COVER SHEET

DYNAMIC SPECTRUM ALLOCATION IN COGNITIVE RADIO USING MARKOV MODELS

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ABSTRACT

In this work we use hidden Markov Models (HMMs) to model and predict the spectrum occupancy of licensed radio bands. The method can dynamically select different licensed bands for its own use with significantly less interference from and to the licensed users. It is found that by predicting the duration of spectrum holes of primary users, the CR can utilize them more efficiently by leaving the band, that it currently occupies, before the start of traffic from the licensed user of that band.

The impact of CR transmission on the licensed users is also presented. It is shown that significant SIR improvements can be achieved using HMM based dynamic spectrum allocation as compared to the traditional CSMA based approach. The results obtained using HMM are very promising and HMM can offer a new paradigm for predicting channel behavior, an area that has been of much research interest lately.

1. INTRODUCTION

The organization of this paper is as follows. First we will briefly introduce cognitive radio and hidden Markov models. The use of HMMs in time series prediction is also discussed briefly. Next we discuss Markov-based Channel Prediction Algorithm (MCPA). Simulation results and conclusions are given later.

Recent measurements have shown that there are frequency bands even in urban areas that are largely unoccupied, some of them are only partially occupied and some are heavily used. These spectrum usage statistics give us a notion of *spectrum holes* which are defined in [1] as bands of frequencies assigned to a primary user, but at a particular time and specific geographical location, the bands are not being utilized by that user. The concept of the utilization of spectrum holes in CR using CSMA based band allocation is shown in Fig. 1. In this technique, the CR network identifies a spectrum hole and uses it until traffic from the primary user is detected. Once it detects primary user's data transmission, the CR jumps out of the band it was occupying and looks for spectrum holes in other bands of interest.

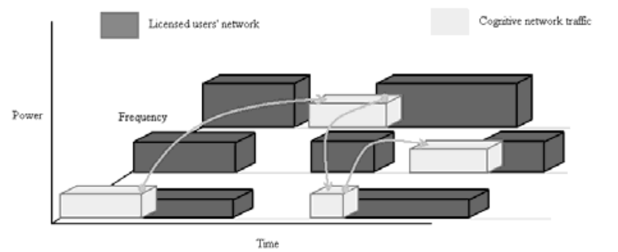

Figure 1: Illustration of spectrum holes in a cognitive radio network. Spectrum allocation is performed using a conventional CSMA based technique.

Spectrum utilization can be improved significantly by making it possible for a secondary user (who is not being serviced) to access the spectrum hole unoccupied by the primary user at the right location and at the right time. Cognitive radio has recently been proposed as a method to promote the efficient use of the spectrum by exploiting the existence of spectrum holes. It observes the current spectrum conditions in the given band, and if it detects no traffic, it may start its data transmission using the same band. While engaged in the transmission, the radio may observe the signal of the incumbent user. In conventional CR design, if such signal is detected, the radio's cognition cycle should direct itself to jump out of the spectrum to minimize interference. It should then look for other available spectrums to continue its data transmission. In this work, we propose a new way of utilizing the spectrum holes. Instead of jumping out from the frequency band after detecting the presence of signal from licensed user, we propose to perform a prediction on its usage behavior and then decide to remain in the same frequency band or move to another band. If correct prediction is performed, the CR can leave the current frequency band before detecting any signal from the primary user. We hope that our method will provide minimal collisions with the signals from the licensed users.

Our methodology can be explained as follows. Different HMMs first train themselves using spectrum usage patterns of the incumbent users and once reliable models are developed, the spectrum manager decides which frequency to use based on the likelihood of spectrum holes of these bands. In this work, usage patterns are assigned binary bits with zeros indicating no traffic and ones indicating that the spectrum is being used by the incumbent user at that particular time. Hence we obtain binary vectors for each frequency band and use these vectors as training sequences for HMMs assigned for different radio bands. The HMMs will then predict the occurrence of spectrum holes in different bands and the cognitive engine will dynamically choose these available frequencies for its use.

2. THEORY

2.1 Hidden Markov Models

A hidden Markov process (HMP) [8] is a doubly stochastic process in which the generation of observation symbols depends on the emission properties of the states. Therefore, a state can generate more than one observation symbol and the state sequence is not directly observable given the observation sequence.

