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Spectral Prediction: Approaches in Cognitive Radio Networks

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Abstract

Due to the number of applications in cognitive radio networks, the importance in spectral prediction has been increased, and several applications have been studied within the organization of cognitive networks, decision, sharing, mobility, and sensing. These claims have been exploited, even more, to aim the reduce of delays in the processing of information and to enhance the efficiency of spectrum use. This research intends to provide a survey and a guide on the latest work on spectral prediction, examining state of the art in the inference of the spectrum in cognitive radio networks. For a better understanding of the prediction roll, the main spectrum prediction techniques were summarized, the applications were categorized, and the relevant research challenges were presented in a distributed manner. Accordingly, we considered a qualitative evaluation of different prediction strategies. Furthermore, this paper will offer a general overview to the readers of the current development proposals for the prediction process in heterogeneous wireless networks and identifies new channels to improve the quality of the service without interruptions. The reviewed articles were summarized and divided into the modern communication technologies as well as the research lines to be improved were organized according to the CR architecture.

Keywords: Cognitive Radio, Prediction, Spectrum.

INTRODUCTION

In the twenty-first century, wireless systems are characterized by a reducing distribution of the radio electric spectrum, fixed radio functions and insufficient network coordination [1]. Unlicensed frequency bands have been achieved acceptable spectrum efficiency. However, they face it to a growing interference that will limit the network capacity and scalability [2]. In fact, the spectrum is an essential resource for the operation of wireless communications [3].Currently, The applications in wireless communications are being increased, exposing that the traditional spectrum allocation scheme is increasingly limited, pointing to a spectrum shortage [4]. It has been reported by the Federal Communications Commission (FCC) that primary users (PU) have sub-employed, assigned resources at every time and everywhere [1]. Therefore, cognitive radio networks (CRN) have been proposed as a path to use and allocate spectrum resources over conventional static spectrum allocation policies [5].

The CRNs have been proposed as a technique for an active spectrum management –knowing as dynamic spectrum access networks (DSA) [6]–. To support further interference, adapt the variability of availability of locals' spectrum, and generate spaces for secondary users (SU). Users who will share the spectrum with the PUs [7]. For instance, CRN must be detected in the environment lost bands of spectrum and adapt to it, since the radio does not have primary rights over any pre-assigned frequency. This functionality will be involved the design of analog and digital network processing techniques to satisfy high radio sensitivity requirements in the band weight [2].

The CRN finds within the broad spectrum, places to occupied when it is required, allowing the use of temporarily available spectrum by transferring the transmission into the spectrum holes, thus obtaining opportunistic access [8]. The last goal of CRNs is to obtain the best spectrum available through cognitive ability and re-configurability [9]. The critical challenge is to share the licensed spectrum without interfering with the transmission of PUs [10] because most of the spectrum is already allocated. To determine the occupation and characteristics of PUs, spectral detection has been used over the years. However, in the process of active detection, mishaps have arisen, such as the speed of detection, the excessive energy consumption, and the detection range, complicating a total control over CRN's. These misfortunes stand due to the lack of knowledge of the non-activated bands and locations as well as the future trends of PU activities in the time-frequency domain [11].

Spectrum prediction is known as a useful complementary technique to spectrum detection to capture the relevant information about the spectral evolution and identify holes in the spectrum. Briefly, spectrum detection determines the state of the spectrum in a passive manner using multiple signals detection methods. Spectrum prediction, besides, is a technique used to infer the state of the spectrum from the information collected in the network and an efficient exploitation of the inherent correlations between them [12]. The predictions of the channel can be used by SU's to decide where and when carrying out a transmission without affecting PU's and trying to minimize the fluctuation between channels, reducing energy and increasing the quality of service (QoS). That is, to decide the detection periods and the occupation duration for a single channel detection scenario. Also, with the predictions collected, assumptions can be made about the channels to be selected and those with the highest probability of vacancy in a broadband multichannel detection scenarios [13].

As the advances in the prediction methods for CRNs have grown up, it is necessary to carry out research that compiles the works in the areas. As well as discuss the issues that currently concern the use of spectrum to prevent future problems. Subsequent, we are going to be mentioned some related work that has run in this aspect. Firstly, an investigation was led in the state of the art of spectrum prediction in cognitive radio networks. Summing up the main spectrum prediction techniques, illustrated the applications and presenting the research challenges that were focused on 3G technologies [7]. Secondly, a compilation of AI learning techniques carried out in studies involving CRN was presented. A description was given about the tasks required in the CR communication process, and the AI systems applied to improve the current process. The research concludes by proposing different points of view and several ways of approaching cognitive radio networks for artificial intelligence at that time 4G networks [14]. Thirdly, a survey and a tutorial on rises in spectrum inference were provided. The most relevant contribution of the research was the introduction of the taxonomy of the spectral prediction from a time-frequency-space perspective. In addition, several applications were described from the standpoint of 5G mobile communication systems [12].

