Hidden Markov Models Based Channel Status Prediction for Cognitive Radio Networks

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Abstract— Cognitive radio (CR) networks can be designed to manage the radio spectrum more efficiently by utilizing of temporarily not used channels in primary users' licensed frequency bands. Here, the spectrum utilization can be improved significantly by spectrum sharing between primary and secondary users (who are not being served by the primary system). In this paper, we propose to use so called Hidden Markov Models (HMM) to predict the spectrum occupancy of sharing radio bands. The results obtained using HMM are very promising and they show that HMM offer a new paradigm for predicting channel behavior in cognitive radio.

1. INTRODUCTION

The Cognitive Radio (CR) technology appears as an attractive solution to effectively allocate the radio spectrum among the licensed and unlicensed users. As spectrum sensing consumes considerable energy, predictive methods for inferring the availability of spectrum holes can reduce energy consumption of the unlicensed users to only sense those channels which are predicted to be idle [9]. Prediction-based channel sensing also helps to improve the spectrum utilization for the unlicensed users. In this paper, we demonstrate the advantages of channel status prediction to the spectrum sensing operation. Under the CR technology, a licensed user is referred to as the primary user (PU) while an unlicensed user is referred to as the secondary user (SU) because of the priority in accessing the licensed user spectrum. In most of the cases, the secondary users in a Cognitive Radio Network (CRN) logically divide the channels allocated to the primary user spectrum into slots [1]. Within each slot the secondary user has to sense the primary user activity for a short duration and accordingly accesses the slot when it is sensed idle. The spectrum access by the secondary user should not cause any harmful interference to the primary user. 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 [2–4]. Due to the hardware constraint, they can sense only part of the spectrum [5]. 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. Alternately, the spectrum sensing module can be made energy efficient by combining the sensing operation with a channel status prediction mechanism. The secondary user may predict the status of a channel based on the past sensing results and sense only if channel is predicted to be idle in next time slot. Thereby, the secondary user may use its sensing mechanism resourcefully. Besides, using channel status prediction, the effective bandwidth in the next slot may be estimated which allows the secondary users to adjust the data rates in advance.

The rest of the paper is organized as follows. In Section 2, we present the related work. In Section 3, we propose two state Markov model to predict channel status. In Section 4, we present the simulation results of our prediction algorithm. Finally, Section 5 concludes this paper.

2. RELATED WORK

The channel status prediction problem is considered as a binary series prediction problem [6]. The channel occupancy in a slot can be represented as busy or idle depending on the presence or absence of a primary user activity. The binary symbols 1 and 0 denote the busy and idle channel status, respectively. Using the binary series, the predictor is trained to predict the primary user activity in the next slot based on past observations. In a multiple channel system, a predictor is assigned to each channel. In Reference [7], a HMM-based channel status predictor was proposed. 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. However, in Reference [7], the accuracy of prediction is not provided. Another HMM-based predictor is also proposed in Reference [8], but it only deals with deterministic traffic scenarios, making it non-applicable in practice. The idea of predictive dynamic spectrum access has been introduced in [10], which aims at the distribution of period length of a channel being idle. HMM has been used to predict the usage behavior of a frequency band based on channel usage patterns in [11] for making the decision of moving to another frequency band or not.

3. PROPOSED ALGORITHM

The Hidden Markov Model is a stochastic model for sequential data. It is a stochastic process determined by the two interrelated mechanisms — a latent Markov chain having a finite number of states, and a set of observation probability distributions, each one associated with a state. At each discrete time instant, the process is assumed to be in a state, and an observation is generated by the probability distribution corresponding to the current state [9]. Two state Markov model may be described at any time as being in one of a set of N distinct states, S_1 and S_2. At regularly spaced discrete times, the system undergoes a change of state (is possibly back to the same state) according to a set of probabilities associated with the state. We denote the time instants associated with state changes as $t = 1, 2, \ldots$, and we denote the actual state at time t as q_t.

Now we formally define the elements of an HMM and explain how the model generates observation sequence. An HMM is characterized by the following [12]:

- N, the number of states in the model. Although the states are hidden, for many practical applications there is often some physical significance attached to the states or to sets of states of the model. Generally the states are interconnected in such a way that any state can be reached from any other state (an ergodic model). We denote the individual states as $S = \{S_1, S_2\}$;

- M, the number of distinct observations symbols per state. The observation symbols correspond to the physical output of the system being modeled;

- The state transition probability distribution $A = \{a_{ij}\}$, where:

$$a_{ij} = P[q_t = S_j | q_{t-1} = S_i] \quad 1 \leq i, j \leq N \tag{1}$$

  For special case where any state can reach any other state in a single step, we have $a_{ij} > 0$.

- The observation symbol probability distribution in state j, $B = \{b_j(k)\}$;

- The initial state distribution $\pi = \{\pi_i\}$, where:

$$\pi_i = P[q_1 = S_i | O, \lambda] \quad 1 \leq i \leq N \tag{2}$$

Given appropriate values of N, M, A, B and π, the HMM can be used as a generator to give an observation sequence:

$$O = O_1, O_2 \ldots O_T \tag{3}$$

The above procedure can be used as both generator of observations, and as a model for how a given observation sequence was generated by an appropriate HMM.

We assume that channel can be observed as being one of the following: state S_1: idle and state S_2: busy as illustrated in Figure 1.

On the Figure 2 we can see HMM predictor algorithm.

