Received October 17, 2016, accepted October 28, 2016, date of publication October 31, 2016, date of current version November 18, 2016.

Digital Object Identifier 10.1109/ACCESS.2016.2623478

Cooperative Spectrum Sensing With Data Mining of Multiple Users' Historical Sensing Data

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This work was supported in part by the National Natural Science Foundation of China under Grant 61390513 and Grant 61631017, in part by the Shanghai Pujiang Program under Grant 13PJD030, in part by the Chen Guang Project through the Shanghai Municipal Education Commission and Shanghai Education Development Foundation under Grant 13CG18, in part by the National Natural Science Foundation of China under Grant 61301159, and in part by the China Postdoctoral Science Foundation under Grant 2015M571635 and Grant 2016T90404.

ABSTRACT Under the case of exponentially growth of wireless services and the scarcity of spectrum resources, cognitive radio (CR) has been proposed to access licensed channels opportunistically, and thus improve spectrum utilization. In CR devices, accurate spectrum sensing is the prerequisite for opportunistic access. The current cooperative spectrum sensing still cannot effectively exploit the temporal correlations among sensing data, especially the correlations between the current sensing data and the historical data. This paper uses sticky hierarchical Dirichlet process-hidden Markov model to exploit the historical sensing data of multiple users, and classifies the historical sensing data into groups according to their latent spectrum states. The proposed spectrum sensing algorithm can fuse the historical sensing data into prior knowledge, which can be used to improve the accuracy in spectrum decision. Furthermore, a rejection process is proposed to filter out some sensing data with high uncertainty in classification, which guarantees the effectiveness of historical sensing data. The simulation results show that the proposed algorithm performs the best, compared with other three typical cooperative spectrum sensing algorithms, in terms of detection probability and false alarm probability. Specifically, when the false alarm probability is 0.2, the proposed algorithm has more than 10% and 60% detection probability improvement under channel signal-to-noise ratio as 0 and −5 dB, respectively.

INDEX TERMS Cognitive radio, spectrum sensing, historical sensing data mining, hierarchical Dirichlet process, hidden Markov model.

I. INTRODUCTION

With the coming of information age, wireless communication has become one of the most important approaches for information transmission [1]. Wireless communication is a special transmission mode which uses electromagnetic wave as carrier. Hence, it is critical to deal with the spectrum allocation issue among different applications. The current spectrum allocation strategy divides the radio frequency (RF) bands into licensed and unlicensed frequency bands, and it is illegal to access licensed bands without permission. According to the survey [2], however, most licensed frequency bands are underutilized.

To solve the problem mentioned above, Dr. Joseph Mitola proposed the cognitive radio (CR) technology in 1998 [3], [4]. CR is defined as an intelligent wireless communication technology based on software defined radio (SDR), which can continuously detect radio environment and dynamically access the opportunistic frequency bands for transmission. Specifically, the CR users can reconfigure the radio parameters, such as the central frequency, transmission power, and modulations. This technology can effectively avoid the interference between existing licensed users and CR users, and improve the spectrum utilization.

In cognitive radio networks (CRNs), there are two kinds of user, that is, licensed user (also called "primary user (PU)") and CR user (also called "secondary user (SU)"). SUs need to observe the radio environment, find out the unoccupied channels, and finally decide whether to access the idle spectrum opportunistically. Such an available spectrum detection process is called as spectrum sensing [5], which is the key technique in CR. In this paper, we mainly focus on cooperative spectrum sensing, and the previously observed historical spectrum sensing data will be exploited to improve spectrum detection performance.

Cooperative spectrum sensing has many advantages, such as solving the problem of hidden nodes, enhancing the spectrum decision performance under low channel signal-to-noise ratio (SNR), and decreasing the hardware cost effectively [6]. However, cooperative spectrum sensing will increase the computational complexity. Furthermore, cooperative spectrum sensing should well address some problems, such as node selection in data fusion, efficient sensing information exchange, and synchronization among SUs.

According to the patterns of information sharing among SUs in CRNs, cooperative spectrum sensing algorithms can be classified into three types, that is, centralized spectrum sensing, distributed spectrum sensing, and trunked spectrum sensing [7]. Centralized spectrum sensing network consists of many SUs and a fusion center (FC), which can gather SUs' sensing data and make a comprehensive decision, and then broadcast such spectrum decision to all SUs. Hence, powerful computation ability is required in centralized spectrum sensing algorithms. Without FC, distributed spectrum sensing can be adopted, where SUs can share sensing information locally and make spectrum decision privately. The trunked spectrum sensing only collects sensing information from SUs with high detection ability to make spectrum decision. Although it increases the computational complexity, it is a good way to improve the performance of spectrum decision [8].

After collecting sensing information from SUs, spectrum decision algorithm (data fusion) will be adopted. Typical data fusions include soft combining, hard combining, and softened hard combining [8]. Furthermore, the cooperative spectrum sensing requires an extra control channel, which should be a dedicated channel, to exchange sensing information and control information.

The challenge in spectrum sensing technology is the uncertainty in observed sensing data, which is caused by channel noise and interruption in radio device [9], [10]. Fortunately, the historical sensing data observed previously, which were observed under the same spectrum state, can be used to reduce the uncertainty of spectrum decision. Furthermore, the sequential spectrum sensing data are temporally correlated, which means their spectrum states may keep consistent in high probability. In this paper, the historical data-assisted cooperative spectrum sensing will be proposed. The historical sensing data will be classified according to their statistical property, and some historical sensing data that can not be classified clearly will be rejected through rejection process. The proposed algorithm leverages sticky hierarchical Dirichlet process-hidden Markov model (sticky HDP-HMM) and fuses the historical sensing data into prior knowledge, which will be integrated into current spectrum decision process using Bayesian inference.

The main contributions of this paper are as followings:

1) Due to the uncertainty of spectrum sensing data, the rejection process is proposed to remove uncorrelated spectrum sensing data, in order to ensure the effectiveness of Bayesian inference.
2) Historical sensing data are fused into prior knowledge using sticky HDP-HMM, where temporal correlation and statistical correlation are exploited, in order to reduce the uncertainty of current spectrum sensing and improve the accuracy of spectrum decision.

The remainder of the paper is organized as follows. In section II, cooperative spectrum sensing scenario and its mathematical model are introduced. In section III, the HDP-HMM model and its extension (i.e., sticky HDP-HMM) are exploited to fuse historical sensing data into prior knowledge. In section IV, a novel cooperative spectrum sensing scheme is proposed, where the sensing data fusion is performed based on sticky HDP-HMM model. In section V, the performances of the proposed spectrum sensing algorithm are shown through simulation, and comparisons are made with some typical spectrum sensing algorithms. Finally, a conclusion of this paper is made in section VI.

