HMM Based Spectrum Sensing in the Presence of Censored Data

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***Abstract*—Spectrum Sensing (SS) techniques play an important role in the Cognitive Radio (CR) systems. In recent years, many spectrum sensing techniques have been proposed in the literature to identify the state of the Primary Users (PUs) in the temporal domain. However, these techniques are usually interested in the current state of channel without consideration to their status in the past. In this paper, we applied Hidden Markov Model (HMM) for SS in Cognitive Radio Network (CRN) and employ an Expectation-Maximization (EM) method to estimate parameters of the HMM in the presence of censored data. Further, we present an optimal likelihood computation for censored data during the online channel status estimation procedure. Simulation results show the effectiveness of the proposed algorithm.**

I. Introduction

With the rapid growth of wireless applications and services in the recent decades, the demand for access to additional frequency spectrum has been increasing dramatically. The radio spectrum resource is a limited resource and is regulated by government agencies. However, recent studies show that the fixed spectrum assignment policy enforced today results in poor spectrum utilization. CRN allows the exibility of spectrum. It enables dynamic spectrum access (DSA) over temporarily unused frequency band (called spectrum holes or white space) already licensed to other PUs. To avoid interference to primary system, such an unlicensed secondary CR user (CU) is allowed to access to the spectrum holes only at particular time and in a specic geographic location, and must abandon it and seek another whenever the PU returns.

The task of seeking spectrum holes to identify spectrum access opportunities is called spectrum sensing. Spectrum sensing can be achieved by a single CU by using basic techniques such as Energy Detection (ED), Matched Filter (MF), Cyclostationary feature Detection (CFD) [1]. The principle of ED is based on the difference between the energy of PU transmission signal and the one of the noise at the receivers. ED based spectrum sensing has low complexity and requires no prior knowledge about the PU. However, its performance is poor when the received SNR is low [8]. A matched filter is obtained by correlating a known signal called template with an unknown signal to detect the presence of the template in the unknown signal. Therefore, with matched filtering detection method, CU needs to know the transmitted waveform [13]. Cyclostationary detection is based on the cyclostationarity of modulated signals. This method is robust when the signal to noise ratio (SNR) is low, however, it requires partial information of the PU signal and has high computation cost [4], [11], [12].

Multipath fading, shadowing and hidden node problems also degrade the performance of single user spectrum techniques. To overcome this issue, Cooperative spectrum sensing (CSS) methods were proposed. By cooperation, sensing information from multiple CU is combined to make the final decision more accurate than the individual decisions. However, this performance improvement is achieved with the tradeoff of additional system hardware [13], [14].

The SS techniques have been proposed in the literature to identify the state of the PU in the temporal domain. Although, CU may predict the status of channel based on the past sensing results, most of these techniques make instantaneous decisions based on current measurement received at the cognitive radio node, and they do not consider the transmission pattern of the PU which can be acquired from past measurements. Thus, sensing performance can be improved by incorporating measurement history into the sensing decision. Moreover, using all available data may enable prediction of the PU activity, which will allow a CU to better plan for its spectrum usage. HMM is used to predict the usage behavior of a frequency band based on channel usage patterns [2]. In [4], [5] the authors have extended their idea of improvising HMM in spectrum sensing. The accuracy of method in predicting the true states of the sub-band is substantiated in [6], [7]. In [9], the Baum-Welch algorithm has been applied to estimate the parameters of the HMM model. Another HMM-based predictor is also proposed in [8], but it only deals with deterministic traffic scenarios, making it non-applicable in practice. When using HMM model most previous authors assumed that all data could be observed [4], [5], [6], [7], [8], [9], [10].

This paper addresses such the problem of missing data when estimating parameters of HMM model. In the HMM framework, the PU transmission pattern can be modeled by either a discrete-time Markov chain or a continuous-time Markov chain. According to our simulation result, we realize that the modeling of the PU activity by using a continuous-time Markov chain only improves the performance when the PU changes its state within a sensing period of CU. Therefore,

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within this paper, we present the proposed method using discrete-time Markov chain.

