (R) with each threshold value used and in selecting the threshold with the lowest risk. In each iteration of the algorithm, the $P_{\mathcal{H}_0}$, $P_{\mathcal{H}_1}$, $P_f(\tau)$ and, $P_m(\tau)$ probabilities are updated (line 1). In the sequence, D_{1st} and D_{2nd} are compared (line 1 and 5). Based on this result, only the thresholds lower (line 3) or higher (line 6) than the current threshold (τ) have they risk updated. Afterwards, the threshold with the lowest risk is selected (line 4 and 7).

The *Feedback Algorithm* reduces the sensing duration by controlling the activations of the *Second Stage*. The algorithm must calculate the interval until the next activation of the *Second Stage* based on the values of D_{1st} and D_{2nd}. The output of this block is the *SS Request*, which is sent only when the calculated interval has expired. When D_{1st} and D_{2nd} converge to the same value, the *Feedback Algorithm* can increase the interval between activations of the *Second Stage*. As a consequence, the sensing duration is reduced because only the *First Stage* is activated. Similarly, if D_{1st} is different from D_{2nd}, the interval between activations of the *Second Stage* is reduced, increasing the sensing duration, but also quickening the threshold adaptation.

Algorithm 1 Bayesian Threshold Learning Algorithm

Require: τ is current decision threshold
Require: τ_{min} and τ_{max} are the min/max value for τ
Require: R is the bayesian risk of each valid threshold
Require: P_f and P_m are the false alarm and miss detection probabilities of each valid threshold
Require: $P_{\mathcal{H}_0}$ and $P_{\mathcal{H}_1}$ are the a priori probabilities
1: Update $P_{\mathcal{H}_0}$, $P_{\mathcal{H}_1}$, $P_f(\tau)$, and $P_m(\tau)$
2: **if** D_{1st} is "occupied" and D_{2nd} is "vacant" **then**
3:     Update R for valid thresholds in $[\tau, \tau_{max}]$
4:     $\tau \leftarrow$ Threshold in $R[\tau, \tau_{max}]$ with the smallest risk
5: **else if** D_{1st} is "vacant" and D_{2nd} is "occupied" **then**
6:     Update R of valid threshold in $[\tau_{min}, \tau]$
7:     $\tau \leftarrow$ Threshold in $R[\tau_{min}, \tau]$ with the smallest risk
8: **end if**

C. Detailing ATA operation

ATA operation can be separated in three states: fast sensing, slow sensing, and adaptation, as illustrated in Fig. 2. When ATA starts its operation, the *Feedback Algorithm* initializes the *interval* between activations of the *Second Stage* to one. During the fast sensing state, the *First Stage* is constantly evaluating the channel occupancy status, while the *Second Stage* and the *Threshold Learning Algorithm* ignore all inputs received. In addition, the *Feedback Algorithm* decrements the *interval* value whenever an evaluation D_{1st} is received. This state finishes when *interval* reaches zero.

In the slow sensing state, the *Feedback Algorithm* sends the *SS Request*. Immediately, the *Second Stage* starts the analysis of the received signal. This state finishes when the *Second Stage* generates the evaluation D_{2nd}. During the adaptation state, the *Feedback Algorithm* compares the most recent evaluations received and calculates the new *interval* value. Similarly, the *Threshold Learning Algorithm* compares the evaluations to learn a new decision threshold τ. Afterwards, the new threshold is applied to the *First Stage*. During the next fast sensing state, the *First Stage* will provide evaluations using the new threshold, whereas the *Feedback Algorithm* will use a different *interval* value.

The drawback of current SS solutions is eliminated in this architecture by allying multi-stage SS with machine learning techniques to dynamically adapt the decision threshold. As a marginal contribution, we propose a mechanism to control the activations of the second stage to reduce the sensing duration. Therefore, we combined the advantages of a multi-stage architecture with the capability of adaptation to different radio

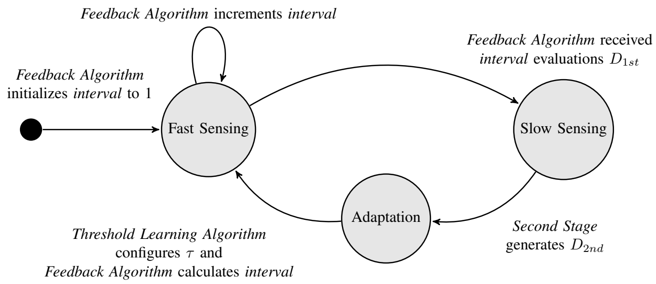


Fig. 2. State machine diagram illustrating the operation of ATA

environments. In the next section the proposed architecture is evaluated and results are discussed.

