ChiMaS: A Spectrum Sensing-based Channels Classification System for Cognitive Radio Networks

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***Abstract*—Cognitive radio devices are able to sense the spectrum of frequencies and share access to vacant channels. These devices usually have a candidate channels list that must be sensed to find a vacant channel. In this paper, we propose a novel system called *ChiMaS*, which is able to manage the candidate channels list implementing three tasks: Analysis, Creation, and Sort. Analysis applies reinforcement learning algorithms to evaluate the channels quality based on their historical occupancy and their conditions; Creation is responsible for creating the Candidate Channels List; and Sort ranks the channels to obtain an Ordered Channels List in terms of quality. Results show that *ChiMaS* manages the candidate channels list following the IEEE 802.22 definition, while it finds the best channel in terms of availability and quality faster than Q-Noise+ algorithm, which was implemented for comparison purpose.**

Keywords*—cognitive radio, channel sensing order, channel list management, reinforcement learning

I. Introduction

Cognitive Radio (CR) devices have been designed to improve the efficiency of spectrum allocation [1]. Such improvement is obtained by enabling these devices to opportunistically access vacant radio frequency channels. However, before accessing a channel, a CR device must decide whether or not that channel is occupied. This decision is performed by the Spectrum Sensing Function (SSF), to find vacant channels and allow multiple devices to share the spectrum without interfering with each other. While selecting a channel, CR devices should also be able to take into account the channel quality. In this sense, the historical occupancy and the channel conditions, which can be measured by the Received Signal Strength Indicator (RSSI) [2], are two of the main characteristics used to determine the channel quality.

Finding the best channel is desirable to provide better transmission conditions to CR devices. However, it is hard to find high-quality vacant channels in short periods of time, since the analysis of channel conditions demands more time than just deciding whether or not the channel is vacant [3]. The amount of time spent to sense the spectrum is also related to the number of channels previously defined to be analyzed. Therefore, the IEEE 802.22 standard [4] defines that CR devices must keep a Candidate Channels List (CCL), in order to limit the duration of the spectrum sensing. Although the IEEE 802.22 standard specified the existence of a list of candidate channels, the classification of the channels in this list was left open to encourage innovation.

In the recent literature, solutions have been presented to sort available channels and quickly select one of them. We organized the solutions into two classes: statistical sorting [5] [6] and reinforcement learning sorting [7] [8] [9]. Both classes aim to dynamically decide in which order channels should be sensed when a device needs to change its operating channel. Towards this aim, the first class is composed of solutions that demand prior knowledge about channel quality metrics, such as the historical occupancy and RSSI of the channel [10]. Based on the defined metrics, statistics are applied to sort the channels according to their quality. The second class, in turn, is composed of solutions that demand no prior knowledge about the channel quality. The knowledge is built over the time by analyzing the transmissions performed by CR devices.

Although broadly applied by current solutions, the approach of analyzing the transmissions performed by CR devices might cause some drawbacks. The first drawback is that the current solutions assume that transmissions occur before CR devices start learning about the channel quality. Since CR devices do not have any prior knowledge about the channel occupancy, this leads to a second drawback related to the probability of a CR device to interfere with other transmissions that may be already occupying the analyzed channel. Finally, another drawback of this current approach is that the chosen channel may not be the best one in terms of quality, especially at the beginning of system operation, since no historical information is available. Therefore, the selected channel may have a high occupancy rate or bad channel conditions, what leads to a low-quality transmission.

To deal with these drawbacks, in this paper we introduce *ChiMaS*, a solution to classify channels in the CCL. The classification of the channels in this list includes three tasks: Analysis, Creation, and Sort, which are defined as follows: *(i)* to analyze the radio frequency channels, *ChiMaS* uses a reinforcement learning based solution, taking into account its historical occupancy and conditions. *(ii)* To create the CCL, only channels considered as vacant are selected. *(iii)* To sort the CCL, scoring and ranking functions are applied to the created list. By evaluating the channels with the spectrum sensing, *ChiMaS* allows CR devices to learn, and consequently find the best available channel, without the need to transmit. The performance of *ChiMaS* is evaluated in a controlled radio environment and the results obtained are compared with the Q-Noise+ algorithm from the literature [8]. Results show that *ChiMaS* is able to find the best available channel faster than Q-Noise+ and to sort CCL in different scenarios.

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The remainder of this paper is organized as follows. In Section II, we present related work on solutions to sort vacant channels. *ChiMaS* is described in Section III. Performance evaluations are presented and discussed in Section IV. Finally, we present the conclusions and future work in Section V.

II. Related Work

Solutions to sort channels have been investigated in the scientific community in the recent past. Therefore, we organize the main solutions in two classes: statistical sorting [5] [6] and reinforcement learning sorting [7] [8] [9]. Statistical sorting assumes that conditions and occupancy of the channel are known. Jiang *et al.* [5] analyzed a scenario in which the occupancy probability of each channel is known. The authors considered a CR network with opportunistic transmissions to find an optimal channel order to achieve the maximum gain in terms of transmission rate. Rostami, Arshad, and Moessner [6] proposed an ordered statistic SSF based on a non-parametric method considering the presence of Additive White Gaussian Noise (AWGN) and assuming that the information about the Signal to Interference plus Noise Ratio (SINR) is known. Although allowing the ordering of the channels, the main limitation of statistic sorting class is the need of prior knowledge about channel characteristics.

