Quickest Spectrum Detection Using Hidden Markov Model for Cognitive Radio

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***Abstract*—The prerequisite of accessing white spectrum is to find and locate it. Our work deals with spectrum detection and recognition under the umbrella of cognitive radio. In the procedure of spectrum recognition, a frequency sweeping device sweeps the wideband spectrum and the samples of the wideband power spectrum density (PSD) are fed into different Hidden Markov Models (HMMs) sequentially. The core idea of sequential detection or quickest detection is borrowed and utilized here from the classical detection theory. In our proposed approach, forward variables from different HMMs are sequentially exploited to generate the decision statistics. The decision can be made any time as long as the condition is met. The motivation of our work is to detect the availability of spectra and recognize the spectra as quickly as possible and thus shorten the time delay of detection so as to improve the spectrum utilization. The PSDs of Wi-Fi signal, CDMA signal and GSM signal are measured using a Spectrum Analyzer (SA). These acquired data are used to train HMMs beforehand. Meanwhile, a fourth HMM is trained by the PSD of blank spectrum. Experimental results shows this proposed approach is effective.**

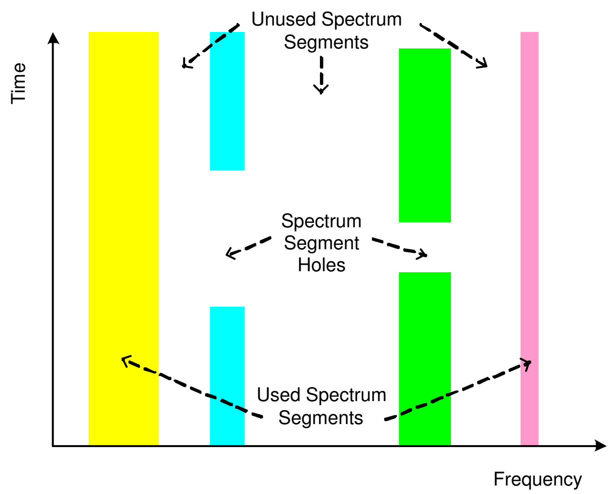

Fig. 1. Unused spectrum segments and spectrum segment holes.

I. INTRODUCTION

The Federal Communications Commission (FCC) opened free white space spectrum on November 4, 2008 [1]. Cognitive radio has been put forward as a more efficient way to share the radio frequency spectrum. Although there have been a few years since the concept of cognitive radio came out, its functions, algorithms, and implementations are still under exploration. One of the key capabilities of cognitive radio is spectrum sensing and management. The first step of spectrum sensing and management is spectrum detection, which detects if the spectrum segments of interest are occupied by primary users, other secondary users, or even jammers. Spectrum detection is the cornerstone of cognitive radio. The accuracy and rapidity of spectrum detection algorithms are vital to cognitive radio.

Traditionally, there are three techniques that can be used for spectrum detection [2], [3]. The most popular technique is energy detection. Although it is simple in terms of implementation, it has several drawbacks. Firstly, it takes time to do average. Secondly, it is not easy to set the threshold. Thirdly, it does not distinguish interference from signal and noise. Moreover, it lacks consideration of joint information. The second technique is matched filter, which maximizes received signal-to-noise ratio. However, it requires demodulation of received signal and dedicated receiver. The third technique is cyclostationary feature detection, which needs more computation resources to obtain the spectral correlation function. Since it is a block transform based technique, it introduces more delay. A cyclostationary approach for signal detection and classification using Hidden Markov Model (HMM) is introduced in [4].

The major contribution of this paper is introducing the combination of HMM and quickest detection to cognitive radio. In this paper, an approach based on HMM and quickest detection for spectrum detection is proposed, by which the radio frequency spectrum is swept continuously and spectrum detection results are output as quickly as possible. Since the proposed approach is based on frequency sweeping and quickest detection, it enables reducing the time delay between when spectrum detection result is output and when the spectrum is sampled. Moreover, it considers the information of a whole spectrum segment instead of that of independent spectrum samples. Thus it enables an increased accuracy of spectrum detection. Besides a detection result, the proposed approach also outputs a recognition result with the category of detected spectrum segment, as well as its starting point and ending point. With the information of detected spectrum segment, more features are enabled for cognitive radio, such as prediction of the time of primary user accessing the detected spectrum segment, and simultaneous access to the detected spectrum segment for both primary user and secondary user.