Mathematically, an HMP can be defined as the pair $\{X_t, Y_t; t \in \mathbb{N}\}$ of stochastic processes defined on the probability space (Ω, F, P). Here X_t and Y_t denote the hidden state sequence and the observation sequence respectively. The finite set (X, Y) is said to be a stationary finite state system (SFSS) if the following conditions are met:

(i) (X_t, Y_t) are jointly stationary

(ii) $\Pr\left(Y_{t+1} = y_{t+1}, X_{t+1} = x_{t+1} \mid Y_1^t = y_1^t, X_1^t = x_1^t\right) =$

$$\Pr\left(Y_{t+1} = y_{t+1}, X_{t+1} = x_{t+1} \mid X_t = x_t\right).$$

The processes X_t and Y_t are called the state and the output of the SFSS respectively. The mathematical model that can generate such a HMP is called a hidden Markov model (HMM). A HMM [6] is a finite state machine in which the observation sequence is a probabilistic function of states. It defers from Markov chains (MCs) [15] where the observation sequences is a deterministic function of states. In case of MCs, the states are directly observable from the observation sequence where as in case of HMMs, the state sequence is not directly observable for the observed data and is hidden. HMMs were first introduced as a pattern recognition tool by Rabiner [7] in the beginning of the 1970's. Ever since, these models are used in many areas of sciences and engineering because of their strong mathematical structure and theoretical basis. Some of these applications are speech and handwriting recognition, DNA sequence analysis, wireless channel modeling, etc.

A discrete time HMM with N states and M symbols consists of an $N \times N$ state transition matrix **P** that defines the probability of transitioning from one state to another or itself, an $N \times M$ output symbol probability matrix **B** that gives the probability of generating different output symbols while being in a particular state, and an N dimensional vector called the initial state probability vector that gives the probability of being in a particular state at the start of the process. A hidden Markov model is denoted as ζ = {**P**, **B**, π}. These parameters can be estimated using the Baum-Welch Algorithm (BWA), which is basically a derived form of the Expectation-Maximization (EM) algorithm for HMMs. Due to the need for an online estimation in real world applications, we use a modified version of the BWA, called as the Forward-only BWA (FO-BWA) that can estimated HMM parameters *on the fly*. Details about FO-BWA can be found from [2].

For the case of binary sequences, the probability of generating the observation sequence given the model ζ can be written mathematically as

$$P(y_1^T \mid \zeta) = \sum_{i_1=1}^{N} \dots \sum_{i_T=1}^{N} \boldsymbol{\pi}\mathbf{B}(y_1)\ \mathbf{P}\mathbf{B}(y_2)\ \mathbf{P} \dots \mathbf{P}\mathbf{B}(y_T)\mathbf{1}' \quad (1)$$

Here $\mathbf{B}(y_k)$ with $k = 1, 2, \dots, T$ denotes the probability of generating symbol y_k from different states. Because of the significantly long data size, we use the logarithm of $P(y_1^T \mid \zeta)$, usually known as log-likelihood. We predict the next behavior of channel by finding the joint probabilities $P(y_1^T, 0 \mid \zeta)$ and $P(y_1^T, 1 \mid \zeta)$.

There seems to be an increased interest in data prediction/forecasting using HMMs recently. Some of the recent work includes stock market forecasting [9, 11], forecasting early conflict in southern Balkans [10] and predicting earthquakes. The main reason of such a wide use of HMM in prediction problems is mainly because of its strong theoretical foundations and tractability. This is mainly because of the fact that using HMM to forecast time series is easily explainable and has solid statistical foundation, properties that are not usually available in Artificial Neural Networks (ANNs) [12] and [14], which is also used frequently for predicting time series.

2.2 Markov-based Channel Prediction Algorithm (MCPA)

The spectrum occupancy is modeled as binary sequence with one determining that the spectrum is occupied at the particular instant by the primary user and a zero denoting that the spectrum is unoccupied at that instant. The spectrum usage pattern is modeled as exponentially distributed with channel occupancy ratio of more than 50% in all cases.

