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A Survey on Spectrum Prediction Methods in Cognitive Radio Networks

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Abstract

The optimization of spectrum usage using cognitive radio methods is one of the actual issues which takes a lot of attention through the latest researches to overcome spectrum scarcity problem. Spectrum prediction technology is the most important function to predict the channel state information, it is considered as an effective way to reduce processing latency and energy consumption, manage spectrum access, and avoid spectrum collision between licensed and unlicensed users. Spectral prediction methods are meanly divided into four categories, Pattern mining prediction, linear prediction methods, prediction methods based on Markov model and prediction methods based on Artificial Intelligence. This paper will provide an updated survey on the main spectrum prediction methods in Cognitive Radio Networks.

Keywords: Cognitive Radio, Spectrum Prediction, Pattern mining prediction, AM, AR, Markov Model, ArtificialIntelligence.

Introduction

Cognitive radio (CR) is the password to open the way for future wireless networks, by its new methods of opportunistic access and efficient management of radio resources, CR can solve the actual problem of spectrum scarcity. In the literature, CR engine is meanly based on five issues to perform its functionalities which are spectrum sensing, spectrum access, spectrum mobility, spectrum sharing, and spectrum prediction. These functionalities are collected in the concept of CR cycle, where a CR intelligent system can be aware of its surrounding environment by learning the radio environment using spectrum sensing, analyzes the frequency elements, detects primary users' activity and decides spectrum opportunities. After that, send the decision to the software defined radio (SDR) unit and thus to the MAC layer.

One of the five main issues of CR is spectrum prediction which is added to this engine to insure a good quality service with safe access for Secondary Users (SUs), far from Primary Users' interferences caused by spectrum sensing delays, processing and decision making delays. Thus, spectrum prediction can be defined as the most useful method for the integration of SUs. The goal of which is to forecast the channel state information by giving us preliminary results about channel occupancy (busy or free). Therefore, an ideal exploitation of spectrum holes.

In the literature, some relevant works have been done in the context of the classification and the citation of the different methods of spectrum prediction in cognitive radio networks (CRNs). Where in [1] authors, in a comparative survey (2017), classified Spectral prediction strategies according to its nature into three categories, regression analysis based methods, spectrum prediction methods based on Markov model, and third one based on machine learning.

The papers in [2] & [3] surveyed and evaluated the state of the art of spectrum prediction in CRNs and summarized its' major techniques and their applications, and addressed the relevant open research challenges. Furthermore, the basic spectrum hole prediction schemes have been studied in [4], its theory and applicability to spectrum prediction, their advantages and shortcomings are highlighted. Then future research direction is discussed.

In this paper, authors provide a survey on spectrum prediction methods in CRNs, where the presented methods are sorted in four categories, Pattern mining prediction, linear prediction, Markov Model prediction methods, and prediction methods based on Artificial Intelligence. The aim of this work is to update the state of the art of spectrum prediction in CRNs, by providing another reading and diverse references more actual and innovative in this field, to be useful in giving an overview for students and researchers.

This article is organized as follows. The necessity of prediction is addressed in Section 2. Where section 3 introduces the prediction techniques and their important features. A summary discusses some perspectives, highlights prediction related issues and outlines methods tendencies, is provided in Section 4, followed by a conclusion in Section 5.

Necessity of prediction in cognitive radio networks

Secondary users in CRNs are claimed to perform spectrum sensing to ensure their opportunistic access to licensed spectrum. This operation especially in real time and by sensing the whole spectrum bands, results in non-negligible time delays and increasing energy consumption. After sensing then detecting spectrum holes, a decision making process is followed, which leads to additional time delay. In this way, a SU will be late in entering the spectrum band, so, it loses a part of its attributed band (underutilization), and thus reduces the spectrum efficiency. This lateness may cause interferences with PUs occupancy bands. Moreover, if multi-CR-users join the spectrum at the same time or at different times with different bandwidth demands and quality of service (QoS) requirements. So, assigning appropriate spectrum bands to the bursty heterogeneous CR service requests will complicate spectrum management using traditional spectrum sharing policies [2].

Therefore, the best way to solve all these problems is the addition of prediction process to spectrum sensing to make this function more intelligent and more efficient. Where, SUs sense only spectrum bands which are predicted to be free in time and space dimensions and selects a high-quality channel for sensing and accessing to increase the efficiency of its dynamic spectrum access instead of sensing the whole licensed bands, which decreases sensing time, meanwhile, reduces the additional energy consumption [2].

