An HMM-based Spectrum Occupancy Predictor for Energy Efficient Cognitive Radio

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Abstract—Spectrum sensing is the cornerstone of cognitive radio technology and refers to the process of obtaining awareness of the radio spectrum usage in order to detect the presence of other users. Spectrum sensing algorithms consume considerable energy and time. Prediction methods for inferring the channel occupancy of future time instants have been proposed as a means of improving performance in terms of energy and time consumption. This paper studies the performance of a hidden Markov model (HMM) spectrum occupancy predictor as well as the improvement in sensing energy and time consumption based on real occupancy data obtained in the 2.4GHz ISM band. Experimental results show that the HMM-based occupancy predictor outperforms a kth order Markov and a 1-nearest neighbour (1NN) predictor. Our study also suggests that by employing such a predictive scheme in spectrum sensing, an improvement of up to 66% can be achieved in the required sensing energy and time.

Keywords—cognitive radio; channel occupancy prediction; energy efficiency; hidden Markov model; spectrum sensing

I. INTRODUCTION

Recent research has shown that a large portion of the licensed spectrum remains unused for more than 90% of the time, resulting in low spectrum utilization [1]. With the increasing demand on high data rate wireless services driven by the continued growth of global population, the problem of radio spectrum utilization has become even more critical.

Cognitive radio (CR) technology has been proposed as one possible solution to addressing spectrum underutilization [2]. In contrast to conventional wireless networks in which all radios operate in a fixed band allocation scheme, in a CR network two different types of users coexist: Primary users (PU) and Secondary users (SU). PUs are conventional radios that operate in the licensed bands, while SUs are CR-enabled radios that obtain awareness of their spectral environment. Spectrum sensing is the process during which the SU senses its spectral environment in order to detect an available spectrum space and opportunistically access it by causing no or minimal interference to other users [3].

Several spectrum sensing techniques have been proposed such as energy detection (ED), matched filter detection and cyclostationary feature detection [4]. Moreover, cooperative spectrum sensing has been introduced as a means of improving spectrum sensing performance by alleviating the hidden terminal problem [5].

In the context of spectrum sensing, prediction refers to the process of estimating the future channel occupancy by exploiting a history of past spectrum sensing outputs. Within this context, the main purpose of our work is to implement an energy and time efficient spectrum sensing scheme based on channel occupancy prediction. In such a scheme, SUs will sense only the channels that are predicted to be unoccupied in future time instants rather than the whole band of interest.

In [6], channel status is considered as a binary time series model and an autoregressive (AR) model is used for predicting the probability of the channel to be occupied by a PU. In [7], an autoregressive moving average model (ARMA) is implemented to predict the received power of TV signals. The performance of hidden Markov model (HMM) predictor was studied in [8], for scenarios with deterministic channel occupancy. This scheme was tested only by simulation. An HMM-based channel status predictor is also proposed in [9]. However, the model’s parameters and performance are not provided. In [10], the performance of an HMM channel state predictor was experimentally evaluated for WiFi signals. The model’s parameters were obtained statistically without employing any training to the model.

In this work we investigate how channel occupancy prediction can be employed as a means of improving spectrum sensing performance in terms of time and energy consumption. More specifically, we show how ED can be efficiently modeled as an HMM and we develop an HMM-based spectrum occupancy predictor. The performance of this predictor is validated through measurements over the 2.4GHz ISM band in a realistic indoor scenario. The prediction performance of the algorithm is studied in terms of the probabilities of detection and false alarm and it is compared with a kth order Markov and a 1NN predictor.

The rest of this paper is organised as follows. Section II discusses the preliminaries of energy detection, describes how it can be modeled as an HMM and presents the HMM-based spectrum occupancy prediction scheme. Section III contains details about the measurement campaign and a brief spectrum occupancy analysis. Section IV presents the results regarding the prediction performance of the HMM-based predictor and demonstrates how the proposed scheme can reduce the requirements in sensing time and energy. Finally, Section V draws the conclusions of this work.