II. COOPERATIVE SPECTRUM SENSING PROCESS AND ITS MATHEMATICAL MODEL

A. COOPERATIVE SPECTRUM SENSING PROCESS

Usually, with the help of CRN infrastructure, cooperative spectrum sensing algorithm can be implemented after collecting all sensing information in CRN base-station (i.e., FC). All SUs involved in cooperative sensing are usually assumed to have the same hidden spectrum state, thus the global spectrum decision made by FC applies to all SUs. However, such an assumption does not accurate in practice, since all SUs may be deployed in a large-scale space and can not share the same spectrum state. Through dividing the whole network into several clusters, clustering CRNs can insure that SUs within a cluster have the same hidden spectrum characteristics, which can not only solve the problem that the spectrum decision of the FC is not consistent with the practical spectrum state of the SUs, but also reduce the energy consumption of multi-hop sensing information transmission to FC [11].

The cooperative spectrum sensing algorithm proposed in this section is mainly used for sensing data fusion of the SUs within the same cluster. The hidden spectrum characteristics and spectrum state transition probability matrix of SUs within the same cluster are assumed consistent. The spectrum sensing and information exchange process of SUs within the same cluster are assumed synchronously, which is controlled by cluster head (CH). Furthermore, we assume the spectrum sensing process is implemented periodically, since continuous spectrum sensing will exhaust SUs' power quickly. The cooperative sensing process of SUs within a cluster is showed in Fig. 1, where a sensing period is consisted of spectrum sensing duration, sensing information exchange duration and sensing interval. SUs collect sensing data only

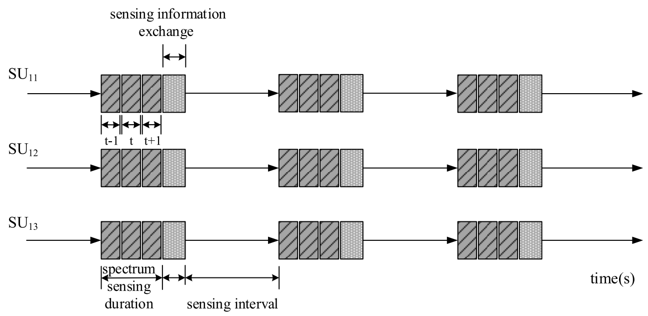

FIGURE 1. Cooperative spectrum sensing process.

in spectrum sensing duration, while they will access idle channels in sensing interval.

After observing radio environment in a sensing period, SUs within the same cluster will transmit the sensing information to CH. CH will make a locally spectrum decision about current channel state using the data fusion algorithm, and broadcast the spectrum decision to SUs within the cluster through control channel.

B. MATHEMATICAL MODEL OF COOPERATIVE SPECTRUM SENSING

In this part, the observation model of spectrum sensing process will be defined and its mathematical model will be given. It is assumed that there are M licensed channels (also called "subcarriers") and N PUs in the network, and SUs can observe multiple samples in each subcarrier during a sensing period [12].

In time domain, the received signal of SU_j can be represented as:

$$r(n) = \sum_{i=1}^{N} h_i(n) * x_i(n) + w(n) \tag{1}$$

where $x_i(n)$ is the transmitted signal of the PU_i, $h_i(n)$ is the channel impulse response (CIR) of wireless channel between PU_i and SU_j, and $\omega(n)$ is the additive white Gaussian noise (AWGN) with mean zero and variance σ^2. If PU_i is turned off, we have $x_i(n) = 0$.

In order to detect the channel state of all channels/subcarriers, it is necessary to transform the time-domain signal to frequency-domain by M-point discrete Fourier transform (DFT). Hence, the spectrum sensing data can be represented in frequency domain, that is,

$$R(k) = \sum_{i=1}^{N} H_i(k) X_i(k) + W(k), \quad k = 0, 1, \ldots, M-1 \tag{2}$$

where $R(k)$, $H_i(k)$, $X_i(k)$, and $W(k)$ are the corresponding DFT coefficients of $r(n)$, $h_i(n)$, $x_i(n)$ and $\omega(n)$. In Eqn. (2), $R(k)$ stands for the channel state of the kth subcarrier [12], and the channel noise $W(k)$ causes the uncertainty of observed signals. In Eqn. (2), the transmitted signals of PUs are assumed passing through a time-varying Rayleigh fading channel. As a result, the real and imaginary parts of $R(k)$ obey independent and identically distributed ($i.i.d.$) Gaussian distribution with zero mean and variance σ_k^2, respectively. In this paper, $R(k)$ is defined as a two-dimensional vector consisting of the real and imaginary parts, thus obeying the Gaussian distribution with covariance matrix $\sum_k$. When the kth subcarrier is unoccupied by PUs, we have $\sum_k = \sigma_0^2 I_2$, and I_2 is a second-order identity matrix. In this paper, the spectrum decision over a single channel will be presented in mathematics and multi-channel spectrum decision can be extended by single channel case very easily [13].

The received signal power $|R_{jt}(k)|^2$ of SU_j in different time slots (see Fig. 1) will be collected by CH through sensing information exchange. CH will filter out some sensing data according to rejection process and calculate the mean value of the remaining sensing information $|R_{jt}(k)|^2$ collected from all SUs at each time instant t. Finally, the received signal power will be treated as independent variables in Bayesian learning model in this paper. The signal power E_{jt} which SU_j observes at time instant t can be represented as:

$$E_{jt} = \left|R_{jt}(k)\right|^2 \tag{3}$$

where $R_{jt}(k)$ denotes the sensing data over the kth subcarrier at time instant t. At time instant t, the sensing data set of N SUs within the cluster can be represented as:

$$\mathbf{E}'_t = \{E_{1t}, E_{2t}, \ldots, E_{Nt}\} \tag{4}$$

After the rejection process, the sensing data are refined and can be represented as:

$$\mathbf{E}_t = \{E_{1t}, E_{2t}, \ldots, E_{rt}\} \tag{5}$$

Then, the fused sensing data can be represented as:

$$y_t = \sqrt{\frac{1}{r}\sum_{j=1}^{r} E_{jt}}, \; E_{jt} \in \mathbf{E}_t \tag{6}$$

It can be assumed that there are T sensing slots in a sensing period, thus the set of sensing data can be represented as:

$$Y = \{y_1, y_2, \ldots, y_t, \ldots, y_T\}, \; y_t \sim Rayleigh(\sigma_t) \tag{7}$$

where σ_t is the parameter in Rayleigh distribution that the sensing data y_t obeys. CH will make a decision of spectrum state according to the statistical property of sensing data $y_t (t = 1, 2, \ldots, T)$ within the cluster.

