A Strategy to Improve Sensing Accuracy of Energy Detection for Distributed Spectrum Management Systems

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***Abstract*—Spectrum sensing has a key role in the dynamic spectrum access' paradigm. Spectrum sensing must be carried out to identify transmissions of licensed users, and therefore, avoid harmful interference on them. In addition, it enables the discovery of opportunities that allow communication between the cognitive radio devices to take place. Energy detection is a spectrum sensing technique with some important advantages: simplicity, low response time and low computational cost. However, this technique has very low accuracy in comparison to other approaches. This paper presents and evaluates a proposal to improve the accuracy of spectrum sensing based on energy detection. Our proposal employs hidden Markov model (HMM) to distinguish signals from licensed devices in scenarios where their SNR values are comparable to the ones from cognitive devices. Performance evaluation using ns-3 simulator have shown that our proposal improves the discovery of transmission opportunities.**

I. Introduction

Frequency spectrum available bands are becoming a very limited and expensive resource due to the many wireless communication technologies deployed. An increasing number of applications and sophisticated mobile devices make user demands for bandwidth increase in a fast pace. In this scenario, where the transmission medium is scarce and the demand has a climbing tendency, efficient use of the resources becomes an obligation.

The limitations imposed by the static spectrum allocation are not a new issue [1]. This approach leaves underutilized opportunities in the frequency spectrum, which can appear in space but they occur mainly in time. Some places have fully available bands that can not be used because they are restricted to licensed users. Spatial opportunities can be explored using geolocation tools and updated databases of spectrum allocation and effective licensed user occupation [2].

Many places around the world, mainly the big cities, present an effective occupation of their whole frequency spectrum. Nevertheless, the average utilization through time is notably low. Even in high density areas, studies show a mean utilization under 20% [3]. That is a great motivation for opportunistic spectrum access which can explore the licensed user's silent periods, also known as *white spaces*, to establish secondary (non licensed) communications. This available capacity can be used to create new communication networks or to improve the performance of already established networks. In cognitive radio networks, specially the ones dedicated to data transfers, distributed approaches have important advantages: nodes can freely move between different topologies and scenarios and adapt; there is no central management point, which represents a failure risk that could compromise the entire network; modern data networks are based on distributed peers, as an example of Mesh networks.

This work's main focus is to improve the detection accuracy of usable *white spaces*. It is not any *white space* that can be considered an effective transmission opportunity, since very short *white spaces* are not useful for many data transmission technologies. Additional comments about this issue are presented later in this paper. In order to take advantage of these opportunities, legacy devices, also known as Primary Users (PU), need to be protected from interference. Users that wish to benefit from white spaces have to sense the channel and look for transmissions coming from a PU. Protection of PUs is a rule, but the main motivation of spectrum sensing is to find opportunities to transmit. As previously noted by [1], detection techniques based in matched filter or cyclostationary feature have high accuracy and are superior to energy detection. Despite of the accuracy disadvantage, energy detection is much simpler to implement, has low cost and is the only option available in any wireless device.

Many papers related to energy detection deal with the problem of PU identification in an environment where its signal level is low, comparable to noise level [4], [5], [6]. This scenario makes energy detection susceptible to false alarms (when noise is erroneously considered PU signal) and missed detections (when PU signal is not detected because is identified as noise). The aforementioned works do not address the presence of SUs and the interference they cause on an specific transmission medium. In [7], SUs are taken into consideration, but they only contribute to noise uncertainty,

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which provides greater difficulty to distinguish the PU from noise.

A different set of problems arises when the sensed PU power is clearly above the noise and there are multiple SUs contending for medium access. In this context, authors [8] have assumed that PU can be accurately detected by some third party solution and the main issue is the optimal use of the spectrum holes. However, the most accurate detection techniques (e.g. cyclostationary feature) are rarely available, since they imply in complex and expensive devices. In this paper, we present an alternative technique that can be employed in any software defined radio device because it depends only on energy detection hardware. Actually, our approach can be used in many conventional radio devices (e.g. 802.11 [9]) in order to improve their dynamic spectrum access capabilities.

The signal energy of every PU along the time can be represented as a stochastic process. In general, this PU process exhibits some features that do not appear in an equivalent SU process. The number of unique PU features can vary according to the PU and SU characteristics. However, it seems very unlikely to find PU and SU with identical behaviors. In this paper, we employ hidden Markov models (HMM) and the basic concept of state permanence to detect those differences and consequently the PU transmissions. Our approach is compared with the traditional energy detection and with a modified scheme, originally proposed for scenarios where PU power is near to noise.