The second class of sorting solutions applies reinforcement learning algorithms to dynamically define the channel order. This learning dispenses any prior knowledge about the channel occupancy, since knowledge is acquired during transmissions. Mendes *et al.* [7] applied the reinforcement learning algorithm called Q-Learning to obtain information about channel occupancy. Q-Learning algorithm calculates a reward for each transmission in a channel. Based on this reward, the algorithm defines the order in which channels must be analyzed. Faganello *et al.* [8] proposed an improvement of Q-Learning algorithm for cognitive sensor networks, called Q-Noise+, which considers historical analysis of channel occupancy and channel conditions based on SINR. Q-Noise+ also calculates the reward considering transmissions of CR devices. Finally, Zhang *et al.* [9] modeled the sensing order selection as a Q-Learning problem, defining the sensing order based on the results of transmissions and historical sensing performed over the channels.

Both classes described above are based on information obtained during the transmissions performed by CR devices. To obtain this information, a device faces the following drawbacks: *(i)* the learning is performed only in the channel in which the CR device transmits, *(ii)* a transmission can cause interference with other transmitters, and *(iii)* the chosen channel may have low availability and poor conditions in the initial transmissions because there is no prior knowledge about the channel characteristics. The main contribution of *ChiMaS* is to deal with these drawbacks, by managing the channel list in order to find the best vacant channel. Moreover, to the best of our knowledge, *ChiMaS* is the first approach to order the channel list using channels quality considering only the SSF results, *i.e.* CR devices are not required to transmit.

III. *ChiMaS* Components

ChiMaS is divided into three classification tasks, as can be seen in Figure 1. The first one, called Analysis, receives information from the SSF regarding the occupancy status of a Global Channels List (GCL). This list comprises a group of channels previously defined to be analyzed by *ChiMaS*. Channels in the GCL can be defined based on some criteria, like unlicensed channels for IEEE 802.22 operation [11], for example. The GCL is processed by a reinforcement learning algorithm to become aware about both the historical occupancy and conditions of each channel. Based on the results of such analysis, the second task, Creation, is responsible for the generation of the CCL. Finally, the third task, Sort, uses a scoring and a ranking function to obtain an Ordered Channels List (OCL), which is the output of *ChiMaS*. The first element of the OCL may be used as the Operation Channel of a Base Station, as defined by the IEEE 802.22 standard [4], while the second element may be considered a good Backup Channel. The Analysis task of *ChiMaS* is presented in Subsection III-A, while Creation and Sort tasks are described in Subsection III-B.

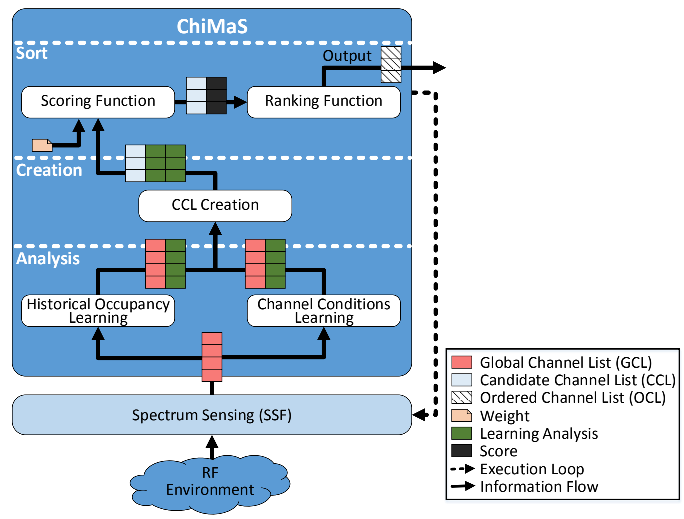


Fig. 1. *ChiMaS* components

A. Analysis Task

The Analysis task receives from the SSF, a GCL containing the channels to be analyzed by *ChiMaS* along with information regarding these channels. At each *ChiMaS* execution, all channels are sensed to prevent sudden changes in channels status do not be perceived. The GCL information is composed of two types of data structures for each channel as defined by the IEEE 802.22 standard and represented in Figure 2. The first data structure is a tuple composed of Signal Vector and Confidence Vector. The Signal Vector contains information regarding the occupancy status of the channel, *i.e*, the result of the SSF. In this case, SSF must indicate if the channel is occupied (0x00), vacant (0xFF) or if it was unable to decide (0x7F). The Confidence Vector carries information about the assurance of the SSF in the current result. The confidence level received by *ChiMaS* varies between 0 (0x00), indicating no confidence and 1 (0xFF), representing full confidence. The second data structure is a vector containing RSSI measurements. This vector ranges from -104dBm (0x00) to +23.5dBm (0xFF). Values outside this range shall be assigned to the closest extreme.

