SPECTRUM PREDICTION IN COGNITIVE RADIO NETWORKS

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ABSTRACT

Spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility are four major functions of cognitive radio systems. Spectrum sensing is utilized to observe the spectrum occupancy status and recognize the channel availability, while CR users dynamically access the available channels through the regulation processes of spectrum decision, spectrum sharing, and spectrum mobility. To alleviate the processing delays involved in these four functions and to improve the efficiency of spectrum utilization, spectrum prediction for cognitive radio networks has been extensively studied in the literature. This article surveys the state of the art of spectrum prediction in cognitive radio networks. We summarize the major spectrum prediction techniques, illustrate their applications, and present the relevant open research challenges.

INTRODUCTION

Currently, the use of wireless frequencies is mainly regulated by centralized authorities (e.g., the Federal Communications Commission [FCC] in the United States) that allocate the spectrum statically in the temporal and spatial dimensions such that the spectrum band assigned to each user is valid for an extended period of time (usually decades) and for a large geographical region (country-wide). An illustration of this static spectrum assignment policy is presented in Fig. 1a. Obviously, large portions of the spectrum remain temporally and/or spatially underutilized/unused. But due to the proliferation of mobile devices in recent years, the demand on bandwidth continues to increase, making dynamic spectrum access a better choice for managing the spectrum resource.

Cognitive radio (CR), which provides the capability to harness the potential of unused/underutilized spectrum (spectrum holes) in an opportunistic manner, is a key enabling technology for dynamic spectrum access. An illustration of the CR technology is presented in Fig. 1b, from which it is easy to observe that CR can significantly improve the overall spectrum utilization when the CR users are allowed to utilize the spectrum holes. A CR network typically involves two types of users: primary users (PUs), who are incumbent licensed users of the spectrum, and CR users (also known as secondary users), who try to opportunistically access the unused licensed spectrum as long as harmful interference to PUs is limited.

To effectively implement the concept of CR networking, CR systems need the capability to perform the following functions [1]: *spectrum sensing*, *spectrum decision*, *spectrum sharing*, and *spectrum mobility*. In spectrum sensing, CR users sense the PU spectrum occupancy status and recognize the spectrum holes in the licensed bands that can be used for their own communications. Based on the sensing results, CR users determine which spectrum band to use (spectrum decision), how to share the spectrum with other CR users (spectrum sharing), and when to evacuate the current spectrum band for the returned PUs (spectrum mobility). Considering the fact that all four of these functions introduce time delays that undermine the spectrum sensing accuracy as well as the spectrum utilization efficiency of CR systems, and PU activities exhibit regularity in both the time and spatial domains, spectrum prediction has been proposed.

Spectrum prediction in CR networks is a challenging problem that involves several subtopics such as channel status prediction, PU activity prediction, radio environment prediction, and transmission rate prediction. In this article, we present an overview of the most important spectrum prediction techniques in CR networks. This article is organized as follows. The necessity for spectrum prediction is addressed, and we introduce the prediction techniques and their applications. Open research issues and challenges are discussed, followed by a conclusion.

NECESSITY OF PREDICTION IN COGNITIVE RADIO NETWORKS

Cognitive radio is a technology that enables secondary users to discover and access the spectrum holes in the licensed bands. CR technology

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includes four major functions, which are presented in Fig. 2.

The operation of the CR functions shown in Fig. 2 can be described as follows. A CR user sequentially senses the spectrum bands and constructs a spectrum pool consisting of all the discovered spectrum holes in the spectrum sensing stage, and selects a channel from the spectrum pool for its own transmission in the spectrum decision stage. In order to enhance the channel capacity, the CR user may share the available channel with other CR users via an appropriate spectrum sharing policy as long as spectrum sharing does not cause transmission collisions. Moreover, the CR user must evacuate its occupied channel when it is required by PUs according to a spectrum mobility policy to guarantee the priority of the PUs and protect PU transmissions.

