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Non-Cooperative Game Joint Hidden Markov Model for Spectrum Allocation in Cognitive Radio Networks

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Abstract

Spectrum allocation is a key operation in cognitive radio networks (CRNs), where secondary users (SUs) are usually selfish – to achieve itself utility maximization. In view of this context, much prior lit literature proposed spectrum allocation base on non-cooperative game models. However, the most of them proposed non-cooperative game models based on complete information of CRNs. In practical, primary users (PUs) in a dynamic wireless environment with noise uncertainty, shadowing, and fading is difficult to attain a complete information about them. In this paper, we propose a non-cooperative game joint hidden markov model scheme for spectrum allocation in CRNs. Firstly, we propose a new hidden markov model for SUs to predict the sensing results of competitors. Then, we introduce the proposed hidden markov model into the non-cooperative game. That is, it predicts the sensing results of competitors before the non-cooperative game. The simulation results show that the proposed scheme improves the energy efficiency of networks and utilization of SUs.

Keywords: *Hidden Markov Model, Non-Cooperative Game, Cognitive Radio Networks, Energy Efficient*

1. Introduction

Cognitive Radio, which is envisioned as a promising technology to promote the efficient spectrum usage, enables the secondary users (SUs, who unlicensed wireless users) to opportunistically access the licensed channels owned by primary users (PUs, who legacy spectrum holders) [1]. And, this scheme is often referred to as opportunistic spectrum access (OSA) [2].

A key challenge of OSA is how to resolve the spectrum allocation where is divided into some licensed channels competition by selfish secondary users. If multiple secondary users access the same channels simultaneously, collisions might occur and data rates may get reduced. In this scenario, a game theoretic framework is an ideal model and analyzation for cognitive radio networks in a distributed way. Due to the SUs selfishness, the non-cooperative game theory is closely connected to the mini/max optimization and typically results in the study of the various equilibria most notably the Nash equilibrium [3].

W. Wang *et.al* proposed a dynamic spectrum leasing in which the primary users actively participate in a

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non-cooperative game with a secondary user by selecting an interference cap on the total interference they willing to tolerate [4]. In [5], J Elias *et. al* modeled a non-cooperative spectrum access game which takes into account the congestion comes into being when secondary user access simultaneously multiple spectrum bands. The non-cooperative game based two oligopoly game models are re-formulated as Cournot and Stackelberg games in [6]. In [7], Duong *et.al* proposed two non-cooperative games, which are named interference minimization game and capacity maximization game for reflecting the target of data radios and voice radios, respectively. And, J.H. Wang et.al analyze the pricing mechanism for monotone Nash equilibrium problems (NEPs) with global constraints and applied it to cognitive radio networks in [8].

All above literature ideally formulated the non-cooperative model base on complete information of cognitive radio networks. However, each SU may not be able to sense all channels due to the limitation of hardware or/ and sensing capability [9] or PUs in a dynamic wireless environment with noise uncertainty, shadowing, and fading. In other words, it is very difficult to obtain complete information (namely, imperfect information) of PUs or CRNs. For this reason, we proposed a non-cooperative game joint hidden markov model for spectrum allocation in CRNs. Furthermore, we propose a new hidden markov model to predict the sensing results of competitors to reduce the collision of SUs and improve the energy efficiency of CRNs and the utility of SUs.

In this paper, we are motivated to consider incomplete information for a non-cooperative game model proposed in [5]. Considering the conclusion, actions taken by SUs do not affect the evolution of the channel state, is drawn in [9]. We introduce a hidden Markov model to improve sensing information completeness for non-cooperative game proposed in [5]. Hidden markov model (HMM) widely leveraged predict channel states in cognitive radio networks, such as [10, 11, 12, 13]. However, since SUs are exclusiveness and selfishness, there is an incentive to require that SUs are able to predict the sensing results of their competitors. Thus, we propose a new hidden Markov model, in which SUs can predict the sensing results of their competitors, and introduce it into the non-cooperative game for spectrum allocation.