Predictive Algorithms

Pattern mining prediction methods. This kind of methods bases mainly on the continuously memorization of the past observations of spectrum energy simples, which will be stocked in a matrix. Then, the prediction will be done according to the most frequent patterns. These prediction techniques which investigate historical frequency spectrum data to predict the next working period spectrum, is considered as a time series prediction problem.

As an example 2-D frequent pattern mining algorithm (2D-FPM) is proposed in [5], where authors represented Channel State Informations (CSIs), over time, across channels, and for deferent wireless services, as a binary sequence of 0s and 1s, through a thresholding process, and by extracting spectrum opportunities then drawing the data distribution, in addition, studying the temporal / spectral / spatial correlation of CSIs, spectral data can be memorized with sufficient informations which facilitates the prediction process. This prediction method first, finds frequent patterns which must be appears no less than 200 times throughout the CSI series in a set of channels. Second, finds associations among these patterns, then build a new prediction pattern to forecast the next states of channel occupancy.

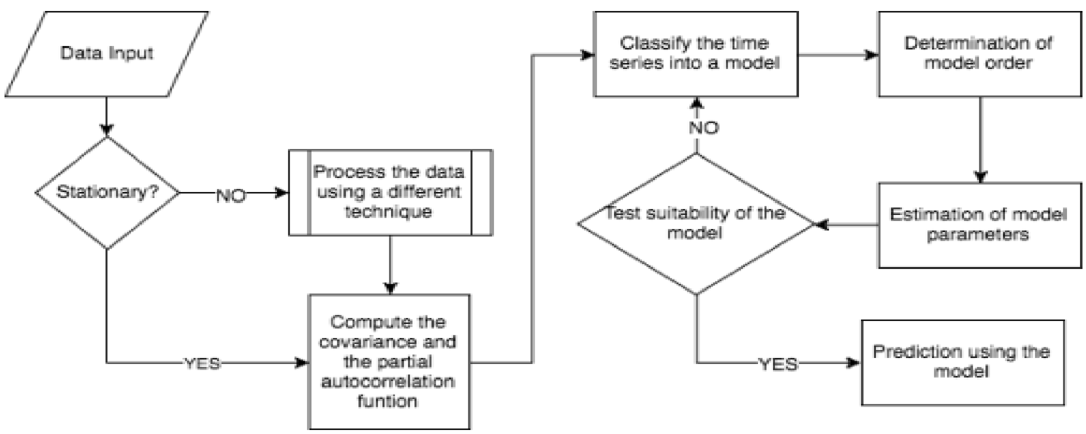
Linear Prediction (LP). LP algorithms mainly include: Mobile Average (MA), autoregressive (AR), Auto-Regressive Moving Average (ARMA) and Auto-Regressive Integrated Moving Average model (ARIMA). LPs are widely used to deduce signal power also to predict spectrum in time domain, due to their remarkable simplicity. Where future values are predicted as a linear function of previous samples [3].

The prediction method based on (MA) shows good performance in predicting the change trend of the numerical sequence. The order-k MA predictor predicts that the next value of a sequence is the average of the last k values in the sequence [6].

Z. Lin et al. in [7] proposed a prediction method based on exponential moving average by combining the EMA prediction and energy detection method, which can predict the energy level in the frequency bands and enhance the spectrum sensing. Experiments show that this method can effectively reduce the spectrum sensing time end energy consumption and improve the efficiency of prediction [1].

AR models are commonly used to approximate discrete random processes. In this prediction approach, a CR user first estimates the model parameters, with Yule-alker equations, maximum likelihood estimation, or other approaches. Then, it inputs the history of observations into the prediction rule, and predicts the future state of the system [2].

However, these methods are mostly based on one-step prediction, and do not improve the performance of AR models in multiple predictions. The problem of updating the regression coefficients with high complexity in the regression model cannot be effectively solved. Thus, the Markov model with better prediction effect is proposed [1].



Prediction method based on Markov model. Commonly used Markov models are: 1st-order Markov model, N-order Markov model, Hidden Markov Model (HMM) stationary & non-stationary, Partially Observable Markov Decision Process (POMDP), Hidden Bivariate Markov Model (HBMM) and Variable Length Markov Model (VMM).