II. Spectrum Sensing and Related Work

Despite recent changes in regulation announced by the FCC [10], relieving SUs from the obligation to sense the spectrum in favor of geolocation databases [11], spectrum sensing is still a key feature to provide the flexibility expected from a cognitive device. According to FCC's rulings, geolocation capability would suffice to achieve PU protection, but this relies entirely on a PU with strictly fixed and known transmission times. Many scenarios do not satisfy these constraints.

Spectrum sensing can be carried out at physical layer or link layer. Each of these approaches use different means and have different perspectives of the medium. At physical layer, the focus is to efficiently detect the primary user's signal, minimizing false alarm and missed detection probabilities.

Link layer sensing is focused on the discovery and maximization of opportunities concurrently with *white space* identification delay minimization, i.e., determine which frequency bands to sense and for how long. In the present work, we use a cross-layer approach, which aims at the maximization of opportunity discovery using physical layer information. This information is basically the result of the energy detection described in section III-A with respect to the slot.

Sensing mechanisms are commonly evaluated using two metrics. In their traditional scope, they are used in a scenario where silent periods are implemented, and during sensing times, only PU signal can be detected:

- P_{fa} (False Alarm probability): the probability of sensor reports the signal presence when it is not there.
- P_{md} (Missed Detection probability): the probability of sensor fails to report a signal in the medium.

At physical layer, these metrics deal with the distinction between a transmitter's signal and noise. The classical problem related to PU identification is the differentiation between a PU signal and noise in a scenario of low SNR (even a negative SNR in some cases). The majority of efforts in the field of spectrum sensing considers the presence of a single PU, which transmits following some statistical distribution, represented by an *On/Off* process. In those cases, signal is considered to be very low, close to the *SNR-wall* [12] and is confused with noise. In such conditions, *Kim et al.* [7] devised a collaborative approach and an optimization of sensing period/sensing frequency in favor of a minimum sensing overhead. Also, a comparison between energy detection and feature detection is presented, deriving a $aRSS_{threshold}$ below which feature detection is preferred.

In [13], *Ghosh et al.* validate the existence of a Markov chain for spectrum bands utilization, based on a PU *On/Off* process, using real-world measurements. Although *Ghosh et al.* use the same approach as we do (HMM), in their work they were concerned with validation and accuracy of an HMM to represent a real world spectrum utilization and we are focused on the use of such a model to differentiate transmission sources in a high *SNR* environment.

In [4], *Sun et al.* introduce a risk factor mechanism by which different P_{fa} and P_{md} pairs can be achieved, using an HMM to detect a PU transmission in low *SNR*. Two algorithms were proposed, *Complete Forward Algorithm* (CFA) and *Complete Forward Partial Backward Algorithm* (CFPB), using energy detection as the underlying observation. Both these approaches are simplifications of the general *Complete Forward-Backward Algorithm*. The main difference between our work and the proposals from *Sun et al* is we work in a high *SNR* scenario, and the transmission from a PU is differentiated from an SU's, not from noise. Additionally, we propose a new model, using different properties of the HMM to conclude about the transmission source.

The problem presented in this work has a fundamental difference from most other approaches. Most sensing techniques rely on coordinated silence periods, therefore the only signal which could be observed comes from the PU. Our approach does not rely on a coordinated silence period, but tries to differentiate signals based on their statistical characteristics. At physical layer, P_{fa} and P_{md} have closed Equations [5], [14] and are related to the classical problem previously discussed. Despite the use of the same metrics, we define them as a simple relation:

$$P_{fa} = \frac{FA}{Off_P} \tag{1}$$

$$P_{md} = \frac{MD}{On_P} \tag{2}$$

where FA is the number of false alarms detected, Off_P is the total observations the PU was not transmitting, MD is the number of missed detections and On_P is the total observations the PU was transmitting.

III. System Model

Wireless medium is full of uncertainties due to many physical phenomena and characteristics such as fading, multipath, propagation issues, etc. Another big uncertainty is related to the transmitter identification. The scenario treated in this work highlights the difficulty in determining a transmission source, more specifically, if the transmitter is a PU or not. Figure 1 shows an example of how the medium can be occupied by a PU and a number of SUs competing for *white spaces*.