II. SPECTRUM OCCUPANCY PREDICTION

A. Spectrum Sensing

Energy detection is one of the simplest spectrum sensing techniques since it requires no prior knowledge of the
received signal [11]. The principle of the ED is that a test statistic $T_s$, is compared with a detection threshold $\lambda$ in order to determine the presence or the absence of a PU in the band of interest. The test statistic can be obtained by the received signal’s energy as:

$$T_s = \sum_{n=0}^{\infty} |y(n)|^2$$  \hspace{1cm} (1)

where $y(n)$ is the received signal of $n$ samples. Hence, the decision rule of the band occupancy can be expressed by the following hypotheses:

$$H_0 : T_s < \lambda \rightarrow \text{unoccupied}$$

$$H_1 : T_s \geq \lambda \rightarrow \text{occupied}$$  \hspace{1cm} (2)

The two metrics for spectrum sensing performance are, the probabilities of detection, $P_d = P(T_s > \lambda | H_1)$, and false alarm, $P_f = P(T_s \geq \lambda | H_0)$. Using the threshold $\lambda$ for hypothesis testing, $P_d$ and $P_f$ are given by:

$$P_d = \frac{\Gamma(u, \lambda / 2)}{\Gamma(u)}$$  \hspace{1cm} (3)

$$P_f = Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda}\right)$$  \hspace{1cm} (4)

where $\Gamma(x, \alpha)$ and $Q_u(x, y)$ denote the incomplete gamma function and the generalised Marcum Q-function respectively, $u$ is the time bandwidth product, and $\gamma$ is the SNR.

B. Hidden Markov Model

An HMM is defined by the tuple $\lambda = (\pi, A, B)$ [12]. The initial state distribution $\pi$ is defined as:

$$\pi = P(q_1 = s_i), i = 1, ..., N$$  \hspace{1cm} (5)

where $N$ is the number of states of a Markov chain with state space $\{S_1, ..., S_N\}$ and $q_i$ denotes the state at time $t$, $q_i \in \{S_1, ..., S_N\}$.

The square transition matrix $A$ contains the transition probabilities defined as:

$$a_{ij} = P(q_{t+1} = j | q_t = i), i, j = 1, ..., N$$  \hspace{1cm} (6)

The emission matrix $B$ has emission probabilities determined as:

$$b_{ij}(o) = P(o = o_n | q_t = S_j), j = 1, ..., N m = 1, ..., M$$  \hspace{1cm} (7)

where $M$ is the number of observations in the emission space $\{v_1, ..., v_M\}$ and $o$ is the observation symbol at time $t$, $o_t \in \{v_1, ..., v_M\}$.

C. HMM for Spectrum Sensing

Assuming that PU transmissions are slotted, channel occupancy can be modeled as a two-state Markov process with transition probabilities:

$$a_{ij} = P(q_{t+1} = j | q_t = i), i, j \in \{0, 1\}$$  \hspace{1cm} (8)

The existence of a PU transmission at time $t$ is then expressed by the following hypothesis:

$$H_0 = \{X_t = 0\} \rightarrow PU \text{ transmission absent}$$

$$H_1 = \{X_t = 1\} \rightarrow PU \text{ transmission present}$$  \hspace{1cm} (9)

However, when the SU senses its spectral environment the actual channel state is not observable due to errors caused by noise and other channel impairments such as shadowing and multipath. Therefore, the fact that the actual channel state is hidden from the SU, allows spectrum sensing to be modeled as an HMM with state space $S = \{0, 1\}$, emission space $V = \{0, 1\}$ and emission probabilities $b_v$ determined by (3) and (4) respectively. The HMM for energy detection is presented in Fig. 1 where $X_t$ denotes the channel occupancy from a PU transmission, and $Y_t$ the SU’s spectrum sensing output.

