Abstract—Response delay problem and measurements of such delays have been reported in Part I. The response delay has a negative impact on the accuracy of spectrum sensing, which is the cornerstone of cognitive radio. In this paper, single-user prediction of channel state is proposed to minimize the negative impact of response delays caused by hardware platforms. Specifically, a modified hidden Markov model (HMM) based single-secondary-user (single-SU) prediction is proposed and examined. In order to have convincing performance evaluation results, real-world Wi-Fi signals are employed to test the proposed approach, where the Wi-Fi signals are recorded at four different locations simultaneously. Experimental results show that the proposed single-SU prediction outperforms the 1-nearest neighbor (1-NN) prediction which uses a detected current state as an estimate of future states. This work is a part of the effort toward building a cognitive radio network testbed.

I. INTRODUCTION

Cognitive radio is an elegant concept, but implementing it is a great deal. As reported in Part I, the response delay issue has been identified, and the minimum response delays of two hardware platforms have been measured and reported. It is wise to take into account the measurement results in algorithm design and implementation.

As mentioned in Part I, various spectrum sensing techniques have been proposed. Implementing effective spectrum sensing schemes is a fundamental part of development effort toward a cognitive radio network testbed [1], [2], [3].

A spectrum sensing scheme uses received signals to detect channel states, and it virtually predicts channel states in the near future simply using previous detected channel states. Intensive work on prediction for spectrum radio as has been reported. In [4], channel occupancy status is converted into binary form, autoregression (AR) model is used for predicting the binary channel status, and generated artificial global system for mobile (GSM) signals are used for testing the prediction. In [5], autoregressive moving average model (ARMA) is employed to predict the power of television (TV) signals in time domain. In [6], an algorithm based on support vector regression and empirical mode decomposition for frequency spectrum prediction in frequency monitor system is introduced. In [7], an interference time ratio that represents the fraction of a primary user’s burst interfered by secondary transmission is proposed to control the transmission probability for secondary users (SUs), which is predicted using conditional probability. This scheme is tested only by simulation. The idea of predictive dynamic spectrum access is introduced in [8], which aims at the distribution of the time length that a channel is idle. The existence of Markov chain for sub-band utilization by primary users (PU) is validated in [9]. Hidden Markov mode (HMM) is used to predict the usage behavior of a frequency band based on channel usage patterns in [10], to decide whether or not to move to another frequency band. And a channel status predictor using HMM based pattern recognition is proposed in [11].

However, none of the previous work takes the time delay incurred by hardware platforms into consideration for prediction. Moreover, the ideas of using HMM for prediction in previous work are all based on pattern recognition. In fact, HMM can be exploited beyond pattern recognition.

The contributions of this paper are summarized as follows. First, an approach for channel state prediction based on modified HMM is proposed. Second, real-world Wi-Fi over-the-air signals are measured and recorded using multiple antennas at different locations at the same time. Thirdly, the performance of the proposed prediction approach is evaluated using the measured Wi-Fi signals in the case of single-SU prediction.

The rest of this paper is organized as follows. Section II proposes the single-SU prediction approach in detail. Section III reports the measurements of Wi-Fi signals. Section IV reports the experimental results. And Section V concludes this paper.

II. CHANNEL STATE PREDICTION USING MODIFIED HIDDEN MARKOV MODEL

In this section, traditional HMM is modified to take into account prediction, and an approach based on the modified HMM for channel state prediction is proposed.