III. STICKY HDP-HMM MODEL

In this section, sticky HDP-HMM model is used to define the latent statistical property of observed sensing data. The sticky HDP-HMM model is suitable for multitask time sequential data analysis. Here, the spectrum sensing data from different SUs can be regarded as multitask time sequential data. The sequential spectrum states are modeled as the firstorder Markov model. The HDP will be adopted to infer the prior distribution of the Markov states transition matrix without knowing the number of spectrum states previously. At present, the HDP-HMM model has been widely used in various engineering fields [14]–[16]. Different from [14]–[16], a self-transition parameter will be used to force the HDP-HMM model to keep the spectrum state in high probability, since the sequential spectrum sensing data are temporally correlated.

A. HMM

HMM is the extension version of Markov model/Markov chain. Markov model is mainly used to describe the process of state changes over time. In many applications, however, the latent states can not be observed directly, which are usually estimated based on the observed data. In such process, latent state transition is inferred through analyzing the sequential observed data. Hence, such a process is called hidden Markov process.

HMM is essentially a dual embedded stochastic process, including a latent state sequence $Z = \{z_1, z_2, \ldots, z_T\}$ and an observed sensing data sequence $Y = \{y_1, y_2, \ldots, y_T\}$. T is the number of observation time slots. HMM generally contains five basic elements: the number of latent states, the number of possible observations, the latent state transition matrix, the emission probability of observed value given latent state, and the initial probability distribution of each state. These basic elements will be included in sticky HDP-HMM model lately. Moreover, there are some classical algorithms to solve some typical issues in HMM, such as forward-backward algorithm to calculate the probability of observed data sequence Y, and Viterbi algorithm to estimate the most possible latent state sequence Z from the observed data sequence Y [16].

B. STICKY HDP-HMM

Chinese restaurant franchise with loyal customers (CRF-LC) is an intuitive description of sticky HDP-HMM model. The introducing of loyal customers in CRF-LC process makes the HDP-HMM model has the property to keep latent state among time-contiguous observations.

It is assumed that there are J chain restaurants, and the customers who want to get into any of them must go through a unified entrance. i.e., the customers must line up at the entrance first, then get into the restaurant respectively. The customers can be defined as $Y = \{y_1, y_2, \ldots, y_T\}$ in chronological order, where T is the number of customers lining up. There are a shared menu $\{\phi_k\}_{k=1}^K$ in all the J chain restaurants, which includes all the dishes. The set of dishes ordered by all the customers is denoted as $Z = \{z_1, z_2, \ldots, z_T\}$, where z_t is the index number of dish ordered by customer y_t in the menu $\{\phi_k\}_{k=1}^K$ (which means $z_t \in [1, K]$). The subscripts t of each element in set Y reflects the sequence of entering the restaurants. The customer y_t could be marked by restaurant number and customer number after getting into a restaurant, i.e., $y_t = y_{ji}$ if the customer y_t is the ith customer in the jth restaurant. In the proposed algorithm, the customer set Y corresponds to sensing data collected by CH and Z corresponds to the latent spectrum state of sensing data.

CRF-LC model is a nonparametric Bayesian learning model, i.e., the number of dishes K in the menu $\{\phi_k\}_{k=1}^K$ and the number of tables D_j in the jth restaurant are not determined beforehand. In addition, CRF-LC model can be decomposed into two steps. The first step is determining the table number d_{ji} for customer y_{ji}. In the model, only one dish is ordered on each table, and ψ_{jt} represents for the dish ordered at tth table in jth restaurant. The customers sitting at the same table will share the same dish, which is equivalent to spectrum sensing data sharing the same Gaussian distribution with covariance matrix ψ_{ji}. The second step is determining the dish number z_{ji} of y_{ji} in the menu $\{\phi_k\}_{k=1}^K$.

Technically, CRF - LC model has two features:

1) The number of customers in each restaurant is not determined beforehand. The customers who want to get into a restaurant must firstly go through a unified entrance, and he/she prefers to enter the restaurant that famous for its special dish ordered by previous customer. For example, if $z_{t-1} = j$, the customer y_t prefer to enter the jth restaurant.
2) The introduction of self-transition parameter κ plays an important role in CRF-LC model, which makes the latent spectrum states (or ordered dishes) keep consistent in high probability among continuous sensing data sequence.

The hierarchical CRF-LC model can be represented as:

$$G_0 \sim DP(\gamma, H) \tag{8}$$

$$G_j \sim DP(\alpha_0 + \kappa, \frac{\alpha_0 G_0 + \kappa \delta_j}{\alpha_0 + \kappa}) \tag{9}$$

where α_0 is the parameter in the first-level DP in standard HDP hierarchical structure, and κ is the self-transition parameter. The process that y_{ji} chooses the table d_{ji} is a random sampling process, that is,

$$d_{ji} \mid d_{j1}, d_{j2}, \ldots, d_{j(i-1)}, \alpha_0, \kappa \sim \sum_{d=1}^{D_j} \frac{n_{jd}}{d-1+\alpha_0+\kappa}\delta_d + \frac{\alpha_0+\kappa}{d-1+\alpha_0+\kappa}\delta_{D_j+1} \tag{10}$$

where n_{jd} is the number of customers at the dth table in jth restaurant, and δ_d is the mass function in the point d. It is shown in Eqn. (10) that, if the customer y_{ji} chooses a new table (choosing the table $D_j + 1$), a dish ψ_{jD_j+1} must be ordered. The dish number z_{ji} is determined by a discrete process *Bernouli*(ρ). The process is shown as followings,

$$\rho = \frac{\kappa}{\alpha_0 + \kappa} \tag{11}$$

$$\omega_{jD_j+1} \mid \alpha_0, \kappa \sim Bernouli(\rho) \tag{12}$$

Then, z_{ji} can be represented as:

$$z_{ji} \mid \bar{z}_{ji}, \omega_{jD_j+1} = \begin{cases} x, & \omega_{jD_j+1} = 0, \\ j, & \omega_{jD_j+1} = 1. \end{cases} \tag{13}$$

where $\bar{z}_{ji}$ is the dish number that obtained in the second-level DP after information fusion among groups. In Eqn. (13), when $\omega_{jD_j+1} = 0$, the dish will be ordered from the following random process for the $D_j + 1$ table,

$$x \mid z_{11}, z_{12}, \ldots, z_{J1}, z_{J2}, \ldots, \gamma \sim \sum_{k=1}^{K} \frac{m_{.k}}{m_{..} + \gamma}\delta_k + \frac{\gamma}{m_{..} + \gamma}\delta_{K+1} \tag{14}$$

where m_{jk} is the number of tables which served with the kth dish in the jth restaurant, $m_{.k}$ is the number of tables which served with the kth dish ϕ_k in all the J restaurants, and $m_{.}$ is the number of tables sitting by customers in all the J restaurants.