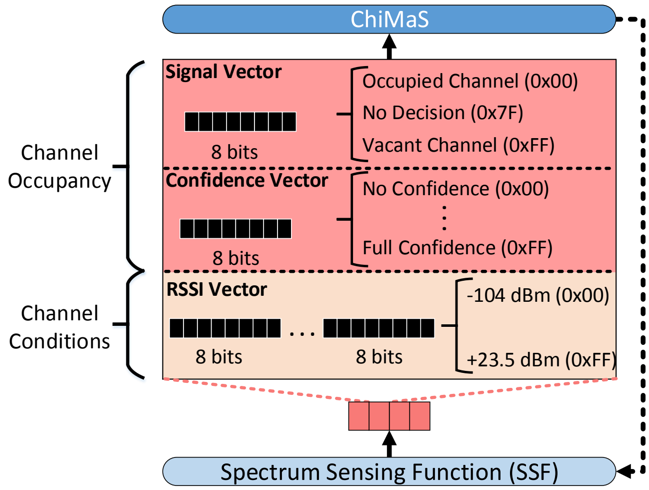


Fig. 2. GCL data structures

GCL contains information about the occupancy status and conditions of each sensed channel. This information is analyzed by two reinforcement learning algorithms to update the historical knowledge about both channels occupancy and conditions. We chose reinforcement learning because it presents a good performance on structured networks solutions, such as the IEEE 802.22 [12]. The results of this analysis allow *ChiMaS* to evaluate the quality of the channels. The reinforcement learning algorithms were implemented adapting the specifications of Q-Noise+, proposed by Faganello *et al.* [8]. The main adaptation we made was to eliminate the need for transmission, which is a drawback of Q-Noise+. Instead, we use information regarding the channel occupancy and conditions collected by SSF to learn about channels quality and compose the OCL. As proposed by Faganello *et al.* [8] we defined weights for each epoch in order to add greater importance to more recent analyzes.

The first learning algorithm of *ChiMaS* is called Historical Occupancy Learning, which is responsible for analyzing the usage profile of the channels. This analysis considers that SSF executions are performed in epochs (t). The goal of this feature is to use SSF information to assess the future occupancy of the channel. Towards this goal, a reward-based approach is applied considering two criteria to calculate Qh, which represents the results of the Historic Occupancy Learning. The criteria used to calculate Qh are: *(i)* the channel occupancy rate in the current epoch (r_t) and *(ii)* the weighted sum of this rate in a defined amount of past epochs (l). The former rate is defined by analyzing every partial analysis conducted by SSF to define whether or not the channel is occupied. This information is obtained in the Confidence Vector, which determines how accurate was the SSF analysis. Let G be the set of channels in the GCL, the Qh of a given channel c for the next epoch is then defined according to Equation 1.

$$\forall c \in G \Rightarrow Qh_t(c) = (1-\alpha)\sum_{i=1}^{l}[w_{t-i}r_{t-i}](c) + \alpha r_t(c) \quad (1)$$

where, $0 \leq \alpha \leq 1$ represents the weight of the reward (r_t) obtained in the last epoch. The higher the α value, the more importance is given to the last epoch and consequently, less importance to past epochs. The number of past epochs to be considered for Qh calculation is defined by l. In this sense, w is the weight of each one of the last l epochs. This value is pondered by the weight of the past epochs, which is $(1-\alpha)$.

Channel Conditions Learning is the second algorithm proposed in *ChiMaS*. This algorithm receives information about the mean RSSI level of a radio frequency channel to obtain knowledge about its conditions and calculate Qn, which represents the results of the algorithm. The criteria used to calculate the Qn are *(i)* the rate of RSSI in the current epoch (η_t) and *(ii)* the weighted sum of this rate in a defined amount of past epochs (l). It is important to highlight that RSSI measurements performed by SSF are considered by *ChiMaS* analysis task only in epochs where the channel is considered vacant, since only noise is present in this case. The Qn for a given channel c is calculated according to Equation 2.

$$\forall c \in G \Rightarrow Qn_t(c) = (1-\beta)\sum_{i=1}^{l}[w_{t-i}\eta_{t-i}](c) + \beta\eta_t(c) \quad (2)$$

where, $0 \leq \beta \leq 1$ is the weight of the current channel conditions, and its complement is the weight of the conditions of past l epochs where the channel was considered vacant. The β value works for the channels condition learning like the α value works for historical occupation learning: higher values implies in more importance to the last epoch and less importance to past epochs. Finally, η is a factor regarding the channel conditions. This factor represents the reward of the Channel Conditions Learning. The better the channel, the higher η is.