A. Hidden Markov Model

An HMM is defined by a tuple $\lambda = \{\pi, A, B\}$ [12], [13], [14]. $\pi$ is the initial state probability vector,

$$\pi = (\pi_1, \ldots, \pi_N)$$

(1)

$$\pi_i = \Pr(q_1 = \theta_i)$$

(2)

where $\Pr(\bullet)$ denotes probability, $N$ is the number of states of Markov chain, $\{\theta_1, \ldots, \theta_N\}$ are the $N$ states, $q_t$ represents...
the state at time \( t \), \( q_t \in \{ \theta_1, \ldots, \theta_N \} \). \( A \) is the state transition probability matrix,

\[
A = (a_{ij})_{N \times N} \\
a_{ij} = \Pr(q_{t+1} = \theta_j | q_t = \theta_i) \quad i, j = 1, \ldots, N
\]

And \( B \) is the emission probability matrix,

\[
B = (b_{jk})_{N \times M} \\
b_{jk} = \Pr(o_t = v_k | q_t = \theta_j) \quad j = 1, \ldots, N, \quad k = 1, \ldots, M
\]

where \( M \) is the number of possible observation values in the observation space \( \{ v_1, \ldots, v_M \} \), \( o_t \) represents the observation value at time \( t \), where \( o_t \in \{ v_1, \ldots, v_M \} \).

Given a parameter tuple \( \lambda \) and a sequence of observation values \( o = \{ o_1, \ldots, o_T \} \), the state sequence that is most likely to have generated the input sequence \( o \) and the likelihood probability can be calculated using the Viterbi algorithm. Let \( \delta_t(i) \) be the maximal probability of state sequence of length \( t \) that ends in state \( i \). A tailored Viterbi algorithm is shown as below.

1) Initialization.

\[
\delta_1(i) = \pi_i b_i(o_1) \quad i = 1, \ldots, N
\]

2) Iteration.

\[
\delta_t(j) = \max_{1 \leq n \leq N} \left[ \delta_{t-1}(i) a_{ij} b_j(o_t) \right] \\
\delta_t(j) = \max_{1 \leq n \leq N} \left[ \delta_{t-1}(i) a_{ij} b_j(o_t) \right] \\
\delta_T(j) = \max_{1 \leq n \leq N} \left[ \delta_T(i) \right] \\
q_T^* = \arg \max_{1 \leq n \leq N} \left[ \delta_T(i) \right]
\]

where \( P^* \) is the calculated likelihood probability and \( q_T^* \) is the estimated state at time \( T \).

Traditionally, the parameters of HMM are trained using a training algorithm like the popular Baum-Welch algorithm, given a sequence of observation values. However, in this paper, a training algorithm for HMM is not employed. Instead, the parameters of HMM are obtained through a simple statistical process over training sequences.

**B. Proposed Single-SU Prediction Approach**

During spectrum sensing, what SUs concern are the availabilities of some sub-frequency-bands of interest within a wide frequency band. An architecture is proposed to predict such availability, as shown in Fig. 1. In the spectrum sensing phase of every time slot, received time-domain signals are transformed into frequency-domain using fast Fourier transform (FFT). Then values from multiple frequency tones within a sub-frequency-band of interest are quantified and fed into a modified HMM as a sequence of observation values. Denote the number of input frequency tones as \( Q \). The quantization can be either scalar quantization or vector quantization. Multiple sub-frequency-bands of interest can be processed in parallel using multiple modified HMMs. Thus, this proposed approach can be applied to any wideband scenarios.

As shown in Fig. 2, for a sub-frequency-band, at the end of spectrum sensing phase of every time slot, an observation value \( o_t \) is obtained for a modified HMM. In each time slot, a sub-frequency-band is associated with a certain channel state, i.e., “busy” or “idle”. It is tricky to obtain the actual channel states in practice. As mentioned in our previous paper, the state verification means can provide information about actual channel states. In this paper, actual channel states are assumed to be determined by such verification means. The maximal verification delay is denoted by \( Y \) in time slots.

In Fig. 2, known observation values, actual channel states, and unknown channel states are labeled. Prediction of channel state is to use known observation values and actual channel states to estimate future channel states. However, in the proposed approach, the definition of HMM is slightly different from the standard form. The modified HMM is defined by (1), (2), (3), (5), as well as the following two equations:

\[
a_{ij} = \Pr(q_{t+X} = \theta_j | q_t = \theta_i) \quad i, j = 1, \ldots, N
\]

\[
b_{jk} = \Pr(o_t = v_k | q_t = \theta_j) \quad j = 1, \ldots, N, \quad k = 1, \ldots, M
\]

where \( X \) is the span of prediction, in time slots, to take care of the maximal possible response delay.