From Eqns. (10)-(14), we can draw the conclusion that there are three cases where $z_{ji} = j$ in CRF-LC model: 1) the customer y_{ji} chooses the existing table with the j th dish (see Eqn. (10)), 2) the customer y_{ji} chooses a new table (the $D_j + 1$th table) with the variable $\omega_{jD_j+1} = 0$ (see Eqn. (13)), 3) the customer y_{ji} chooses a new table with the covered variable $\omega_{jD_j+1} = 1$ and still chooses the jth dish with a probability. In the proposed cooperative spectrum sensing algorithm, the CRF-LC model could achieve the exploitation of the temporal correlations among sensing data, and thus the spectrum decision performance can be improved.

Historical sensing data is exploited based on sticky HDP-HMM model, and the inferred PU state transition matrix is used as priori knowledge to improve spectrum decision performance. The PU state transition probability matrix is shared by all SUs in CRF-LC model. The shared state transition probability matrix can be represented as $\{\pi_j\}_{j=1}^{J}$. The latent state index z_t of sensing data y_t can be represented as:

$$z_t \mid \{\pi_j\}_{j-1}^{J}, z_t \sim \pi_{z_{t-1}} \quad t = 1, 2, \ldots, T \tag{15}$$

Then, the Eqns. (8) and (9) can be rewritten as:

$$\beta \mid \gamma \sim GEM(\gamma) \tag{16}$$

$$\pi_j \mid \beta, \alpha_0, \kappa \sim DP(\alpha_0 + \kappa, \frac{\alpha_0\beta + \kappa\delta_j}{\alpha_0 + \kappa}), \quad j = 1, \ldots, J \tag{17}$$

The process of updating prior knowledge is just updating HMM state transition probability matrix.

C. THE PROPOSED ALGORITHM WITH STICKY HDP-HMM

The sticky HDP-HMM model will classify the historical sensing data according to their latent states, then update the Rayleigh distribution parameters σ_t of each latent state. The distribution of sensing data y_{ji} is

$$y_{ji} \mid \{\phi_k\}_{k=1}^{K}, z_{ji} \sim Rayleigh(\phi_{z_{ji}}) \tag{18}$$

where the parameter σ_{ji} corresponds to dish $\phi_{z_{ji}}$, and ϕ_k is draw from the primitive distribution H, i.e., $\phi_k \mid H, \lambda \sim H(\lambda), k = 1, \ldots, K$. The sensing data with the same hidden state will share the same distribution parameters ϕ_k.

The probability graphical model of sticky HDP-HMM model is shown in Fig. 2. The sticky HDP-HMM model is

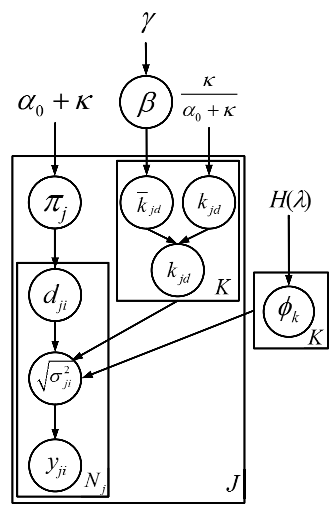

FIGURE 2. The probabilistic graphical model of sticky HDP-HMM hybrid model.

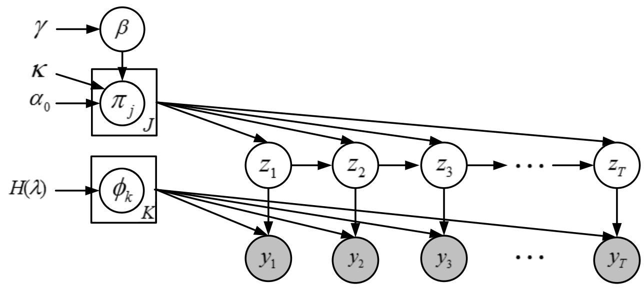

FIGURE 3. The probability graphical model of the proposed algorithm using sticky HDP-HMM.

a nonparametric Bayesian learning model with J restaurants and K unique dishes, where the exact value of J and K are unknown previously. The probability graphical model of the proposed algorithm with sticky HDP-HMM model is shown in Fig. 3 (N_j is the number of customers in the j th restaurant). In addition, sticky HDP-HMM hybrid model introduces the self-transition parameter κ to achieve the latent state preservation property in sensing data.

There are two reasons that sticky HDP-HMM model is adopted in the proposed algorithm, that is, (1) the PU state transition probability matrix can be inferred based on the historical data mining and be used as prior knowledge to improve the performance of spectrum decision, and (2) sensing data with the same latent spectrum state will be fused together according to their statistical correlation. In the following section, a rejection process will be proposed to filter out some imperfect historical sensing data in order to further improve the performance of spectrum decision.

IV. THE PROPOSED COOPERATIVE SPECTRUM SENSING WITH HISTORICAL SENSING DATA

In this section, a novel cooperative spectrum sensing algorithm based on historical sensing data mining is proposed, where rejection process and Bayesian theory will be integrated. In the following, the rejection process will be proposed, and the prior knowledge updating process will be presented in details.

A. REJECTION PROCESS-HISTORICAL SENSING DATA REFINING

In decision theory, rejection process can reduce the error probability effectively by eliminating the data with huge uncertainty. The spectrum sensing decision is a special case in decision theory, since it decides whether the channel is available or not according to the sensing data. In the proposed algorithm, it is required to predict the state z according to the input vector y.