Fig. 1 illustrates unused spectrum segments and spectrum segment holes. Since at a given time spectrum segment hole is equivalent to unused spectrum segment, in the rest of this paper both unused spectrum segment and spectrum segment hole are called unused spectrum segment for convenience.

This paper is organized as follows. Quickest pattern recognition using HMM are addressed in Section II. Details of frequency sweeping based spectrum detection and recognition are presented in Section III. Experimental results are reported in Section IV, followed by a conclusion in Section V.

II. Combining HMM with Quickest Detection

A. HMM

It is well known that HMM is used for pattern recognition, such as speech recognition [5], for a long time. Take a simple case as an example. Given a pattern set $\mathbf{p} = [p_1, p_2, \ldots, p_Q]$ and an observation sequence $\mathbf{o} = [o_1, o_2, \ldots, o_T]$, find a pattern p_q, $q = 1, 2, \ldots Q$, that most likely generates the observation sequence. The first step is to employ training algorithm like Baum-Welch algorithm to derive a set of HMM parameters $\lambda = \{\pi, \mathbf{A}, \mathbf{B}\}$ for each pattern $p_q \in \mathbf{p}, q = 1, 2, \ldots Q$. The inputs for training a HMM can be multiple observation sequences $\mathbf{O} = [\mathbf{o_1}, \mathbf{o_2}, \ldots, \mathbf{o_L}]^{'}$ and each observation sequence $\mathbf{o_l}$ contains multiple observations $o_t \in \mathbf{o_l}$, where $\mathbf{o_l} = [o_1, o_2, \ldots, o_T], l = 1, 2, \ldots L, t = 1, 2, \ldots T$. Note that the effective length T for each observation sequence is not necessarily to be equal. Assume there are N states $\mathbf{s} = \{s_1, s_2, \ldots, s_N\}$ and M possible observation values in the observation space $\mathbf{v} = \{v_1, v_2, \ldots, v_M\}$ after quantization.

In λ, $\mathbf{A}$ is defined as the state transition matrix,

$$\begin{array}{l} (\mathbf{A})_{i,j} = \Pr\left(s_j \text{ at } t+1 \,|s_i \text{ at } t\right) \\ i, j = 1, 2, \ldots, N \end{array} \tag{1}$$

where $(\bullet)_{i,j}$ denotes the entry at the i-th row and the j-th column of matrix or vector, and $\Pr(\bullet)$ means the probability. $\mathbf{B}$ is defined as the observation matrix,

$$\begin{array}{l} (\mathbf{B})_{i,j} = \Pr\left(v_j \text{ at } t \,|s_i \text{ at } t\right) \\ i = 1, 2, \ldots, N \\ j = 1, 2, \ldots, M \end{array} \tag{2}$$

Because HMM considered here is static, the value of $\mathbf{A}$ and $\mathbf{B}$ is independent of t. π is defined as the initial state probability vector,

$$(\pi)_{i,1} = \Pr\left(s_i \text{ at } t = 1\right) \tag{3}$$

For simplicity, $a_{ij} = (\mathbf{A})_{i,j}$, $b_i(v_j) = (\mathbf{B})_{i,j}$ and $\pi_i = (\pi)_{i,1}$.

After HMM parameters are obtained through training, the likelihood probability p_{viterbi} of an input observation sequence $\mathbf{o}$ with a given set of HMM parameters λ can be calculated using Viterbi algorithm shown as below.

