Spectrum Sensing in Cognitive Radio Based on Hidden Semi-Markov Model

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Abstract. Spectrum sensing is one of the key technologies in cognitive radio systems. Efficient spectrum sensing can improve the communication network throughput and reduce the possibility of frequency collision. Hidden Markov Model (HMM) is a common spectrum sensing algorithm, which can enhance the energy detection (ED) algorithm by using historical observation information under unsupervised conditions. However, this algorithm assumes the regularity of the primary user occupying the spectrum to obey the Markov property. If the assumption is inconsistent with the facts, the performance of the algorithm will deteriorate. So, we propose a spectrum sensing algorithm based on Hidden Semi-Markov Model (HSMM) in this paper. It can solve the shortcoming of HMM because it has a high-order timing representation capability. Numerical simulations show that this model can effectively improve the detection performance of ED. It improves the SNR tolerance of 4 dB, or shortens the sensing time to a quarter of the time that the traditional ED method takes. In addition, the proposed algorithm is applicable to more scenarios than HMM. When the Markov property of the spectrum state fails, the proposed algorithm still performs better than HMM.

Keywords: Cognitive radio · Spectrum sensing · Hidden Semi-Markov Model

1 Introduction

Along with the rapid development and wide application of wireless communication technology, the shortage of spectrum resources has become more prominent. Cognitive radio is one of the effective approaches to solve this problem [1]. It improves network throughput by discovering and utilizing idle spectrum resources. In cognitive radio systems, efficient sensing of spectrum holes

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is essential. In recent years, many scholars have studied spectrum sensing and achieved brilliant results. Spectrum sensing can be divided into multiple types depending on the sensing scene [2]. In terms of the number of sensing nodes, spectrum sensing is divided to single-node sensing and multi-node cooperative sensing. Multi-node cooperative sensing can effectively alleviate shadow fading, multipath fading, hidden terminals and other issues in single-node sensing through spatial diversity gain. In terms of perceived bandwidth spectrum sensing can be divided into narrowband spectrum sensing and wideband spectrum sensing. The classic three spectrum sensing algorithms, energy detection, matched filtering detection, and cyclostationary feature detection are for all narrowband spectrum sensing algorithms, while in wideband scenarios, the available spectrum sensing methods are based on compressed sensing theory.

In this paper, we improves the traditional single-node and narrow-band spectrum sensing algorithm by introducing the time series model. A large number of measured data show that the primary users have certain regularity on the occupied state of the licensed spectrum [3,4]. If the regularity will be properly utilized, the spectrum sensing performance can be effectively improved [5]. In the existing researches, the spectrum state is usually modeled as a Markov model as shown in the Fig. 1, which assumes that the state of the spectrum at the current time is related to the "work" or "idle" state of the spectrum at the previous moment; and spectrum sensing is modeled as a hidden Markov model (HMM)[6]. The spectrum state obeying Markov property is invisible to the observer and is a hidden variable. The visible observed variable is uniquely determined by the state variable at the current moment through a probability transfer mechanism. The probability transfer mechanism is generally assumed to be a Gaussian channel. Experiments indicate that, by introducing the HMM framework, the detection performance of traditional spectrum sensing algorithms such as ED can be effectively improved in unsupervised scenarios.

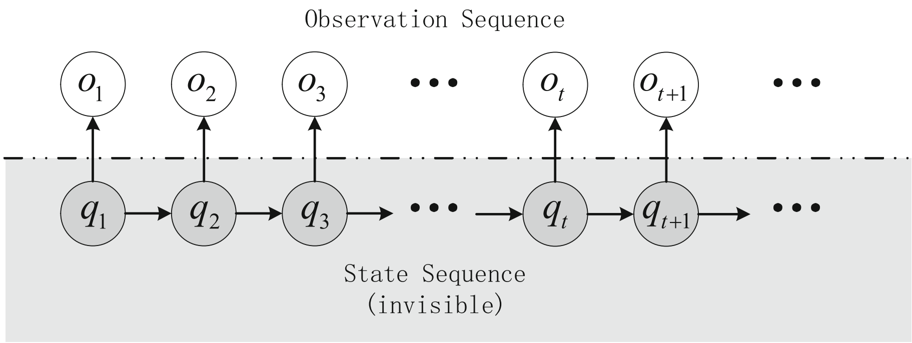

Fig. 1. Hidden Morkov model.