In spectrum sensing, the spectrum state can be divided into two types: 1) the channel is not being occupied by PU (case H_0); 2) the channel is being occupied by PU (case H_1). In addition, the sensing data space can be divided into $\mathcal{R}_0$ and $\mathcal{R}_1$. If the sensing data $y \in \mathcal{R}_0$, the decision $z = H_0$, else the decision $z = H_1$. Hence, the decision error probability p_m can be represented as:

$$p_m = p(y \in \mathcal{R}_0|H_1) + p(y \in \mathcal{R}_1|H_0) = \int_{\mathcal{R}_0} p(y|H_1)dy + \int_{\mathcal{R}_1} p(y|H_0)dy \tag{19}$$

According to Eqn. (19), there must be $p(y|H_0) > p(y|H_1)$ in space $\mathcal{R}_0$ and $p(y|H_1) > p(y|H_0)$ in space $\mathcal{R}_1$ to minimize decision error probability p_m. If the value of $p(y|H_1)$ and $p(y|H_0)$ are approximate the same or both of their absolute value is small, however, it is risky to classify the input sensing data into any type, thus the proposed algorithm will filter out these data with high uncertainty. Such a sensing data refining process is called rejection process.

The rejection space $\mathcal{R}_{reject}$ is defined by setting a rejection threshold $\theta(\theta \in [0, 1])$. In details, if the likelihood probabilities $p(y|H_1)$ and $p(y|H_0)$ of the received signal y are both less than a threshold value, y is located in rejection space, and will be rejected. The rejected historical sensing data will not be included in the spectrum decision process. The rejection space $\mathcal{R}_{reject}$ is defined as:

$$\mathcal{R}_{reject} = \mathcal{R}_{reject0} \cap \mathcal{R}_{reject1} \tag{20}$$

where,

$$\mathcal{R}_{reject0} = [\eta_0, +\infty], \int_{-\infty}^{\eta_0} p(y|H_0)dy > 1 - \theta \tag{21}$$

$$\mathcal{R}_{reject1} = [-\infty, \eta_1], \int_{-\infty}^{\eta_1} p(y|H_1)dy < \theta \tag{22}$$

Such a rejection process is shown in Fig. 4 with known distribution of H_1 and H_0. The rejection space $\mathcal{R}_{reject}$ can be calculated according to Eqns. (20-22), where the green space is $\mathcal{R}_{reject0}$ and the red space is $\mathcal{R}_{reject1}$.

According to the above analysis, the detailed steps of sensing data rejection process in the proposed algorithm are shown in Table I. By using rejection process, the proposed algorithm proposed can filter out the sensing data with high

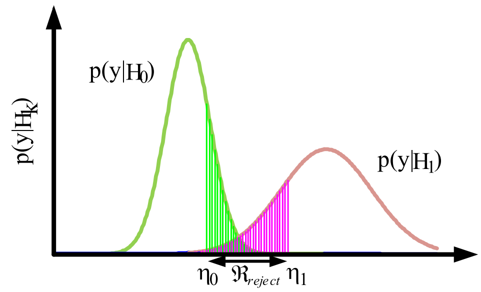

FIGURE 4. Rejection space definition.

TABLE 1. Rejection process.

Input The sensing power set $\{E_{jt}\}_{n=1}^{N}$ of all the N SUs in the cluster at the moment t; The rejection parameter θ.
Execution 1) If $E_{jt} \in \mathcal{R}_{reject}$, the sensing data will be rejected; If $E_{jt} \notin \mathcal{R}_{reject}$, the sensing data will be kept and added to the set $\mathbf{E}_t$ (see Eqn.(5)). 2) With the filtered sensing data set $\mathbf{E}_t = \{E_{jt}\}_{j=1}^{r}$, the statistical mean value of the sensing data can be calculated using Eqn.(6) in CH.
Output The average energy y_t of sensing data at the moment t (see Eqn.(6)).

uncertainty and improve the effectiveness of historical sensing data mining.

B. HISTORICAL SENSING DATA MINING ALGORITHM

In this section, the detailed steps of the proposed cooperative spectrum sensing algorithm will be presented. We assume that the channel state transition probability is stable in statistics. Moreover, the sensing data under the same latent channel state share the same distribution.

The sensing data with the same latent channel state will be grouped into a class in sticky HDP-HMM model. After the spectrum state of each sensing data is estimated, the PU state transition probability matrix (i.e., priori knowledge) is updated. At the same time, the sensing data assigned with the same group will be used to estimate the distribution parameters, which will be used to make spectrum decision finally. As an example, Fig. 5 shows the classification results of historical sensing data using sticky HDP-HMM model. Please note that we use the sensing data $R(k)$ instead of y_t in the proposed sticky HDP-HMM classification algorithm. For simplicity, we use R_t to represent the sensing data at time instant t.

Please note that R_t is assumed a random variable obeying Gaussian distribution, i.e., $R_t \sim N(\mu_t, \sigma_t^2)$, whose mean and variance are updated according to the sensing data observed.

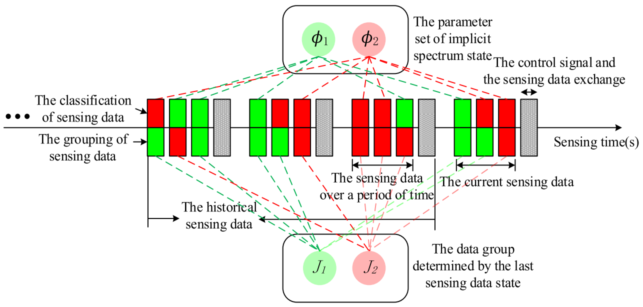

FIGURE 5. The classification results of sensing data using sticky HDP-HMM model.

Obviously, the Gaussian distribution is determined only by two parameters μ_k and σ_k^2, thus ϕ_k is defined as a two-dimensional vector, i.e., if $z_t = k$, $\phi_k = (\mu_k, \sigma_k^2) = (\mu_t, \sigma_t^2)$. The conjugate prior distribution of Gaussian distribution with unknown mean and variance is normal-inverse-gamma distribution. From the Bayes' viewpoint, hence, the mean and variance are treated as random variables with distribution $(\mu_k, \sigma_k^2) \sim N - \Gamma^{-1}(\lambda, \nu, \alpha, \beta)$. The updating process of the mean and variance is represented as:

$$\begin{aligned} p(\mu_k, \sigma_k^2 \mid \{R_t \mid z_t = k\}) \\ \propto p(\{R_t \mid z_t = k\} \mid \mu_k, \sigma_k^2) \cdot p(\mu_k, \sigma_k^2) \end{aligned} \tag{23}$$