By making use of these four functions, CR users can opportunistically utilize the unused licensed spectrum for their own communications. However, several shortcomings are identified, which hinder the capacity enhancement of CR networks:

- Sensing the wideband spectrum results in non-negligible time delays [2].
- Spectrum decision based on real-time sensing results undermines the spectrum utilization efficiency due to the time delays introduced by spectrum sensing and spectrum decision [3].
- In spectrum sharing, CR users may join at different times with different bandwidth demands and quality of service (QoS) requirements. Assigning appropriate spectrum bands to the bursty heterogeneous CR service requests may lead to considerable time delays, which results in low efficiency in traditional spectrum sharing policies.
- Carrier sense multiple access (CSMA)-based traditional spectrum mobility policy always results in transmission collisions since the CR user does not evacuate its occupied channel until the appearance of the PU is detected [4].

To overcome these shortcomings, prediction-based techniques have been extensively studied. In prediction-based spectrum sensing [2, 5–7], a CR user can skip the sensing duty on some channels that are predicted to be busy, thus reducing the sensing time and energy consumption. In prediction-based spectrum decision [4, 5, 8], a CR user predicts the quality of the channels in terms of the idle probabilities, idle durations, and other properties, and then selects a high-quality channel for sensing and accessing to increase the efficiency of its dynamic spectrum access. In prediction-based spectrum mobility [4, 8, 9], a CR user predicts the appearance time of PUs and evacuates the channel before the start of the PU transmissions. To the best of our knowledge, prediction-based spectrum sharing has never been addressed in literature. Nevertheless, it is obvious that the existence of a prediction-based spectrum sharing model can help predict the requests of CR users in the time, space, and frequency domains, based on which the spectrum bands can be pre-assigned for effective spectrum sharing before CR requests come. Such a process can better exploit the channel capacity and reduce the response delay.

All these prediction-based methods have demonstrated that prediction is an effective way to improve the performance of CR networks. In the following section we summarize the most typical prediction techniques and their applications in CR networks.