The scope of this investigation is to provide the reader a guideline of studies on tools of prediction in CRNs. The work will be mentioned the most relevant predictive algorithms in CRNs and their operation, highlight the most recent prediction works and finally point to the current prediction problems depending on the type of communications technology. Therefore, the reader may have a medium that will allow to excelling in their prediction in CRN as well as be able to welcome contributions and address contributions in future research on CRN prediction material.

This work is organized as follows. In section II, the role of prediction in cognitive networks will be mentioned shortly. In Section III, we present the most used prediction algorithms in CR. Section IV will be presented different works in the CR prediction. In Section V, we discuss current mishaps and future problems within the RCs. Finally, the conclusions will be shown in Section VI.

SPECTRUM PREDICTION

Spectrum prediction is a promising approach to enhance cognitive radio functions. Extensive research has been carried out on various prediction techniques and applications in CR networks. However, it still needs the effort to develop spectrum prediction designs, provide accurate long-range spectrum predictions, and design prediction schemes for PU activities [7]. The spectral inference over the years has determined the occupation and the characteristics of the PUs. However, in the process of active detection, some inevitable problems arise, difficult the control of cognitive radio networks [11]. To overcome these issues, some prediction paths have been presented and has been widely studied.

Spectrum detection is relevant for unlicensed users since it determines the availability of a channel in the spectrum of the PU. Therefore, SU will detect inactive channels.However, spectrum detection consumes considerable energy which can be reduced by using inference methods to discover holes in the spectrum. If a process reaches a low error probability in predicting inactive channels, the spectrum uses could be improved [15]. Traditionally SU detection techniques have been based on current observations. The channel changes after detecting a PU cause unavoidable interruptions. While proactive spectrum access based on spectrum occupancy model, predicts the status of the PU using the inactivity times of the expected channel and changing channels with longer inactive times in a preventive manner [8].

Regarding spectrum mobility, the literature is based on the search for suitable scenarios where SU can continue the session of data transmission without interruption. The selection of the target channel for the handover of the spectrum is not a trivial task since it depends on many factors, such as the capacity of the channel, the availability of the channel at the time of the handover and the probability that the channel will be available in the future. A wrong channel selection will cause multiple spectrum transfers on a single channel at the same time, corrupting the performance of the transmission. Another proper path is the prediction of availability of the target channel, to reduce the interference of the PUs. Using the prediction, a partial spectrum detection can be performed instead of conventional full detection, reducing the discovery delay during the handover of the spectrum [16].

If we talk about the modes of inference that involved spectrum decision, we have three relevant aspects. The deterministic traffic is the first of them, which is a matter of prediction which looks for the identification of channels. Learning of its external environment, classifying the primary traffic and applying the appropriate spectrum decision methods to predict the idle time of the PU [14]. Based on the GPS location, the packet server of the network can obtain relevant information that allows registering activities and predicting future free spaces and thus characterizes the RF environment [17]. The second relevant aspect is the creation of databases with the activities of heterogeneous users. A significant challenge is the creation of reliable information systems that allow both PUs and SU activity models to be stored. Using the learning capability of the CR, the history of spectrum usage information can be used to predict the future profile of the spectrum [18]. The third aspect to be mentioned is the frequency of operation, which is a reconfigurable parameter in CRNs. Predictive models that allow to dynamically reconfigure the central frequency of CR according to the changes in the environment.

PREDICTIVE ALGORITHMS

Linear Prediction (LP)

LP algorithms are considered as an important member of statistics and mathematics, where future values are predicted as a linear function of previous samples. LPs are widely used in digital signal processing, to infer signal power, due to their remarkable simplicity. They have also been implemented for the prediction spectrum in the time domain [19], [20]. The most common linear prediction models include the Auto-Regressive

(AR) model, the Mobile Average (MA) model, the model of Auto-Regressive Moving Average (ARMA) and the Auto-Regressive Integrated Moving Average model (ARIMA).