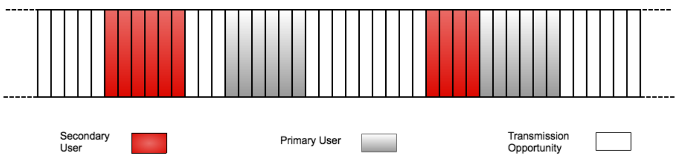


Fig. 1. Medium usage pattern

In this scenario, time is discrete and seen as a fixed duration *slot* sequence. Slot duration can represent hardware characteristics, such as response delay, and for the energy detector we assume a microsecond order. A sequence of consecutive slots comprehends a window. Windows have fixed length (in number of slots) and can be fit to represent the medium in two ways: as *block windows* and as *sliding windows*. Block windows advance in time in a block by block fashion, in which each slot is part of a single window, and then discarded. Sliding windows have a FIFO structure, *i.e.*, most recent slot is added in the end of a queue while the oldest is removed, in order to keep the window size constant. Figure 2 shows a sliding window moving in time.

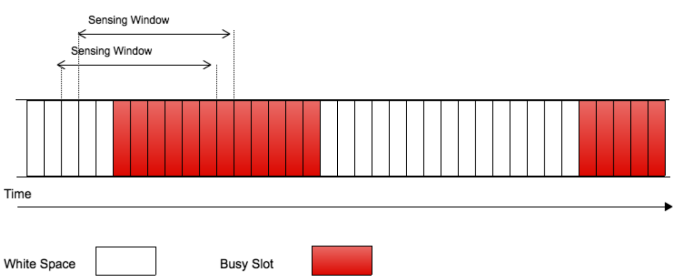


Fig. 2. Sliding window.

The strategies evaluated in this paper are based on a sliding window of observations. Given the order of magnitude defined for the slot duration (microseconds) compared to a typical transmission duration (milliseconds or even seconds), partially occupied slots are unlikely to be seen and little impact is expected from them on overall sensing mechanisms evaluation.

A. Energy Window Detector

The energy detector consists of a sliding window of observations and occupation parameters that will ultimately determine the status of the medium. Each observation is actually a specific reading of the medium, which corresponds to its situation comprehended in a slot time. As time is a continuous flow, modeled here by a continuous sequence of slots, observations can be used to represent time in full (by making observations on every time slot) or through the collection of samples. Figure 3 shows an illustration of an observation window composed of samples of slots in time. The use of sampled observation windows dramatically reduces simulation time and brings no loss of generalization to the problem.

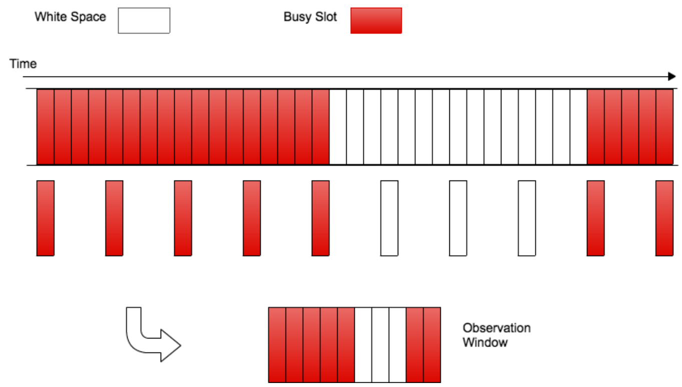


Fig. 3. Sampled observation window

The problem of identifying a PU by energy detection is modeled as a binary hypothesis on each slot of a sliding window and a window occupation parameter, as the following:

$$Y_t = \begin{cases} W_t \quad \text{t = 1, 2, ..., T} \quad H_0 \text{ signal absent} \\ W_t + X_t \quad \text{t = 1, 2, ..., T} \quad H_1 \text{ signal present} \end{cases} \tag{3}$$

where Y_t is the energy level at instant t, W_t is noise, X_t is a transmitter's signal power and T is the slot duration. Mean slot signal level is defined by Z_y:

$$Z_y = \frac{\int_{t=1}^{T} Y_t}{T} \tag{4}$$

The mean calculated by Equation 4 implies the sensor should listen to the medium for the duration of the slot. Mean signal level can be approached by a different perspective, illustrated by Figure 4, where mean energy level is equivalent to a low duration high energy reading. By using this approach, we can achieve better responsiveness from the sensor and avoid recalculations.

One of the parameters to the energy detector is ϵ, a slot occupancy threshold, which represents the percentage of the slot time that should contain a signal level above noise. Another parameter is Y_z, the equivalent mean that is desired in order to consider the slot busy.

