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Hidden Markov Model based Channel state prediction in Cognitive Radio Networks

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***Abstract*— Cognitive Radio (CR) appears as a more attractive solution for the efficient use of the radio frequency spectrum and has gained much interest in the field of research in recent years. Spectrum sensing is the main objective of the cognitive radio and detects the presence of the idle channel of the frequency spectrum. Cognitive radio, an intelligent spectrum sensing technology detects the spectrum holes or white spaces in the spectrum which reallocates this idle spectrum to unlicensed users called Secondary Users (SU) and without causing harmful interference to licensed users called Primary Users (PU). Normally prediction-based channel sensing carried out for the efficient utilization of spectrum for the unlicensed users using different prediction models and probability theory-based algorithms available in the literature. In this paper, we proposed a methodology for the prediction of channel state using Hidden Markov Model (HMM). A comparative analysis is carried out between the proposed technique with that of the traditional spectrum sensing technique and the accuracy of the predictor is established through numerous simulations. From the simulation results, conclusions are drawn and discussed.**

Keywords*—** *Hidden Markov Model (HMM),* ***Channel status prediction, Spectrum Sensing, Cognitive radio.

I. Introduction

Now-a-days, many researchers are interested in Cognitive Radio (CR) technology. We can say that the CR is the extended technology of Software Defined Radio. With the ever growing demand for high data rate spectrum, wireless applications face several challenges. The efficiency of the wireless communication depends mainly on how the Radio Frequency (RF) spectrum is allocated to the end users. According to Federal Communications Commission (FCC) [1], cognitive radios (CR) are defined as radio systems that continuously perform spectrum sensing, dynamically identify unused spectrum, and then operate in those spectrum holes where the licensed (primary) radio systems are idle. The spectrum-sensing modules in wireless technologies over the last decade have left us on the threshold of another spectrum management strategy. CR always senses Primary users (PU) appearing on the channel and must evacuate from that channel for preventing PU from interferences. For this purpose, CR should include a functionality of being able to find new relevant channel to move. So, CR must evaluate the quality of empty channels. CR system is an intelligent wireless communication system that is aware of its surrounding environment. CR implementations face many technical challenges, including spectrum sensing, dynamic frequency selection, adaptive modulation, and wide band frequency-agile RF front-end circuitry [2]. CR users need to detect the licensed user's presence or absence in order to utilize the spectrum efficiently. This technique is known as spectrum sensing. In order to enhance spectrum sensing performance, cooperative sensing with among CR users has to be used. More specifically, CR enables secondary users (SUs) to perform a series of operations as follows: 1) spectrum sensing to predict what spectrum is available and recognize the presence of the primary user (PU) when a PU reoccupies the licensed channel; 2) spectrum management to select the best available channel from the spectrum pool for special services; 3) spectrum sharing to coordinate access to all available channels with other SUs; and 4) spectrum mobility to vacate the channel as soon as possible when a PU is detected. Based on these backgrounds, we propose HMM and Multi user random based channel prediction techniques and implemented using MATLAB.

It is able to improve the efficiency of spectrum allocations by implementing dynamic spectrum allocation. Inadequacy of the RF spectrum resource transpires due to fixed frequency allocation by the regulatory bodies in each region is one of the major problems in allocating it to specific applications. Moreover the allocated RF spectrum is not fully utilized efficiently. In this paper, we present a novel approach for high precession spectrum sensing for CR using Hidden Markov Model (HMM). The accuracy of the proposed method is substantiated using extensive simulations.