However, the HMM is a nearest neighbor model, it only assumes that there is a correlation between the two states at the adjacent time [7]. Therefore, when a high-order temporal correlation in the regularity of the spectrum state holds, the Markov model will be unsuitable and the spectrum sensing performance will be limited. In view of this situation, the literature models the spectrum state of the hidden layer as a high-order Markov model to obtain high-order temporal representation ability [8]. However, the complexity of the model increases exponentially as the model order increases, which makes the training of the model difficult, and even unavailable when the order is high.

To reduce the complexity in high-order Markov model, this paper models the spectrum state of the hidden layer as a semi-Markov model, and proposes a spectrum sensing algorithm based on the hidden semi-Markov model (HSMM) [9]. Compared with the high-order Markov model, the semi-Markov model has a certain simplification in the high-order time series correlation. It only cares about the relationship between state switching and state duration, so retains most of the high-order timing representation capability. Simulation results show that the proposed algorithm has wider applicable scenarios than the HMM-based spectrum sensing algorithm. When the spectrum state obeys different regularities, the proposed algorithm still obtains better detection performance than the HMM-based algorithm.

The rest of the paper is organized as follows: The second part describes the sensing model, the third part introduces the model algorithm, including the model parameter learning method in the unsupervised scene and the online estimation method of the spectrum state. The fourth part gives the simulation test to verify the performance of the proposed algorithm, the fifth part summarizes the full paper.

2 Spectrum Sensing Model

HSMM is an extension of HMM. Its hidden state transition probability is no longer a constant, but a variable related to state dwell time. It overcomes the limitation of model in Markov assumption. The model can described by quaternary symbol $\lambda = (\boldsymbol{\pi}, \boldsymbol{A}, \boldsymbol{P}, \boldsymbol{B})$.

$\boldsymbol{\pi}$ is initial state probability vector,

$$\boldsymbol{\pi} = (\pi_0, \pi_1) \tag{1}$$

where

$$\pi_i = P\left(q_1 = s_i\right), i = 0, 1 \tag{2}$$

indicates the probability when the initial state of the hidden state sequence q_1 is s_i. For the spectrum state, this paper makes a binarization hypothesis, i.e. s_0 indicates spectrum is idle, s_1 represents spectrum being occupied.

$\boldsymbol{A}$, $\boldsymbol{P}$ indicate the transfer relationship of the hidden state sequence, the hidden state sequence can be regarded an assemble of state segment. $\boldsymbol{A}$ is the state transition probability matrix,

$$\boldsymbol{A} = \begin{bmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \tag{3}$$

where a_{ij} indicates the transition probability that state s_i transfers to state s_j. Since the state segment must be transferred to another state in the end, its self-transition probability is 0. $\boldsymbol{P}$ is the state dwell time probability matrix,

$$\boldsymbol{P} = \begin{bmatrix} P_0\left(1\right) & P_0\left(2\right) & \dots & P_0\left(D\right) \\ P_1\left(1\right) & P_1\left(2\right) & \dots & P_1\left(D\right) \end{bmatrix} \tag{4}$$

where D is the maximum dwell time, $P_i\left(d\right)$ denotes the probability when state segment is in the state s_i and its dwell time is d. Then, the transition probability of the hidden state sequence is defined as

$$a_{i(j,d)} = P\left(q_{[t+1:t+d]} = s_j | q_{t]} = s_i\right) = a_{ij} p_j\left(d\right) \tag{5}$$

where the inclusive symbol '[', ']' is used to indicate the left and right inclusiveness in time, for example, $q_{[t+1:t+d]} = s_j$ indicates that the state sequence is s_j from time t+1 to time $t+d$, but at time t and time $t+d+1$ must not be s_j; $q_{t]} = s_i$ infers that the state sequence at time t is s_i, and at time $t+1$ must not be s_i, but at time $t-1$ may or may not be s_i. Then, the probability that the state at time $t+\tau$ is s_j when the state at time t is s_i can be gain by

$$P\left(q_{t+\tau} = s_j | q_t = s_i\right) = \sum_{d=\tau}^{D} a_{i(j,d)}, \tau \leq D \tag{6}$$