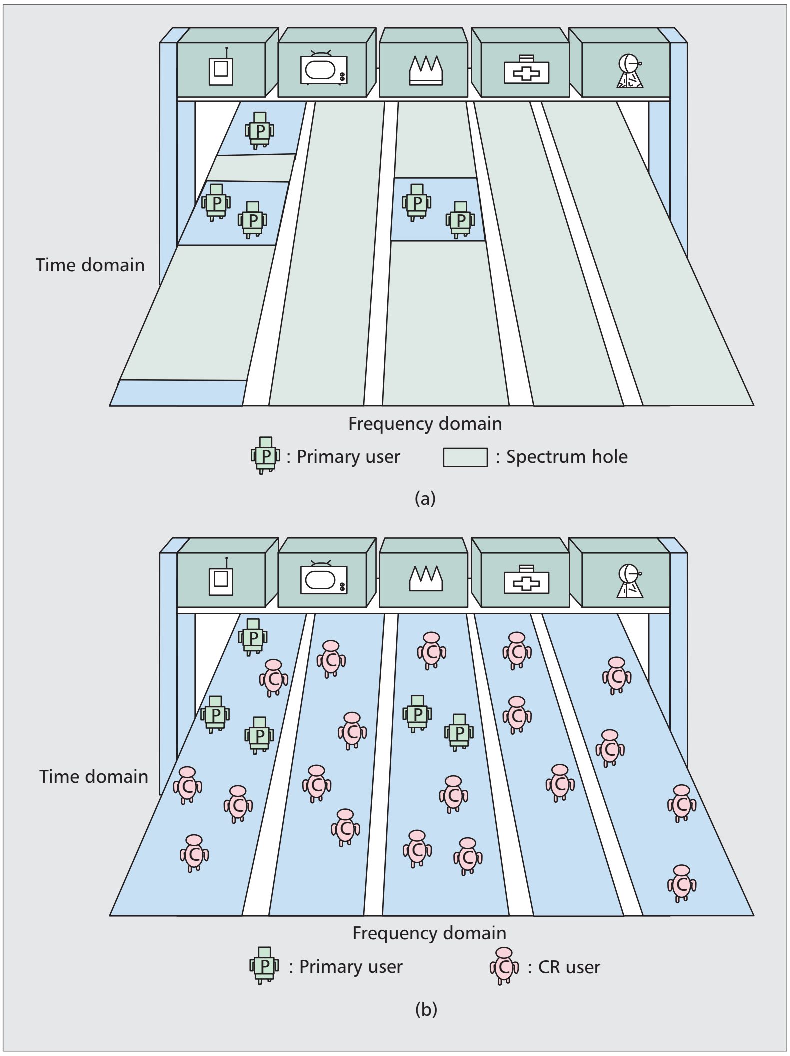

Figure 1. *a) Static spectrum assignment policy; b) cognitive radio technology.*

Typical Prediction Techniques

In this section, we introduce a few prediction techniques and their applications in CR networks. Two widely used prediction methods, hidden Markov models and neural networks, are introduced first, followed by the presentation of Bayesian inference-based prediction, moving average-based prediction, autoregressive model-based prediction, and static neighbor graph-based prediction. Finally, we present a table to summarize the surveyed prediction methods and their applications.

Hidden Markov Model-Based Prediction

A hidden Markov model (HMM) can be considered as a generalization of a mixture model that consists of two processes: the variation of the hidden states is a Markov process, and the observation under a specific hidden state is a normal random process. In CR networks, the channel