In this paper, an approach for prediction of channel state using Hidden Markov Model (HMM) is proposed. The predicted channel states are output together with corresponding probabilities that are helpful to subsequent decision. Numerical results show that the proposed approach for prediction of channel state is effective. The proposed approach for prediction of channel state can be used together with traditional spectrum sensing techniques for spectrum sensing. And it can also be utilized to provide predictive information to upper-level modules of cognitive radio. Cognitive radio devices have the ability to dynamically select their operating configurations, based on environment aspects, goals, profiles, preferences etc. The proposed method aims at evaluating the various candidate configurations that a cognitive transmitter may operate in, by associating a capability e.g., achievable bit-rate, with each of these configurations. It takes into account calculations of channel capacity provided by channel-state estimation information (CSI) and the sensed environment, and at the same time increases the certainty about the configuration evaluations by considering past experience and knowledge through the use of Bayesian networks. Results from comprehensive scenarios show the impact of our method on the behavior of cognitive radio systems, whereas potential application and future work are identified.

II. REVIEW OF RELATED WORK

Cognitive radio (CR) techniques provide the capability of detecting spectrum holes and sharing the spectrum in an opportunistic manner. There are some related studies on prediction and hidden Markov model (HMM). The idea of predictive dynamic spectrum access has been designed with spectrum predictor by R. Min et al. [2], which aims at the distribution of period length of a channel being idle. T. Clancy and B. Walker have utilized multi-step ahead prediction to control the interference time ratio [3]. The Hidden Markov Model (HMM) [4] is a powerful statistical tool for modeling generative sequences that can be characterized by an underlying process generating an observable sequence. HMM is used for modeling & analyzing time series or sequential data in various fields today, such as automatic speech recognition, crypt analysis, natural language processing, computational biology, bioinformatics etc. With its prior knowledge, HMM is concerned about the unobserved sequence of hidden states and the corresponding sequence of related observation. S. Yarkan and H. Arslan proposed binary time series for spectrum occupancy characterization and prediction [5] and P. Chang-hyun et al. proposed a channel status predictor using HMM based pattern recognition [6]. Hao He et al. [7] developed, an adaptive spectrum sensing scheme to improve the throughput of cognitive radio (CR) users. The new scheme takes the variation of wireless channels into consideration and requires no prior knowledge of primary user activity statistics. At the beginning of each time frame, this adaptive sensing scheme adjusts the spectrum sensing parameters according to the latest sensing results and channel state information (CSI) of the time-varying channels. Numerical results showed that the adaptive spectrum sensing scheme significantly outperformed the traditional spectrum sensing scheme.

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A HMM-based channel status predictor was proposed by I. Akbar and W. Tranter [8] to predict the usage behavior of a frequency band based on channel usage patterns for making the decision of moving to another frequency band or not. The primary user traffic follows Poisson process with 50% traffic intensity (i.e., 50% channel time is occupied by the primary users). The secondary user will use the whole time slot if the slot is predicted idle. Another HMM-based predictor is also proposed by Akbar and W. Tranter, but it only deals with deterministic traffic scenarios, making it non-applicable in practice. Z. Chen et al. [9] employed first-order HMM to predict channel state for spectrum sensing. A major constraint of first order HMM is that a state only depends on one immediate previous state. Prediction using higher-order HMM is proposed to make a better use of the information of historical states for prediction of future states. To minimize the interference to the primary users, the secondary users need a reliable spectrum sensing mechanism. Several spectrum sensing mechanisms were proposed in literature [10-12]. Due to the hardware constraint, they can sense only part of the spectrum [10]. The spectrum sensing policies distribute the spectrum sensing operation among different groups of nodes. The existence of Markov chain for sub-band utilization by primary users (PU) has been validated by C. Ghosh et al. [13]. Qunwei Li and Zan Li proposed [14] a sequential sensing scheme based on Suprathreshold Stochastic Resonance (SSR). They address the theoretical bound to achieve potential performance improvement and give the applicable algorithm of the SSR-based sequential sensing scheme. On the other hand, due to the energy constraint, the secondary users may not have the willingness to waste energy to sense the spectrum part which is very likely to be busy. Hence, the key issue is to let the secondary users efficiently and effectively sense the channels in the licensed spectrum without wasting much energy. One way to alleviate this problem is, by using spectrum sensing policies such as given in Reference [10, 11].