$\boldsymbol{B}$ is the observation probability matrix,

$$\boldsymbol{B} = \left[b_i\left(v_n\right)\right], i = 0, 1; n = 0, 1, \dots \tag{7}$$

where v_n is observation space, and

$$b_i\left(v_n\right) = P\left(o_t = v_n | q_t = s_i\right) \tag{8}$$

indicates the probability that the observed variable o_t is v_n when the state q_t is s_i. We assume the propagation channel is a Gaussian channel. So, when the observed variable is signal energy, the observed probabilities are subject to different Gaussian distributions, i.e. $b_0\left(o_n\right) \sim N\left(\mu_0, \sigma_0^2\right)$ and $b_1\left(o_n\right) \sim N\left(\mu_1, \sigma_1^2\right)$, where $\mu_0 = n\sigma_n^2$, $\sigma_0^2 = 2n\sigma_n^4$, $\mu_1 = n(\sigma_n^2 + \sigma_s^2)$, $\sigma_1^2 = 2n\sigma_n^2(\sigma_n^2 + 2\sigma_s^2)$. n is the number of samples, σ_s^2 is primary user's signal energy level and σ_n^2 is the noise level [10].

The generation process of HSMM's state sequence and observation sequence is shown in Fig. 2. The state segment is described by (i_n, d_n), where i_n is the state of the segment n and d_n denotes the duration of this segment. Firstly, a series of state segments are generated. Different state segments correspond to different states and durations respectively, and state segments with respect to the same state must not be adjacent. Then, these state segments are mapped onto the time series to generate a state sequence. Subsequently, the observation sequence is generated correspondingly. It should be noted that, in general, for the observer only the observation sequence is visible in the entire model, and the shaded parts in the figure are hidden.

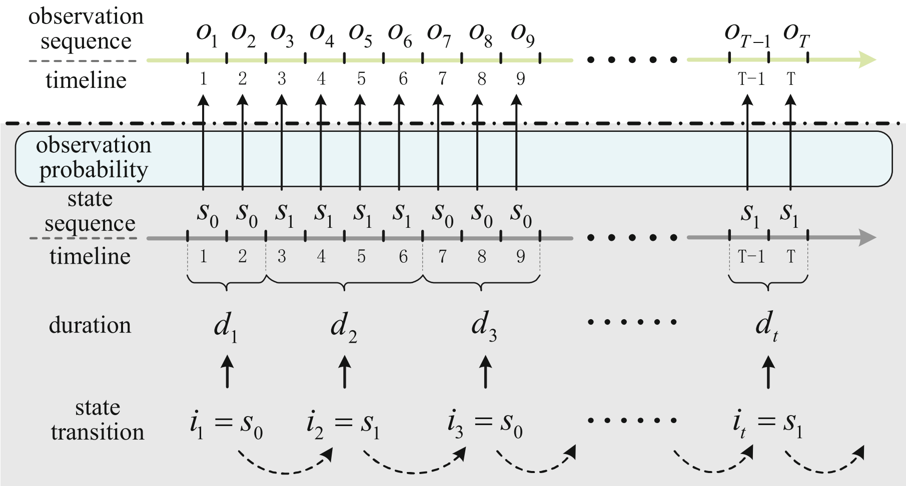

Fig. 2. Hidden Semi-Morkov model.

3 Learning and Estimation Algorithm

3.1 Model Parameter Learning

Cognitive radio systems often work in unfamiliar environment, and the priori information of primary user is usually unavailable. So spectrum sensing algorithms should have the ability of unsupervised learning.

Given an observation sequence $\boldsymbol{O}_{1:T} = [o_1, o_2, \ldots, o_T]$, the parameters of HSMM can be estimated based on the EM algorithm by means of parameter re-estimation. We shall first define the forward probability and backward probability of HSMM as

$$\alpha_t(i) = P\left(q_{t]} = s_i, o_{1:t} | \lambda\right) = \sum_{d \in D} \alpha^*_{t-d+1}(i)\, p_i(d)\, u_t(i, d) \tag{9}$$

$$\alpha^*_{t+1}(i) = P\left(q_{[t+1} = s_i, o_{1:t} | \lambda\right) = \sum_{j \in \mathbf{S} \backslash \{i\}} \alpha_t(j)\, a_{ji} \tag{10}$$