The slot is thus declared occupied (or busy) if:

$$\epsilon T \leq \frac{\int_{t=1}^{\epsilon T} Y_t}{Y_z} \tag{5}$$

Finally, the energy window detector considers the presence of a PU if there are $\rho\tau$ slots occupied in the window, where

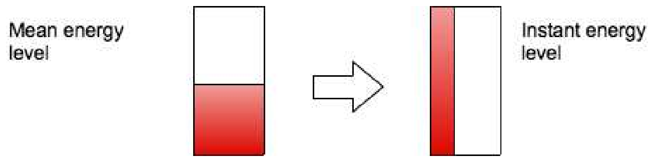


Fig. 4. Mean power level and instant power level.

ρ is the window occupancy percentage parameter and τ is the window size in number of slots.

IV. HMM DETECTORS

PUs normally exhibit an statistically well described access pattern. Moreover, this pattern tends to show little variation along time. There is a number of pattern recognition techniques to identify a state distribution in a complex system [15]. In this work, we developed a technique based on HMM.

The HMM approach considers the existence of a Markov process that describes the system, but that process can not be directly observed. Instead, each state emits an observable symbol. From an observer's point of view, symbols could have been emitted from any state of the system with a given probability. This feature of the HMM makes it a powerful tool to describe the wireless environment, and specifically, to describe the transmission pattern of a desired entity.

From the standpoint of a device sensing the medium, the symbols that can be observed are modeled as 0 (absence of energy) or 1 (energy in the medium). The origin of a signal, when it is present, is hidden and by using an HMM which represents a PU's transmission pattern, it is possible to determine, with some probability, if the PU was the source that generated the observed symbols.

An HMM modeling (represented by λ) is described by the following elements:

- **Initial Probabilities:** define the probability each state i has of being the first in the system (π_i).
- **Transition Probabilities:** define the transition probability from one state i to another j (or to the same), a_{ij}.
- **Observation Probabilities:** represent the probability of, being in a given state i, observe a symbol O ($b_i(O)$).
- **State Set (N):** set of states that describe the system.
- **Observable Symbols Set (M):** Set of symbols that can be observed from the state set.

The choice of the elements that compose the HMM directly affects the model's performance in representing a particular phenomena. Special attention should be devoted to the state number choice which best represents the Markov process. Although there is no deterministic mechanism to derive the state set that best represents the process, observing its behavior usually brings a perception of the different phases involved. The other elements, which hold the probabilities that represent the process, are obtained by a procedure called *training*. This procedure can be done basically through two algorithms: *Baum-Welch* and *k-Means*.

Two HMM based detectors were devised and evaluated. The first is derived from the *Complete Forward-Backward* (CFB) algorithm. This approach was also evaluated by *Sun et al* in [4] but under different circumstances: low signal power (comparable to noise level) and the objective was to differentiate a real transmission signal from background noise. The second, called *Transmission Word Detection* (TWD), is a new proposal based on the concept of state permanence and the probability that a sequence of equal symbols of a given length be observed. Additional details are presented in section IV-B.

The PU under consideration is an entity that transmits its data using some form of fixed length data frame and known modulation and bit rate. By observing the PU's transmission cycle, a 3-state model was devised to describe its transmission signature. Each state represents a phase within a transmission cycle and after the *trainning* process each state can be correlated to one such phase. Without loss of generality, we declare a given correspondence as: state 0 represents the period of time the PU is silent; state 2 represents the period when the PU is actively transmitting a data frame; state 1 is the small silent periods that can be seen between the end of a data frame and the beginning of the next one.

In a scenario where the PU is the only source of transmissions, this model promptly recognizes it's "signature", but when the medium can receive third party transmissions, a new approach needs to be taken. When SU's compete for *white spaces*, the PU pattern is not entirely present, as the silent periods would be used for SU transmission. The model then has to try and match the observations to the hidden states that correspond to PU transmission (states 1 and 2 in our representation). The two methods described below try to accomplish this task by two different approaches.

A. Complete Forward-Backward Algorithm Adaptation

The CFB algorithm, described in [4], is the traditional *forward-backward* algorithm as shown in [16] and an incorporated idea of fixing different costs to each kind of possible error (false alarm or missed detection) so any given pair of P_{fa} and P_{md} can be achieved. Making this costs equal to 1 is equivalent to the standard algorithm.

CFB uses two different probabilities, associated with the observation window available at any given instant t. These probabilities are forward ($\alpha_t(i)$) and backward ($\beta_t(i)$) and are defined below:

$$\alpha_t(i) = P(O_1...O_t, S_t = i|\lambda) \;\; i \in N \;\; t = 1, 2, ..., \tau$$
$$\beta_t(i) = P(O_{t+1}...O_T|S_t = i, \lambda) \;\; i \in N \;\; t = \tau - 1, ..., 1 \tag{6}$$

The $\alpha_t(i)$ is the probability of observing a symbol sequence $O_1O_2...O_t$ and at time instant t the hidden state is i, given an HMM λ. Backward probabilities have a similar meaning: $\beta_t(i)$ is the probability that hidden state at instant t is i and from then on, a symbol sequence $O_{t+1}O_{t+2}...O_\tau$ is observed, given an HMM λ.