D. HMM-based Prediction Scheme

Given the model’s parameters $\lambda = (\pi, A, B)$ and a sequence $Y = \{Y_1, Y_2, ..., Y_t\}$ of past spectrum sensing outputs, the Viterbi algorithm is employed to determine the channel occupancy sequence $X_t$ that is most likely to have generated the input sequence.

Let us denote the Viterbi’s output sequence as $O$. The main objective of the predictor is to estimate the symbol $O_{t+1}$ based on the past observations of length $T$. The Baum Welch Algorithm (BWA), is used to estimate the model’s parameters so that the probability of the given sequence $O$ has been generated by model $\lambda, P(O|\lambda)$, is maximized.

After training the HMM parameters, the joint probabilities of an observation $O_t$ to be followed by an unoccupied $P(O_t, 0|\lambda)$ and by an occupied channel $P(O_t, 1|\lambda)$ at the future time slot $T + 1$ are calculated. The occupancy of the channel at time instant $T + 1$ is predicted according to the following decision rule:

$$\begin{align*}
\text{if} \quad & P(O_t, 0|\lambda) \geq P(O_t, 1|\lambda) \rightarrow O_{t+1} = 0 \\
\text{if} \quad & P(O_t, 0|\lambda) < P(O_t, 1|\lambda) \rightarrow O_{t+1} = 1
\end{align*}$$  \hspace{1cm} (10)

![Fig. 1. HMM for energy detection.](image-url)
III. SPECTRUM OCCUPANCY MEASUREMENTS

A. Measurement Campaign

Occupancy measurements were conducted in the 2.4GHz ISM band, in an indoor environment. ISM band was considered because the duration and access intervals from WiFi and Bluetooth are random which poses an extra challenge for the channel occupancy prediction compared to deterministic wireless systems such as broadcast TV.

The measurement equipment consisted of a R&S FSL6 spectrum analyser, configured as per Table I, a laptop and a 3dBi omni-directional vertically polarised antenna with a frequency range of 2200MHz to 2600MHz. The measurement campaign took place inside an urban building, in the third floor of a four-floor building in the central campus of University of Bedfordshire.

In this scenario the measurement equipment emulates a SU that performs spectrum sensing and provides an insight of the perceived PU activity by a SU in a CR network in an indoor environment. For this scenario, the total bandwidth of 83.5MHz is divided into 16 channels of 5MHz bandwidth each. The sensing time equals to the spectrum analyser’s sweep time of 820ms and hence the sensing time for each channel is approximately 51ms. The spectral environment in the ISM band over 500 sensing slots is presented in Fig. 2.

Table I. Measurement configuration

<table>
<thead>
<tr>
<th>Frequency Range</th>
<th>2.4000 – 2.4835GHz</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency Span</td>
<td>83.5MHz</td>
</tr>
<tr>
<td>RBW</td>
<td>10kHz</td>
</tr>
<tr>
<td>VBW</td>
<td>30kHz</td>
</tr>
<tr>
<td>Sweep time</td>
<td>820ms</td>
</tr>
<tr>
<td>Detector Type</td>
<td>RMS</td>
</tr>
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B. Spectrum Occupancy Analysis

The metrics used to describe spectrum occupancy in this work are: duty cycle, channel occupancy and transition rate. Duty cycle, $D_f$, is defined as the portion of time during which the power of a frequency channel exceeds the detection threshold and is defined by (11).

\[
D_f = \frac{1}{N} \sum_{n=1}^{N} X_n
\]

where $N$ is the number of sensing events and $X_n$ is the channel state as described in Section II-B.

The percentage of the channels that are occupied in a frequency band at a given time is determined by channel occupancy. A straightforward estimate of channel occupancy is given by:

\[
z = \frac{N_{\text{occupied}}}{N_{\text{total}}}
\]

where $N_{\text{occupied}}$ is the number of channels that exceed the detection threshold and $N_{\text{total}}$ is the total number of channels in the band of interest.