The rest of the paper is organized as follows. In Section II, we formulate the HMM based method for spectrum sensing and present the Forward algorithm for decoding the HMM in order to estimate the channel status. Section III presents the EM algorithm for parameter estimation of emission probability density function of the HMM, and incremental update method for re-estimation formulas. In Section IV, a treatment method for computing likelihood of censored data is presented. The effectiveness of the proposed method is evaluated in Section V and the conclusions is presented at the end of the paper.

II. Formulation of HMM in Spectrum Sensing

In [6] a hidden Markov model (HMM) is used to combine RSSI (Received Signal Strength Index) measurements and channel utilization information for channel status estimation. The hidden states comprise the possible channel status, of which reference RSSI fingerprints have been recorded in the training phase. The estimation of the channel status can then be carried out either by the Forward algorithm or by the Viterbi algorithm. While the former computes the probability of being in a certain state by gathering the probabilities over all possible predecessor states, the latter considers only the most probable predecessor. In the following we consider the Forward algorithm.

Let $s_t \in S(S = \{0, 1\})$ denote the value that the hidden state variable takes at time t, which we identify with the status of the considered channel at time t: $s_t = 0$ or $s_t = 1$ indicates that the channel is free at time t and the channel is busy at time t, respectively. Further, let $\mathbf{x} = [x_1, \dots x_t]$ be the sequence of RSSI measurements up to time t. Our goal is to compute $P(s_t{=}j|x_{1:t})$, i.e., the probability of being in state j for all possible channel status S, given all RSSI values measured so far. Using Bayes' rule, the probability can be expressed as follows:

$$\begin{aligned} P(s_t{=}j|x_{1:t}) &= \frac{P(s_t{=}j, x_{1:t})}{p(x_{1:t})} \\ &\propto p(s_t{=}j, x_{1:t}) =: \alpha_t(j), \end{aligned} \tag{1}$$

where the so-called Forward variable $\alpha_t(j)$ is the probability of being at time t in state j, while having observed the sequence of $x_{1:t}$.

The forward variable can be written as follows

$$\begin{aligned} \alpha_t(j) &= \sum_i p(s_t{=}j, s_{t-1}{=}i, x_{1:t}) \\ &= \sum_i p(x_t|s_t{=}j, s_{t-1}{=}i, x_{1:t-1}) \\ &\quad \cdot P(s_t{=}j|s_{t-1}{=}i, x_{1:t-1}) \\ &\quad \cdot P(s_{t-1}{=}i, x_{1:t-1}). \end{aligned} \tag{2}$$

Applying the properties of the HMM, which are depicted in the graphical model of Fig. 1, and assuming the RSSI measurements to be statistically independent of each other given the user location, we arrive at

$$\begin{aligned} \alpha_t(j) = &\sum_i p(x_t|s_t{=}j) \\ &\cdot P(s_t{=}j|s_{t-1}{=}i) \cdot \underbrace{P(s_{t-1}{=}i, x_{1:t-1})}_{=\alpha_{t-1}(i)} \end{aligned} \tag{3}$$

which is a recursion of the forward variable.

Equation (3) shows how the different knowledge sources are combined. The transition probabilities $P(s_t{=}j|s_{t-1}{=}i)$ indicate how likely the channel status changes from i to j within one time step. The choice of the transition probabilities thus encodes our knowledge about the channel utilization information. The term $p(x_t|s_t{=}j)$ is the likelihood of the RSSI measurement x_t, assuming the channel status is j. Its computation is described in the next section.

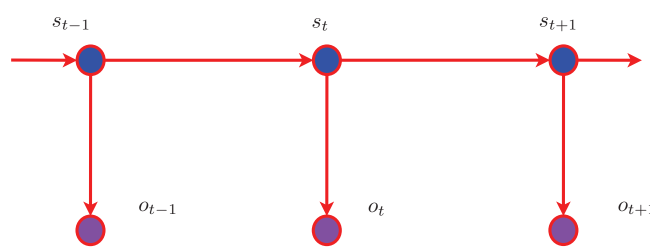

Fig. 1. Hidden Markov Model.