Forward and backward probabilities can be calculated by the following recursive procedures, as shown in [16]:

1) Initialization:

$$\alpha_1(j) = \pi_j b_j(O_1), \quad 1 \leq j \leq N \tag{7}$$

2) Induction:

$$\alpha_{t+1}(j) = \left[\sum_{i=1}^{N} \alpha_t(i) a_{ij}\right] b_j(O_{t+1}), \quad 1 \leq t \leq \tau - 1 \quad 1 \leq j \leq N \tag{8}$$

1) Initialization:

$$\beta_\tau(j) = 1, \quad 1 \leq j \leq N \tag{9}$$

2) Induction:

$$\beta_t(j) = \sum_{i=1}^{N} a_{ji} b_j(O_{t+1}) \beta_{t+1}(j), \quad t = \tau - 1, \tau - 2, ..., 1, \quad 1 \leq j \leq N \tag{10}$$

At each time slot, a new observation is produced, creating a different observation window from the previous one, therefore forward and backward probabilities have to be re-calculated.

From both α and β, the a posterior probability ($\gamma_t(i)$) is defined:

$$\gamma_t(j) = \frac{\alpha_t(j)\beta_t(j)}{P(O|\lambda)} = \frac{\alpha_t(j)\beta_t(j)}{\sum_{i=1}^{N} \alpha_t(i)\beta_t(i)} \tag{11}$$

A posterior probability $\gamma_t(j)$ can be understood as the probability of observing a symbol sequence $O_1 O_2 ... O_t$ and the hidden state, at instant t, is j and from this same instant and hidden state, observing the symbol sequence $O_{t+1} O_{t+2} O_\tau$. This is normalized by the term $P(O|\lambda)$, which is the probability of observing the full symbol sequence in the observation window, given the HMM λ. The algorithm then simply chooses the state that has the greatest a posterior probability at the end of the observation window:

$$S_\tau = \arg \max_{1 \leq i \leq N} [\gamma_\tau(i)] \tag{12}$$

The CFB Detector considers the PU as the transmission source if states 1 or 2 are the most probable states.

B. Transmission Word Detection (TWD)

PU transmissions can be seen as a sequence of symbols that together form a recognizable pattern. An analogy can be made between sounds of the speech and symbols, where a sequence of sounds form a word that should be recognized. The name *Transmission Word Detection* illustrates the idea of a sequence of symbols that form a "word" from the transmitter, and hence, should be identified among other "sounds".

Traditionally, an HMM is represented as a graph whose vertices are states and edges are possible transitions between states. This graph would have loops in every vertices, which means that every state can have a transition to itself. Implicit in this description is the concept that once a state is reached, with a some probability, there would be a number of observations generated from this state. Depending on the particular state reached, the probability that a series of symbols are generated from this state is high. This implicit situation, in some cases, may provide a better representation of the system if it can be made explicit. TWD employs the concept of explicit state duration densities in HMMs.

The CFB defines the source of the signal based on the a posterior most probable state. TWD uses a similar judgment but applies different concepts. States 1 and 2 are still modeled the same way as in Section IV, but the goal is not to define the specific most probable state in which the system resides at a time instant. This new model intends to derive the probability that states 1 or 2 could generate an observed sequence. A high probability in this case indicates that the observed symbols came from a PU transmission and a low probability reasons that, though signal could have been detected, it is not likely to be from a PU.

The probability that an observation sequence was originated by an HMM λ ($P(O|\lambda)$) is given by the calculation of forward probabilities only:

$$P(O|\lambda) = \sum_{i \in C} \alpha_\tau(i), \quad C \subseteq N \tag{13}$$

Since we are only interested in the states that represent the PU transmission, $C = \{1, 2\}$. This model has no transitions from a state to itself and instead, a duration probability density is defined for each state ($p_i(d)$) [16]:

$$p_i(d) = (a_{ii})^{d-1}(1 - a_{ii}) \tag{14}$$

As a consequence, forward probabilities need to be adjusted. A maximum duration (D) is defined both to limit the calculation costs (which are greatly increased from normal forward calculations) and to better represent a particular state. In our model, the state that actually expresses a PU signal in the medium is state 2, and therefore, maximum duration is defined from Equation 14 and the expected value of the geometric distribution:

$$\begin{aligned} &Pr(X = k) = (1 - f)^{k-1} f, \\ &E[X] = D = \tfrac{1}{f}, \\ &D = \tfrac{1}{1 - a_{ii}} \end{aligned} \tag{15}$$

$Pr(X = k)$ is the probability that the kth transition (out of k transitions) is the first to be from a state i to a different state j, therefore, $f = (1 - a_{ii})$. D is the expected X, or the number of expected transitions from a state to itself before a transition to another state occurs.