According to Eqn. (23), the posterior distribution is also a normal-inverse-gamma distribution, whose hyper-parameter $(\lambda_k, \nu_k, \alpha_k, \beta_k)$ can be updated as:

$$\lambda_k' = \frac{\nu_k \lambda_k + D\overline{R}}{\nu_k + D} \tag{24}$$

$$\nu_k' = \nu_k + n \tag{25}$$

$$\alpha_k' = \alpha_k + \frac{n}{2} \tag{26}$$

$$\begin{aligned} \beta_k' = \beta_k + \frac{1}{2}\sum_{d=1}^{D}(R_d - \overline{R})^2 + \frac{D\nu}{D+\nu}\frac{(\overline{R} - \lambda_k)^2}{2} \\ (z_d = k, d = 1, 2, \ldots, D) \end{aligned} \tag{27}$$

where $\overline{R}$ is the mean of sensing data assigned to a group and D is the number of sensing data which are assigned to the kth latent state. The likelihood function of sensing data R_t can be represented as:

$$f(R_t; \widehat{\mu}_k, \widehat{\sigma}_k^2) = t_{2\alpha'}(R_t \mid \lambda', \frac{\beta'(\nu' + 1)}{\nu'\alpha'}), \quad z_t = k \tag{28}$$

The detailed steps of the proposed classification algorithm are provided in Table II, where $n_{k_1k_2}$ is the number of sensing data R_t which has $z_{t-1} = k_1, z_t = k_2$ in the set $\{R_t\}_{t=1,\ldots,T}$, and n_k is the number of sensing data which has $z_{t-1} = k$ in the set $\{R_t\}_{t=1,\ldots,T}$. In Table II, each restaurant is equivalent to a SU, and the corresponding customer is equivalent to historical sensing data in the restaurant.

The proposed sensing data classification algorithm based on sticky HDP-HMM model is presented in Table II,

TABLE 2. The proposed spectrum sensing state classification algorithm.

Input

After the $n-1$th iteration, the assigned hidden spectrum state is denoted as $\{z_t^{n-1}\}_{t=1}$, and the global state transition probability is $\beta^{(n-1)}$.

Iteration

1. Assignment$\{z_t\}_{t=1,\ldots,T} = \{z_t^{(n-1)}\}_{t=1,\ldots,T}$, $\beta = \beta^{(n+1)}$. Run the following steps over each sensing data R_t in the set $\{R_t\}_{t=1,..,T}$ sequentially. Please note that the notations $t, t+1, \cdots T$ denote the time instants of sensing data acquirement, which is shown in Fig. 1.

(1) Decrease $n_{z_{t-1}z_t}$,$n_{z_tz_{t+1}}$ by 1, respectively. Then updating the parameters of Gaussian distribution, that is,

$$(\widehat{\mu_k}, \widehat{\sigma_k{}^2}) \leftarrow (\widehat{\mu_k}, \widehat{\sigma_k{}^2}) \ominus R_t \tag{29}$$

(2) Calculating the probability that R_t is assigned to the kth hidden state,

$$\begin{aligned} & f_k(R_t) = \\ & (\frac{\alpha_0\beta_{z_{t+1}} + n_{kz_{t+1}} + \kappa\delta(k, z_{t+1}) + \delta(z_{t-1}, k)\delta(k, z_{t+1})}{\alpha_0 + n_k + \kappa + \delta(z_{t-1}, k)}) \cdot \\ & t_k(R_t; \widehat{\mu_k}, \widehat{\sigma_k{}^2}) \cdot (\alpha_0\beta_k + n_{z_{t-1}k} + \kappa\delta(z_{t-1}, k)) \\ & k = 1, 2, ..., K \end{aligned} \tag{30}$$

where $\delta(a, b)$ is a mass function, a is the previous state, and b is the current state. If $a = b$, $\delta(a, b) = 1$, otherwise $\delta(a, b) = 0$.

Calculating the probability that R_t is assigned a new state(i.e., the $K+1$th state),

$$f_{K+1}(R_t) = \frac{\alpha_0^2\beta_{\overline{K}}\beta_{z_{t+1}}}{\alpha_0 + \kappa} t_{K+1}(R_t; \widehat{\mu_{K+1}}, \widehat{\sigma_{K+1}{}^2}) \tag{31}$$

where $\beta_{\overline{K}} = \sum_{k=K+1}^{\infty} \beta_k = 1 - \sum_{k=1}^{K} \beta_k$. Eqns.(30) represents the posterior probability that the sensing data R_t assigned to kth state, and Eqns.(31) represents the probability to a new state.

(3) Sampling from the discrete distribution from Eqns.(30)-(31) and determining the hidden state z_t,

$$z_t \sim \sum^{K} f_k(R_t) \cdot \delta(z_t, k) + f_{K+1}(R_t) \cdot \delta(z_t, K+1) \tag{32}$$

If $z_t = K+1$, the discrete distribution β should be updated, which includes four steps: 1) sampling the random variable $b(b \sim Beta(1, \gamma))$, and let $\overline{K} = K + 1$. 2) assignment: $\beta_{\overline{K+1}} = (1-b)\beta_{\overline{K}}$. 3) assignment: $\beta_{\overline{K}} = b\beta_{\overline{K}}$. 4) adding 1 to the number of classes K, i.e., K is updated to $\overline{K}$.

(4) Increasing $n_{z_{t-1}z_t}$ and $n_{z_tz_{t+1}}$ by 1, and including R_t into sensing data set of hidden state $z_t$and updating the corresponding distribution parameters,

$$z_t = k : (\widehat{\mu_k}, \widehat{\sigma_k{}^2}) \leftarrow (\widehat{\mu_k}, \widehat{\sigma_k{}^2}) \oplus R_t \tag{33}$$

TABLE 2. ***(Continued.)*** **The proposed spectrum sensing state classification algorithm.**

2. Parameter updating: Let $\{z_t^{(n)}\}_{t=1,...,T} = \{z_t\}_{t=1,...,T}$. Determining whether there is a state k which makes $n_{.k} = 0, n_{k.} = 0(k = 1, ..., K)$. If there is, removing the kth statethen updating the discrete distribution $\beta(\beta_{\overline{K}} = \beta_{\overline{K}} + \beta_k, \overline{K} = K + 1)$, and reducing K by 1.

3. Obtaining the value of the variable ω_j, and setting $\{m_{jk}\}_{(j,k)\in\{1,...,K\}^2}$ and its transformation $\{\overline{m}_{jk}\}_{(j,k)\in\{1,...,K\}^2}$ as:

(1) For $j = 1, ..., K$, sampling the random variable x under the condition of $n = 1, 2, ..., n_{jk}$ sequentially,

$$x \sim Ber(\frac{\alpha_0\beta_k + \kappa\delta(j,k)}{n + \alpha_0\beta_k + \kappa\delta(j,k)}) \tag{34}$$

If $x = 1$, increase m_{jk} by 1.