Parameters of the modified HMM, \( \{ \pi, A, B \} \), are estimated statistically. The equations for extracting parameters of the modified HMM from a training sequence are listed below:

\[
\pi_i = \frac{1}{L-X} \sum_{t=1}^{L-X} \text{Eval}(q_t = \theta_i) \quad i = 1, \ldots, N
\]
state prediction approaches. First, the frequency bands that are used to record the Wi-Fi signals at different locations at the same router, downloading data at a date rate of 2.3 MB/s. In order to evaluate the performance of channel state prediction approaches proposed in Section II using real-world data, there are several reasons to consider Wi-Fi as PUs in evaluating channel state prediction approaches. First, the frequency bands that Wi-Fi employs are unlicensed, which means experiments on these bands can be conducted without asking the regulators for permissions. Second, the durations that Wi-Fi devices occupy the channel and the durations that the channel is kept idle are as small as microseconds. This fact enables recording a plenty of Wi-Fi accesses in a short time. Thirdly, the durations and intervals of Wi-Fi accesses are random, which poses additional challenge for channel state prediction. It is hard to learn and predict Wi-Fi accesses. Thus, Wi-Fi signals are ideal for evaluating prediction approaches.

The experiment is conducted in an indoor environment. A laptop computer accesses the Internet through a wireless Wi-Fi router, downloading data at a date rate of 2.3 MB/s. In order to record the Wi-Fi signals at different locations at the same time, the DPO, Tektronix DPO72004, is connected with four antennas with a frequency range of 800 MHz to 2500 MHz distributed at four locations. Antennas 1, 2 and 3 are three, two and two meters away from the router, respectively, but a metallic board is placed between antenna 3 and the router to emulate a non-line-of-sight (NLOS) propagation. Antenna 4 is placed closely to the router, so it can monitor the actual channel states. Since the DPO can record 250 M samples per channel, by setting the sampling rate to 6.25 GS/s, the maximum duration of one measurement is 40 ms.

The other method, named “AB”, uses A and B for the prediction, which is defined by (17), (9), and (10), with \( T = 1 \).

\[
\delta_1(i) = a_{ji}b_j(0_t)
\]
\[
q_{1-Y} = \theta_j
\]
\[
i = 1, \ldots, N
\]

Using either method, predicted channel state \( q^*_T \) in (10) and the corresponding likelihood probabilities \( P^* \) in (9) can be calculated.

\[\begin{align*}
& (14) \\
& \alpha_{ij} = \frac{\sum_{t=1}^{L-X} \text{Eval}(q_{1+Y} = \theta_j | q_{1-Y} = \theta_i)}{\sum_{t=1}^{L-Y} \text{Eval}(q_{1-Y} = \theta_i)}
\end{align*}\]

\[\begin{align*}
& (15) \\
& b_{jk} = \frac{\sum_{t=1}^{L-X} \text{Eval}(o_{t} = v_k | q_{1+X} = \theta_j)}{\sum_{t=1}^{L-X} \text{Eval}(q_{1+X} = \theta_j)}
\end{align*}\]

\[\begin{align*}
& (16) \\
& \text{Eval}(\bullet) = \begin{cases} 
1 & (\bullet) \text{established} \\
0 & \text{otherwise}
\end{cases}
\]
clearest due to the shortest propagation, while the signal from antenna 3 is the weakest because of NLOS.

IV. PERFORMANCE EVALUATION

In this section, the proposed single-SU prediction is evaluated using the measured Wi-Fi signals in Section III.

The sampling interval is in picoseconds and 40-ms Wi-Fi signals are recorded at four different locations corresponding to channel 1, 2, 3 and 4. The measured Wi-Fi signals from channel 1, 2, and 3 are fed to three independent SUs for prediction, while the measured Wi-Fi signal from channel 4 is served as an indicator of channel states and fed to all the three SUs for reference.