III. Treatment of Censored Data for Parameter Estimation of Emission Probability Density Function

In this section, we utilize the EM algorithm for estimating parameters of emission probability density functions of the HMM which are Gaussian data as developed in [15]. Since our purpose is to estimate the channel status in CRN, the HMM has only 2 possible states, i.e., free and busy. For each state, its emission probability density function is needed to be estimate. Let $\mathbf{y} = y_1, ..., y_N; y_i \in \mathbb{R}$ be the complete data where N is the number of RSSI observations and where the y_i are independent and identically distributed random variables with Gaussian probability density function (PDF) $p_Y(y_i) = \mathcal{N}(y_i; \mu, \sigma^2)$. Observable are $\mathbf{x} = x_1, ..., x_N$, where $x_i = \max(y_i, c)$, where c is censoring threshold for each sample. The purpose is to develop a parameter estimation method for $\theta = (\mu, \sigma^2)$ of the underlying Gaussian. Here we assume that $\mathbf{x}$ can be noise only data or PU signal data for the free channel or busy channel respectively.

Employing the EM algorithm considering that $\mathbf{y}$ and $\mathbf{x}$ are the complete and the incomplete data. Expectation of the log-likelihood of the complete data given the observed data is computed as follows

$$Q(\theta; \theta^{(\kappa)}) = E\left[\ln\left(p_Y(\mathbf{y}; \theta)\right) |\mathbf{x}; \theta^{(\kappa)}\right] \tag{4}$$

$$= \sum_{i=1}^{N} \int_{-\infty}^{\infty} \ln\left(p_Y(y_i; \theta)\right) p\left(y_i|x_i; \theta^{(\kappa)}\right) dy_i \tag{5}$$

where κ is the iteration index and $\theta = (\mu, \sigma^2)$ is parameter to be estimated.

In [15] authors have shown that the following iterative algorithm

$$\mu^{(\kappa+1)} = \frac{1}{N}\frac{I_1(\theta^{(\kappa)})}{I_0(\theta^{(\kappa)})}\sum_{i=1}^{N} z_i + \frac{1}{N}\sum_{i=1}^{N}(1-z_i)x_i \tag{6}$$

$$\left(\sigma^2\right)^{(\kappa+1)} = \left[\frac{I_2(\theta^{(\kappa)})}{I_0(\theta^{(\kappa)})} - 2\mu^{(\kappa)}\frac{I_1(\theta^{(\kappa)})}{I_0(\theta^{(\kappa)})} + \left(\mu^2\right)^{(\kappa)}\right]\frac{1}{N}\sum_{i=1}^{N} z_i + \frac{1}{N}\sum_{i=1}^{N}(1-z_i)\left(x_i - \mu^{(\kappa)}\right)^2. \tag{7}$$

delivers unbiased and efficient parameter estimates. Where binary variable z_i indicates whether an observation is clipped ($z_i = 1$) or not ($z_i = 0$), and

$$I_j(\theta^{(\kappa)}) = \int_{-\infty}^{c} y^j \mathcal{N}\left(y; \theta^{(\kappa)}\right) dy \tag{8}$$

Further, for updating parameters of emission probability density function, incremental parameter update is available which reduces the computational cost dramatically. With EM algorithm, the incremental update of parameters can be derived analytically, assuming that w.l.g the first K test statistics is number of observable data. Eq. 6 and 7 can be re-written as

$$\mu^{(\kappa+1)} = \frac{N-K}{N}\frac{I_1(\theta^{(\kappa)})}{I_0(\theta^{(\kappa)})} + \frac{1}{N}\sum_{i=1}^{K} x_i \tag{9}$$

$$\left(\sigma^2\right)^{(\kappa+1)} = \frac{N-K}{N}\left[\frac{I_2(\theta^{(\kappa)})}{I_0(\theta^{(\kappa)})} - 2\mu^{(\kappa)}\frac{I_1(\theta^{(\kappa)})}{I_0(\theta^{(\kappa)})} + \left(\mu^2\right)^{(\kappa)}\right] + \frac{1}{N}\left(\sum_{i=1}^{K} x_i^2 - 2\mu^{(\kappa)}\sum_{i=1}^{K} x_i + M\mu^{2(\kappa)}\right). \tag{10}$$