IV. Performance Evaluation

The evaluation of the proposed architecture, as well as the results, are presented in this section. The experimental scenario and parameters are detailed in Subsection IV-A. Finally, results are presented in Subsection IV-B.

A. Experimental Scenario and Parameters

Our scenario comprises the operation of a cognitive radio in a public safety radio channel. Thus, we used two Universal Software Radio Peripheral N210 (USRP)[1] devices: one was designated as the public safety licensed user and the other as the cognitive radio. An application was developed using the GNU Radio toolkit[2] and deployed in the licensed user USRP to control the ON and OFF periods. During the OFF period the spectrum is not occupied by the licensed user, while during the ON period the spectrum is occupied. These periods were modeled according to a continuous-time Markov process with two states, as illustrated in Fig. 3. This model has been widely adopted in the literature because it approximates the spectrum usage pattern of public safety radio channels [7]. Moreover, the literature usually considers two probabilities for channel occupancy, which are $P_{ON} = 10\%$ (seldom occupied), and 90% (often occupied). In our work we also considered these two values. Finally, the duration of the ON and OFF periods followed a Poisson distribution with mean and variance (σ) equal to 3 seconds.

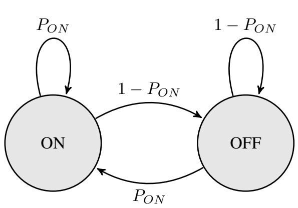


Fig. 3. Markov chain for the licensed user

A second application was deployed in the cognitive radio to control the signal reception and execute the SS. Aiming to compare ATA with other solutions, this application was designed to execute five different SS solutions: (I) ED, (II) WFD, (III) CFD, (IV) the two-stage hierarchical architecture proposed by Maleki, Pandharipande and, Leus [4], referred to TSHA, and (V) ATA. In addition, ATA results were obtained using two different combinations of sensing techniques. The first combination used the ED and the WFD in the First and Second Stages, respectively, and the second combination used the ED and the CFD. Moreover, the decision thresholds (th) of the other sensing techniques were configured to satisfy a probability of false alarm (P_{FA}) of 0%, 10% and 50%. In practice, P_{FA} will be defined by regulatory agencies and is expected to be $\leq 10\%$ [3]. Therefore, we used two values that fall in the practical expected range (0% and 10%) and a higher value (50%) to verify the impact in the accuracy. It is worth noticing that the First Stage of ATA did not use the decision threshold th because its decision threshold is adapted by the Threshold Learning Algorithm. Finally, we gathered results considering that the licensed user signal was received with a SNR of -20, -15, -10, -5, 0, and 5 dB.

Additional parameters considered in the scenario can be observed in Table I. The licensed user transmits at 700 MHz with 200 kHz bandwidth, using the BPSK modulation. The number of signal samples (N_{samp}) considered in all sensing techniques was fixed at 1024. We used as the Threshold Learning Algorithm the one proposed by Gong, with τ of -75 dB, $\tau_{min} = -120dB$, and $\tau_{max} = 0dB$. The Feedback Algorithm adjusted the *interval* value using the exponential equation *interval* $= 2^x$, where x is decreased when the evaluation of the *First* and *Second Stages* are different and incremented otherwise. Moreover, x is initialized with 0 and the maximum value allowed for *interval* is 64, thus, the maximum value for x is 6. Each experiment was executed for 20 seconds and repeated 30 times. Finally, the plots are shown with errors bars using a confidence level of 90%.