1) Initialization.

$$\begin{array}{l} \delta_1(i) = \pi_i b_i(o_1) \\ i = 1, 2, \ldots, N \end{array} \tag{4}$$

2) Iteration from $2 \le t \le T$ and $1 \le j \le N$.

$$\delta_t(j) = \max_{1 \le i \le N} \left[\delta_{t-1}(i)\, a_{ij}\right] b_j(o_t) \tag{5}$$

3) Termination.

$$p_{\text{viterbi}} = \max_{1 \le i \le N} \left[\delta_T(i)\right] \tag{6}$$

Meanwhile, Forward-Backward algorithm can be used to calculate the likelihood function $p_f(\mathbf{o}|\lambda)$, in which $\alpha_t(i)$ is called forward variable [6].

1) Initialization.

$$\begin{array}{l} \alpha_1(i) = \pi_i b_i(o_1) \\ i = 1, 2, \ldots, N \end{array} \tag{7}$$

2) Iteration from $2 \le t \le T$ and $1 \le j \le N$.

$$\alpha_t(j) = \left[\sum_{i=1}^{N} \alpha_{t-1}(i) a_{ij}\right] b_j(o_t) \tag{8}$$

3) Termination.

$$p_f(\mathbf{o}|\lambda) = \sum_{i=1}^{N} \alpha_T(i) \tag{9}$$

B. Combining HMM with Quickest Detection

Now the question is that if the observation sequence $\mathbf{o}$ to be recognized is embedded in a longer observation sequence $\mathbf{x} = [x_1, x_2, \ldots, x_K]$, how can we find the appearance of a predefined pattern as quickly as possible? And how can we determine the category of the pattern?

Suppose the hypothesis testing problem is,

$$H_0: \quad x_k = n_k \qquad 1 \le k \le K \tag{10}$$

$$H_1: \left\{ \begin{array}{cc} x_k = n_k & 1 \le k < k_0 \\ x_k = o_{k-k_0+1} & k_0 \le k < k_0 + T \\ x_k = n_k & k_0 + T \le k \le K \end{array} \right. \tag{11}$$

where n_k is additive white Gaussian noise and k_0 is the starting position of $\mathbf{o}$ in $\mathbf{x}$.

Quickest detection can be introduced to answer the first question, while HMM can be exploited to answer the second question. A beautiful bridge between quickest detection and forward variable in HMM was built in [7], [8]. Thus, this problem can be solved by using the following procedure.

1) Initialization of variables. Set threshold S_{th}. Let $k = 0$ and $n = 1$.
2) Initialize the Forward-Backward algorithm for HMM. And let $S_0 = 0$.
3) Iteration. $k = k + 1$,

$$S_k = \max\left\{0, S_{k-1} + g(k; n)\right\} \tag{12}$$

where

$$g(k; n) = \ln\left(\frac{\Pr_{H_1}\left(x_k \,|x_{k-1}, \ldots, x_n\right)}{\Pr_{H_0}\left(x_k \,|x_{k-1}, \ldots, x_n\right)}\right) \tag{13}$$

If S_k is forced to be zero by the max operation, then $n = k + 1$ and goto step 2).

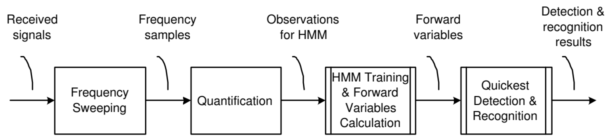

Fig. 2. Overall architecture and dataflow of the proposed approach.

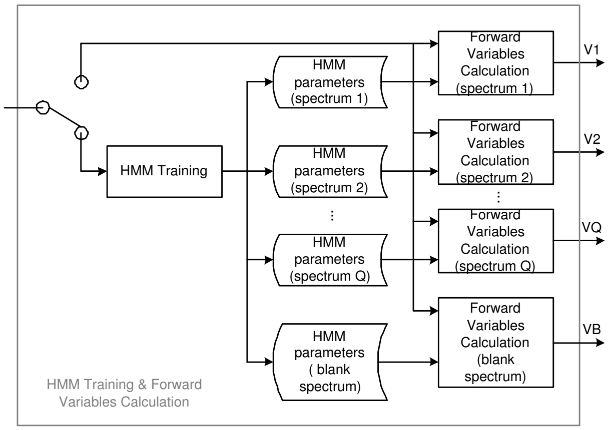

Fig. 3. Architecture of the "HMM training and calculation of forward variables" module.