Eq. 9 and Eq. 10 indicate that for incremental update, it is only necessary to store the summation of observable data $\sum_{i=1}^{K} x_i$, summation of square of observable data $\sum_{i=1}^{K} x_i^2$, number of observable data K and number of total measurements N. When there are some new RSSI measurements available, using the estimated parameters of the previous estimation procedure as the initial values and using incremental update formulas, the required time to produce next estimated noise power is much less than the necessary time to estimate noise power from scratch. Incremental update method allows HMM parameter updating during the operation of the CRN with reasonable processing period.

IV. Treatment of Sensored Data for Likelihood Computation

During state estimation we need to compute the likelihood $p(x_t|s_t)$ of an observation x_t for an hypothesized channel status s_t. To account for censored data this is carried out as follows

$$p(x_t|s_t) = \begin{cases} \mathcal{N}(x_t; \hat{\mu}_{s_t}, \hat{\sigma}^2_{s_t}), & \text{if } x > c \\ I_0(\hat{\mu}_{s_t}, \hat{\sigma}^2_{s_t}), & \text{if } x = c \end{cases}. \tag{11}$$

Here, $(\hat{\mu}_{s_t}, \hat{\sigma}^2_{s_t})$ are the estimated parameters of the state s_t. $I_0(\hat{\mu}_{s_t}, \hat{\sigma}^2_{s_t})$ is computed using Eq. 8.

It is noted that censored data can be used to compute likelihood using this procedure instead of ignoring them in case of regular likelihood computation. As a consequence, it improves the state estimation performance.

V. Simulation Results

In this section we are going to evaluate the effectiveness of the proposed method for spectrum sensing in cognitive radio network. Because real data is not available, we will consider artificially generated data only.

In order to validate our proposed method and examine the accuracy of the Forward algorithm, a typical case is considered. To compare with the proposal in [6], the simulation setup is produced in the same ways as described there. Assuming that in training period, the channel utilization percentage is 70%, employing this information, we define the transition matrix as follows

$$A = \begin{pmatrix} 0.7 & 0.3 \\ 0.7 & 0.3 \end{pmatrix} \tag{12}$$

The initial probability for each state of the HMM must satisfy the following equation:

$$\pi_0 + \pi_1 = 1 \tag{13}$$

In this simulation, we also employ the knowledge of channel utilization to define the initial probabilities: $\pi_0 = 0.7$ for busy channel and $\pi_1 = 0.3$ for free channel.

These transition matrix and initial probabilities are fixed during the simulation process. Simulation procedure has 4 steps as follows:

- Step 1: Use the initial probabilities and transition matrix, generate the Markov state sequence of length L = 100, resulting in a path $s_1, s_2, \cdots, s_{100}$.
- Step 2: Generate data $y_1, y_2, \cdots, y_{100}$ using the simulated path $s_1, s_2, \cdots, s_{100}$. The generated data $y_{1:100}$ is then censored with the censoring threshold $c = -120$ dBm which is the minimum observable RSSI of the receiver. The censored data is denoted as $x_1, x_2, \cdots, x_{100}$, where $x_i = max(y_i, c)$.
- Step 3: Apply the Forward algorithm detailed in Section II to the data $x_1, x_2, \cdots, x_{100}$ to predict the underlying path as $\hat{s}_1, \hat{s}_2, \cdots, \hat{s}_{100}$.
- Step 4: Prediction accuracy (PA) is computed by

$$PA = \frac{\#\{1 \le k \le 100 : \hat{s}_k = s_k\}}{100} * 100 \tag{14}$$

Step 1 to 4 are repeated for 100 times. The performance of the proposed methods are shown in Fig. 2, Fig. 3 and Fig. 4