AR models are commonly used to approximate discrete random processes. AR process of order *p*, denoted by *[AR - p]* can be expressed by eq. (1) [19]:

$$X(k) = \sum_{j=1}^{p} \phi_k X|k-j| + \omega_k \qquad (1)$$

where $X(k)$ and ω_k are the observation and noise values at the k-th instant. ϕ_k is the weighting parameter of the AR model. On the other hand, the MA order model can be proposed as follows eq. (2) [21],

$$X(k) = \sum_{j=0}^{q} \delta_k \omega_k |k-j| \qquad (2)$$

where $X(k)$ and ω_k are the same values of the model AR, while δ_k is the weighting parameter of the model MA with $\delta_0=1$.

The ARMA model is a combination of the AR and MA model to form a self-regressive moving average model, showing better performance in the prediction of cyclic behavior channels compared to the prediction of Bluetooth and WiFi that have more random behavior [22].The ARMA model is represented by eq. (3):

$$X|k| + \sum_{j=1}^{p} \phi_k X|k-j| = \sum_{j=0}^{q} \delta_k \omega_k |k-j| \qquad (3)$$

with the same considerations as eq. (1) and eq. (2).

In Fig. 1, it explains the general structure of the linear precision algorithms, where once the input data is obtained, it is evaluated if they are stationary. If the input is not stationary, the information is estimated with a different technique; otherwise, the covariance and partial self-correlation functions are computed. Once the function is calculated, the time series is classified in a model, the order of the model is determined, and the regression parameters are estimated. Finally, it is confirmed if the model fits it, based on the tests, it is classified in another type of model, or finally, the predicted model is used.

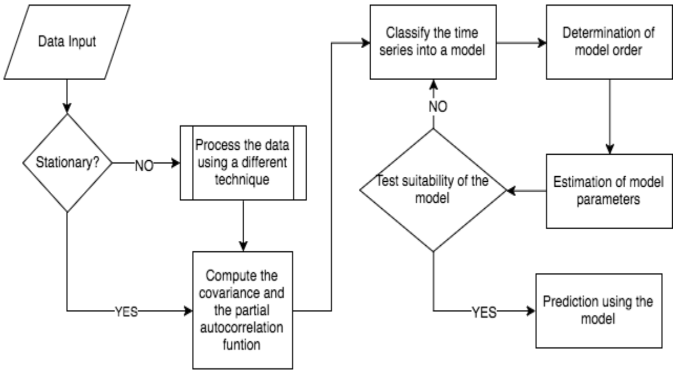

Figure 1. LP structure.
Source: Adapted from [12]

Markov Models (MM)

Markov models are useful when a decision problem involves a risk that is continuous over time, when the timing of events is important and when important events can occur more than once. In the case of CRN, it could detect the state of the spectrum periodically, based on the channels evaluation is correct, we can be made the following approximations. The variable t_i (where i = 0,1,2,…,n) denote the detection periods. At each instant t_i, it is considered that the state of the nth channel S_n is in use or inactive. $S_n(t_i) \in \{Busy; Free\}$. The CR network determines the state by comparing the energy measured in channel n with a threshold value u, eq. (4) [23],

$$S_n(t_i) = \begin{cases} 1 \text{ if } e_n(t_i) \geq u \\ 0 \text{ if } e_n(t_i) < u \end{cases} \qquad (4)$$

where: $e_n(t_i)$ is the energy measured in channel n at time t_i. If $S_n(t_i)=1$ then the spectrum is occupied from time t_i to t_{i+1} [23]. With those approximations, we can then shape a sequence of states that allow predicting CR behavior using the Hidden Markov Model (HMM).

An HMM is a stochastic process created by two interrelated probabilistic functions. One of these functions is the Markov chain mentioned above with a finite number of states. The other is a set of random functions, called alphabet, in which each function generates a symbol related to a state in the Markov chain.