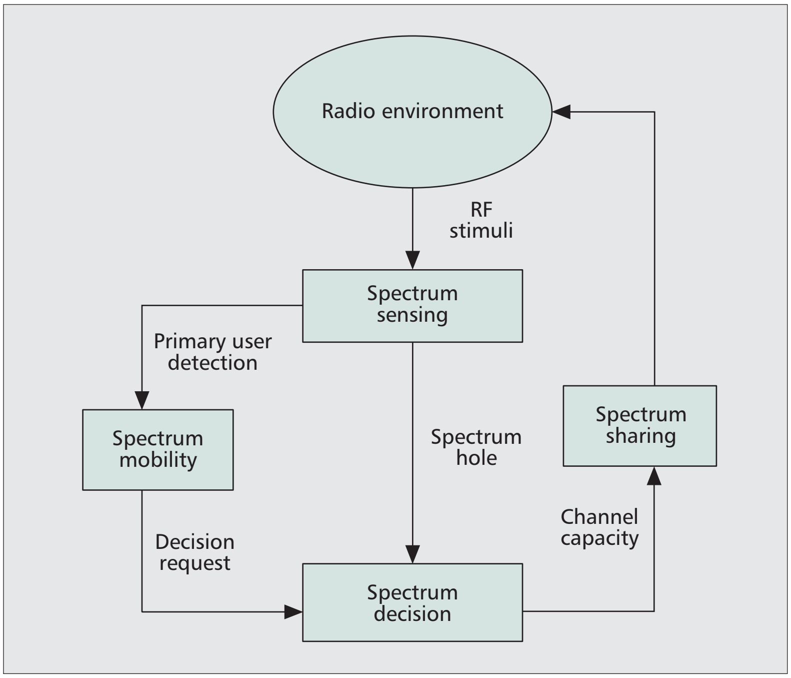

Figure 2. *Operation of the cognitive radio functions.*

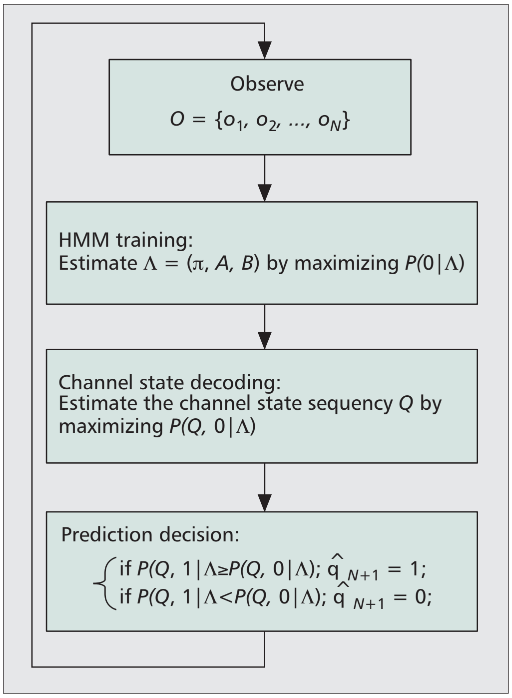

Figure 3. *HMM-based prediction.*

occupancy states (busy or idle) are hidden since they are not directly observable, and the sensing results of the CR users are the observation of the channel states. Define the hidden state space as $X = \{x_1, x_2\}$, with $x_1 = 0$ and $x_2 = 1$, indicating that the channel is idle and busy, respectively. Similarly, define the observation state space as $Y = \{y_1, y_2\}$, with $y_1 = 0$ and $y_2 = 1$ indicating that the spectrum sensing result is idle and busy, respectively. Let q_n denote the channel state on time slot n and o_n denote the corresponding sensing result. Then an HMM can be described by its parameters $\Lambda = (\pi, A, B)$, where π is the initial state probability distribution: $\pi = [\pi_i]_{1\times 2}$, $\pi_i = P(q_1 = i)$, $i \in X$; A is the state transition probability matrix: $A = [a_{ij}]_{2\times 2}$, $a_{ij} = P(q_{n+1} = j | q_n = i)$, $i, j \in X$; and B is the emission probability matrix: $B = [b_{jk}]_{2\times 2}$, $b_{jk} = P(o_n = k | q_n = j)$, $j \in X$, $k \in Y$.

In HMM-based prediction [5, 6], the only prior knowledge of a CR user is the spectrum sensing results within N time slots, denoted by $O = \{o_1, \ldots, o_N\}$, with $n \in \{1,\ldots, N\}$ and $o_n \in Y$. Having this knowledge, the CR user takes the following three steps, shown in Fig. 3, to make an HMM-based prediction:

- HMM training: In this process, the observation sequence $O = \{o_1, \ldots, o_N\}$ is used as a training sequence to train an HMM model and estimate its parameters. The Baum-Welch algorithm is one of the most commonly used HMM training algorithms, in which the HMM parameters are estimated by maximizing the probability of observing the sequence O.
- Channel state decoding: Solving the optimization problem $Q = \arg\max P(Q,O | \Lambda)$ according to the Viterbi algorithm to decode the unknown channel state sequence $Q = \{q_1, \ldots, q_N\}$, with $n \in \{1, \ldots, N\}$ and $q_n \in X$, which generates the observation sequence $O = \{o_1, \ldots, o_N\}$.
- Prediction decision: Given the estimated parameters and decoded channel states, the future channel state can be predicted according to the following rule:

$$\begin{cases} \text{if } P\left(Q,1\middle|\Lambda\right) \geq P\left(Q,0\middle|\Lambda\right); \hat{q}_{N+1} = 1(\text{busy}); \\ \text{if } P\left(Q,1\middle|\Lambda\right) < P\left(Q,0\middle|\Lambda\right); \hat{q}_{N+1} = 0(\text{idle}); \end{cases}$$

where $\hat{q}_{N+1}$ is the predicted channel state in time slot $N + 1$.

The HMM-based prediction method has been widely used in CR networks. In [3], HMM-based channel state prediction was proposed to minimize the negative impact of the response delays caused by hardware platforms. The authors claimed that spectrum sensing introduced time delays that reduce the accuracy of the sensing results. Therefore, spectrum decision based on real-time spectrum sensing may lead to transmission collisions between CR users and PUs. Nevertheless, spectrum decision based on channel state prediction can provide an effective way to tackle the problem since CR users gain information on the current channel states from the spectrum sensing results, and on future channel states from the prediction results. By selecting a channel that is sensed as well as predicted to be idle, CR users can improve the spectrum utilization efficiency and reduce the interference with PUs. In [4], HMM-based prediction is used to design a smart spectrum mobility scheme. This study indicates that the CSMA-based traditional spectrum mobility model always results in transmission collisions since a CR user does not evacuate its currently occupied channel before the detection of PUs. However, in prediction-based smart spectrum mobility [4], also known as proactive channel switching, a CR user predicts the idle duration of the channel and the appearance time