Having modeled the PU transmission as a Markov process, the transition rate is defined as the probability of the channel to change from an occupied to an unoccupied state ($a_0$) and vice versa ($a_1$). Therefore, the transition rate can be used as a metric of the channel’s complexity in terms of PU activity.

In order to determine the duty cycle, the channel occupancy, and the transition rate, the received power is compared to a detection threshold given by [13]:

\[
\lambda = P_n + Q^{-1}(P_n)\sigma
\]

where $P_n$ is the CR noise floor given by (14), $Q(.)$ is the Gaussian function, $P_n$ is the target probability of false alarm, and $\sigma$ is noise variance. The noise statistics can be empirically obtained by replacing the antenna with a match load at the spectrum analyser’s RF input. The CR noise floor is given by:

\[
P_n = -174 + 10\log_{10} B + NF
\]

where $-174 (\text{dBm} / \text{Hz})$ is the noise power spectral density, $B (\text{Hz})$ the bandwidth of the sensed band and $NF (\text{dB})$ is the equipment’s noise figure. For a bandwidth of 83.5MHz and a $P_n = 0.1$, the detection threshold equals to -95dBm.

A summary of the spectrum occupancy statistics of the 2.4GHz band is presented in Table II.
TABLE II. ISM-BAND STATISTICS

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Duty cycle</th>
<th>Channel occupancy</th>
<th>Transition rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>9%</td>
<td>31%</td>
<td>0.56</td>
</tr>
<tr>
<td>Mean</td>
<td>53%</td>
<td>53%</td>
<td>0.85</td>
</tr>
<tr>
<td>Max</td>
<td>100%</td>
<td>93%</td>
<td>1.03</td>
</tr>
</tbody>
</table>

IV. NUMERICAL RESULTS

A. Prediction Performance

The prediction performance of the HMM-based predictor described in Section II is evaluated using the measured data from Section III. The prediction performance is evaluated in terms of True Positive Rate (TPR) and False Positive Rate (FPR). TPR expresses the rate of correct predictions of “busy” channels while FPR expresses incorrectly predicted “idle” channels as “busy”. In order to be consistent with the terminology of spectrum sensing $P_D$ will be used for TPR and $P_{fa}$ for FPR. A combination of higher $P_D$ and lower $P_{fa}$ suggests a better prediction performance.

A 1NN prediction scheme and a Markov predictor were developed as benchmarks for performance comparison [14], [15]. A 1NN predictor uses the current spectrum sensing output in order to predict future channel states as:

$$X_{t+1} = X_t$$  \hspace{1cm} (15)

where $X_t$ is the current channel state and $X_{t+1}$ future channel state.

A kth-order Markov predictor considers the latest k terms of a spectrum sensing history sequence. Its prediction process is described as:

$$X_{t+1} = \begin{cases} 0, & \text{if } N(x_{t-k+1}, 0) > N(x_{t-k+1}, 1) \\ 1, & \text{otherwise} \end{cases}$$  \hspace{1cm} (16)

where $N(x_{t-k+1}, 0)$ and $N(x_{t-k+1}, 1)$ is the number of times that sequence $x$ is followed by 0 and 1, respectively.

The prediction performance of the HMM-based predictor was verified for two different scenarios. In the first scenario, one-step (time-slot) ahead predictions were performed using the three different prediction schemes for each one of the 16 channels. In the second scenario, the HMM-based and the 1NN predictor perform channel occupancy predictions for the whole band, i.e., all of the 16 channels for each sensing event. The history length was set to 100 for the HMM-based and the Markov predictor in both scenarios.

Fig. 4 illustrates how the prediction performance varies with the transition rate of the channel. Both the HMM-based and 1NN predictors are more robust to channel conditions and outperform the Markov one, with a mean $P_D$ of 0.91 and 0.86, respectively. This is because the Markov predictor’s estimates are determined by the transition probabilities of the last k terms of the history. This leads to lower prediction accuracy for higher transition rates which in turn results in a mean $P_{fa}$ of 0.81.