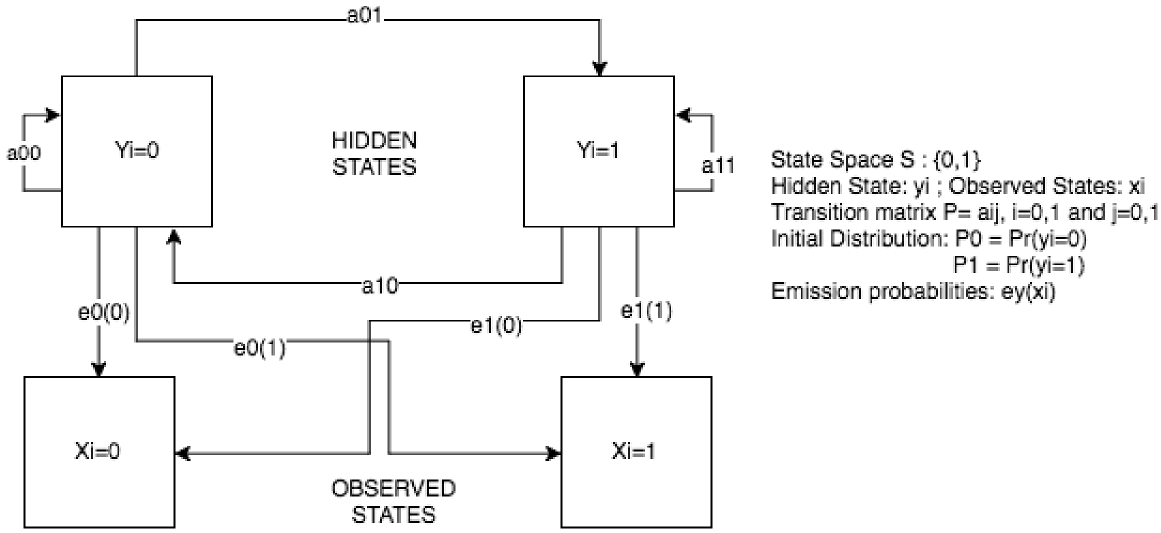

Figure 2. Description of a HMM.

Source: Adapted from [24]

A broad concept of HMM is represented in Fig. 2. A system over discrete time *(1, 2, 3, ...)* is changing stochastically from one state to another, within a defined state space S [24]. Y_n can be represented as the state in which the system is located at the time t_i, assuming that the process is Markovian, the evolution of the sequence ($Y_1, Y_2, ...$) will be hidden. However, the hidden sequence can be represented by a sequence of alphabet symbols $\Omega= \{0, 1, 2, ..., N\}$. A state k can produce a symbol b from a distribution on all possible symbols $b = \{0, 1, ..., N\}$ and its probability can be represented as eq. (5) [24]:

$$e_k(b) = Pr(X_n = b|Y_n = k) \qquad (5)$$

e_k is known as emission probability. The system in state i can emit any symbol of the alphabet with the following distribution eq. (7):

$$\begin{array}{ll} \textit{System State :} & i, i = 0,1,2,\cdots,M \\ \textit{Alphabet :} & 0\;\;1\;\;2\;\;\cdots\;\;N \\ \textit{Emission Probability :} & e_i(0)\;e_i(1)\;e_i(2)\;\cdots\;\;e_i(N) \end{array} \qquad (6)$$

X_n will represent the observable states, and will emit a symbol b by the system at time t_i. The process $X_1, X_2, ...$ is independent with each X_n taking values $0,1,2, ... N$ with the following distribution eq. (7):

$$\begin{array}{ll} Pr(X_n = b|Y_n = i) = & e_i(b), \\ b = & 0,1,2,\cdots,N \\ i = & 0,1,2,\cdots,M \end{array} \qquad (7)$$

Methods based on MM work well under the assumption of having a state evolution in the spectrum without memory –*markovian*–, where the future state depends only on the relevant information about the present, not on the information of the distant past [24].

Bayesian Inference (BIF)

The BIF model has been a classic prediction method in CRN. Usually BIF has been implemented as a critical part of Markov systems. Indeed, the BIF scheme can be defined in briefly as a derive probability distributions of the system. Those distributions are going to be described as follows [25]:

- The prior probability distribution p of a parameter θ denoted as $P(\theta)$, is often a subjective experimental evaluation on θ before the data is taken into account.
- The posterior probability distribution is the distribution of a system parameter θ accustomed to the data $X=\{x_1, x_2, ..., x_n\}$ observed from an experiment. Therefore, the posterior probability distribution of θ can be denoted by $P(\theta|X)$.
- The likelihood function of the parameter θ is denoted as $L(\theta|X)$ and defines the probability of the observed data $X= \{x_1, x_2, ..., x_n\}$ based on parameter θ. That is, $L(\theta|X) = P(X|\theta)$. The likelihood function is often used to estimate the system parameter from a set of statistical data [25].

Based on the above definitions, the following expression is obtained using the Bayes rule eq. (8):

$$P(\theta|X) = \frac{P(X|\theta) \cdot P(\theta)}{P(X)} \qquad (8)$$

The BIF has the function of calculating the posterior probability distribution according to the Bayes rule, from the prior probability distribution and the likelihood function. Therefore, the main problem is to specify a prior probability distribution for each parameter. The selection of a prior one has a significant influence on the complexity of the subsequent computation.