4) Termination. If $S_k > S_{\mathrm{th}}$, then the procedure is terminated and the appearance of the pattern is announced. Otherwise, goto step 3).

Based on the definition of forward variable in [6], we have

$$\Pr\left(x_k \left| x_{k-1}, \ldots, x_1 \right.\right) = \frac{\Pr\left(x_k, x_{k-1}, \ldots x_1\right)}{\Pr\left(x_{k-1}, \ldots x_1\right)} \quad (14)$$

$$= \frac{\sum\limits_{i=1}^{N} \alpha_k\left(i\right)}{\sum\limits_{i=1}^{N} \alpha_{k-1}\left(i\right)} \quad (15)$$

In order to avoid numerical underflow as k in (14) becomes larger, a scaling operation is applied to forward variables [7]:

$$\begin{array}{c} \hat{\alpha}_1\left(i\right) = \alpha_1\left(i\right) \\ i = 1, 2, \ldots, N \end{array} \quad (16)$$

and for $2 \leq t \leq T$ and $1 \leq j \leq N$,

$$\hat{\alpha}_t\left(j\right) = \frac{\left[\sum\limits_{i=1}^{N} \hat{\alpha}_{t-1}\left(i\right) a_{ij}\right] b_j\left(o_t\right)}{\sum\limits_{i=1}^{N} \hat{\alpha}_{t-1}\left(i\right)} \quad (17)$$

III. Frequency Sweeping based Spectrum Detection and Recognition

Detecting available spectrum segments is a basis of cognitive radio. The information of the availability of spectrum segments and the category of primary user who is accessing the spectrum segment is important for cognitive radio to utilize unused spectrum segments. How to detect the availability of spectrum segments as quickly as possible? And if a spectrum segment is unavailable for cognitive radio, what kind of primary user is occupying this spectrum segment? For answering these two questions, an approach for spectrum detection and recognition is proposed in this section.

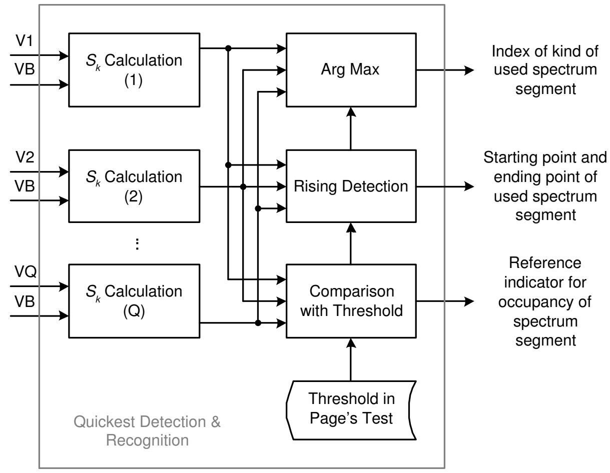

Fig. 4. Architecture of the "quickest detection and recognition" module.

Quickest detection and HMM have been applied to this approach. Different spectra of primary users or secondary users are treated as different patterns. For each pattern, an HMM is built. The whole spectrum under continuous sweeping is considered as a long observation sequence. Fig. 2 shows the overall architecture and dataflow of the proposed frequency sweeping based spectrum detection and recognition approach.

A frequency sweeping device outputs the frequency spectrum samples of received time-domain signals in real-time. Then the frequency spectrum samples are fed into a quantifier to limit the values of the frequency spectrum samples to a certain subset of integers, i.e., observation space. These quantified frequency spectrum samples are called observations for HMMs, which are inputs for HMMs.

There are two phases for HMM in this approach, i.e., training phase and recognition phase. In training phase, observation sequences calculated from known spectrum segments are used to train different HMMs, which is a learning process. Baum-Welch algorithm can be employed to process input observation sequences and generate parameters of HMMs. Training is usually done offline. As shown in Fig. 3, parameters of multiple HMMs are obtained after training phase and stored for future use. In the proposed approach, an additional HMM is built in training phase, which models the "blank" spectrum. It means that no particular primary user or secondary user but thermal noise is present. No forward variables are calculated in training phase.