Forward probabilities are calculated in two parts, first by storing the values of the first D time instants:

$$\alpha_1(i) = \pi_i p_i(1).b_i(O_1), \tag{16a}$$

$$\alpha_2(i) = \pi_i p_i(2) \prod_{s=1}^{2} b_i(O_s) + \sum_{j=1, j\neq i}^{N} \alpha_1(j) a_{ji} p_i(1) b_i(O_2), \tag{16b}$$

$$\alpha_3(i) = \pi_i p_i(3) \prod_{s=1}^{3} b_i(O_s) + \sum_{d=1}^{2} \sum_{j=1, j\neq i}^{N} \alpha_{3-d}(j) a_{ji} p_i(d) \cdot \prod_{s=4-d}^{3} b_i(O_s) \tag{16c}$$

until $\alpha_D(i)$.

For $t > D$, the remaining forward values are given by:

$$\alpha_t(i) = \sum_{j=1}^{N} \sum_{d=1}^{D} \alpha_{t-d}(j) a_{ji} p_i(d). \prod_{s=t-d+1}^{t} b_i(O_s) \tag{17}$$

Computation of both forward and backward probabilities have an exponential decrease in value and for window sizes as small as 50, large negative exponents dominate. Besides that, in order to perceive if a given symbol sequence is likely to have been originated from the states of interest, a scaling procedure is needed.

Scaling should depend exclusively on the time instant t when it is carried out, so it can be equally applied to any state. A proposal of such is demonstrated in [16]:

$$c_t = \frac{1}{\sum_{j=1}^{N} \alpha_t(j)} \tag{18}$$

$$\alpha_t(i)^* = \alpha_t(i) * c_t$$

where $\alpha_t(i)^*$ is the scaled value and c_t are scaling coefficients related to time instant t.

This method clearly addresses the issue of values that tend to zero, but they do not reflect the actual relation between the observation sequence and the probability that this sequence came from a PU. In the event that the observation window is full of busy slots generated by an SU transmission, the probability produced by Equation 13 would be close to 1 if the scaling from equation 18 is used. This is due to the fact that the scaling coefficients are the sum of αs of all states and, when a signal is detected (independent of the source), $\alpha_t(2)$ would account for the great majority of that sum. Multiplying $\alpha_t(2) * c_t$ would then give a value close to 1.

Different scaling coefficients were elaborated, in order to reflect the real relation between forward probability values and the source of observations. By Equation 18 it can be inferred that the smallest c_t corresponds to an observation that has high probability to have been originated by a PU only (the sum of forward values would be higher than one originated from an SU). Storing the smallest scaling coefficients would enable a comparison point to a window in which a PU transmission had occurred. On the other side, this value should be updated to reflect the cases where the PU is transmitting but an SU may be taking advantage of *white spaces*. In such a situation, the PU pattern is not perfectly present, but it contributes to a coefficient that is higher than the case where there's only a PU transmission and lower than the case where only an SU transmission is observed.

At each instant t, a new c_t candidate is calculated. Current c_t values are updated according to the following algorithm:

if $candidateC_t \leq currentC_t$ **then**
  $currentC_t \leftarrow candicateC_t$
else
  $currentC_t \leftarrow (weight * candidateC_t) + (1 - weight) * (currentC_t)$
end if

where $weight$ is the coefficient to the exponential moving average.

TWD determines the presence of a PU by calculating:

$$PUProb = \alpha_\tau^*(1) + \alpha_\tau^*(2), \tag{19}$$

the probability that either states (1 or 2) generated the observed symbol sequence. If $PUProb$ is high enough, the presence of the primary user is declared as the most likely.