The 1st-order Markov model is the simplest prediction method from its structure, a few estimation parameters, and prediction accuracy, because it depends only on the relevant information about the present to predict the future state, not on the information of the distant past, which make it a memory-less model [3], it is also the most suitable model for forecasting time series. But its shortcoming is that it involves a decision delay which decrease the spectrum efficiency. In order to overcome this shortcoming, authors proposed the N-order Markov model, which takes into account more historical information, but it is found that with the increase of order, complexity exponentially grows, which leads to the increase of the prediction delay of the model [1].

In [8], Z. Hong et al proposed a spectrum prediction method based on High-order Hidden Bivariate Markov Model, (H^2BMM), by supporting the advantages of high-order (consideration of more prior states) with the Hidden Bivariate HBMM (modeling multi-sub-states channel behavior) to predict channel states for stationary SU, then approached the advanced H^2BMM to take in account SUs mobility by adjusting the training method of H^2BMM. To improve the performances of their approach a comparison with the conventional HMM prediction approaches has been done under three main factors; transient state probability, prediction steps and order of HBMM. Whereas, H^2BMM improved the best results comparing with the conventional approaches, but in a higher-prediction-steps, the prediction accuracy decreases for both. In addition, this method can extract the hidden correlation between adjacent observations (prior states) which increase the prediction accuracy.
Furthermore, authors in [9] investigated Non-Stationary Hidden Markov and Hidden Bivariate Markov Models to build a parallel (multi-channel) predictive spectrum sensing using real-time collected data (from the public safety frequency band). The model parameters have been estimated by adaptive Expectation Maximization (E-M) Baum algorithm, in order to test the performances of the proposed method in a simple cognitive spectrum sharing scheme designed by the authors.

Prediction method based on Artificial Intelligence.

Neural Networks. Artificial Neural Network (ANN) is an artificial copy inspired from human nervous system, introduced by the neurophysiologist W. McCulloch and the logician W. Pitts in 1943 [10]. ANN is a complex computational structure composed of nonlinear neurons which are arranged in layers (input, hidden layers and output layer), and highly interconnected using adaptive weights connections to report information from the previous layer to the next. Neurons are basically the processing elements which receives the weighted sum of its inputs and produces an output via a nonlinear activation function [11].
In this way, ANN are classified as nonlinear regression, discriminant, and data reduction models [11]. Thereby, it is considered as a mechanism to analyze large amounts of data and learning from data to find patterns and detect nonlinear relationships by learning from examples then constructing an input-output mapping for the problem [12], this make it an easy learning and generalization model, but it needs a large amount of training data to ensure high accuracy prediction [1].
In the literature, the most common type of ANN used in spectrum prediction is MLPNs (Multi-layer linear perceptron networks). MLPNs are linear combined layers of neurons, defer from its training method, it can be trained using several methods such as back propagation (BP), genetic algorithm (GA), or combinations of methods, depending on the size of the network and its application, in the aim of enhancing the network performances [4].
In [13] & [14] authors used the (BPMLP) as a spectrum predictor to improve CR spectrum utilization and reduce sensing time and energy. Where in [13] they evaluate the performance of the MLP predictor under Stationary & Non-Stationary traffic conditions for various traffic scenarios. Whereas, it achieves more than 60% of spectrum exploitation using MLP predictor, which can discover more idle slots than a CR sense device and reduces around 51% of energy consumption. In an author hand, authors in [14] proposed system model for future wireless communication network (LTE- Advanced (5G)) based on the integration of back-propagation trained Neural Network (BPNN) in cognitive users with prediction (CUP) control units, to predict the next state information, then sense only channels predicted to be vacant. System performances has been evaluated in the term of mean square error.

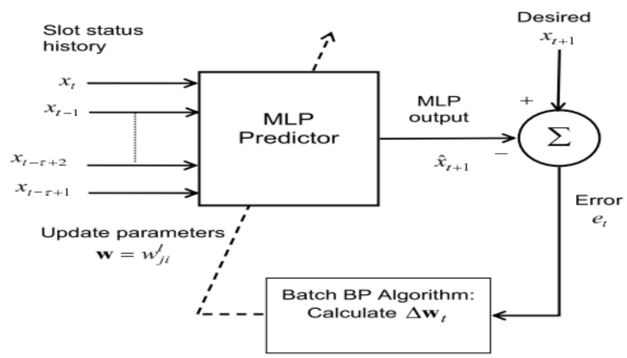


Fig 2. MLP predictor with BP training algorithm [13].