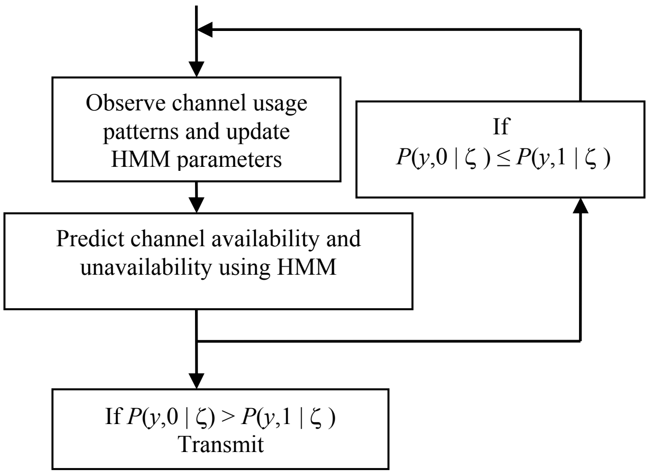

Figure 2: Flowchart of the MCPA for a single primary user case.

Let us now explain the Markov-based Channel Prediction Algorithm (MCPA) that is used to predict the behavior of different channels and then performs spectrum allocation dynamically. Binary sequences are obtained based on channel statistics as explained earlier. Different HMMs are then trained for each frequency band of interest using these binary sequences. Forward-only BWA is used to obtain the parameters of HMMs, namely the state transition matrix **P**, output symbol probability matrix **B**, and the initial state probability vector π. The flowchart of the algorithm in case of single primary user is shown in Fig. 2.

We predict channel behavior by finding the joint probabilities $P(y_1^T, 0 \mid \zeta)$ and $P(y_1^T, 1 \mid \zeta)$. If we observe $P(y_1^T, 0 \mid \zeta) > P(y_1^T, 1 \mid \zeta)$, this means that the probability of a particular frequency band being unoccupied is higher than the probability of it being occupied. We compare the two probabilities with a threshold δ such that the channel is used when

$$P(y_1^T, 0 \mid \zeta) - P(y_1^T, 1 \mid \zeta) \ge \delta \qquad (2)$$

Simulations are performed using this criterion with different values of δ. Results of these simulations are shown later. Due to large data size, the true likelihood of the process tends to zero and we use split data likelihood [5] to estimate the true value of likelihood. Because of extremely low numerical values of these probabilities, we use the logarithm of these probabilities and find the ratio of log-likelihoods to compare it with a threshold δ. In this process, the observation sequence is segmented into blocks of equal length and these blocks are considered mutually independent. The overall likelihood of the observed process is then the product of individual likelihoods. Mathematically, for block size of m and a total of n blocks, we can write

$$P(y_1^T \mid \zeta) = \prod_{k=1}^{n} P(y_{1+m(k-1)}^{mk} \mid \zeta) \qquad (3)$$

The graphical illustration of MCPA technique is shown in Fig. 3. Note that the CR traffic leaves a particular band before the detection of data transmission from the primary user. In this way, we can significantly reduce the impact of CR network on the licensed users. Simulation results have shown significant improvement in the SIR of licensed users by using the MCPA.

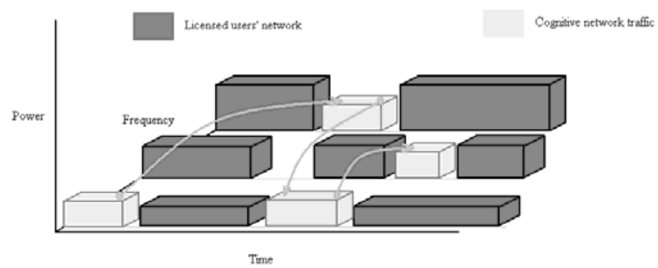

Figure 3: Illustration of dynamic spectrum allocation using MCPA.

The case of multiple primary users is just an extension of single user case. Different log-likelihood ratios are calculated and the channel that gives the highest probability of being unoccupied among all channels is selected for data transmission.

3. SIMULATION RESULTS

We present the simulation results with four licensed users (here called interferers) and one unlicensed user. Each interferer has a unique spectrum usage pattern that has the occupancy probability of not less that 50%. Fig. 4 shows the graphical representation of the simulation setup. The four licensed users use their respective spectrum independently from each other and their transmissions follow the exponential distribution, which is a widely popular assumption. The slot duration of both primary user and CR network is assumed to be same here. Also, the system is assumed to be interference limited and noise is ignored in this study.