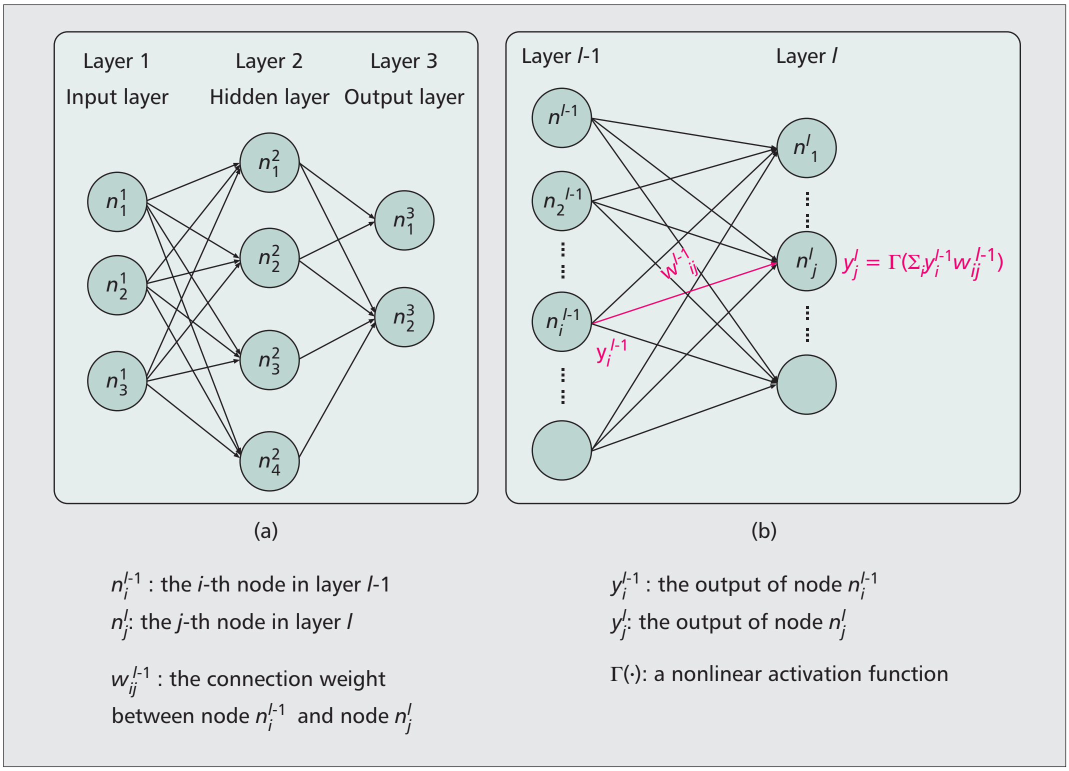

Figure 4. *Multilayer perceptron neural networks: a) an example neural network model; b) the computing process of a neuron,* n_j^i.

A multilayer perceptron is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. In MLP based prediction, the input data is the history observations while the output is the prediction of the future states.

of the PUs, and leaves the incumbent channel before detecting any signal from the PUs. Therefore, it can efficiently reduce transmission collisions and interference with the PUs. In this scheme, the authors modeled the channel usage pattern as a binary series with 0 indicating no traffic on the channel and 1 indicating that the channel is currently occupied. By using the HMM-based prediction method, a CR user can predict the channel states in the near future and make a transmission decision accordingly. The CR user can continue to transmit if the predicted result is idle, and evacuate the channel if the predicted result is busy. After the evacuation decision is made, the CR user switches to another channel. In order to solve the switching channel selection problem, [9] proposed an HMM-based prediction approach, in which each CR user computes a hopping sequence according to the predicted channel availability information and switches channels according to the sequence.

Multilayer Perceptron Neural-Network-Based Prediction

A multilayer perceptron (MLP) is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate outputs. In MLP-based prediction [6, 7], the input data is the history observations, while the output is the prediction of the future states.

As shown in Fig. 4, an MLP consists of three or more layers (an input and an output layer with one or more hidden layers) of nodes in a directed graph. Each node in one layer connects with a certain weight to every node in the next layer. Excluding the nodes at the input layer, each node is a neuron (or computing unit) that calculates a weighted sum of the input and transforms the sum through a nonlinear activation function $\Gamma(\cdot)$.

The main challenge in MLP neural-network-based prediction is the training of the model, that is, changing connection weights of the graph. The training process can be described as follows:

- Process each piece of observation and produce corresponding output.
- Calculate the error in each output compared with the expected value.
- Adjust the connection weights by minimizing the error in the entire output.