In the reference [15] M.I.Taj et al presented a new structure for spectrum prediction, using two stage framework. First, RF frequency spectrum is modeled and decomposed as multivariate chaotic time series using Exponential Moving Average, and exploiting the special cyclostationary features of PU signal. Second, the modeled and simplified signal (trivariate RF time series) is entered as input to the Elman Recurrent Neural Network (ERNN), to predict time series evolution. ERNN training is very delicate, thus, authors used Levenberg-Marquardt (LM) numerical method as a training algorithm. The algorithm is tested for UMTS frequency band, and obtained a very slight prediction error.

*SVM.*Support Vector Machine (SVM) based classifier is introduced by Vapnik in 1990. This type of classifiers are useful to solve discrimination and regression problems, function approximation and detection of very weak signals. Based on VC-dimensional theory and structural risk minimization principle, SVM can tackle these problems and therefore can avoid over-fitting of empirical risk problem. The SVM is a non-parametric, nonlinear learning technique which means automatic selection of model parameters and high generalization ability which made it widely used in the fields of data mining and spatio-temporal spectrum sensing problems. In addition, SVM model is simple in structure and easy to train with small training data sets compared with Neural Nets, but for large scale data sets, SVM performances decreases [1], [16]–[18].

Accordingly, SVM has been applied in Cognitive radio issues by combining it with other conventional, hitherto, fully-fledged …, and Empirical mode decomposition (EMD) techniques to overcome or reduce some of their shortcomings, depending on the sighted/outlined application performances [19].

Empirical mode decomposition (EMD) (Norden. E. Huang, 1998), is very suitable to SVM model properties dealing with nonlinear and non-stationary signal analysis and time frequency resolution better than STFT, Wigner-ville distribution, and Wavelet transform. EMD decomposition capability makes any complicated signal appears as simpler frequency components with strong correlation, and thus easier to be analyzed [16].

Table 1. Features and limitations of SVR [16].

Features and Advantages	Limitations
▪ Dealing with nonlinear and non-stationary data (nonlinear prediction); ▪ Time-series forecasting; ▪ Guarantee global minima; ▪ Adaptive to complex systems.	▪ Neglects the inherent characteristics of time series; ▪ Imperfect detection of the local data tendency ; ▪ Weak forecast precision.

To overcome these shortcomings Reference [16] merged the EMD with Support vector regression (SVR) methods (which employs SVM) to investigate the advantages of nonlinear and non-stationary signal decomposition with time-series forecasting using SVM capabilities, as a prediction algorithm called EMD-SVR. First, EMD decomposes the frequency spectrum series into several signal branches. Then, SVR is applied to each signal branch to perform spectrum prediction, and last, the overall forecasting value is obtained as the sum of the partial predicted values. The EMD-SVR model has been evaluated using Mean squared error (MSE), root-mean-squared relative error (RMSRE) and squared correlation coefficient (SCC) as performance indices, then compared with AR and common SVR prediction methods. The EMD-SVR model provides much more accurate prediction results than the AR and common SVR models, and can be useful for nonlinear, non-stationary and strong complexity data prediction in a Frequency monitor system (FMS).

*Deep Learning.*LSTM is a specific Recurrent NN structure that considered as the most effective and suitable tool in classifying, processing and making predictions dialing with time series data and their long-range dependencies more accurately than conventional RNNs. A common LSTM unit is composed of a cell memory that saves the past input sequence history, an input gate, an output gate and a forget gate, these three gates controls the information flow. LSTM network has the ability to process a large amount of diverse data dimensions, complex and nonlinear features, in addition to its property of selectively remembering patterns for long durations of time [20].

In the reference [20], authors proposed a new structure to perform Spectrum sensing and prediction, where, SUs are not obliged to waste power and time for continuous Spectrum sensing, because this job is attributed to distributed low-cost spectrum sensors (LCSS) which are deployed in different areas to provide the Fusion Center (FC) by predicted spectrum occupancies (Local predictions LPs). FC fuses (spatial fusion) the received LPs to make a decision which will be sent to the SBS based on SU location information, to decide the transmission strategies. Each LP unit represents an LSTM (Long Short-Term Memory) Deep learning model. LSTM based Deep-learning model is designed to capture the temporal dependencies on the SU's spectrum measurements and spatial fusion with Inverse Distance Weighting (IDW) nonlinear interpolation method is adapted to exploit the spatial correlation of SU and LCSS, then, a cooperative decision is made to decide the channel state information. Simulation results showed a good performances in minimizing sensing time and energy consumption, and make appeared the priority of cooperation in spectrum prediction for SUs.