$$\beta^*_{t+1}(i) = P\left(o_{t+1:T} | q_{[t+1} = s_i, \lambda\right) = \sum_{d \in D} p_i(d)\, u_{t+d}(i, d)\, \beta_{t+d}(i) \tag{11}$$

$$\beta_t(i) = P\left(o_{t+1:T} | q_{t]} = i, \lambda\right) = \sum_{j \in \mathbf{S} \setminus \{i\}} a_{ij} \beta^*_{t+1}(j) \tag{12}$$

where

$$u_t(i,d) = \prod_{\tau=t-d+1}^{t} b_i(o_\tau) \tag{13}$$

The boundary conditions are

$$\alpha^*_t(i) = \begin{cases} \pi_i, t = 1 \\ 0, \ t < 1 \end{cases} \tag{14}$$

and

$$\beta_t(i) = \begin{cases} 1, t = T \\ 0, t > T \end{cases} \tag{15}$$

Using forward probability and backward probability, we can derive the probability of the model state s_i with duration d ending at time t as

$$\eta_t(i,d) = P\left(q_{[t-d+1:t]} = i, o_{1:T} | \lambda\right) = \alpha^*_{t-d+1}(i) \, p_i(d) \, u_t(i,d) \, \beta_t(i) \tag{16}$$

Consider that there is

$$\begin{aligned} P(q_{t:t+1} = s_i, o_{1:T} | \lambda) = P(q_t = s_i, o_{1:T} | \lambda) - P\left(q_{t]} = s_i, o_{1:T} | \lambda\right) \\ P(q_{t:t+1} = s_i, o_{1:T} | \lambda) = P(q_{t+1} = s_i, o_{1:T} | \lambda) - P\left(q_{[t+1} = s_i, o_{1:T} | \lambda\right) \end{aligned} \tag{17}$$

We can derive the probability of the state s_i at time t with the complete observation sequence $o_{1:T}$ as

$$\begin{aligned} \gamma_t(i) &= P(q_1 = s_i, o_{1:T} | \lambda) \\ &= \gamma_{t-1}(i) + P\left(q_{[t} = s_i, o_{1:T} | \lambda\right) - P\left(q_{t-1]} = s_i, o_{1:T} | \lambda\right) \\ &= \gamma_{t-1}(i) + \alpha^*_t(i) \, \beta^*_t(i) - \alpha_{t-1}(i) \, \beta_{t-1}(i) \end{aligned} \tag{18}$$

The boundary condition is

$$\gamma_1(i) = P(q_1 = s_i, o_{1:T} | \lambda) = P\left(q_{[1} = s_i, o_{1:T} | \lambda\right) = \pi_i \beta^*_1(i) \tag{19}$$

With the above probability, the model parameters can be re-estimated by the following formula [9]

$$p_i(d) = \frac{\sum_t \eta_t(i,d)}{\sum_d \sum_t \eta_t(i,d)} \tag{20}$$

$$\mu_i = \frac{\sum_t \gamma_t(i) \, o_t}{\sum_t \gamma_t(i)} \tag{21}$$

$$\sigma_i^2 = \frac{\sum_t \gamma_t(i) \left(o_t - \mu_i\right)^2}{\sum_t \gamma_t(i)} \tag{22}$$

3.2 Online Estimation of Spectrum State

The common method to estimate the hidden state for HSMM is the Viterbi algorithm [11], but it is a smoothing algorithm and is not suitable for online estimation of spectrum states. Therefore, we use the state estimation method based on posterior probability. In HSMM, the historical observation data can be used to extract a priori estimation of the spectrum state to be detected. By combining the estimated a priori state and the current observation with the current observation, the posterior estimation of the state can be obtained. The test decision formula is

$$P\left(q_t = s_1 | o_{1:t}, \lambda\right) \gtrless \gamma \tag{23}$$

where γ is the probability decision threshold. When $\gamma = 0.5$, this formula is Maximum a posteriori probability (MAP) detection, which is the detection with the lowest average error rate.