After the training process, prediction can be made by providing the newest observation as the input to the MLP model.

Tumuluru *et al.* applied the MLP-based prediction method to spectrum sensing in CR networks [6, 7]. In their approach, each CR user predicts the future channel states by using an MLP-based predictor and senses only those channels that are predicted to be idle. Such targeted spectrum sensing can reduce the energy consumption of CR users.

Bayesian-Inference-Based Prediction

Bayesian inference (BIF) is an approach of inference where Bayes' rules are utilized to update the probability distribution of a hypothesis when additional evidence data is learned.

In CR networks, a CR user can compute a prior probability distribution (also known as *prior*) of each system parameter θ, denoted by $P(\theta)$, from experimental subjective assessments, We observe that prediction has been employed to improve the performance of the CR network in terms of reducing the delay of finding available channels, decreasing the energy consumption, minimizing the interference with primary users, and improving the network throughput.

before any data is taken into account. Through n time-slot spectrum sensing, some observed data $X = \{x_1, x_2, \cdots, x_n\}$ are collected. Then the CR user computes a likelihood function of parameter θ, denoted by $L(\theta|X)$, as the probability of the observed data given that parameter. That is, $L(\theta|X) = P(X|\theta)$. After acquiring the prior probability distribution and the likelihood function, BIF can be used to derive the posterior probability distribution of the system parameter θ conditioned on the data $X = \{x_1, x_2, \cdots, x_n\}$. In BIF-based prediction, the CR user first derives the posterior probability distribution $P(\theta|X)$ according to Bayes' rule

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

and then uses the derived posterior to predict the data to be observed.

In our work [5], we designed a BIF-based channel quality prediction method for CR networks. In our approach, we modeled the spectrum sensing process as a non-stationary HMM (NSHMM), estimated the model parameters, which carry the information about the expected duration of the channel states and the spectrum sensing accuracy (detection accuracy and false alarm probability) of the SU, via a BIF approach, and predicted the channel quality according to the inferred channel idle duration and spectrum sensing accuracy. After our prediction process, each channel is associated with a predicted channel quality. Then the channels are ranked in descending order of the predicted quality. Our simulation-based performance study indicated that the ordered sequence can be used for both spectrum sensing (sensing the channels sequentially according to the ordered sequence) and spectrum decision (selecting the first channel of the sequence) to improve the network performance in terms of network throughput and time cost of finding available channels.

Moving-Average-Based Prediction

Moving average (MA)-based prediction [10] is commonly used to predict a trend in a sequence of values. Consider a history sequence of length N; a k-order MA predictor predicts the next value of the sequence as the average of the last k values in the sequence. To enhance the influence of the most recent observations on the prediction result, an upgraded version of MA-based prediction, exponential MA (EMA)-based prediction, can be implemented, where exponentially decreasing weighting factors are applied to older observations.

In [2], EMA-based prediction is used to enhance the spectrum sensing performance. Each CR user collects the history energy level of the channels as observations and predicts the future energy level via an EMA based-predictor. Then the CR user skips the sensing duty on those channels whose predicted energy level is higher than a preset threshold (considered as occupied by the PUs). Through this approach, the whole spectrum sensing time and energy consumption can be reduced.

Autoregressive-Model-Based Prediction

The autoregressive model (ARM), a kind of linear prediction formula, can also be used to predict the future states of a CR network based on the previous observations [8]. In this approach, the prediction decision is made according to the prediction rule: $\hat{X}_T = \sum_{i=1}^{p} \varphi_i X_{T-i} + \omega_T$, where $\hat{X}_T$ is the predicted state at future time T, X_{T-i} is the observation at time $T - i$, p is the order of the autoregressive model, φ_i, $i = 1, 2, \cdots, p$, is the parameter of the model, and ω_T is the white noise at time T.

In ARM-based prediction, a CR user first estimates the model parameters φ_i, $i = 1, 2, \ldots, p$, with Yule-alker equations, maximum likelihood estimation, or other approaches. Then it inputs the history observations into the prediction rule, and predicts the future state of the system as $\hat{X}_T$.