The prior probability distribution and the posterior probability distribution are conjugated if the posterior P (θ | X) is in the same family as the prior P (θ). In fact, the prior probability distribution is called the previous conjugate of the probability. The choice of a reasonable previous conjugate is usually an effective way to simplify the subsequent calculation [25].

Support Vector Machine (SVM)

SVMs are a class of learning methods which optimization criterion consists of a compensation between the minimization of the training error and the minimization of the quadratic norm of the parameter vector.

The vector resulting is a regularization, which establishes the generalization capacity of the machine. In short, it will be being improved the performance concerning non-regularized methods. For a regression model of the form $y[i]=\boldsymbol{w}^T\boldsymbol{x}[i]$, the function that includes both terms are eq. (9) [26]:

$$L = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N} l(\xi_i + \xi'_i) \tag{9}$$

controlled by the limitations

$$\begin{aligned} \boldsymbol{w}^T\boldsymbol{x}[i] - y[i] &= \xi_i + \varepsilon \\ -\boldsymbol{w}^T\boldsymbol{x}[i] + y[i] &= \xi'_i + \varepsilon \\ \xi_i, \xi'_i &\geq 0 \end{aligned} \tag{10}$$

where $l(\cdot)$ is a convex cost function, C is the compensation parameter and ξ_i, ξ'_i are the losses variables. According to the restrictions, if the error is between ± ε, the losses variables must be positive or zero, therefore the error is not taken into account. Otherwise, for positive or negative errors, the contribution of the loss variables is minimized. Applying Lagrange multipliers α_i, α'_i to each restriction eq. (10) the function will point to:

$$-\frac{1}{2}(\alpha-\alpha')^T K(\alpha-\alpha') + (\alpha-\alpha')^T y - \varepsilon_1{}^T(\alpha-\alpha') \tag{11}$$

with conditionals eq. (12)

$$\begin{aligned} w &= X(\alpha-\alpha') \\ K &= X^T X \end{aligned} \tag{12}$$

where α is a vector that contains all Lagrange multipliers and X contains all training input vectors in column form. The above function is usually solved through quadratic programming. In the prediction of the spectrum it is assume a linear model given by eq. (13) [27]:

$$y[n] = \sum_{k=1}^{K} a_k \cos\left(\frac{2k\pi}{K}n\right) + b_k \sin\left(\frac{2k\pi}{K}n\right) \tag{13}$$

$$x[n] = \left(1, \cdots, \cos\left(\frac{2k\pi}{K}n\right), \cdots, 1, \cdots, \sin\left(\frac{2k\pi}{K}n\right), \cdots\right)^T \tag{14}$$

Therefore, to calculate the spectrum, the terms eq. (12) are solved, and then, the terms a and b are calculated using eq. (14). Applying over the spectrum the estimation at the frequency $\omega_k=2k\pi/K$ we have eq. (15):

$$Y(k) = \|a_k + jb_k\|^2 \tag{15}$$

In comparison with the DFT spectrum, no noise is assumed. In contrast, SVM is implemented cost function that is zero between ±C, and linear beyond ±ε±C, giving more robustness against Gaussian interference. In addition, the regularization parameter improves the generalization concerning the quadratic criterion implicit in the DFT. It must be in mind that instead of using sinusoids as approximate functions, ad-hoc symbols can be used as modulated pulses to improve the approximation to the spectrum, where an a priori knowledge of the signal is available [26].

Artificial Neural Networks (ANN)

The ANN structure is a series of simple extremely interconnected processes known as neurons, which are used to mimic how the human brain learns. An ANN is mostly an artificial model of a human neuronal system, whose the core elements are also neurons, used to process information in the cognitive sense [27]. Mathematically, an artificial neuron consists of the following components; (a) A group of incoming connections – *synapses in dendrites* – (b) A number of outgoing connections – *synapses in the axon*– and (c) An activation value assigned to each neuron - *the potential membrane in the biological neuron*–. The connecting force between two neurons are captured by a weight value. The basic model for a neuron j is given as eq. (16) [28]:

$$o_j(w_j, b_j, n_j) = f\left(b_j + \sum_{i=k}^{N} n_{jk} \cdot w_{jk}\right) \tag{16}$$