Once HMMs for known spectrum segments are bulit, recognition phase becomes ready. In recognition phase, the switch in Fig. 3 is switched up and thus training process is bypassed. Conventionally, Viterbi algorithm is applied for HMM based pattern recognition and the likelihood probabilities of input observation sequences is given by (4), (5), (6). While in the

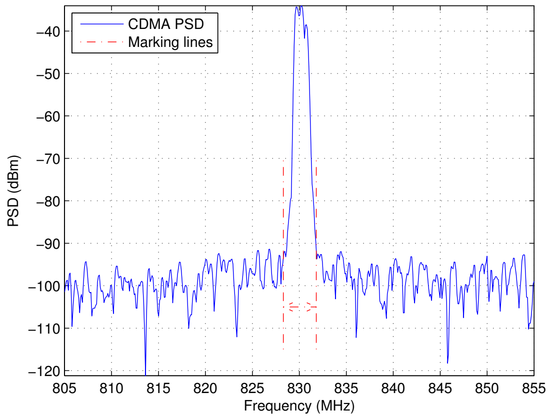

Fig. 5. PSD of CDMA.

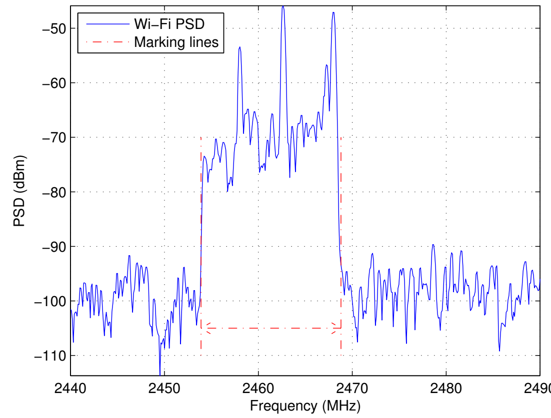

Fig. 7. PSD of Wi-Fi.

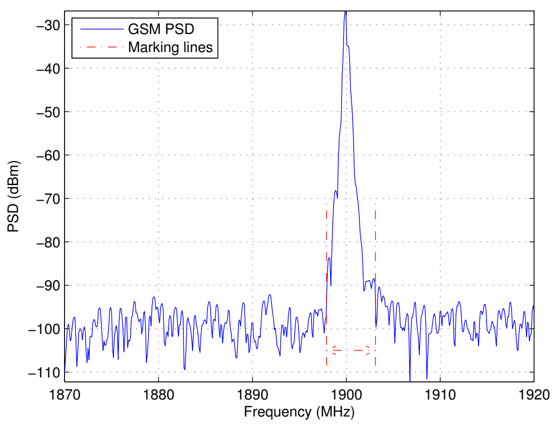

Fig. 6. PSD of GSM.

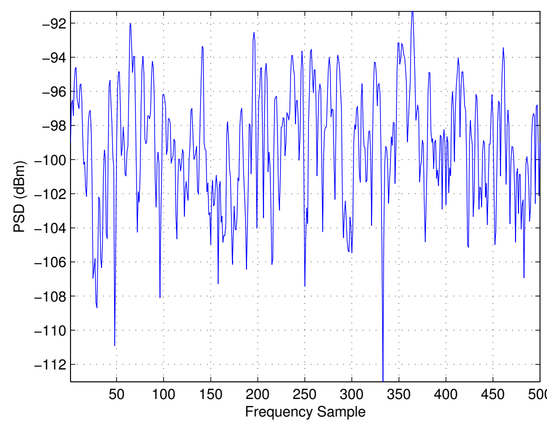

Fig. 8. PSD of blank spectrum.

proposed approach, Forward-Backward algorithm is employed to calculate forward variables, as shown in (7), (8), (9). Each forward variables calculation submodule in Figure 3 calculates forward variables sequentially based on input observation sequences and the parameters of corresponding HMMs. Then the calculated forward variables are delivered to the "Quickest Detection and Recognition" module, as shown in Fig. 4.