(2) Sampling the random variable $\omega_j, j = 1, ..., K$

$$\omega_j \sim Binomial(m_{jj}, \rho(\rho+\beta_j(1-\rho))^{-1}), \quad j = 1, 2, ..., K \tag{35}$$

where ρ is the self-transfer probability, i.e., $\rho = \kappa/\alpha_0 + \kappa$. According to the sampling result of the set $\{m_{jk}\}_{(j,k)\in\{1,...,K\}^2}$ and the variable $\omega_j, j = 1, ..., K$, the elements in $\{\overline{m}_{jk}\}_{(j,k)\in\{1,...,K\}^2}$ can be calculated as

$$\overline{m}_{jk} = \{\begin{matrix} m_{jk} & ,j \neq k; \\ m_{jj} - \omega_j & ,j = k. \end{matrix} \tag{36}$$

4. Updating the global discrete distribution β as:

$$\beta^{(n)} \sim Dir(\overline{m}_1, \overline{m}_2, ..., \overline{m}_K, \gamma) \tag{37}$$

where the number of hidden spectrum state K is previously unknown. However, if we preset the states number $K = 2$, the spectrum states only have two kinds: (1) the channel is idle (H_0), and (2) the channel is occupied (H_1). In the simulation part, we fix $K = 2$. Then, the decision of spectrum state is obtained by sticky HDP-HMM classification instead of the decision threshold in the proposed algorithm.

The proposed algorithm is based on the non-parametric HMM, whose computation complexity has been analyzed well in [12]. The proposed algorithm calculates Eqns. (29)-(37) sequentially. Hence, the computation complexity for each historical sensing data is $O(K)$ in one iteration, where K is the number of assigned channel states. From our experimental observations, the convergence occurs after 20 rounds of iterations, which can be regarded as a fast convergence speed according to todays high-performance CPU.

V. SIMULATIONS

In this section, the performance of the proposed cooperative spectrum sensing algorithm will be evaluated through simulations. The PU's wireless access channel states are labeled as {0, 1}. Label "0" represents that PU is turned off while label "1" represents that the channel is occupied by PU. The PUs wireless access pattern obeys the first-order Markov process with transition probability $p(0|1) = p(1|0) = 0.05$. In addition, the received signals are experienced through time-varying Rayleigh fading channel. The sensing data are observed in the durations of sensing period (see Fig. 1).

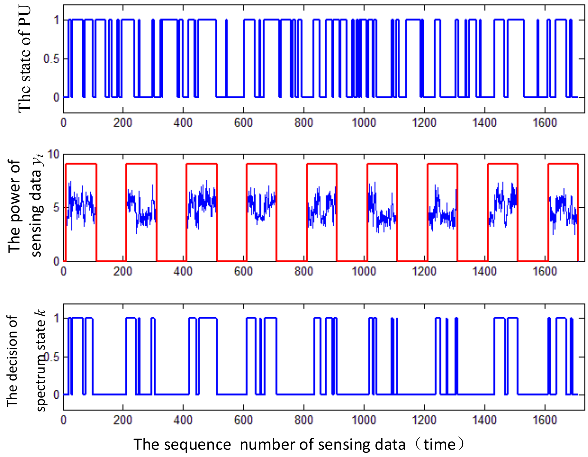

FIGURE 6. **Comparisons between the estimated channel state and the practical case.**

Fig. 6 shows the spectrum state of the practical PU states and the spectrum decision results using the proposed cooperative spectrum sensing algorithm, where there are 10 SUs and their received SNR are set to 0dB. Due to the periodical spectrum sensing process proposed in section II, the SUs within the cluster uniformly execute the spectrum sensing only at the period labeled by red windows as shown in Fig. 5. One can see from Fig. 6 that the estimated spectrum states using the proposed algorithm are approximately the same as the practical PU states, and the spectrum decision performance will be good under such low SNR.

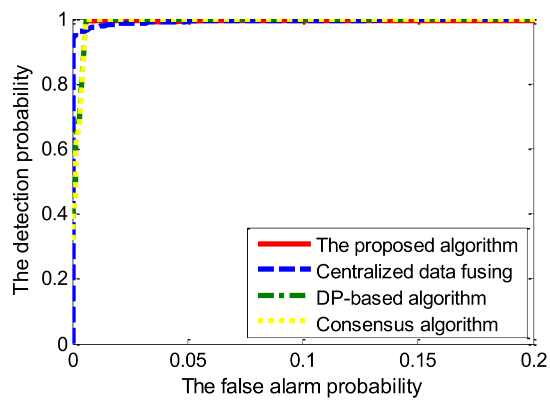

FIGURE 7. **Spectrum sensing performance comparisons under channel SNRs=5dB.**

The performance of spectrum sensing algorithm can be measured by detection probability P_d and false alarm probability P_f, We consider four different spectrum sensing cases, and the simulation results are plotted in Figs. 7–10. In Fig. 7,

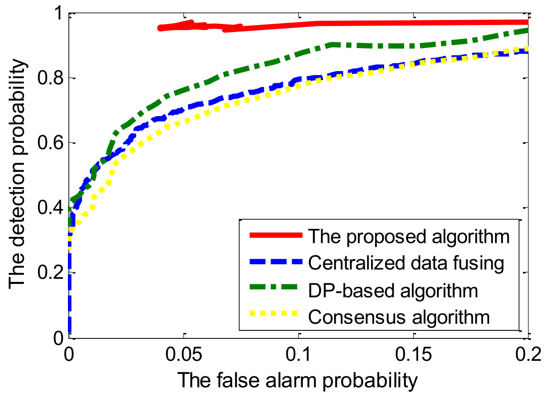

FIGURE 8. Spectrum sensing performance comparisons under channel SNRs=0dB.

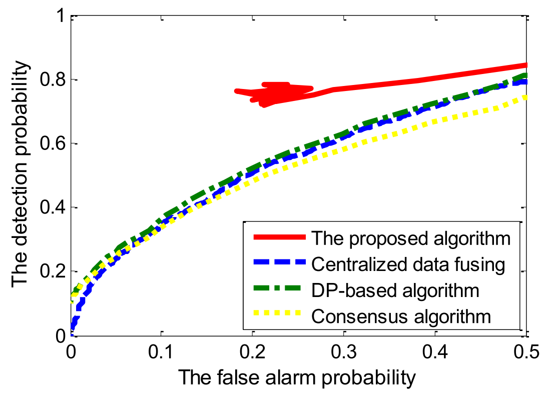

FIGURE 9. Spectrum sensing performance comparisons under channel SNRs=−5dB.