4. PERFORMANCE EVALUATION

In order to determine of the proposed solutions we conducted experiments using a computer simulation technique. We selected the Matlab simulation environment.

4.1. Experimental Setup

The Figures 3–6 are showing the activity of users in each channel (blue colour) and the prediction results (red colour — predicted state).

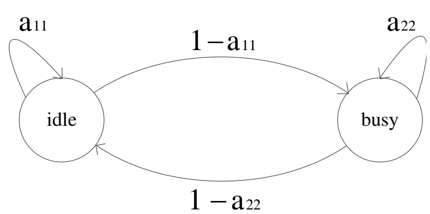

Figure 1: Two states Markov model.

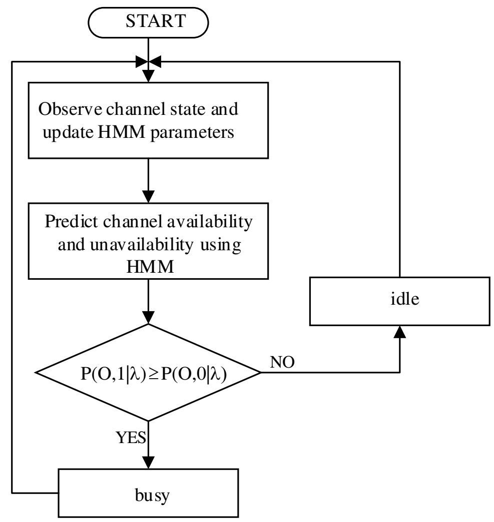

Figure 2: HMM predictor.

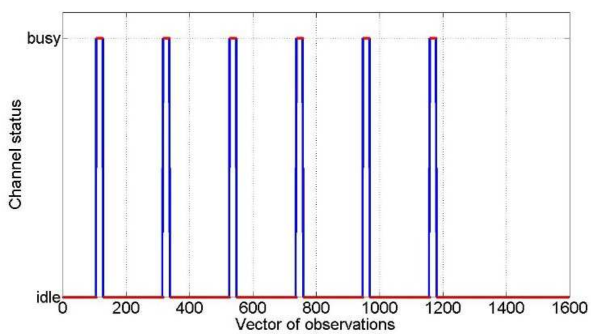

Figure 3: Channel 1. Length of vector of observations: 1560. Number of symbols correctly predicted: 1542. Number of symbols incorrectly predicted: 18.

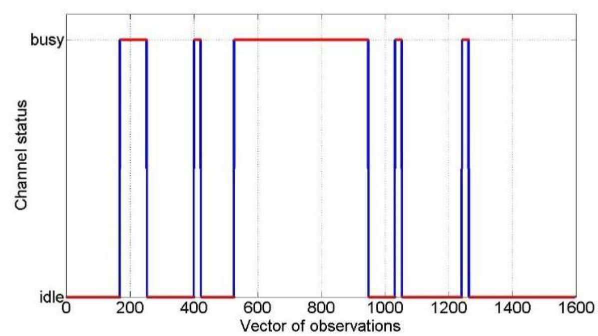

Figure 4: Channel 2. Length of vector of observations: 1560. Number of symbols correctly predicted: 1545. Number of symbols incorrectly predicted: 15.

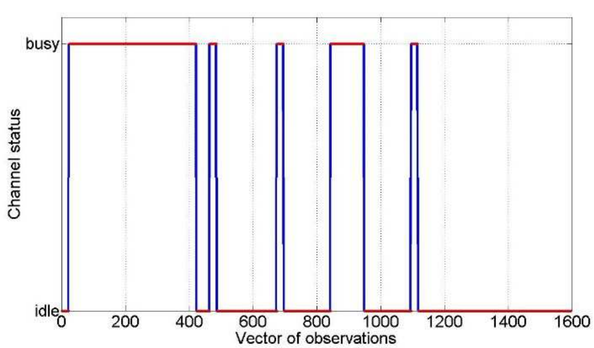

Figure 5: Channel 3. Length of vector of observations: 1560. Number of symbols correctly predicted: 1545. Number of symbols incorrectly predicted: 15.

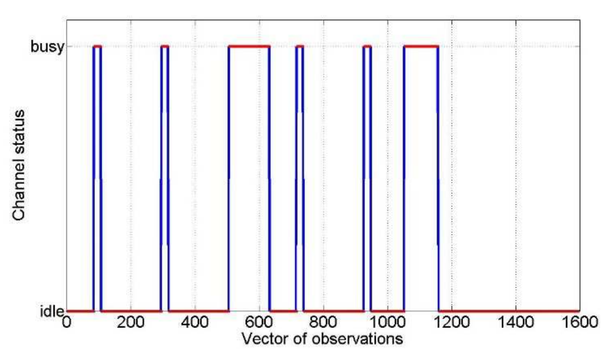

Figure 6: Channel 4. Length of vector of observations: 1560. Number of symbols correctly predicted: 1542. Number of symbols incorrectly predicted: 18.

5. CONCLUSIONS

In this paper we have attempted to present the theory of Hidden Markov Models from the simplest concepts of two state model. The results show that our model can be utilize for modelling PU activity for Cognitive Radio. Our simulation results show how channel occupancy prediction may help to reduce the number of channel switches that a SU may have to perform in a CR network. This should lower interference level experience by the PU, due to SU activity, and may potentially have a positive effect on SU throughput, since less transmission time will be wasted on channel switching.

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