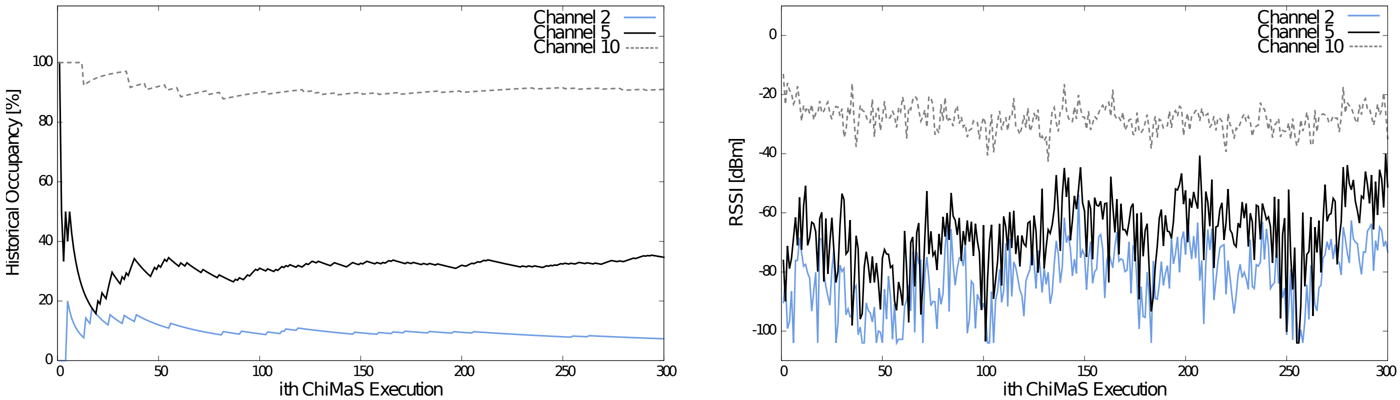
B. Creation and Sort Tasks

In the Creation task, the CCL Creation function receives the GCL from the Historical Occupancy Learning and Channel Conditions Learning and creates the CCL taking into account the occupancy status of every channel in GCL. Only vacant channels are used to create the CCL. The results of the analysis of both historical occupancy and channel conditions of vacant channels are also part of the created list. It is important to emphasize that in the next execution all channels are sensed and analyzed, even those considered occupied by SSF in the current execution.

The Sort task is responsible for sorting the CCL using two functions, called Scoring and Ranking. The former receives the weight of both historical occupancy and channel conditions to calculate a score associated with each channel. The latter sorts the list according to the results of the Scoring function. The obtained score is called Q-Value and indicates how suitable a channel is for opportunistic transmissions, considering its historical occupancy and conditions. In this sense, let C be the set of channels in the CCL. The Q-Value of a given channel $c \in C$ is obtained using Equation 3.

$$\forall c \in C \Rightarrow Q_{-Value} = \gamma * Qh_{t+1}(c) + (1-\gamma) * Qn_{t+1}(c) \quad (3)$$

where γ is the weight of historical occupancy, and $(1-\gamma)$ represents the weight of channel conditions. The score of



(a) Historical Occupancy

(b) Channel Condition

Fig. 3. Radio Frequency Scenario

each channel is then processed by a Ranking function, which is responsible for finishing the sort and creating the OCL. Therefore, the most suitable channel for transmission (channel with the highest Q-Value) will be placed at the beginning of the OCL, while the worst channel (lowest Q-Value) will be at the end of the list.

Once presented and explained each component of *ChiMaS*, in Algorithm 1 we present the pseudo-code detailing the execution sequence of *ChiMaS*, exploring the components presented in this section in order to better understand the entire *ChiMaS* execution. After defining the GCL, the SSF is invoked to obtain information about current channels occupancy and conditions (line 1). Then, during the Analysis Task, Q_h and Q_n values of each channel are calculated for the current epoch t (0, line 2). The Historical Occupancy Learning (Q_h) and the Channel Conditions Learning (Q_n) for each channel are calculated based on the past epochs (lines 8 and 10), resulting in its respective reward value (lines 12 and 13). Next, the Creation task analyses the availability of each channel (line 19), including in the CCL only channels available during the last sensing (C in the algorithm, line 20). Finally, in the Sort task the resulting Q-Value for each channel is calculated by the Scoring function (line 27), attributing the predefined weights for both Q_h and Q_n. The final values are used by the Ranking function to create the OCL (O in the algorithm, line 29), ordered from the best channel (highest Q-Value) to the worst (lowest Q-Value).

Algorithm 1 *ChiMaS* Operation

1: $G \leftarrow SSF(GCL)$
2: $t = current\_epoch$
3:
4: *# ANALYSIS:*
5: **for** each $c \in G$ **do**
6:     **for** $i = 1$ to l **do**
7:         *# OccupancyLearning:*
8:         $c[Q_h] = c[Q_h] + c[w[t]] * c[r[t-i]] + \alpha * c[r[t]]$
9:         *# ConditionsLearning:*
10:         $c[Q_n] = c[Q_n] + c[w[t]] * c[\eta[t-i]] + \beta * c[\eta[t]]$
11:     **end for**
12:     $c[Q_h] = (1-\alpha) * c[Q_h]$
13:     $c[Q_n] = (1-\beta) * c[Q_n]$
14:     t++
15: **end for**
16:
17: *# CREATION:*
18: **for** each $c \in G$ **do**
19:     **if** $isFree(c)$ **then**
20:         $C \leftarrow append(c)$
21:     **end if**
22: **end for**
23:
24: *# SORT:*
25: **for** each $c \in C$ **do**
26:     *# Scoring:*
27:     $c[Q\text{-}Value] = \gamma * c[Qh[t+1]] + (1-\gamma) * c[Qn[t+1]]$
28: **end for**
29: $O \leftarrow Ranking(C)$
30:
31: **return** O