In [8], an autoregressive spectrum hole prediction model was proposed. Each CR user estimates the model parameters using Yule-alker equations and predicts the future channel states according to the prediction rule. No specific application was indicated for this prediction method in this article, but intuitively, it can be used for spectrum decision and spectrum mobility: a CR user can select a channel that is predicted to be idle for its own use during the spectrum decision stage, or evacuate the channel it currently occupies when the channel is predicted to be busy in the near future for spectrum mobility.

Static-Neighbor-Graph-Based Prediction

In [10], a static neighbor graph (SNG)-based predictor was designed to predict future PU locations according to the pre-collected topology information of PU mobility. A directed graph representing the PU mobility history is first constructed as follows: When a CR user observes the PU move from location i to location j, it adds a directed edge (i, j) to the graph and sets the weight of the edge to $\omega_{ij} = 1$ if the edge (i, j) is not in the graph; or it adds 1 to the weight of the edge, $\omega_{ij} = \omega_{ij} + 1$ if the edge (i, j) is in the graph. After the construction of the graph, a normalization procedure is performed on the weights of the edges such that $\forall i$, $\Sigma_j \omega_{ij} = 1$. Then the PU mobility property is predicted as follows: If the current location of the PU is i, and the CR user finds location i in the graph, it returns a list (j, ω_{ij}) for all edges (i, j) and then predicts the future location of the PU as $j = \arg\max \omega_{ij}$. Using SNG-based PU mobility prediction, more useful information on the network topology can be obtained, and the routing protocol performance of the network can be improved.

Summary of the Prediction Applications in CR Networks

In the previous subsections, we have introduced six typical prediction techniques and their applications in CR networks. We observe that prediction has been employed to improve the performance of the CR network in terms of reducing the delay of finding available channels, decreasing the energy consumption, minimizing

Methodology \ Application	For spectrum sensing	For spectrum decision	For spectrum mobility	For PU mobility prediction
HMM-based prediction		[3]	[4, 9]	
MLP-based prediction	[6, 7]			
BIF-based prediction	[5]	[5]		
MA-based prediction	[2]	[8]	[8]	
ARM-based prediction	[2]	[8]	[8]	
SNG-based prediction				[10]

Table 1. *The example applications of the prediction techniques in CR.*

Extensive research has been performed on various prediction techniques and applications in CR networks. However, effort is still needed to design prediction-based spectrum sharing methods, provide long-term accurate spectrum prediction, and devise PU activity map prediction schemes.

the interference with PUs, and improving the network throughput. The applications of each prediction method are summarized in Table 1. Note that since different prediction methods are designed for different performance improvement objectives, no performance comparison study is carried out here. Besides, Table 1 only lists the reported applications based on each prediction technique. Future research may reveal more applications for each prediction approach. Also note that prediction-based methods have their drawbacks too. For example, they require more memory space for history observation storage and more computational power for prediction result calculation.

Open Issues and Research Challenges

In this section we discuss several open issues and research challenges that need to be investigated for the development of prediction methods in cognitive radio networks.

Prediction for spectrum sharing: To the best of our knowledge, no prediction method for spectrum sharing has been proposed. The difficulty of this research lies in the prediction of CR user activities. Due to the heterogeneous property of CR users and the uncertainty property of CR communications, it is hard to predict the service requests of the CR users in time, space, and frequency domains. Thus, it is difficult to coordinate the spectrum sharing between CR users through prediction.

Long term prediction: As we observe from earlier, most existing research simply focuses on predicting the system states of the next time slot. It is challenging to make an accurate long-term prediction due to the error accumulation problem.

PU activity map prediction: Prediction in a single domain (time, space, or frequency) can only provide unilateral information of the future states of the system to CR users. If we could predict a PU activity map, which provides information regarding PU-occupied spectra, their physical positions, and their transmission powers, it would certainly benefit CR users and PUs to provide more efficient utilization of the spectrum resource. However, this is a difficult task since all the prediction methods need history observations, which indicates that extended spectrum sensing is needed to construct a history PU activity map before prediction can be conducted.

Conclusion

Spectrum prediction is a promising approach for better realization of cognitive radio functions. Extensive research has been performed on various prediction techniques and applications in CR networks. However, effort is still needed to design prediction-based spectrum sharing methods, provide long-term accurate spectrum prediction, and devise PU activity map prediction schemes.

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