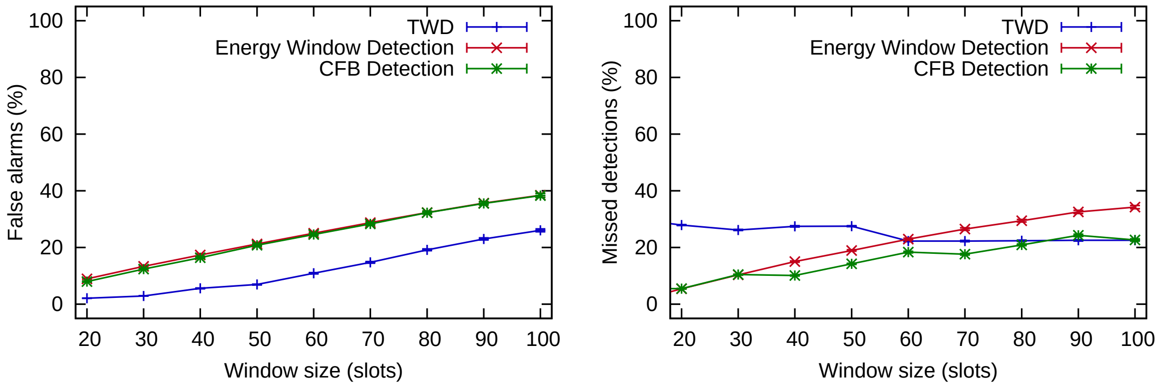
V. Performance Evaluation

The evaluation of the proposed detectors was carried out using the ns-3 (version 3.10 from the development tree) modified to include some new features, such as: 1) Creation of a new module derived from the *wifi*, and extended to integrate cognitive radio functionalities. 2) A modification to the DCF mechanism from the IEEE 802.11 standard in order to represent a PU (do not wait for *backoff*, transmit whenever there's a queued packet). 3) Creation of applications that work as medium sensors. 4) Changes to the *On/Off* application to better illustrate a PU's behavior.

The HMM used in the CFB and TWD was trained using a sample run of the simulator where one million symbols representing the PU's activity were collected. Training was done by the *Baum-Welch* algorithm implemented in JAHMM [17], and was run for 1,000 iterations. Slot time in all simulations is 100 μs, PU packet size is 1500 *bytes* long, transmitted at physical data rate of 1 Mbps and fed by a 100Kbps CBR application.

TWD, CFB and Energy Window Detector were evaluated regarding the effects of the observation window size on both metrics (P_{fa} and P_{md}). Additionally, all three detectors are evaluated considering multiple competing SUs. Both tests were performed in the presence of a PU that transmits at will, a node that undergoes energy detection and a node that executes the HMM based detectors. This last two nodes act only as sensors. The PU transmissions occupy roughly 10% of the simulation time. Also, both tests were run with $\epsilon = 0.50$, $\rho = 0.10$ and the moving average coefficient for the scaling coefficients computation in TWD is 0.35.

One important parameter for the TWD is the definition of the threshold above which the probability calculated in Equation 19 is considered to be high enough to declare the presence of the PU. During a series of tests carried out, this value was fixed to 85%, but future work includes ways of better estimating this value and how it can be adjusted during



(a) False Alarm

(b) Missed Detection

Fig. 5. Window size influence on sensoring.

simulation. The mean values are presented with confidence interval bounds at a confidence level of 99%.

A. *Observation Window Size Evaluation*

The point of this evaluation is to determine how well the sensing mechanisms can capture the PU alone and what is the impact of the observation window size to the considered metrics. With that in mind, there are no SUs in this case, and the expected result is the detectors can effectively recognize the PU's access pattern.

As can be seen by Figure 5(a), false alarms rise as observation window sizes increases. That can be explained for all curves by the mechanism of the sliding windows. For a window length of τ, each slot is part of the next τ new windows and even after the PU is off, slots that marked its transmissions still exist in subsequent windows, therefore, the longer the window, the longer this slots are taken into account. An important point that needs attention is the existence of an optimal window size that is specific to the PU transmission pattern. Although only TWD uses the concept of state permanence, the value obtained for D in Equation 15 reflects a reality of the medium, common to all three detectors, which is the probable number of busy slots a PU transmission produces. In our simulation, this value is 14 and therefore, window sizes close to this number produce better results.

Missed detections on the other hand have a different behavior, as seen in Figure 5(b). TWD had only small modifications as window size increases. This is due to the fact that the detector looks for transmission patterns, and free slots have little effect on this. A window that is significantly bigger than D, in this evaluation, is composed in great part by free slots. Energy detection, differently from TWD, had a tendency similar to the one for false alarms. The sliding window mechanism again can explain the energy detector's behavior. The Energy Window Detector has a latency to declare PU presence, represented by ρ described in section III-A. The bigger the window, the longer the PU transmission needed in order for the mechanism to declare PU presence. CFB in this case showed considerable advantages over TWD for some window sizes due to the way it works. As the PU is the only transmitter, CFB can easily associate the observed symbols to the states that mark PU transmission.