In order to obtain the posterior probability of the state in real time, we propose an iterative calculation method, which has lower computational complexity. Firstly, define an auxiliary joint probability as

$$\zeta_t\left(i\right) = P\left(q_t = s_i, o_{1:t} | \lambda\right) \tag{24}$$

Thus, we have

$$P\left(q_t = s_i | o_{1:t}, \lambda\right) = \frac{\zeta_t\left(i\right)}{\sum\limits_j \zeta_t\left(j\right)} \tag{25}$$

$$P\left(q_t = s_i, o_{1:t-1} | \lambda\right) = \frac{\zeta_t\left(i\right)}{b_i\left(o_t\right)} \tag{26}$$

Referring to the formula (17) and using the formula (26), we can obtain

$$\zeta_t\left(i\right) = \left[\zeta_{t-1}\left(i\right) + \alpha_t^*\left(i\right) - \alpha_{t-1}\left(i\right)\right] b_i\left(o_t\right) \tag{27}$$

The boundary condition is

$$\zeta_1\left(i\right) = \pi_i b_i\left(o_1\right) \tag{28}$$

In this way, the real-time observation data o_t at each time is obtained, the posterior probability of the current system state can be estimated by recursive calculation $\zeta_t\left(i\right)$, and the state estimation result is obtained by formula (23). Besides, it is necessary to calculate $\alpha_t\left(i\right)$ and $\alpha_{t+1}^*\left(i\right)$ for facilitating the next estimate.

4 Numerical Simulation

In this part, we verify the performance of the proposed algorithm by Monte Carlo simulation. In order to simulate the spectrum patterns, we generate a state sequence based on the queuing theory model which is commonly used in time series modeling [12], and then create the observation sequences via Gaussian channel. Considering the impact of different spectrum usage patterns to detection performance, two sets of data are generated for numerical simulation based on M/M/1 and Ek/Ek/1 models commonly used in queuing theory. The specific parameters are shown in the Table 1.

Table 1. Simulation data model parameters.

Model	SNR	N	Distribution	Distribution parameter
M/M/1	−10 dB	300	Negative exponential distribution	$\lambda = [1/9, 1/6]$
Ek/Ek/1	−10 dB	300	Erlang distribution	$k = [100, 80]$ $\theta = [0.29, 0.25]$

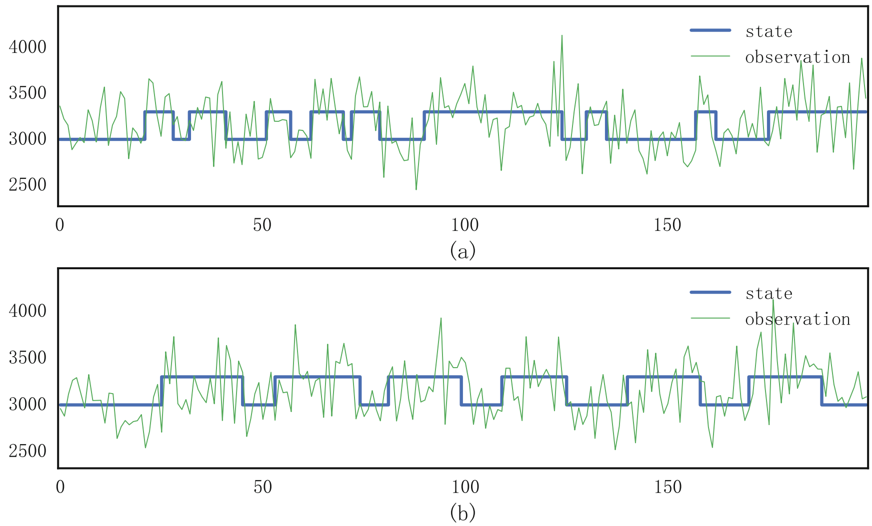

Fig. 3. Simulation data: (a) M/M/1; (b) Ek/Ek/1.

All spectrum sensing algorithms can achieve a good detection performance when the SNR is high. In order to differentiate the detection performance of different algorithms, we set a simulation environment with low SNR.The simulation data is shown in Fig. 3.

Figure 4 compares the detection performance of the three algorithms ED, HMM and HSMM under different simulation data models. It can be seen from the observation of the ROC curve that the detection performance of HMM and HSMM is better than ED, showing that rational usage of the correlation among time series effectively improve the effect of spectrum sensing.