III. PROPOSED MODEL

3.1 HMM based Channel state predictor

The channel status predictor is a part of the channel selector .The channel selector is composed of a channel manager, channel environment evaluator and channel status predictor. The Fig.1 shows the overview of the channel selector.

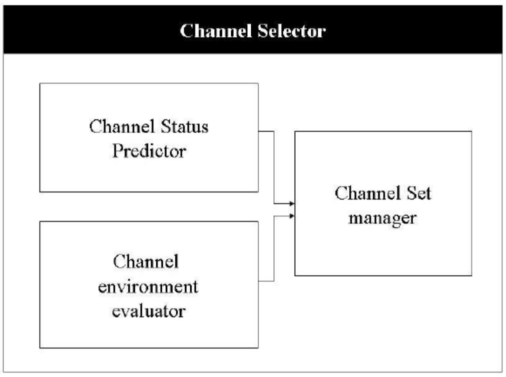

Fig 1 Channel selector overview

Chang-Hyun Park et al. presented in their paper “HMM based Channel Status predictor for Cognitive Radios” [6]. To implement the dynamic spectrum management, they considered two components in their channel selector. A channel state predictor is part of this module and enables the channel selector to make its decision.

HMM algorithm would study the data sequence available from the communication history and could be used for channel state prediction.

HMM model could be represented by a parameter 'λ' given by

$$\lambda = (A, B, \pi) \quad (1)$$

Where 'A' is transition probability, 'B' is emission probability and 'π' is initial state probability and a sequence of observations

$$O = (o_1, o_2 \ldots o_T). \quad (2)$$

The conditional probability P (O|λ) was necessary to calculate the posterior probability and usage of simple probabilistic analysis resulted in a very intensive computation method.

An auxiliary variable called *forward variable* α_t (i), defined as probability of a partial observation sequence (o_1, … o_t) when analysis was terminated at time *t* and state *i*, was introduced and is given by

$$\alpha_t (i) = P (o_1, o_2,\ldots,o_t, q_t = i \mid \lambda) \quad (3)$$

Similarly, *backward variable* β_t (i) was defined as probability of partial observation sequence

(o_{t+1}, ... o_T) given that the current state is *i* is given as

$$\beta_t (i) = P (o_{t+1}, o_{t+2},\ldots,o_T, q_t = i , \lambda) \quad (4)$$

it was shown that P (O|λ) could be expressed as summation of αt(i) and βt(i) over all the states '*i*'

$$P (O|\lambda) = \sum_{i=1}^{N} P(O, q_t = i|\lambda) = \sum_{i=1}^{N} \alpha_t(i)\, \beta_t(i) \quad (5)$$

Now, posterior probability could be calculated using forward and backward variables respectively expressed as

$$\xi_\tau (i,j) = \frac{\alpha_t(i)\, a_{ij}\, \beta_{t+1}(j) b_j(o_{t+1})}{\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_t(i)\, a_{ij}\, \beta_{t+1}(j) b_j(o_{t+1})} \quad (6)$$

and $$\gamma_t (i) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{i=1}^{N} \alpha_t(i)\, a_{ij}\, \beta_t(i)} \quad (7)$$

The relation between γ_t (i) and ξ_t (i, j) is given by

$$\gamma_t (i) = \sum_{j=1}^{N} \xi_t(i, j), \; 1 \le i \le N, 1 \le t \le M \quad (8)$$

Lastly, using Baum-Welch algorithm the parameters of our starting model λ = (A, B, π) through the *re-estimation formulae* is calculated as

$$\overline{\pi_i} = \gamma_1 (i), 1 \le i \le N \quad (9)$$

$$\overline{a_{ij}} = \frac{\sum_{t=1}^{T-1} \xi_t(i,j)}{\sum_{t=1}^{T-1} \gamma_t(i)}, 1 \le i \le N, 1 \le j \le N \quad (10)$$

$$\bar{b}_j(k) = \frac{\sum_{t=1}^{T} \gamma_t(j)}{\sum_{t=1}^{T} \gamma_t(i)} 1 \le j \le N, 1 \le k \le M \quad (11)$$

and hence the posterior probability was maximized.