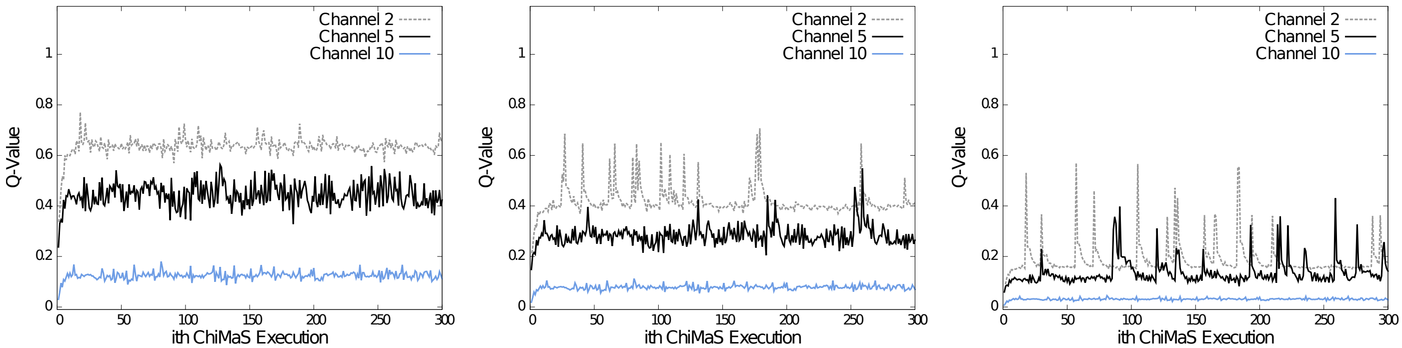
IV. Evaluation and Results

The methodology used for assessing the performance of *ChiMaS*, the experimentation parameters, and their values are presented in Subsection IV-A. Experimental results obtained in a controlled radio frequency environment are presented and discussed in Subsection IV-B.

A. Evaluation Methodology

ChiMaS was evaluated using GNU Radio framework[1] and USRP2 radio front-end[2]. SSF was performed considering eleven channels, using a combination of energy detection and waveform detection algorithms proposed in a previous work [13]. The occupancy rate of each channel is modeled following a Poisson distribution, as proposed by Gosh *et al.* [14]. The mean and variance of this distribution, which give the channel occupancy rate was varied from 0 to 1 in steps of 0.1. To assess the channel conditions, RSSI is measured during SSF. The resulting RSSI is fit into a range described by the η factor to be used as a reward for the Channel Conditions Learning. This factor assumes values according to Table I. RSSI value of a channel may vary between +23.5dBm and -104dBm, as

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



(a) γ=0.8 (b) γ=0.5 (c) γ=0.2

Fig. 4. Q-Value analysis

defined in the IEEE 802.22 standard [4].

TABLE I. RSSI LEVEL CORRESPONDENCE

RSSI value	Corresponding η
+23.5dBm > RSSI $\geq$ -30dBm	0
-30dBm > RSSI $\geq$ -60dBm	0.2
-60dBm > RSSI $\geq$ -80dBm	0.5
-80dBm > RSSI $\geq$ -90dBm	0.75
-90dBm > RSSI > -104dBm	0.90
RSSI $\leq$ -104dBm	1

ChiMaS is configured to consider a history of 3 epochs (l) for both Historical Occupancy Learning and Channel Conditions Learning. The current epoch weight for both α and β was set to 0.5 and the past epochs weights (w), defined from the most recent to the oldest one, are 0.45, 0.35, and 0.2, respectively. These values were chosen to give a higher importance to more recent epochs because it is important to consider the current state of the channel in scenarios with high RSSI variability. Moreover, it avoids the selection of overloaded channels or intermittent use, like sensor TV channels or sensor networks. γ was set to 0.8, 0.5, and 0.2, while the Channel Conditions Learning weight is $1 - \gamma$. It implies in three different setups to compute the Q-Value used for sorting the CCL. This values were selected to explore both situations where one weight is higher than the other (*e.g.* $\gamma = 0.2$ or $\gamma = 0.8$) and where the weights are balanced ($\gamma = 0.5$). We performed 300 executions of *ChiMaS* for each evaluation, guaranteeing a confidence interval of 95%.