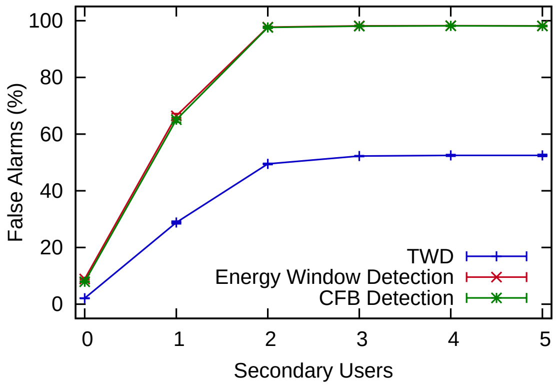
B. *Number of Competing SUs Evaluation*

In this evaluation the number of competing SUs ranges from 0 to 5. SUs were configured with a 11Mbps physical data rate and a 1Mbps CBR application on an *On/Off* distribution that yields a different access pattern from the PU's. SUs are common wifi nodes communicating in pairs. In this evaluation, window size is fixed at 20 slots.

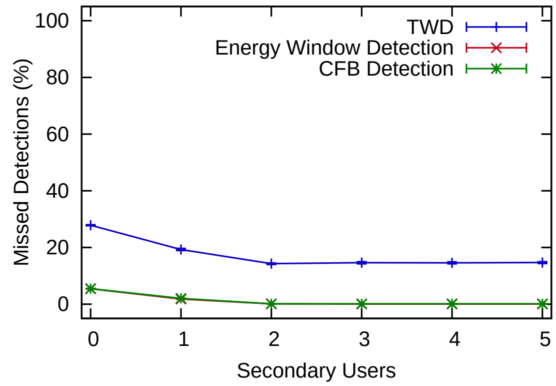
It is important to note that both the PU and the SU have a transmission pattern that can be described by an HMM. If both patterns are too close to each other, the TWD would behave essentially the same way the CFB does, which is very close to the energy window detector. The opposite also holds, very dissimilar patterns help improve the detection results.

With 3 contending SUs, a stationary tendency can be observed in both figures 6(a) and 6(b). For the energy window detector, the false alarm rate is close to 100%. This result shows that from the total time slots observed and which the PU was not transmitting, almost all of them had SU transmissions. Equation 1 makes it clear that if the number of false alarms increases, other transmissions are in place. In other words, all *white spaces* were being used. In fact, although the curves are not present due to space restrictions, the energy window detector can effectively report the size of all *white spaces* encountered and this result shows that 99% of them have 1 slot in size. On Figure 6(b), energy window detector apparently had good results, but in fact, the low rate of missed detections is due to the fact that the detector was declaring the presence of a PU during almost all the simulation. This result is in fact very bad, once no *white spaces* were found.

Both Figures 6(a) and 6(b) also show that the TWD captured the PU transmission pattern reasonably well, recognizing when transmissions were originated from SUs and avoiding false alarms. On the other hand, missed detections remained close to 20%. The level of missed detections is directly associated to the interference the PU is expected to receive, often expressed



(a) False Alarm



(b) Missed Detection

Fig. 6. Influence of the number of competing SUs.

as a maximum collision probability. Different technologies have intrinsic interference tolerance levels [8], allowing the SU to be more or less conservative regarding the maximum missed detection level permitted. The CFB did not bring any advantages to the energy detection. This could be explained by the two major differences it has to the TWD: the explicit state duration embedded in the forward probabilities calculations and the way that the transmission states are treated; CFB obligatorily declares one of the states of the HMM as the most probable, using Equation 18 standard scaling procedure, which fails to recognize when an observed transmission has low probability of being originated from the PU. As a consequence, CFB observes a signal in the medium much like the way energy detection does.

VI. Conclusion

The TWD strategy, based on HMM, significantly improves energy detection accuracy, producing better false alarm metrics and so improving *white space* discovery. Improvements on the algorithms, specially related to the scaling coefficients and the *PUProb* threshold definition are expected extensions to this work. With minor adjustments, TWD can also be used to predict channel status and aid the overall sensing mechanism by avoiding to sense channels that have high probability of being occupied by a PU.

The use of HMM to identify the source of a transmission eliminates the need of the mandatory silence period (when no SUs can transmit). The improved accuracy in PU identification makes SUs free to coordinate among them or even to access the medium at the same time, by using an interference avoidance mechanism. In summary, our solution can improve the performance of dynamic spectrum access.

In future work, we are interested in evaluating the potential of Kullback-Leibler Distance to measure the difference between PU and SU processes.

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