can be expressed graphically as Fig. 3

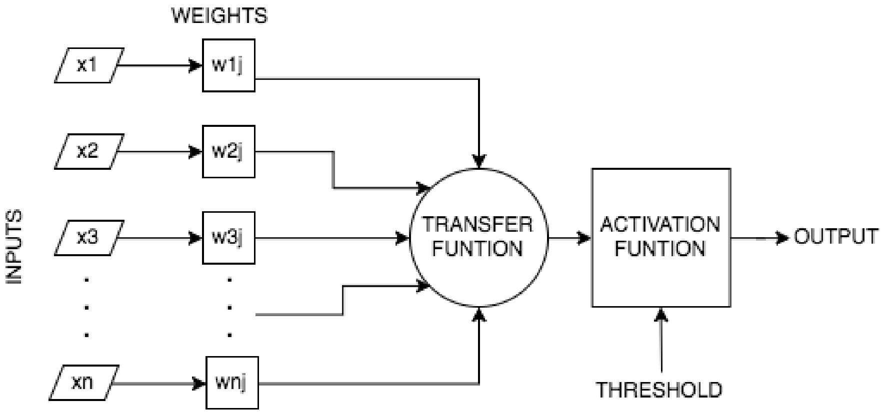

Figure 2. Scheme of a ANN.

Source: Adapted from [28]

where n_{jk} is the input signal of the neuron j to the neuron i, $n_j=[n_{j1}, n_{j2},...n_{jN}]$ is the vector of the input signal of the neuron j, w_{jk} is the value of each input weight, $w_j=[w_{j1},w_{j2},...,w_{jN}]$ is the vector of input weights of the neuron j, o_j is the output signal of the neuron j, b_j is the bias of the neuron j and $f(\cdot)$ is a non-linear activation function. The bias value can change the activation function, which is critical to successful learning process.

The activation function can be represented as consecutive ANN, where the classic form of the activation function is given by the binary Heaviside step function [29]. However, by the using of linear activation functions, many neurons must be used in the calculation beyond the linear separation. In the other hand, an ANN constructed using the linear activation functions in eq. (16) can not reach a stable state after training, because the value of the activation function will increase without limit. To avoid this drawback, we can choose, $f(\cdot)$ in eq. (16) as a normalizable activation function, for example, the sigmoidal activation function instead of a linear activation function. The selection of a type of activation functions in ANNs depends on the objectives sought, such as analytical capacity, computational power and the representation of output signal (logistic or continuous). In essence, an ANN is a composition of multiple neurons connected in different ways and operating using different activation functions [28].

Remarks in prediction methods

Base on the predictive algorithms mentioned above, we are going to be presented the most relevant advantages and disadvantages of the techniques. The Table 1. will be organized and summarized the critical aspects of inference methods, as well as some current developments in the area of AI. That joint together are going to strengthen their advantages and reduce their weaknesses.

Table 1. Comparison between prediction methods.

Method	Benefits	Limitations	supporting highlight
LP	- Low complexity for low orders - Guaranteed convergence - Does not need Threshold	- Requires training information - Depends on stationary processes - Large accumulative error for high orders	- Average Relative Change[30] - Genetic Algorithms [31] - Polynomial Models[32]
MM	- Robustness in the processing of time sequences - Flexibility in non-stationary scenarios - Strong statistical bases	- Need large memory - Difficult to find the optimal number of states - Discrete Gaussian models are not competent	- Multivariate Gaussian Distribution [33] - Bayesian Approach [34] - Multiscale Entropy [35] - Baum-Welch[36]
BIF	- Confidence Intervals does not affect a priori knowledge - Update the probability distributions in each observation - It is modular, allowing the addition of variables and analysis after implement	- Intensive computing time - Find prior functions can become complex - Unsecured converage	- Dynamic Reliability [37] - Gaussian analyst process [38] - Hierarchical prior model[39] - Tensor decomposition[40]

SVM	- Non-dependent model - Does not depend on linear, or stationary processes - Few parameters to set - Captures the inherent characteristics better thatn others	- Kernel Selection - Learning takes time - The problem must be formulated as class-2 classification	- Partial swarm optimization [41] - Bayesian approach [42] - Least square [43] - Wavelet Transform [44]
NN	- Adaptation to unknown situations - Non-linear modeling of functions - High accuracy and noise tolerance - Suitable for continuous or discrete enviroments	- Possible Over-fitting of training - High computing cost - Multiple configuration structures - Almost impossible to edit or tune	- Fuzzy Structure [45] - Evolutionary Algorithms [46], [45] - ARMA [47]

Source: Adapted from [12], [48], [49], [50].