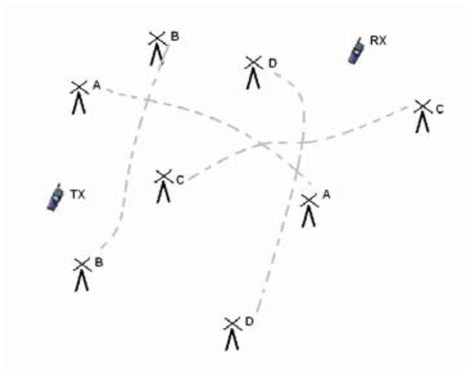

Figure 4: Simulation scenario with four licensed users and one cognitive radio transceiver labeled as 'TX' and 'RX'. The primary users are labeled using upper case alphabets (A, B, C, and D).

Figure 5(a), 5(b), 5(c) and 5(d) show the statistics of spectrum usage by the first, second, third and fourth primary users respectively. The first plot shows the frequency of consecutive time slots when a particular spectrum is occupied whereas the second plot shows the frequency of consecutive unoccupied slots.

We present a comparison with a conventional CSMA based spectrum allocation technique and our proposed method of HMM based dynamic spectrum allocation. In CSMA based spectrum allocation scheme that we adopt, the CR uses the channel when it observes no activity by the primary user and quits it whenever it senses that the primary user has started sending data through that channel (which may be very difficult to perform in practice). So we expect some degradation in terms of SIR of the primary user because of the interference from the CR network that can not be completely avoided using the CSMA based approach. However, these possible collisions can be avoided by using the MCPA approach as the CR leaves the channel before the start of data transmission by the primary user. We perform a study to observe the impact on the licensed users by using these two techniques. We vary the power of the CR signal while keeping the powers of licensed signals constant and calculate the SIR at the receiver of the primary users. The CDFs of the SIRs in both cases (CSMA and MCPA) are plotted in Fig. 6. We can see an improvement of approximately 12dB by using Markov based dynamic spectrum allocation approach.

Table I shows the BERs for different values of δ and their corresponding throughput for different ratios of log-likelihoods. As we can see that the increase in this ratio gives better performance in terms of BER. At the same time, the throughput decrease because of tougher constraints that the radio has to fulfill in order to transmit its data. Fig. 7 is the BER plot for the different values of log-likelihood ratios used in the simulation. It also shows the average throughput associated with different values of threshold δ. It can be seen that increasing δ improves the BER performance of the CR, but at the same time it reduces the average throughput of the CR system. Figure 8 shows the percentage of time CR uses these four licensed bands for its data transmission.

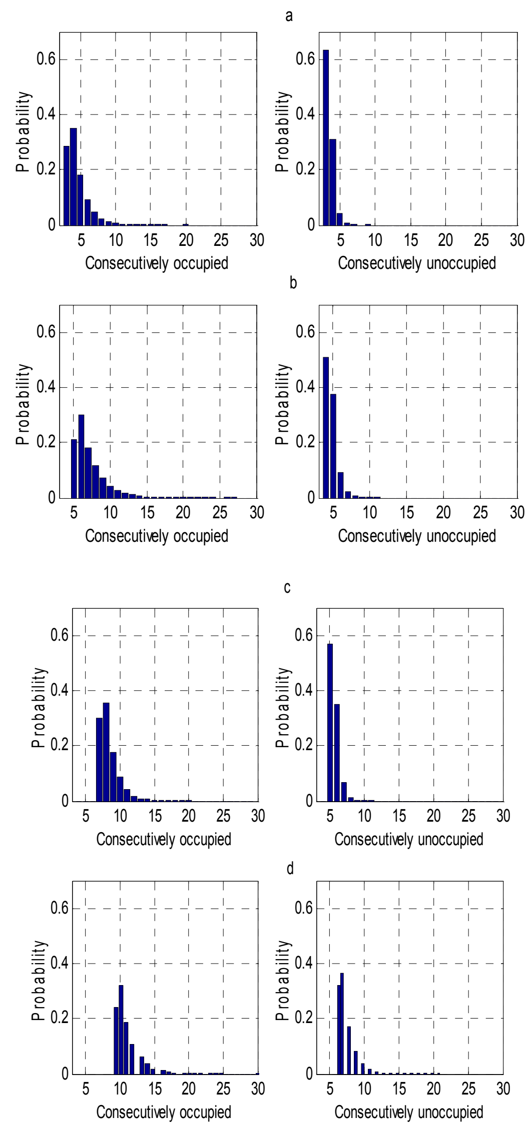

Figure 5: Spectrum usage patterns of (a) - first licensed users, (b) - second licensed user, (c) - third licensed user and (d) - fourth licensed user.