Comparing the performance of HMM and HSMM in two simulation data models, the detection performances of the two algorithms in M/M/1 model are almost the same, while in Ek/Ek/1 model, HSMM is obviously better than HMM. Figure 5 explains the reason for this difference. The simulation data generated by the M/M/1 model has an approximate negative exponential distribution of the dwell time probability of each state in the state sequence. Both HMM and HSMM can learn and match this pattern well. However, for the simulation data generated by the Ek/Ek/1 model, the dwell time distribution is a

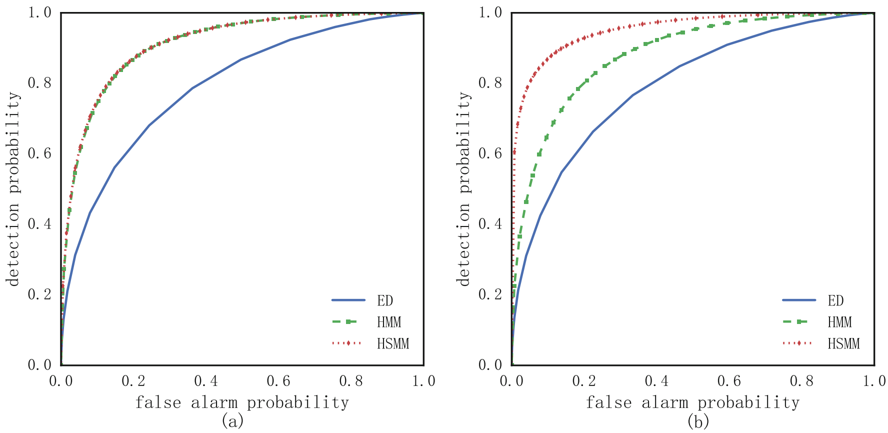

Fig. 4. ROC : (a) M/M/1; (b) Ek/Ek/1.

slightly right-biased bell-shaped distribution. In this case, only HSMM matches this pattern well. Table 2 gives the corresponding KL divergence which describes the effect of the match quantitatively. As we have analyzed, HMM's KL divergence in Ek/Ek/1 is large, indicating HMM mismatches the simulation data. So the detection performance of HSMM is not as good as HSMM's.

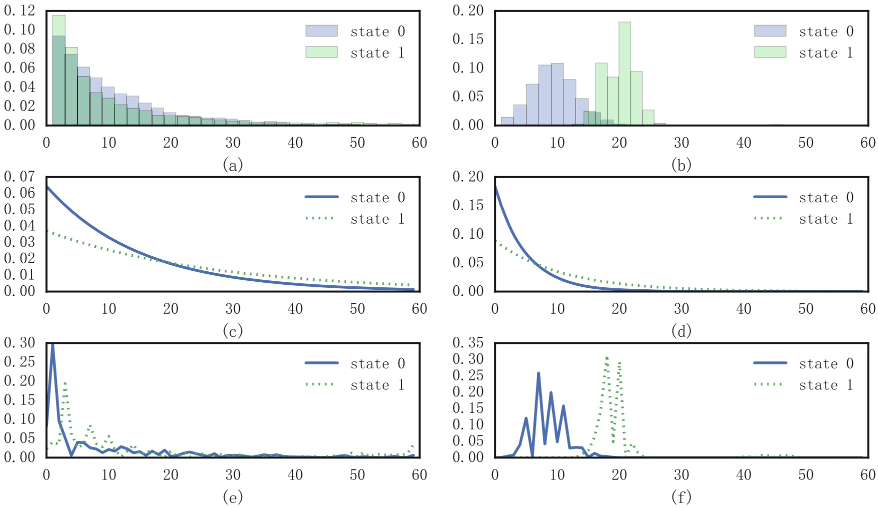

Fig. 5. Dwell time distribution: (a) simulation data from M/M/1; (b) simulation data from Ek/EK/1; (c) HMM for M/M/1; (d) HMM for Ek/Ek/1; (e) HSMM for M/M/1; (f) HSMM for Ek/Ek/1.

In summary, compared to HMM, HSMM-based spectrum sensing algorithm is more applicable, and it does not require the spectral state to obey Markov property.

Setting the detection probability as a constant $P_d = 0.95$ and fixing the remaining parameters, we can study the influence of different factors on the detection performance of the algorithm by observing the false alarm probability. Figure 6 shows the detection performance under different SNR. HSMM also has poor detection performance under low SNR, but its SNR tolerance is average 4dB higher than ED. This means HSMM can work properly in a lower SNR environment.