In this module, Page's Test is employed [7], [8], [9]. Each S_k calculation module in Fig. 4 takes the forward variables calculated both from its corresponding forward variables calculation submodule in Fig. 3 and from the forward variables calculation submodule for "blank" spectrum as inputs. (12), (13), (14), (16), (17) present the calculation procedure. Then the calculated S_ks are all fed to the comparison submodule, the rising detection submodule, and the Arg Max submodule in Fig. 4.

The comparison submodule compares each S_k with a given threshold. If any S_k is greater than the threshold, a reference indicator for occupancy of spectrum segment is output, which indicates that the spectrum segment being swept is occupied. At the same time, an enabling-signal is sent to the rising detection submodule. The rising detection submodule records the starting points and the ending points of the rising parts of S_k curves. Once it receives the enabling-signal sent by the comparison submodule and all the S_k curves begin to go down, it outputs the positions of starting point and ending point that it records. And an enabling-signal is sent to the Arg Max submodule from the rising detection submodule. Then the Arg Max submodule outputs the index of the S_k curve that achieves the maximum value at the ending point. After that, all the S_ks are reset to zero and forward variables calculation submodules are reinitialized.

The process of spectrum detection and recognition in the proposed approach is summarized as follows.

1) Initialization. $k = 0$. $S_{i,0} = 0$, for $i = 1, 2, ..., Q$, where Q is the number of kinds of known spectra, and $S_{i,k}$ represents the k^{th} sample of S for the i^{th} kind of known spectrum. Initialize forward variables calculation submodules.
2) Iteration. $k = k + 1$. Calculate $S_{i,k}$, for $i = 1, 2, ..., Q$. If $S_{i,k}$ is forced to be set to zero by the max operation in 12, then goto step 1).

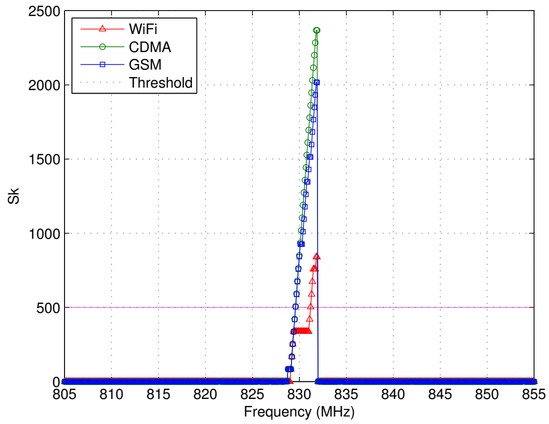

Fig. 9. S_k for CDMA spectrum detection and recognition.

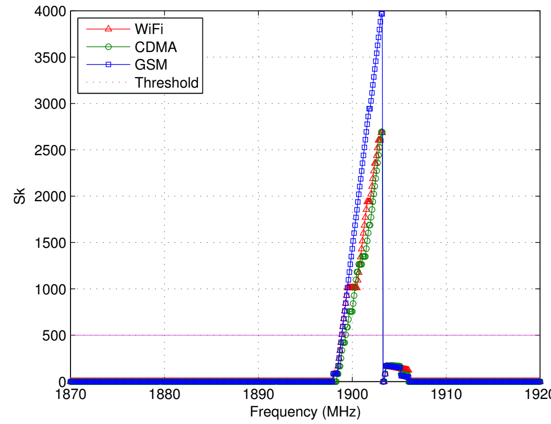

Fig. 10. S_k for GSM spectrum detection and recognition.