Due to the limitation of measurement equipment, 40 ms is the maximum duration that Wi-Fi signals can be recorded. By setting the length of time slot to 20 μs, there are 2000 time slots available for performance evaluation. It may take one or two time slots for the channel state to change, which can reflect actual channel state changes.

The duration of the spectrum sensing phase of a time slot is set to 4 μs, just one fifth of the length of a time slot. In the following, prediction spans of one to three time slots are considered in evaluating the prediction performances.

The proposed prediction approach is configured as follows. Referring to the architecture shown in Fig. 1, scalar quantization is used, quantified frequency-domain data from one frequency tone of 2.418 GHz are served as observation values, and they are fed into the modified HMM. Unless otherwise stated, the parameters $M$, $N$, and $Q$ for the single-SU prediction are set to 288, 2, and 1, respectively. The $\{\pi, A, B\}$ parameters of the three modified HMMs for three single SUs are obtained beforehand using (13) (14) (15) and the measured Wi-Fi signals from channel 1, 2 and 3, respectively.

For comparison purpose, another single-SU predictor called 1-nearest neighbor (1-NN) is employed as reference. 1-NN simply uses current detected or sensed channel state as an estimate of future channel states:

$$q_{t+X} = q_t$$  \hspace{1cm} (18)

where $q_t$ is the channel state for current time slot $t$, and $q_{t+X}$ is the predicted future channel state $X$-slot ahead. $q_t$ is determined by the following hypothesis:

$$q_t : o_t > \begin{cases} \text{busy} \\
\text{idle}\end{cases} th$$  \hspace{1cm} (19)

where $o_t$ is the non-quantified observation value from current time slot $t$, and $th$ is a threshold. In our evaluation, all SUs use the same default value of $th$ and it is pre-determined using all the non-quantified observation values from channel 3, since the weakest measured Wi-Fi signal comes from channel 3. $th$ simply takes the middle between two averages, one is the average of non-quantified observation values from all “idle” slots and the other is the average of non-quantified observation values from all “busy” slots. The 1-NN approach seems simple, but it is not easy to beat it in terms of prediction performance.

The prediction performance is evaluated using two metrics: probability of detection ($P_D$) and probability of false alarm ($P_{FA}$). Similar to their meanings in the case of detection, in the case of prediction, $P_D$ means the rate that a prediction approach predicts the channel state correctly when the actual channel state is “busy”, whereas $P_{FA}$ means the rate that it fails to predict the channel state correctly when the actual channel state is “idle”. Obviously, a combination of higher $P_D$ and lower $P_{FA}$ stands for a better prediction performance.

Considerations of choosing between the “πB” method and the “AB” method for the proposed prediction approach are summarized as follows. When $Y = 0$, using the “AB” method can achieve a higher prediction performance with the measured Wi-Fi signals. However, in a typical case of $Y > 0$, the performance of the “AB” method would be degraded. On the other hand, the “πB” method is independent of $Y$, but its performance is slightly lower. Thus, it is recommended to use the “πB” method for the proposed prediction approach when $Y > 0$, and this method is employed in the following performance evaluation.

Three independent single-SU predictors of the same type run both the proposed prediction approach and the 1-NN approach. Each single-SU predictor uses one channel of measured Wi-Fi signals as its input. Fig. 5, 6 and 7 show their performances. Overall speaking, at the cost of slight increase of complexity, the proposed single-SU prediction is robust to channel conditions and outperforms the 1-NN predictor. It is also confirmed that the performance degrades fast as the prediction span increases, suggesting that the response delay is non-negligible.

V. CONCLUSION

The response delays have been taken into account in designing a strategy for channel state prediction, and the strategy has been tested using real-world Wi-Fi signals recorded at four locations simultaneously. An approach of single-SU prediction...
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