TABLE II. TABLE OF PARAMETERS

Parameter	Default Value
Number of channels (C)	11
Current epoch weight (α and β)	0.5
Past epochs (l)	3
Past epochs weights (w)	[0.45, 0.35, 0.2]
Historical Occupancy Learning weight (γ)	0.8, 0.5, and 0.2
ChiMaS Executions	300
Confidence interval	95%

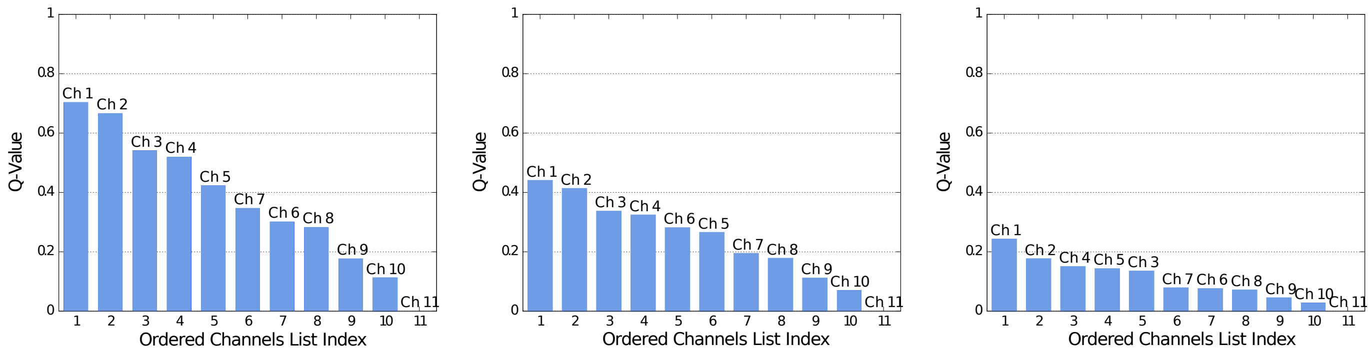
In the first scenario, we measured the average historical occupancy of TV channels, as shown in Figure 3 (a). We also analyzed the channel conditions, based on the RSSI observed during SSF, as can be seen in Figure 3 (b). In this analysis, channel 2 presented a low occupancy rate, of approximately 10%, and good conditions, since its RSSI is about -85dBm. On the other hand, channel 10 had a high occupancy rate, close to 90%, and a higher RSSI (-30dBm), resulting in a worse channel compared to channel 2. Furthermore, channel 5 presented intermediate values for both the occupancy rate and channel conditions, about 30% and -70dBm, respectively. This scenario was used as input to evaluate the process implemented by *ChiMaS* to manage the CCL.

B. Experimental Results

In the first analysis performed, we investigate the impact on Q-Value of three different setups of weights for *ChiMaS* operation, as can be seen in Figure 4. In the first setup, shown in Figure 4 (a), we consider $\gamma = 0.8$, representing a weight of 80% for historical occupancy and 20% for channel conditions. In the second setup, the weights are balanced, as can be seen in Figure 4 (b), while, in the third setup, shown in Figure 4 (c), we consider $\gamma = 0.2$.

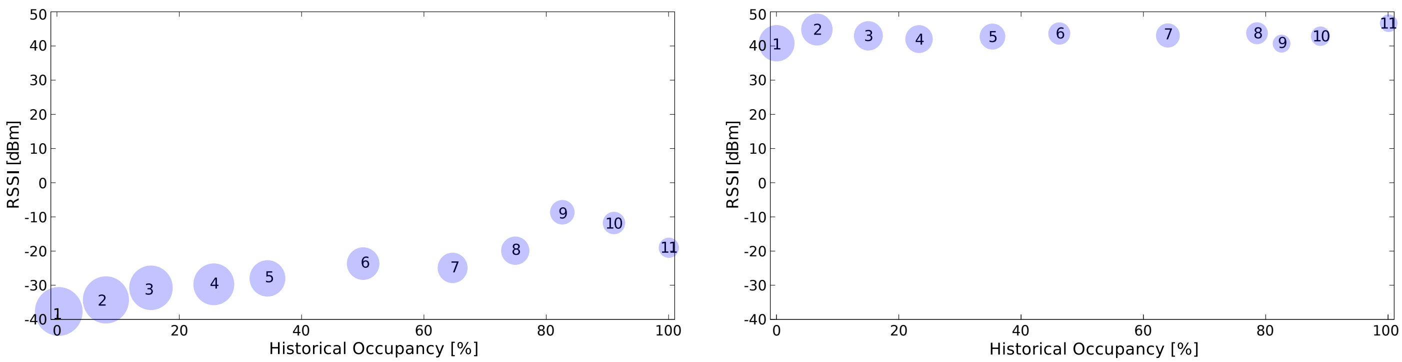
Analyzing the behavior of channels in different setups, it is possible to observe that Q-Value decreases as γ decreases. It occurs because the historical occupancy varies less than the channel conditions, as shown in Figure 3. Therefore, as γ reduces, the variations on RSSI tend to result in peaks in the Q-Value of the observed channels. Another important analysis regards the behavior of channel 2 in the same setups. As can be seen in Figure 4 (c), the Q-Value of this channel presents a higher variability when compared to the remaining setups. This variation was caused due to two reasons. The first one is related to the higher weight attributed to the channel conditions. The second one is due to the frequent changes on the RSSI of the analyzed channel, causing variations in the η factor, as defined in Table I. Similar behaviors are observable in other channels as well. However, in the remaining visualized channels, the intensity of Q-Value changes is lower than in channel 2 because the historical occupancy and channel conditions change smoothly, as shown in Figure 3. This evaluation allows us to conclude γ must be defined according to the radio behavior. For example, in a very noisy environment γ may be configured to a small value, aggregating more importance to channels conditions learning. In contrast, with good signal propagation conditions, γ can be set with higher values, making the analysis of channels historical occupancy more effective.

