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Online Spectrum Sensing in Cognitive Radio

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Abstract. Spectrum sensing is an essential part for cognitive radio which is used for directly or indirectly estimating the states of primary users (PUs) to find spectrum holes for second users (SUs). Nowadays, some online spectrum sensing algorithms have been proposed but most of them ignore the time complexity which influences the efficiency of spectrum sensing. In this paper we propose a new filter algorithm named Mixed filter to address this problem. Leveraged by the Hidden Markov model, this algorithm provides an alternative way to estimate parameters of the model online. Extensive simulations have been conducted and the simulation results show that the proposed method can reduce the computational complexity and shorten the executing time withoug out reducing the accuracy.

Introduction

In physical level spectrum sensing, the condition of spectrum cannot be detected directly. Thus, transforming the problem into estimating the states of primary users (PUs) or channel state are the solutions. However, observation data is not the real state of PUs, and the primary users need a series of measures to evaluate the true condition. The paper mainly researches the algorithm in mathematical way. Existing solutions can be classified into off-line and online modes. Off-line scenarios based on batch inference process download data (after gathered) to infer target component. In [1], Olusegun Peter Awe provides the robust blind spectrum sensing technique which is used in multi-antenna cognitive radio networks. This technique is based on the Variational Bayesian learning only on off-line circumstances. [2] employs the Viterbi algorithm in Hidden Markov model.

But on-line ways prefer to make the update step continuously during the data entry providing real-time results. The [3] proposes the maximum likelihood and Bayesian inference to estimate the channel-usage patterns online for determining the presence/absence of PUs. And a parallel algorithm [4] was used as the recursive estimation of sparse signal to estimate all elements with closed-form expression. A variant of the Baum-Welch algorithm are used in non-stationary model to estimate the parameters [5]. [6] employs sequential Monte Carlo technique with sufficient statistics to estimate the transition matrix of the model.

However, these algorithms do not consider the influence of time complexity during the process of sensing, which will lead to inefficient communication performance on the higher layer protocol, e.g., the transport layer, as TCP is very sensitive to the end to end delay [7-9]. The paper brings up the alternative technique of Mixed filter to adapt to

the changing environment and sorts of data, and the filter can reduce the running time and smooth the results to make spectrum sensing faster and more stable.

The rest of this paper is organized as follows: Section 2 introduces the other online solutions in forecasting parameters of the Hidden Markov model. The Mixed filter is presented in detail in Section 3. Section 4 mainly shows the numerical settings and results. And the conclusion is given in Section 5.

Foundations

Hidden Markov Model

This paper will build the model in mathematical way. And Hidden Markov model will be employed in telecommunication, and the transition probability matrix in online algorithm is designed as time-invariant parameter to simulate the real dynamic environment.

Hidden Markov model (HMM) is assumed as Markov Process with hidden states, which is usually used in temporal pattern recognition such as speech, handwriting and others for the optimal nonlinear filtering problem. Many papers drive forward-backward procedure as solution that was first described by Ruslan L. Stratonovich [10]. And the Viterbi algorithm is employed along with forward-backward. These methods take on the same responsibility as Bayesian smoothing to compute the maximum a posteriori (MAP) of Hidden Markov model.

According to the principle, the model can be described as follows:

$$f\left(x_t' \middle| x_{t-1}'\right) = Mu_{x_t'}\left(A_t x_{t-1}'\right) \tag{1}$$

$$f(y_t' | x_t') = Dir_{y_t'}\left(\rho x_t' + 1_{2,1}\right) \tag{2}$$

$$f\left(A_t \middle| A_{t-1}\right) = Dir_{A_t}\left(kA_{t-1} + 1_{2,2}\right) \tag{3}$$

where x_t is set as the real state of primary user, which indicates if the spectrum is occupied. The two states alternate in {0, 1}, representing the idle and busy state of spectrum respectively, and y_t denotes the observation data among every inference process, which is continuously distributed in (0, 1). Transition matrix A_t is the transition probability of hidden states changing over time. To adapt to the math framework, the calculate parameters are changed as $x_t' = [x_t, 1 - x_t]$, $y_t' = [y_t, 1 - y_t]$ respectively. *Mu* and *Dir* are multinomial distribution and Dirichlet distribution respectively. The system picks them as conjugate pair for convenience. ρ and k are constant to adjust the probability inferring x_t' through y_t' and distance between A_{t-1} and A_t. And $1_{2,1}$, $1_{2,2}$ are 2 *times* 1 and 2 *times* 2 matrices with all elements equal to one, which can change dimension along with the number of states of the model. These equations are the basement of later derivation.