Table 2. Algorithm's KL divergence for different simulation data

		Simulation data model	
		M/M/1	Ek/Ek/1
Algorithm model	HMM	0.31	1.91
	HSMM	0.30	0.18

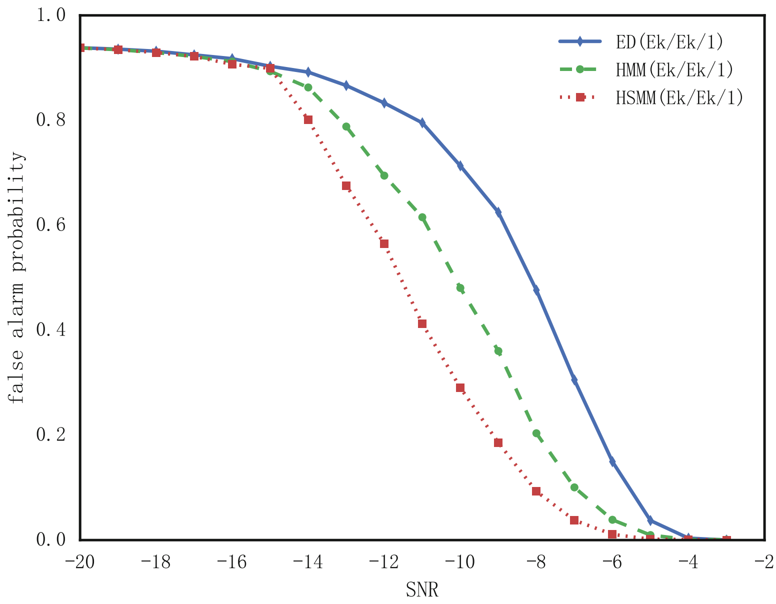

Fig. 6. Algorithm's detection performance with different SNR.

Figure 7 shows the detection performance under different length of sampling. The length of the sampling determines how long it takes to sense. The shorter the sensing time is, the higher reuse rate of idle spectrum resources and the lower probability of frequency conflicts will be obtained. When the detection performance is the same, the length of sampling required by HSMM is only almost a quarter of ED and a half of HMM, which significantly shortens the time of spectrum sensing.

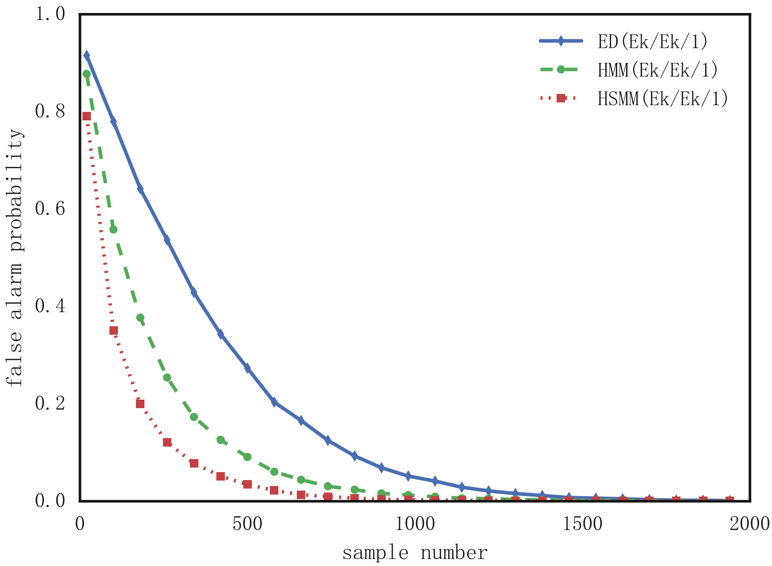

Fig. 7. Algorithm's detection performance with different sample number.

5 Conclusion

We propose a spectrum sensing algorithm based on HSMM. Compared with the traditional ED algorithm, it enhances the detection performance by rationally utilizing the high-order timing relationship of the spectrum state, and can work normally in a lower SNR environment. In addition, its sensing time is shorter, which is only almost a quarter of ED's. The algorithm has a wider application range than the HMM-based spectrum sensing algorithm. It can obtain better detection performance when there are arbitrary timing laws in the spectrum state.

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