Once analyzed the impact of the Q-Value in the *ChiMaS* operation, we defined a GCL composed by 11 channels to be classified, showing the final result of *ChiMaS* classification over an predefined GCL. The occupation and conditions of the channels present in the GCL where configured to vary from



(a) γ=0.8 (b) γ=0.5 (c) γ=0.2

Fig. 5. Channel list analysis



(a) TV Scenario (b) Wi-Fi Scenario

Fig. 6. OCL analysis

the best channel (channel 1) to the worse (channel 11). As described at the beginning of this section, the occupancy rate of each channel is modeled following a Poisson distribution, as proposed by Gosh *et al.* [14] and the channels conditions where varied between +23.5dBm and -104dBm.

The first evaluation over the 11 channels was made to analyze the impact of γ variation in the composition of the OCL. In Figure 5, we show the results regarding the OCL, where the x-axis represents OCL index and the y-axis represents the Q-Value calculated for each channel. Analyzing the best channel of the first setup, we can observe that the Q-Value is around 0.7. As γ decreases, channel 1 remains as the best channel. However, the Q-Value of all channels is reduced. Another interesting result we can observe in Figure 5 is the behavior of channels in the middle of the OCL, since their positions tend to vary as the setup is changed. For example, channel 5 is one of the most affected by the changes in weight parameters. In setup (a), channel 5 is placed in the 5th position, moving to 6th place when the weights are balanced (b), and finally moving to the 4th position in (c). On the other hand, the channels at the end of the OCL tend to keep a constant position in the ranking, because the learning features of the Analysis task are reward-based. Therefore, as the Q-Value of these channels is low, a small reward is obtained.

Another analysis conducted in this paper is a comparison between two different scenarios: (a) TV channels scenario and (b) Wi-Fi channels scenario. We assume a setup where $\gamma = 0.5$ in both scenarios. The results regarding such comparison are presented in Figure 6, where both the historical channel occupancy (x-axis) and the channel conditions (y-axis) are correlated with the final Q-Value (circles). The larger the size of the circle, the greater the Q-Value of the channel.

In Figure 6 we can also analyze the outputs of the learning algorithms in the Analysis task. As shown in Figure 6 (a), the best channel is the one with higher Q-Value, *i.e.* channel 1. This channel is the one with the lowest historical occupancy rate and the best channel conditions. On the other hand, the worst channel (*i.e.* channel 11) is highly used and presents bad channel conditions, resulting in the lowest Q-Value. The results regarding the second scenario are presented in Figure 6 (b). We can observe that despite the average RSSI is higher in the second scenario, *ChiMaS* remains able to manage the CCL. Another conclusion we can take from the plots is that considering the analyzed scenarios, (a) is more suitable for operation of CR devices. It is justified because the average Q-Value is higher than in scenario (b).

Finally, we present a comparison between *ChiMaS* and Q-Noise+ algorithms. Q-Noise+ parameters are set to the same values used by Faganello *et al.* [8]. In this specific analysis, both algorithms are compared considering a variable amount of channels ranging from 1 to 48. We perform a comparison between the time spent by *ChiMaS* and Q-Noise+ to analyze these channels, considering a sensing time of 2 seconds for both algorithms and a transmission time of 2 seconds for Q-

Noise+. The results obtained are shown in the Figure 7.

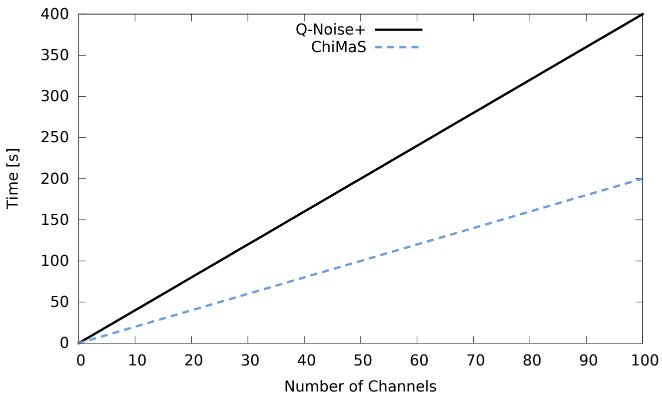


Fig. 7. Time analysis

Figure 7 shows that the time necessary to analyze the channels linearly grows, for both algorithms, as the number of channels to be analyzed increases. However, as the number of channels increase, Q-Noise+ time grows considerably faster than *ChiMaS* time. This behavior occurs because the time demanded by *ChiMaS* depends only on the number of channels to be analyzed and the sensing time, while Q-Noise+ also needs to consider the transmission duration in the composition of the total demanded time.

In Table III, we highlight the main differences between *ChiMaS* and Q-Noise+. Each evaluation performed by *ChiMaS* analyzes a set of channels, defined before starting its execution, while Q-Noise+ is able to analyze only one channel per execution. It could lead to a situation where some channels are never analyzed by Q-Noise+, since when it is analyzing a reasonable channel, it tends to keep transmitting in this channel, without searching for better possibilities. To calculate the reward of the learning process, *ChiMaS* evaluates the Confidence Vector, while Q-Noise+ needs to transmit over the channels to calculate its reward, which may cause interference with transmissions performed by other devices.