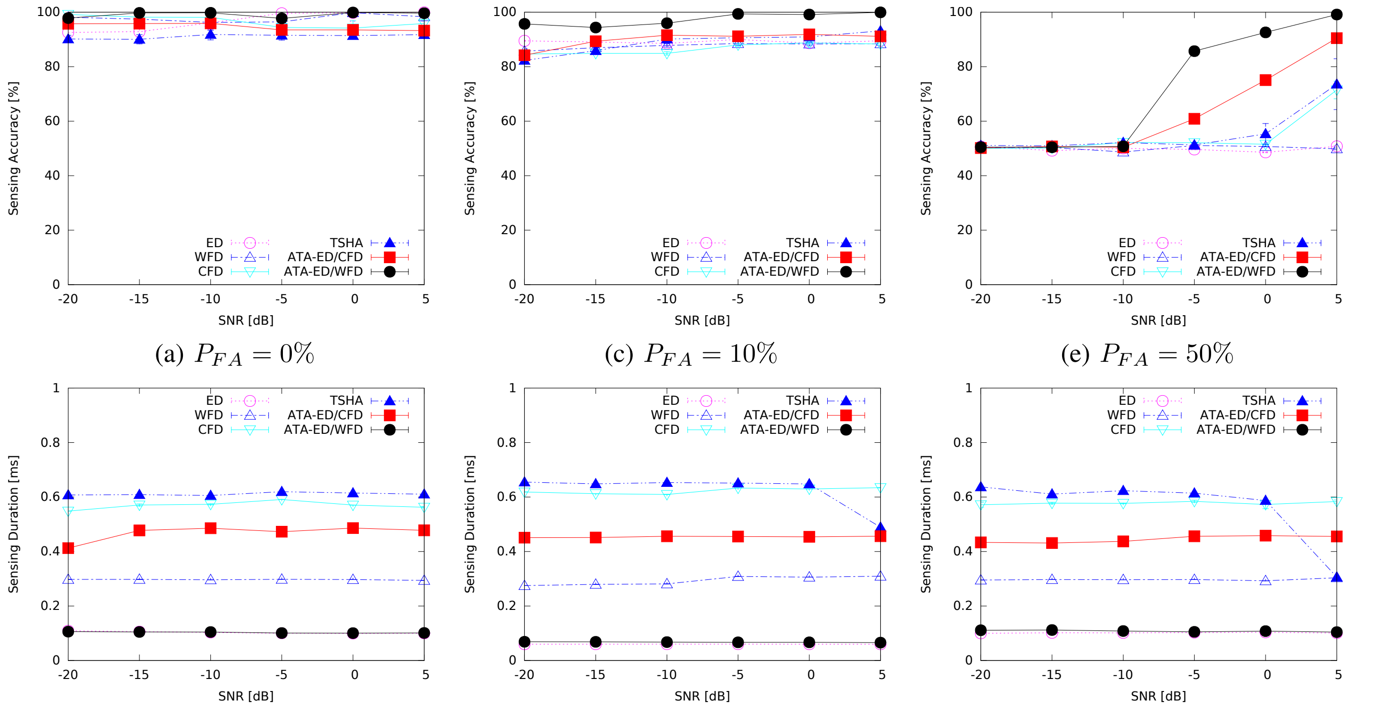
TABLE I
Evaluation parameters

Parameter	Value
Licensed User Central Frequency	700 MHz
Licensed User Signal Bandwidth	200 kHz
Licensed User Modulation	BPSK
N_{samp}	1024 samples
τ, τ_{min}, and τ_{min}	-75, -120, and 0 dB
P_{FA}	0%, 10% and 50%
SNR	-20, -15, -10, -5, 0, and 5 dB
th	Based on the P_{FA} and SNR
b	2
I_{max}	64 activations
P_{ON}	10% and 90%
ON/OFF duration	Poisson distribution with $\sigma = 3$
Execution Time	20 s
Confidence Level	90%

B. Results

We separated the results obtained in two figures: Fig. 4 shows the results for $P_{ON} = 10\%$, while Fig. 5 depicts the results for $P_{ON} = 90\%$. Each figure is divided in six subfigures: (a), (c), and (e) show the accuracy for $P_{FA} = 0\%$, 10%, and 50%. Similarly, subfigures (b), (d), and (f) show the

[1]http://www.ettus.com; [2]http://www.gnuradio.org



(a) $P_{FA} = 0\%$ (c) $P_{FA} = 10\%$ (e) $P_{FA} = 50\%$

(b) $P_{FA} = 0\%$ (d) $P_{FA} = 10\%$ (f) $P_{FA} = 50\%$

Fig. 4. Results obtained for $P_{ON} = 10\%$

sensing duration. The x-axis always is the SNR of the licensed user signal at the cognitive radio.