Fig. 5 shows that the HMM-based predictor has a better overall prediction performance. This figure, presents the Receiving Operating Characteristics (ROC) curve for the HMM-based and the 1NN curve for the second scenario. The HMM-based predictor’s ROC curve dominates in the ROC space which means that the HMM-based predictor outperforms the 1NN predictor. However, the superior performance of the HMM-based predictor comes at the cost of increased complexity which is expressed as the number of multiplications during the training phase. The BWA algorithm’s complexity scales to $N^2T$ [12]. Hence, for a 2-state HMM ($N = 2$) with a history length of $T = 100$, 400 multiplications are performed. In a CR network, it is critical that the prediction process is completed in a time frame smaller than the sensing time. In a desktop PC with a 1.8GHz processor and 3GB of RAM the prediction process performed in approximately 200ms. This means that for the considered scenario the channel occupancy prediction is completed 620ms before the spectrum sensing process.

B. Energy Efficient Spectrum Sensing

Let us now consider a CR network with an operating bandwidth $B$ divided into $N$ shared channels between the PUs and SUs. Each channel $N_i$ has different PU occupancy statistics and it is sensed by the SU using ED over a constant sensing period of $T_{sense}$.
At each sensing event $S_t$, the SU senses the whole band and stores a history of the spectrum sensing outputs in its memory. In such a scenario, spectrum sensing requires an $E$ unit of energy, in Joules, and a $t$ unit of time, in seconds, per sensed channel. By employing spectrum occupancy prediction to the spectrum sensing mechanism, the SU will have to sense only the number of channels that have been predicted to be unoccupied, $(N_{\text{pred}})$ at the next time instant rather than the whole band of interest. Hence, the improvement in sensing energy and time can be expressed as:

$$E_{\text{imp}} = E \times \left[ \frac{N - N_{\text{pred}}}{N} \right] \% \quad (17)$$

$$T_{\text{imp}} = t \times \left[ \frac{N - N_{\text{pred}}}{N} \right] \% \quad (18)$$

Next, the performance of a conventional ED is compared with that of the predictive method in the scenario described Section III. Both sensing schemes operate under the same conditions, in a CR network with 16 channels of 5 MHz, and have the same sensing performance in terms of $P_{fa}$ and sensing time, with $P_{fa} = 0.1$ and $T_{\text{norm}} = 0.52$ ms. Fig. 6 presents a comparison between a conventional ED and predictive ED in terms of the required sensing time at each sensing event. It is obvious that the sensing time and hence the sensing energy, are significantly reduced if spectrum occupancy prediction is employed. From (17) and (18), it can be seen that the percentage of improvement is the same for both the sensing time and energy. Table III presents the improvement in sensing time and energy for different channel occupancy statistics over 500 sensing events. Our results suggest that proposed sensing scheme achieves an improvement for up to 66% with a prediction error rate from 0.00 to 0.28.

V. CONCLUSION

In this paper we described how ED can be modeled as an HMM. We developed and experimented evaluated the prediction performance of an HMM-based spectrum occupancy prediction scheme. Our results confirm that the HMM-based predictor outperforms a Markov and a 1NN predictor. It was also found that by employing prediction to an ED spectrum sensing scheme, an improvement of up to 66% can be achieved in energy and time consumption, compared to conventional energy detection.

<table>
<thead>
<tr>
<th>Channel occupancy (%)</th>
<th>Improvement (%)</th>
<th>Error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>33</td>
<td>46</td>
<td>0.14</td>
</tr>
<tr>
<td>40</td>
<td>53</td>
<td>0.14</td>
</tr>
<tr>
<td>46</td>
<td>53</td>
<td>0.28</td>
</tr>
<tr>
<td>53</td>
<td>46</td>
<td>0.14</td>
</tr>
<tr>
<td>60</td>
<td>53</td>
<td>0.00</td>
</tr>
<tr>
<td>60</td>
<td>66</td>
<td>0.00</td>
</tr>
</tbody>
</table>

REFERENCES