TABLE III. COMPARISON OF *ChiMaS* AND Q-NOISE+

Characteristic	***ChiMaS***	**Q-Noise+**
Number of channels analyzed per execution	N Channels	One channel
Time spent to find the best channel	Depends on the number of analyzed channels	The best channel may never be found
Reward method	Confidence Vector analysis	Transmission Analysis
Interference with primary user	No interference	May interfere with primary users

V. CONCLUSIONS AND FUTURE WORK

In this paper we presented *ChiMaS*, a novel system able to manage the CCL defined in the IEEE 802.22 standard. Three classification tasks are proposed: Analysis, Creation, and Sort. One of the main contributions of *ChiMaS* is to eliminate the need for transmissions in order to learn about the quality of the channels. Instead of transmitting, our proposed system receives, from SSF, information regarding the channel occupancy, the confidence in its result, and RSSI measurements. Results were obtained using a controlled radio environment and showed that *ChiMaS* is able to find the best available channel and sort the CCL in different scenarios, according to different setups.

As future work, we intend to consider a CR network where a central node performs the channel classification and disseminates the OCL to CR devices through a control channel. Additionally, we plan to apply rules for channel dissemination aiming to provide quality of service for applications in the context of CR networks. One possible approach to apply rules should be managing the channel dissemination by using pricing related techniques.

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REFERENCES

[1] I. Mitola, J. and J. Maguire, G.Q., "Cognitive radio: making software radios more personal," *IEEE Personal Communications*, vol. 6, pp. 13–18, 1999.

[2] C. Bas and S. Ergen, "Spatio-Temporal Characteristics of Link Quality in Wireless Sensor Networks," in *IEEE Wireless Communications and Networking Conference (WCNC)*, April 2012, pp. 1152–1157.

[3] I. Akyildiz, W.-Y. Lee, M. Vuran, and S. Mohanty, "A survey on spectrum management in cognitive radio networks," *IEEE Communications Magazine*, pp. 40–48, 2008.

[4] IEEE, "IEEE Standard for Information Technology - Telecommunications and information exchange between systems Wireless Regional Area Networks (WRAN) - Specific requirements Part 22:," *IEEE Std 802.22*, pp. 1–680, 2011.

[5] H. Jiang, L. Lai, R. Fan, and H. Poor, "Optimal selection of channel sensing order in cognitive radio," *IEEE Transactions on Wireless Communications*, vol. 8, pp. 297–307, 2009.

[6] S. Rostami, K. Arshad, and K. Moessner, "Order-Statistic Based Spectrum Sensing for Cognitive Radio," *IEEE Communications Letters*, vol. 16, no. 5, pp. 592–595, 2012.

[7] A. Mendes, C. Augusto, M. da Silva, R. Guedes, and J. de Rezende, "Channel Sensing Order for Cognitive Radio Networks Using Reinforcement Learning," in *IEEE Conference Local Computer Networks (LCN)*, Oct 2011, pp. 546–553.

[8] L. Faganello, R. Kunst, C. Both, L. Granville, and J. Rochol, "Improving Reinforcement Learning Algorithms for Dynamic Spectrum Allocation in Cognitive Sensor Networks," in *IEEE Wireless Communications and Networking Conference (WCNC)*, April 2013, pp. 35–40.

[9] Y. Zhang, Q. Zhang, B. Cao, and P. Chen, "Model free dynamic sensing order selection for imperfect sensing multichannel cognitive radio networks: A q-learning approach," in *IEEE International Conference on Communication Systems (ICCS)*, Nov 2014, pp. 364–368.

[10] M. Vallejo, J. Recas Piorno, and J. Ayala Rodrigo, "A Link Quality Estimator for Power-Efficient Communication Over On-Body Channels," in *IEEE International Conference on Embedded and Ubiquitous Computing (EUC)*, Aug 2014, pp. 250–257.

[11] FCC, "In the Matter of Unlicensed Operation in the TV Broadcast Bands: Second Report and Order and Memorandum Opinion and Order," Federal Communications Commision, Tech. Rep., 2008.

[12] M. Bkassiny, Y. Li, and S. Jayaweera, "A Survey on Machine-Learning Techniques in Cognitive Radios," *IEEE Communications Surveys Tutorials*, no. 99, pp. 1–24, 2012.

[13] M. Kist, L. Faganello, L. Bondan, M. Marotta, L. Granville, J. Rochol, and C. Both, "Adaptive Threshold Architecture for Spectrum Sensing in Public Safety Radio Channels," in *IEEE Wireless Communications and Networking Conference (WCNC)*, March 2015, pp. 287–292.

[14] C. Ghosh, S. Pagadarai, D. Agrawal, and A. Wyglinski, "A framework for statistical wireless spectrum occupancy modeling," *IEEE Transactions on Wireless Communications*, vol. 9, pp. 38–44, 2010.