We can observe that single-stage techniques presented low variability in the accuracy for a fixed P_{FA}, since the accuracy of these techniques is related only to the P_{FA}. In addition, the sensing duration of the single-stage techniques presented a similar behavior. For $P_{FA} = 0\%$, in Fig. 4(a), all evaluated techniques presented a very high accuracy. This occurred because $P_{FA} = 0\%$ is well suited for channels with low occupancy probability. As for the sensing duration, both combinations of ATA were better than TSHA, as shown in Fig. 4(b). More precisely, TSHA had a sensing duration of approximately 0.6 ms, while ATA-ED/CFD and ATA-ED/WFD had a duration of 0.55 ms and 0.11 ms. It is worth highlighting that ATA-ED/WFD achieved the highest accuracy and a sensing duration similar to the single-stage ED, *i.e.,* it was 6 times faster than TSHA.

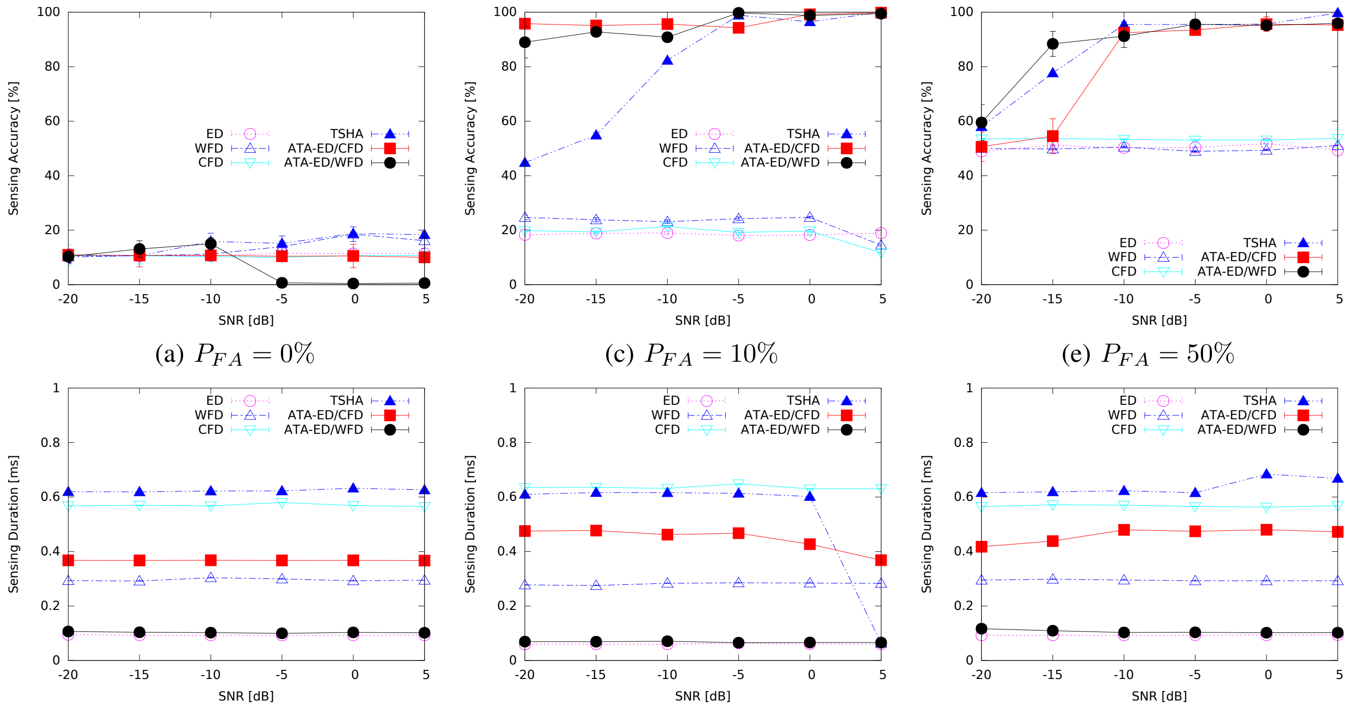
Results regarding the accuracy for $P_{FA} = 10\%$ can be observed in Fig. 4(c). In this case, the accuracy presented a small decrease when compared to the previous P_{FA}. This occurred because the sensing techniques declared the channel as vacant more often, even if the channel occupancy probability was the same. Besides, both combinations of ATA achieved a higher accuracy than TSHA. Moreover, ATA presented a lower sensing duration than TSHA for all SNRs, as shown in Fig. 4(d).