Fig. 2 and Fig. 3 show the percentage of estimation accuracy when employing regular ML method and EM method, respectively, for parameter estimation of the emission probability density functions of the HMM. Fig. 4 shows the comparison of the performance of spectrum sensing between 2 approaches. As can be seen in Fig. 4, the proposed method obviously

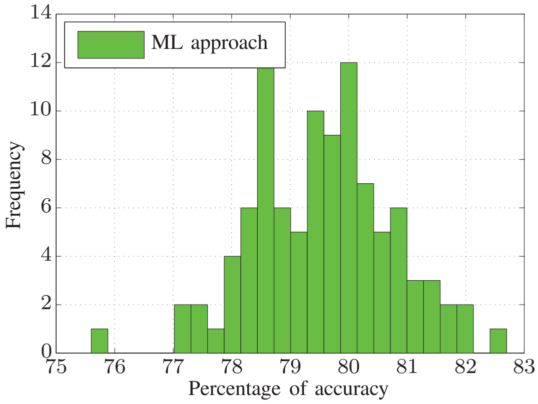

Fig. 2. Percentage of accuracy when employing regular ML method for HMM parameter estimation (ML approach).

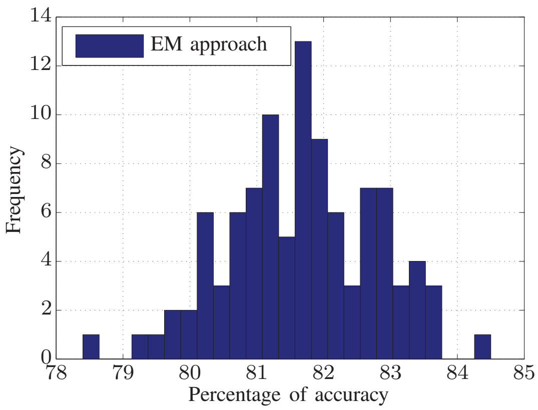

Fig. 3. Percentage of accuracy when employing EM method for HMM parameter estimation and treating of censored data when computing likelihood (EM approach).

outperforms the other by the mean of channel status estimation accuracy. The observed improvement is approximately 3%. It must be noted that the simulation was performed for the case of very low SNR. In case of high SNR, the performance of the proposed method is in the same order with the conventional energy detection based method.

VI. Conclusions

In this paper, HMM based method was employed to estimate channel status of a CRN. As far as we acknowledge, the previous research have not considered the censored data during the procedure of HMM parameter estimation in the training phase and likelihood computation in the classification (channel status estimation) phase. Therefore, this paper tried to address such the censoring problem by employing EM algorithm for HMM parameter estimation. Further, the likelihood computation procedure also took into account the problem of censored data. Simulation results demonstrate that the proposed method is able to produce reasonable channel status estimation accuracy in case of very low SNR. Performance of proposed method was compared with another HMM based method, considerable

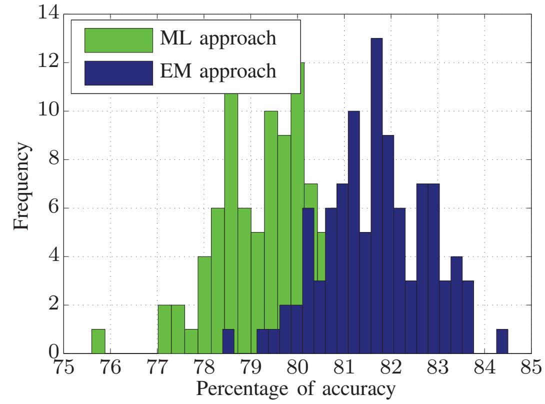

Fig. 4. Performance comparison between EM approach (proposed method) and ML approach.

improvement of classification result was observed. It can be also concluded that HMM based spectrum sensing is the promising approach for the CRN system where SRN is pretty low.

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