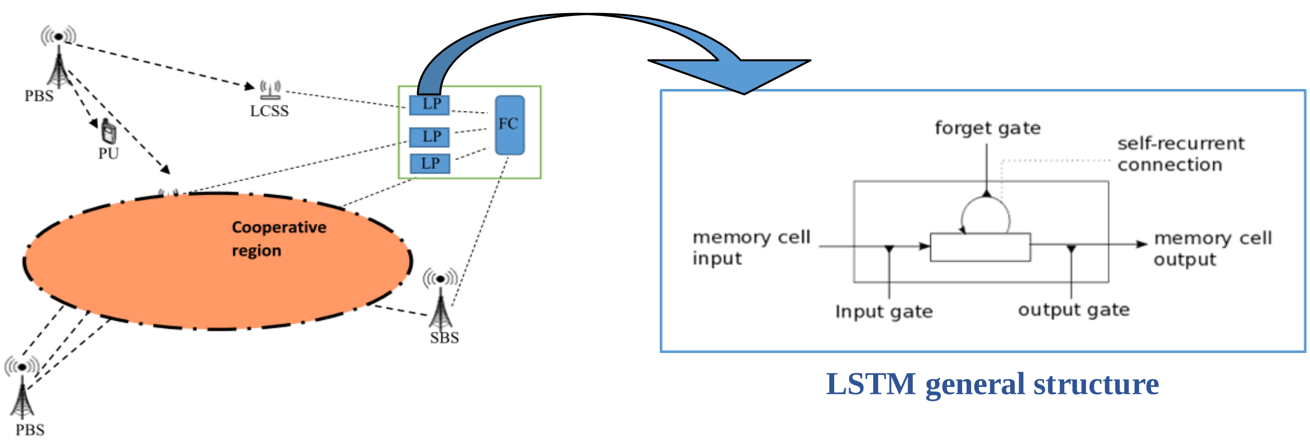


Fig 2. Cooperative spectrum prediction model [20].

Summary and Perspectives

- From this paper, it can be summarized that spectrum prediction is an essential function to be integrated in all new wireless services devices which belongs to CR network.

- Prediction concept has been studied in CRNs, until now, for two issues: spectrum prediction and mobility prediction, but the third issue which hasn't been studied yet, is spectrum sharing prediction [2]. It still waited to be extensively studied and modeled, because of it's extremely importance in cooperative spectrum sharing, in giving safe access to all CR secondary users, and consequently insuring an efficient spectrum management.
- Two states based spectrum sensing and prediction techniques [1], which limit the channel state information only in (busy and idle) may lost some good opportunities to be captured. Therefore, the exploitation of multi-state spectrum prediction may enhance the probability of better utilizing the spectrum opportunities, where the spectrum occupancy may be classified at least into three levels, busy, idle and underutilized, and it may exceed to predict PU's signal phase, modulation, or slot times to investigate even a small opportunity.
- The prediction of the next state information depends mainly on the historical observed data. Hence, the memorized data may be an axial factor to distinguish the different prediction methods. It means that all these methods varies from: which data to be memorized? Also, How to detect or estimate this data? And how to process and manage these information? to predict the next state information. Accordingly, each prediction method depends on the spectrum information extracted (energy, power, voltage, waveform, parameters (model parameters, phase, amplitude, velocity) or signals correlation like HMM...).

Conclusion

Spectrum Prediction is a promising approach for the realization of an effective cognitive radio network which provides a good quality of service (QoS), optimized spectrum utilization, and better spectrum sharing. In this paper an overview on the various prediction techniques in CRNs has been presented. The aim of this work is to provide, readers especially researchers, a collection of summarized references for spectrum prediction, by highlighting the most important features and limitations of each prediction method followed by some examples, to simplify the selection of their favorite methods. The presented references are selected according to its innovative methods, especially articles used hybrid mechanisms which optimize the performances of the classical methods and overcome some of its limitations, and emphasized on the latest works in this field.

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