In Fig. 4(e) we can observe that both combinations of ATA achieved an accuracy similar to the other techniques for all SNR below -5 dB for a $P_{FA} = 50\%$, . However, for SNRs $\geq$ -5 dB, ATA's accuracy is considerably higher. We highlight that for a SNR of 5 dB, TSHA presented an accuracy of approximately 73% while ATA-ED/CFD achieved 90%, and ATA-ED/WFD 99% In addition, Fig. 4(f) shows that the sensing duration of both combinations of ATA were lower than TSHA.

Fig. 5 shows the results for $P_{ON} = 90\%$. Fig. 5(1) shows that the accuracy was severely degraded for $P_{FA} = 0\%$, *i.e.,* the channel was often occupied and the P_{FA} made the sensing techniques declare the channel as vacant. This combination of P_{ON} and P_{FA} made the learning algorithm converge the decision threshold to an erroneous value, *i.e.,* a value in which the *First Stage* always declared the channel as vacant, matching the evaluations provided by the *Second Stage*. In addition, the sensing duration of both combinations of ATA were lower than TSHA, as shown in Fig. 5(b).

Fig. 5(c) shows that the accuracy greatly increased for $P_{FA} = 10\%$. Both combinations of ATA surpassed the accuracy of the other sensing techniques for SNR values below -5 dB. The main different between ATA and TSHA occurred for a SNR of -20 dB. In this case, TSHA achieved an accuracy of 44%, while ATA-ED/CFD achieved 95% and ATA-ED/WFD 88%. In addition, Fig. 5(d) shows that both variations of ATA presented a lower duration than TSHA.

The accuracy and sensing duration for $P_{FA} = 50\%$ are shown in Figs. 5(e) and 5(f). In this case, ATA is better than TSHA for all SNR values below -10 dB, while TSHA and ATA presented a similar accuracy for higher values. However, ATA greatly outperformed TSHA regarding the sensing duration.



(a) $P_{FA} = 0\%$ (c) $P_{FA} = 10\%$ (e) $P_{FA} = 50\%$

(b) $P_{FA} = 0\%$ (d) $P_{FA} = 10\%$ (f) $P_{FA} = 50\%$

Fig. 5. Results obtained for $P_{ON} = 90\%$

By analyzing the results obtained when $P_{ON} = 10\%$, lower values of P_{FA} led to a better accuracy. Inversely, when $P_{ON} = 90\%$, lower P_{FA} values led to worst accuracies. This is an expected behavior, as highlighted by Macaluso *et al.* [11]. However, ATA was capable to achieve a higher accuracy when $P_{FA} = 10\%$, independently of P_{ON}. Therefore, we can conclude that ATA greatly improves the current state-of-the-art sensing techniques by allowing the cognitive radio to correctly detect the licensed user under different occupancy probabilities and for different SNR values.

V. Conclusion

In this paper we proposed an Adaptive Threshold Architecture for spectrum sensing in public safety radio channels. The proposed architecture comprises a Sensing Component and a Machine Learning Component. The first one is a multi-stage SS which combines two SS techniques to provide accurate and updated evaluations regarding the channel occupancy status. The second one applies machine learning techniques to adapt the decision threshold and a feedback algorithm, which reduces the sensing duration.

Results were obtained in an experimental radio environment that emulates public safety radio channels. Outcomes showed that the proposed architecture outperforms other single-stage and multi-stage solutions considering a licensed user with different occupancy probabilities and signal qualities. Directions for future investigations include the consideration of radio channels with frequency selective fading effects and the analysis of other machine learning algorithms.

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