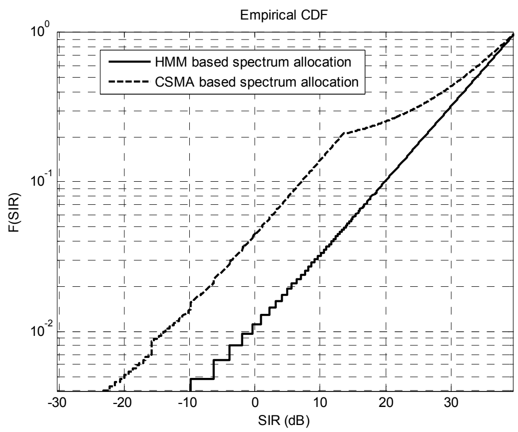

Figure 6: Comparisons of the primary user's SIR using CSMA based and MCPA based schemes.

TABLE I
PERFORMANCE OF THE MCPA IN TERMS OF BIT ERROR RATE AND THROUGHPUT.

Ratio of log-likelihoods	No. of bits transmitted	BER	Throughput %
~0	4352	0.0294	98.25
0.0005	7905	0.0248	81.66
0.0030	4384	0.0212	69.55
0.0040	3016	0.0196	63.98
0.0059	5579	0.0151	48.15
0.0060	21794	0.00059	32.05
0.0063	47074	0	27.47

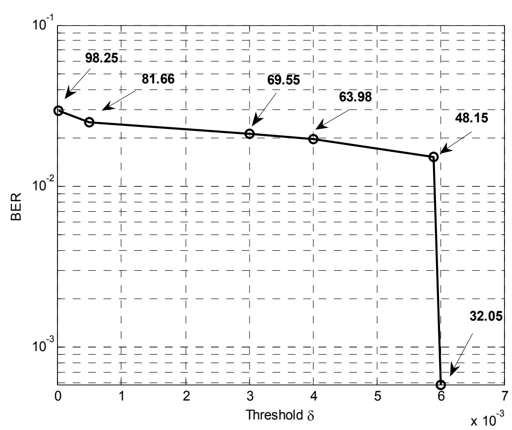

Figure 7: Performance of MCPA with four primary users.

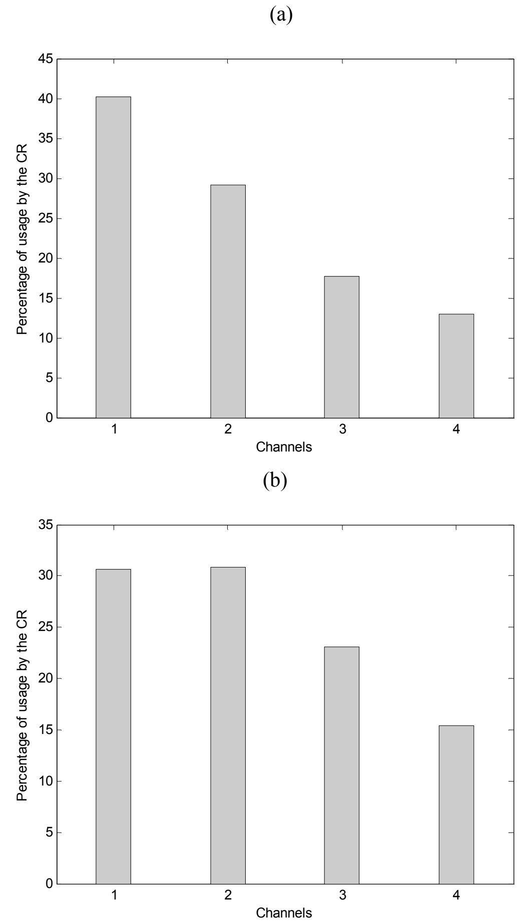

Figure 8: Percentage of time the cognitive radio uses four radio bands using (a) - CSMA based scheme and (b) - MCPA based scheme.

4. CONCLUSION

We conclude that HMMs can significantly aid in dynamic spectrum allocation in cognitive radio by performing accurate predictions of the channel states of licensed users. We see that by properly tuning HMM parameters we can obtain the performance comparable to BPSK case with just AWGN noise present in the system even though the CR is using frequency bands that are used by the primary users more than 50% of the time. This obviously comes with the cost of lowering the throughput as we put more strict condition on the use of licensed channel by increasing the threshold.

5. REFERENCES

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