With the parameters of HMM available, the MATLAB simulator was ready for implementation. A pattern was loaded into the simulator and in the manner related above, the HMM trained and found its parameters and decided the most likely next state.

IV. SIMULATION RESULTS

In this section, we represent simulation result in order to confirm performance improvement of the proposed system model using MATLAB. The graph is plotted for secondary user (SU) output sensed by cognitive radio (CR) against channel state. Here, the evaluation parameter SU can be defined as the ratio of number of idle slots discovered by the secondary user to the number of idle slots available in the system over a finite period of time. The comparative analysis is carried out with respect to random and HMM based techniques. Comparative plot for SU by varying number of channels is shown from Fig 2 through Fig 4. The result also says that SU decreases with increase in the number of channel state. Therefore, we can conclude that the accuracy of prediction rate by the simulator can be further improved by using higher order algorithms.

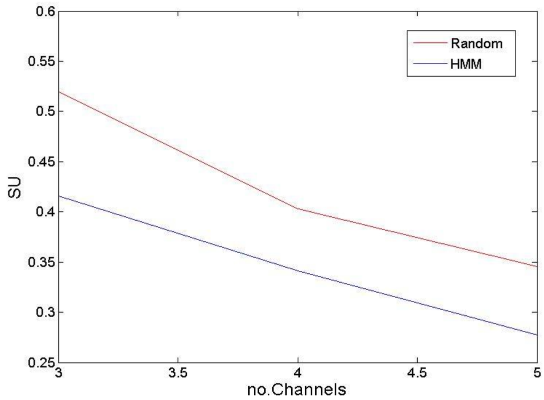

Fig 2: SU plot for varying channels (5-channel)

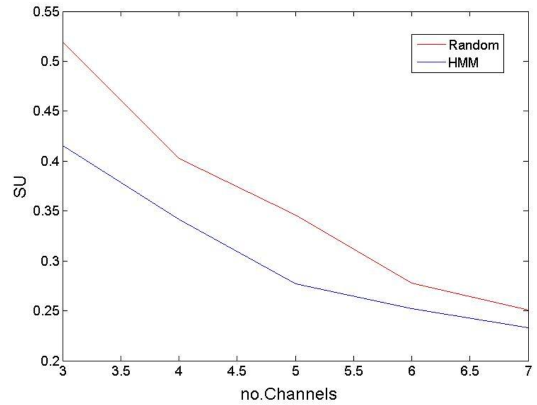

Fig 3: SU plot for varying channels (7-channel)

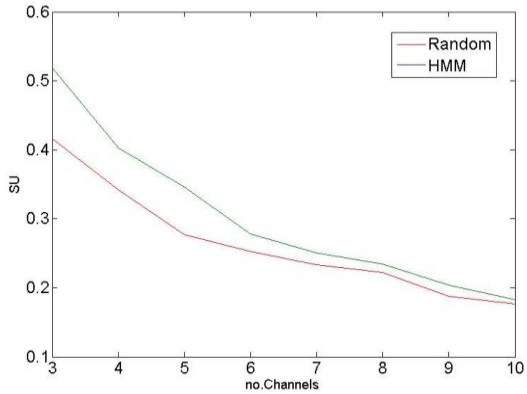

Fig 4: SU plot for varying channels (10-channel)

V CONCLUSIONS

Cognitive radio is the technology for using radio resources effectively. Channel status prediction plays a very important role as a part of CR. We have demonstrated that models that contain less number of channels do provide better evaluation parameter SU. The proposed HMM based technique provides better results and hence, shows the efficiency of the technique. However the simulation results say that the technique has a disadvantage with the increase in the number of channels. In order to improve the success rate higher order Hidden Markov Model and/or artificial intelligence based neural network based techniques are suggested.

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