Bayesian Filter and Particle Filter

Bayesian filtering and smoothing are formulated according to Bayesian inference and have three marginal distributions to choose for solving different problems, such as

filtering distributions, smoothing distributions and prediction distributions [11]. As estimation questions in spectrum sensing, the filtering algorithm will focus on the first two distributions.

In HMM, the marginal results can be calculated as integral form. However, it is very unavailable. To simplify the calculation, filtering is treated as an operation that involves the data message and distributions between parameters. Furthermore, smoothing process is a posteriori form of estimation. Specifically, smoothing part is usually employed with filtering reconstructing better former state to get more accurate current state [12]. Bayesian filtering is a recursive algorithm which can be interpreted as a process of continuously estimating the state or probability function of the system. [13] is the one of the first explorations of iterative Bayesian estimation and the article gives a detailed description of the principle and procedure of Bayesian filtering.

The parameter θ_t is $\theta_t = [x_t, A_t]$ in this paper. The Bayesian online update process includes time update and data update as Fig1 shows [14].

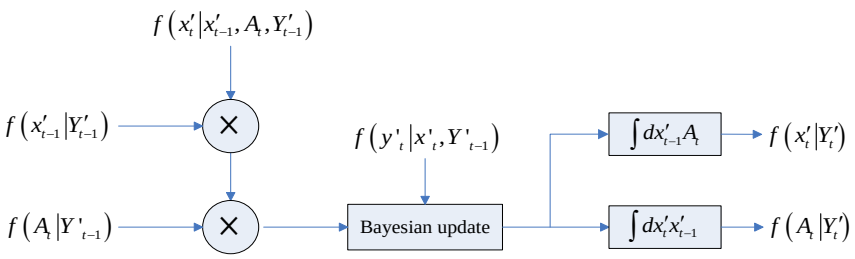

Fig 1. Bayesian filtering for the HMM model with unknown transition matrix

Bayesian update is following the Bayes rule. Y'_t is the aggregative data which collects all observation states till time t. And the iterative steps of observation states, hidden states and transition matrix in model are computed as follows:

$$\tilde{f}(x'_t|Y'_{t-1}) \propto \tilde{f}(x'_t|x'_{t-1})\,\tilde{f}(x'_{t-1}|Y'_{t-1}) \tag{4}$$

$$\tilde{f}(x'_t|Y'_t) \propto f(y'_t|x'_t, A_t)\,\tilde{f}(x'_t|Y'_{t-1}) \tag{5}$$

$$\tilde{f}(A_t|Y'_{t-1}) = Dir_{A_t}(Q_t) \tag{6}$$

$$\alpha_t \propto (y'_t)^{\rho} \circ \exp\left(\widehat{[\ln A_t]_T}\,\beta_t\right) \tag{7}$$

$$\beta_t \propto \alpha_{t-1} \circ \exp\left(\widehat{[\ln A_t]_T}\,\alpha_t\right) \tag{8}$$

$$Q_t = Q_{t-1} + \alpha_t [\beta_t]_T \tag{9}$$

$$\widehat{\ln(a_{i,j})} = \psi_\Gamma(q_{i,j,t}) - \psi_\Gamma\left([1_{2,1}]_T\, Q_t 1_{2,1}\right) \tag{10}$$

where α_t, β_t and Q_t are shaping parameters. α_t and β_t represent point estimate of real state x' and x'_{t-1} respectively. $\circ$ is the hadamard product, and $[\cdot]_T$ is the transpose of the element. $a_{i,j}$ is the element of A_t indicating the probability of ith state to jth state. $\psi_\Gamma(\cdot)$ is the Digamma function.

Particle filters are sequential Monte Carlo methods based on point mass (or "particle") representations of probability densities, which can be applied to any state-space model [15]. The most popular "Bootstrap" algorithm is one of the first practical implementations of the processor to the tracking problem. It is the most heavily applied of all PF techniques due to its simplicity [16]. This filter can be used as an approximation tool to track the state of Hidden Markov model, focusing on the process of updating transition matrix. Particle filter carries out resampling step to avoid the weights turning to zero.