3) If $S_{i,k}$ is great than the threshold S_{th}, for any $i = 1, 2, ..., Q$, then the comparison submodule outputs a reference indicator for occupancy of spectrum segment and sends an enabling-signal to the rising detection submodule.
4) If the S_k curve that later goes the highest begins to rise, the position of the starting point of rising is recorded by the rising detection submodule. If all of the S_k curves begin to drop, the position of the ending point of rising is recorded.
5) If the rising detection submodule receives an enabling-signal and all of the S_k curves begin to drop, then the positions of recorded starting point and ending point are output, and an enabling-signal is sent to the Arg Max submodule.
6) If the Arg Max submodule receives an enabling-signal, then it outputs the index of the S_k curve that achieves the maximum value at the ending point, and goto step 1).
7) Goto step 2).

IV. Experimental Results

Experimental testing has been done in the Wireless Networking Systems Lab of Tennessee Technological University. A Spectrum Analyzer (SA) is used to sweep the spectrum and output the measured power spectrum densities (PSDs) of spectrum segments. The model of the SA is Rohde & Schwarz FSEM20 with 10 dB RF attenuation and 500 points per sweep. Three categories of primary user's spectrum are chosen for testing the proposed approach, i.e., Code Division Multiple Access (CDMA), Global System for Mobile communications (GSM), and Wi-Fi. A blank spectrum is needed for calculating S_ks. The PSDs of their spectra have been measured, as shown in Fig. 5, Fig. 6, Fig. 7, and Fig. 8.

Then the samples of these PSDs are quantified respectively with 64 levels. The HMMs are trained in advance with 5 states using the quantified PSDs. And the whole quantified PSDs are regarded as observation sequences for HMM recognition.

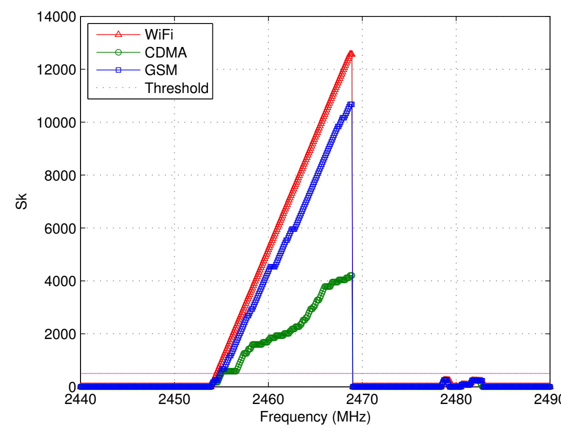

Fig. 11. S_k for Wi-Fi spectrum detection and recognition.

Using the proposed approach, the S_k curves for detection and recognition of CDMA, GSM, and Wi-Fi spectra are shown in Fig. 9, Fig. 10, Fig. 11. From these figures it can be observed that where no primary user's spectrum is present, the curves of S_k are close to zero. And where primary user's spectrum exists, the corresponding parts of S_k curves go up sharply and beyond the threshold. Given a proper threshold, quickest detection of the existence of primary user's spectrum can be achieved. Since the curve that goes the highest indicates the final recognition result, according to the figures, the recognition results are all correct for CDMA, GSM, and Wi-Fi.

After the category of detected spectrum segment is obtained, the bandwidth of the spectrum segment can be determined. The bandwidth that this detected spectrum segment occupies depends on the turning points of the highest curve in the S_k figure. The span between the turning point that the curve begins to go up sharply and the turning point that the curve begins to drop suddenly is the bandwidth of the detected spectrum segment. The bandwidths, starting points and ending points detected by the proposed approach for the spectra of

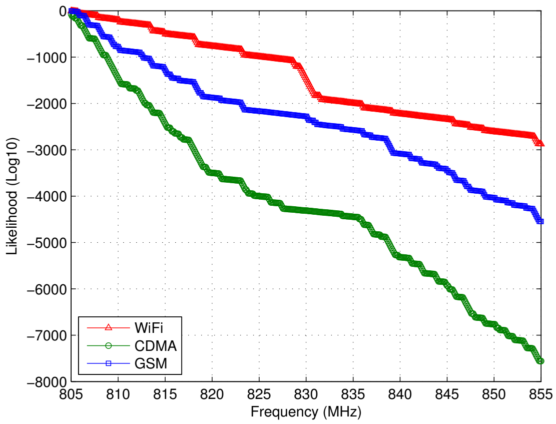

Fig. 12. p_{f} for CDMA spectrum recognition.