According to the characteristics mentioned in Table 1, the following assessments can be made. Although LP methods have computationally low costs and guarantee a convergence, its accuracy is not good due to accumulating errors is increasing with the order of the problem. For the MM, BIF and NN models, their initial configuration is not straightforward since the shape of among of states, the formalization of the prior functions, and the structural selection of the neuronal models respectively are not simple tasks. In contrast, SVM's configuration depends on the setting of very few parameters. It can be observed how some prediction techniques have been implemented with similar complementary methods such as LP, SVM, NN using evolutionary algorithms. MM and BIF have been implemented employing Gaussian techniques. MM and SVM routines execute Bayesian approaches. It has been shown the versatility of prediction techniques and being able to make comparisons of performance and efficiency by having some points in common.

PREDICTIVE APPLICATIONS

Round prediction in cognitive radios, different proposals have been presented. We will mention the most relevant ones and proceeded to classify them according to the type of inference. Within the cellular networks are the GSM, 3G, 4G and LTE technologies. In the wireless networks are WiFi, WLAN, WiMax and in the theoretical section the investigations based their results on random data that simulated some communication network.

Table 2. Survey of prediction methods in CR

Technology	Spectrum Prediction	Cellular Networks	Wireless Networks	Tv	Data Simulate
LP	To perform spectrum prediction, where the output is used to improve the sensing accuracy and reduce the sensing cost.	[52, 55]	[21, 56]		[19, 57, 58]
MM	These kinds of models work well under the assumption of memory less, property existing in the spectrum evolution state.	[20, 24, 59]	[23, 60–63]	[63]	[3, 65]
BIF	Used for predict probabilities of some type of signal, such as energy.	[65]	[25]		[66]
SVM	It has been implemented in predictions where geospatial assumptions are made.	[67, 68]			[26, 69–71]
ANN	Used for predictions which show correlation. Better prediction accuracy over other models.	[73, 69]	[74–77]	[69, 78–80]	[71,81–84]

There are others several works developed and it is relevant to mention them. Although they do not use the prediction techniques discussed above, they represent significant contributions to prediction in cognitive radio networks. In [84], routing and topology control problems are studied in mobile ad hoc networks (CR-MANETs) and a cognitive topology control scheme based on distributed prediction (PCTC) is proposed to provide greater routing capacity in CR-MANET. In [85], the SUs use online learning techniques for the regression of the transmission power received in different licensed frequency bands. Also, the probability of the state of each primary user occupied or inactive is predicted based on the results of the power regression. The proposed strategy can not only save time and energy, but also improve the performance of the SU. In [86], a new modeling method of spectrum measurement is proposed for several essential frequency bands by the use of Daubechies waves. The method uses the analysis of the spectrum and predicts using regression. The strategy in [87]is

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based on the fusion of prediction and spectrum monitoring techniques implementing the AND and OR fusion rules, for the detection of PU emergence during data transmission. The authors in [88] propose a new MAC called sense-and-predict (SaP), where each secondary TX decides whether to access or not according to the prediction of the level of interference in RX. In [89], a new stochastic cognitive anti-jamming game model is used in multi-agent environments. Which each autonomous broadband cognitive radio, aims to predict and avoid transmissions from other radios, as well as a dynamic interference signal.

CURRENT MISHAPS AND FUTURE PROBLEMS

In this section, we will explore some current and future research paths in the field of prediction within cognitive radio networks. We divided the problems according to the research methodologies of the CRN, spectrum division, spectrum decision, mobility spectrum and spectrum detection. Spectrum detection is a critical aspect of spectrum inference applications since they aim to explore inactive spectrum holes. The emerging paradigms of spectrum detection are in the domain of time, frequency, and spatial dimensions. Inference techniques are widely used to infer as many empty channels as possible and improve detection performance as well as reduce energy consumption, and time between changes. Several aspects such as centralized allocation of the spectrum, selection of decentralized channels, the adaptation of the physical layer rate and access dynamic to the spectrum, have been investigated.

The spectrum mobility in the CRNs has an ambiguous interpretation. On one side, it refers to the spectral transfer from one band to another, due to the appearance of PUs or interference evasion, field widely studied in prediction. On the other side, the mobility of CR and PU, for example, in vehicular CRNs, can also affect the geographically surrounding spectrum environment regarding imposing additional interference, changing channel conditions, and spectrum availability. Field no so widely studied and with few contributions. In spectrum exchange, there are different understandings in the literature. The concept of spectrum sharing is interchangeable with the theories of dynamic access to the spectrum. Which consists of three paradigms of spectrum use: underlying, superimposed and interconnection. This perception of spectrum exchange makes its meaning too broad to cover all aspects of CRNs.On the other hand, the spectrum exchange focuses on the underlying mode, which will allow the CRs to operate in the same band, at the same time. Allowing tolerant threshold between bands. The inference of spectrum in division is mainly associated for the support and mediation between CR and PUs [12].