In order to have a better understanding of the theory, this part will drive Bootstrap filter as an example to explain the process:

1) Take $A^{(j)}$ from the importance distribution

$$A^{(j)} \sim Dir\left(kA_{t-1} + 1_{2,2}\right) \tag{11}$$

2) Calculate the weights

$$w_{j,t} = w_{j,t-1} f\left(y'_t \middle| \beta_t, \hat{A}_{t-1}\right) \tag{12}$$

3) If necessary, resample the weights and replace old ones

Mixed Filter

To explore the alternative way to solve the sensing problem with new inspiring thoughts, this part proposes a new algorithm through these theories, which combines Bayesian filter and Particle filter together as the Mixed filter.

The nature of the thought is that the Mixed filter picks the update of transition matrix of Particle filter and put it into the Variational Bayesian filter to make the sensing faster and more stable. During the process, the algorithm chooses the particles as the candidate weights for the estimation transition matrix. And the update of real state of PUs is calculated as the Expectation Maximization Algorithm comparing to the Variational Bayesian. They are similar except the treatment of the logarithm of transition matrix. The Bayesian part is mainly depend on the Q factor, while the EM only solves the logarithm directly. But the main core of the Mixed filter is still derived from the Bayesian theory.

In theoretical analysis, the choosing method can absorb the advantages of these algorithms. This alternative method can represent the advantages of Bayesian filter and particle filter. Smoothing step is the replacement of the Viterbi, which can make the estimation of the state of PUs more stable and accurate than Particle filter. Furthermore, the update process of transition matrix of Particle filter is authentically simpler than Variational Bayesian filter, which can make the selecting process faster. That will try to make a Mixed filter as a better alternative way to sense the Physical Layer detecting the PUs.

Simulation

The above theory has already described the practicability of the new algorithm. For simplicity, the number of particle sets which is as the same as the iteration times is 40. The number of Soft-bit sequence is 2000 each time. ρ could be set as 2. The prior of transition matrix can be decided as $A_t = [0.5, 0.5; 0.5, 0.5]$, and this will not influence the real estimation results. The original data is simulated as Hidden Markov chain to imitate the communication environment. The paper analyzes in misclassification error, tracking ability and running time respectively. Misclassification error censuses the mean-square error between real and estimate state. Tracking ability can appear the flexibility and stability of the algorithm. Running time represents the time of model learning.

From Table 1, it is the misclassification error in Variational Bayesian filter, Particle filter and Mixed filter. And these methods all have good accuracy. To test the running time between these algorithms, the timing module has put in the Matlab program.

And the running time of Variational Bayesian filter, Particle filter and Mixed filter are represented in Fig2. Obviously, the running time of Mixed filter is less than Variational Bayesian filter and Particle filter.

Table 1 . Misclassification error in Variational Bayesian filter, Particle filter and Mixed filter

	VB filter	Particle filter	Mixed filter
MSE	257.8974	256.1749	256.1026

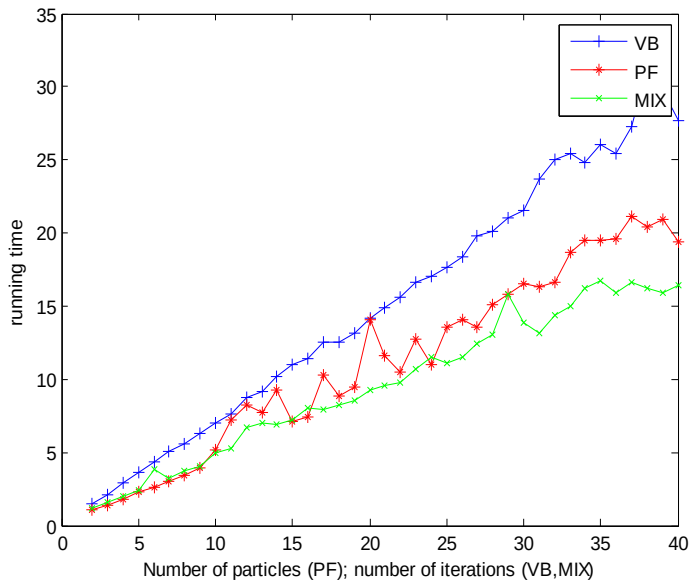

Fig. 2. Running time among Variational Bayesian filter, Particle filter and Mixed filter

To get the further analysis of the new algorithm, the paper tests the estimation of the transition matrix. Fig3, 4, 5 compare the transition curve that can influence the estimation accuracy of PUs. These figure show that the curve of estimation transition matrix fluctuate along with the real variant transition matrix. And the peak-to-peak value of estimation curves in Variational Bayesian filter is larger than Particle filter and Mixed filter. However, the mixed filter range of variation is the smallest among the curves, which represents that the Mixed filter is not sensitive to changing transition matrix influence as VB filter and Particle filter , however the Mixed filter can still get

nice accuracy results. I think that the Mixed filter enhances the smoothing function during the mixing process.