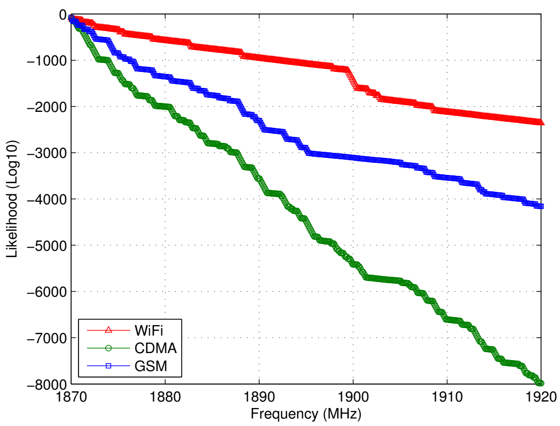

Fig. 13. p_{f} for GSM spectrum recognition.

CDMA, GSM, and Wi-Fi are listed in Table I, which are also marked as red dash-dot lines in Fig. 5, Fig. 6, and Fig. 7, for the purpose of comparison with the actual spectrum peaks.

TABLE I. Detected Starting Points, Ending Points and Bandwidths.

Kind of spectrum segment	Starting point	Ending point	Bandwidth
CDMA	828.3 MHz	831.8 MHz	3.5 MHz
GSM	1897.9 MHz	1903.1 MHz	5.2 MHz
Wi-Fi	2453.9 MHz	2468.8 MHz	14.9 MHz

Conventional HMM recognition using Viterbi algorithm does not work well for recognizing the swept spectrum. Because when the spectrum is swept, exact starting points and ending points of spectrum segments are hard to be determined. Thus errors will accumulate outside of the range of the spectrum segments, which affects the final decision of recognition. Moreover, the recognition process using Viterbi algorithm does not contain a "reset" step. So the highest likelihood curves output by Viterbi algorithm can not represent recognition results correctly. In addition, for Viterbi algorithm, the presence of recognized spectrum segment will not be announced until the whole spectrum segment is swept, which introduces much time delay for spectrum detection. Fig. 12, Fig. 13 and Fig. 14 give

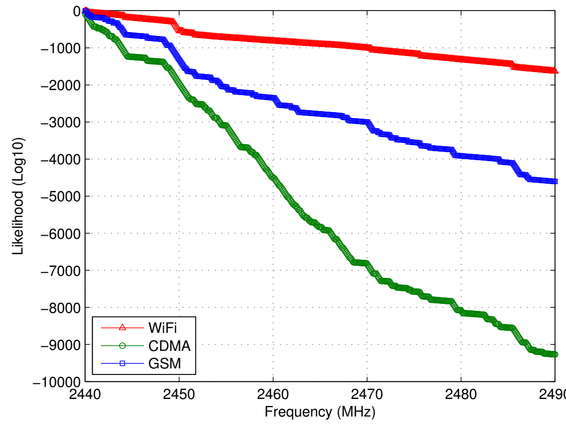

Fig. 14. p_{f} for Wi-Fi spectrum recognition.

illustrations that the exact starting points and ending points of spectrum segments are unknown. Conventionally, the curve that goes above other curves corresponds to the recognition result. From the figures it can be observed that the recognition results are totally unexpected. That is why Viterbi algorithm is not adopted for recognition in this situation.

V. Conclusions

An approach for quickest spectrum detection and recognition for cognitive radio has been proposed in this paper. HMM and quickest detection are utilized. The proposed architecture and algorithm have been presented. The spectra of CDMA, GSM, Wi-Fi and blank spectrum have been measured and used for performance evaluation of the proposed approach. Experimental results have demonstrated that the proposed approach is effective.

In this paper, PSDs are used as the inputs of HMM. In the future, more features extracted from measured signals besides PSD should be explored.

Acknowledgment

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