Fig. 4 displays a distribution of inference studies in each CRN architectures. This research topic has great potential for future research since it defines the prediction limits in each sharing, decision, mobility, and detection in prediction. It will facilitate the deepening and therefore improvement of the QoS. Certainty, there are still many unsolved challenges waiting for new contributions. Based on the compilation of the works included in this paper, a range of possible paths of advancement, open problems, and research trends were summarized.

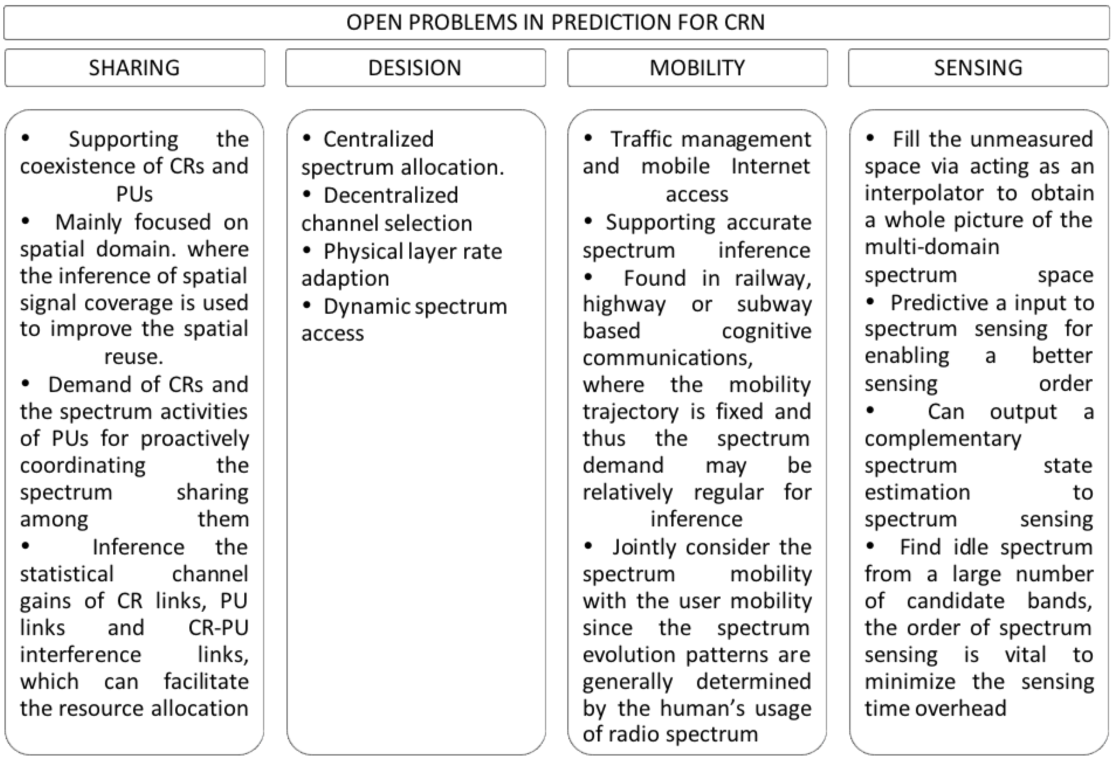

Figure 4. Division of prediction problems in the CRNs.

Source: The Authors.

CONCLUSIONS

Spectral prediction is a promising technique for improving spectrum exploitation in cognitive radio networks. In this article, we review recent advances in spectrum inference based on an extensive study of existing literature. First, we present the basics in spectrum inference, second, the most famous predictability. Then we explored several spectrum inference applications and finally from a global perspective point of view future problems.

We offer a comparative analysis of the advantages and challenges of various spectrum inference techniques. In addition, we review the applications of spectrum inference in existing and future wireless networks, including channel occupancy, spectrum mobility, spectrum sensing, spectrum sharing, spectrum decision. We also highlight a range of open questions and research trends that influence the actual deployment of spectrum inference. We conclude that the primary objective of existing and future studies on spectral prediction in CRNs is to achieve a compromise between the inconsistent aims of improving prediction accuracy, reducing their computational complexity and the memory requirement. This forms a fruitful research area.

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