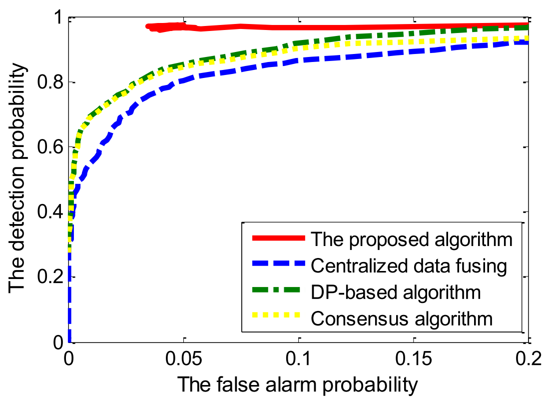

FIGURE 10. Spectrum sensing performance comparisons under channel SNRs=5dB/0dB/−5dB.

the number of SUs is set to 10 and the SNR of received signals are set to 5dB. In Fig. 8, the number of SUs is set to 10 and the SNR of received signals are set to 0dB, which corresponds to the case of Fig. 6. In Fig. 9, the number of SUs is set to 10 and the SNR of received signals are set to −5dB. In Fig. 10, the number of SUs is set to 10, and there are two SUs with received SNR 5dB, six SUs with received SNR 0dB and the rest two SUs with received SNR −5dB. Fig. 10 shows a practical scenario that different SUs have different SNRs. For comparisons, the performance of three typical cooperative spectrum sensing algorithms, which are Energy detection based cooperative spectrum sensing (centralized spectrum sensing algorithm) [17], [18], Consensus spectrum sensing algorithm [19], and DP-based spectrum sensing algorithm [13] in order to illustrate the effectiveness of the proposed algorithm.

Since the proposed algorithm applies to cooperative spectrum sensing within a cluster, we assume that the SUs share the same PU state at any time instance and thus share a spectrum state transition probability matrix. However, the received SNRs of SUs may be quit different, see Fig. 10. From Figs. 8–10, one can clearly see that the proposed algorithm can improve the detection probability P_d for 10%, 60% and 5% compared with other three typical algorithms at the false alarm probability $P_f = 0.2$. In addition, due to huge uncertainty in sensing data under low SNRs, the rejection process will filter out some sensing data randomly, the proposed algorithm is unstable under the case $P_d = 0.7$ and $P_f = 0.2$, see in Fig. 8 for example.

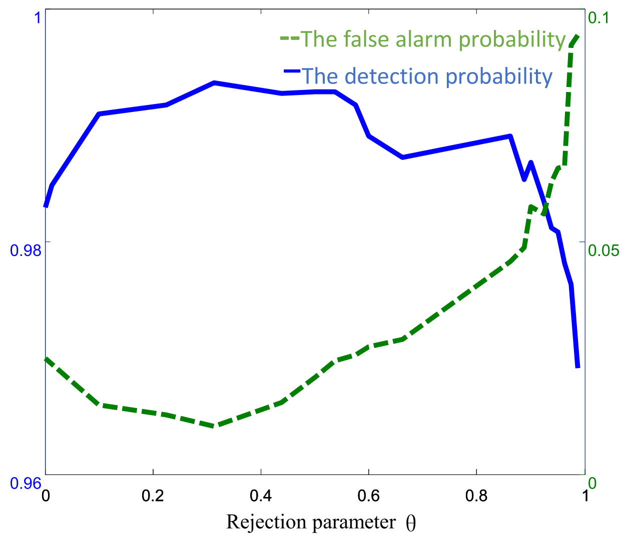

FIGURE 11. Spectrum sensing performance under different rejection parameter settings.

Fig. 11 is the trend of the detection probability and the false alarm probability under different rejection parameter setting. The simulation scenario is a cluster with 10 SUs and their received SNRs are 3dB. It is shown that when rejection rate is 0.3, the detection probability is maximum and the false alarm probability is minimum, which means there is an optimal rejection space where the rejection rate is 0.3. Hence, it is important to determine a proper rejection parameter in the rejection process to refine historical sensing data. Determining the optimal rejection parameter θ in theory is too complicated. In Fig. 11, one can see that the detection probability curve is not convex. However, the suboptimal rejection parameter can be found with gradient descent method.

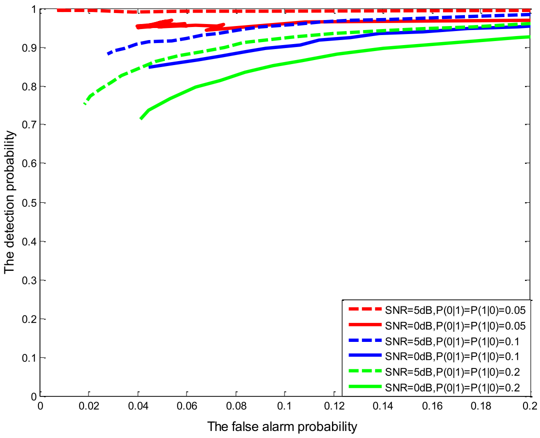

FIGURE 12. Spectrum sensing performance under different transition probabilities.

In this paper, we only consider the case that the received signals from PUs are stable in statistics. When the received PU signal is not stable, the proposed probabilistic graphical model will perform poor. In Fig. 12, we consider two less-stable cases where the transition probabilities $p(0|1) = p(1|0)$ are set to 0.1 and 0.2, respectively. The SNRs in such two cases are set to 5 and 0, respectively. The simulation results are compared with the cases in Figs. 7–8. The comparisons in Fig. 12 shows that the proposed algorithm performs poor when the PU states change quickly.

VI. CONCLUSIONS

In this paper, a novel cooperative spectrum sensing algorithm has been proposed, where the sticky HDP-HMM model is adopted to exploit the historical sensing data. The historical sensing data has been refined through rejection process, in order to filter out some sensing data with high uncertainty. Then, the refined sensing data are fused into prior knowledge, and the PUs' state transition probability will be inferred. Such prior knowledge will be integrated into current spectrum decision. Under three different low channel SNR ($\leq 5dB$) cases, the simulation results show that the proposed algorithm has more than 10%, 60%, 5% detection probability improvement under false alarm probability 0.2, compared with centralized spectrum sensing algorithm, Consensus spectrum sensing algorithm, and DP-based spectrum sensing algorithm, respectively.

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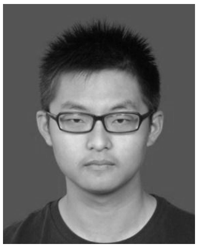

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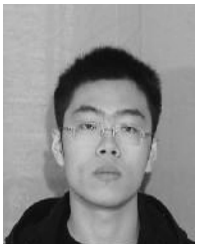

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