Conclusion

This article discusses the methods of physical sensing in the online scenario. We analyze the principle of Bayesian filter and Particle filter. Afterwards, we propose a new filter by mixing the core parts of them and properly adopt it to the online spectrum sensing. The simulation results show that the new filter has a good accuracy, less running time and stronger stability compared to both the Variational Bayesian filter and Particle filter.

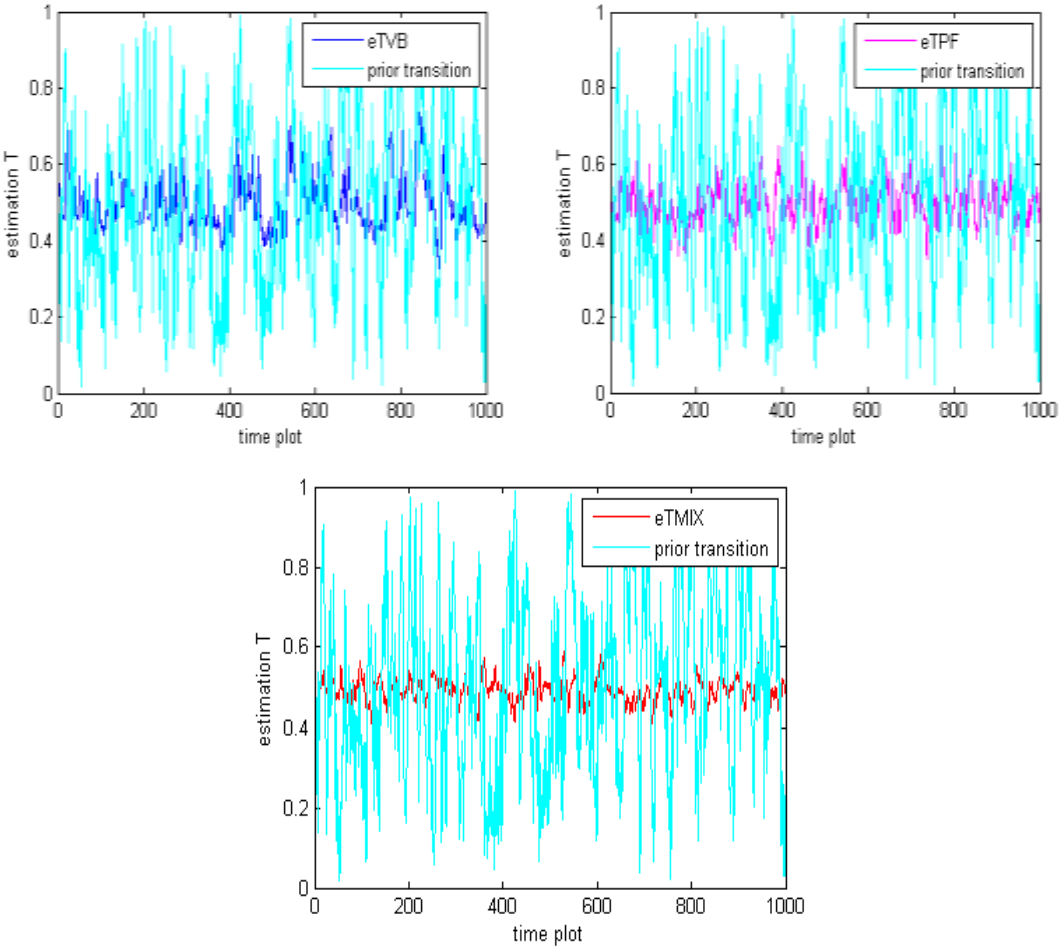

Fig. 3.4.5. Tracking ability in Variational Bayesian Filter, Particle Filter, and Mixed Filter

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