The rest of this paper is organized as follows. In Section 2, we give a description of the system. In Section 3, we discuss the proposed HMM-based prediction scheme and non-cooperative game joint it in detail. The simulation results are discussed in Section 4. Finally, we make a conclusion in Section 5.

2. System Model

In this paper, we consider a CRNs referred in [14], where SUs intercommunicating by exploiting channels unused by PUs. In order to ensure contention among SUs, we use CSMA (carrier sense multiple access) to randomly allocate channel times among competing SUs. We assume there are m independent and stochastic heterogeneous primary channels and n selfish SUs, denoted as $m=\{1,2,...,M\}$ and $n=\{1,2,...,N\}$, respectively. We also assume that each SU is a dedicated transmitter-receiver pair and exchange signaling message through the dedicated control channel. Furthermore, we divide time into equal slots of length T, and label these discrete time slots as $t=1,2,\ldots$. Similarly to [10], we denote $Y_t \in \{0,1\}^m$ as the current channel usage pattern of PUs; If the channel $c \in m$, the $Y_t(c)$ is 1, vice versa. We denote $X_t^n(c)$, the c channel allocation decision of nth SU at the time t.

We denote γ_i as the signal-to-interference ratio (SIR) of ith $(i \in n)$ SU, it is defined as [11]

$$\gamma_i = \frac{w}{R} \times \frac{h_i p_i}{\sum_{j \neq i} h_j p_j + \sigma^2} \qquad (1)$$

where w is the available spread-spectrum bandwidth; R is information transmission rate; σ^2 is the AWGN power at the receiver, and h_i is path gains. For simplicity, we represent $\alpha = \frac{w}{R}$, which is spreading gain. The interference to ith SUs can be denoted as $I_i = \sum_{j \neq i} h_j p_j + \sigma^2 \ (j \in n, j \neq i)$. Thus, Eq. (1) can be rewritten as

$$\gamma_i = \alpha \frac{h_i p_i}{I_i}$$

From Eq. (1) we can make a conclusion- the greater interference I_i, the SIR is. The interference I_i comes from the competitors of ith SUs. Hence, for ith SUs, it is significant to know whether competitors appear on the same channel.

3. A New Hidden Markov Model

In much prior literature, the non-cooperative game models are introduced for spectrum allocation in CRNs, such as [5]. In this paper, we introduce the non-cooperative game model referred in [5]. The detail above non-cooperative game can be found in [5]. Hence, we will not devote a large segment to discuss it in here.

3.1 Hidden Markov Model

In cognitive radio networks, sensing the environment is usually done by estimating the status of the primary user as being active or idle. It is amenable to estimating a state variable from some given noisy and possibility incomplete observation. Indeed, much literature formulated the problem as that of estimating the state of hidden markov model (HMM). In [12], authors utilized the hidden markov model for estimating the current channel state and predict the next channel state.

3.2 The Proposed Hidden Markov Model

The probability of ith SUs makes a decision of the channel c, is denoted as $P\left(X_t^i(c) \mid Y_t(c)\right)$. As aforementioned, $Y_t(c)$ is the current channel c usage pattern of PUs, namely, the truth state of the channel c in the interval t; $X_t^i(c)$ is ith SUs made a decision of channel status of the channel c. We assume k is binary hypothesis test, 0 means channel is occupied by PUs and vice versa. Hence, we can obtain expression $Y_t(c) \in \{y_t(c) = k\} (k = 0,1;\ c \in m)$ and $X_t^i(c) \in \{x_t^i(c) = k\} (k = 0,1;\ 1 \le i \le N; c \in m)$.

Proposition 1: We assume ith SUs make a decision of channel status of the channel c in the interval t, denoted as $x_t^i(c)$; the competitor jth SUs make a decision of the same channel c in the interval t, denoted as $x_t^j(c)(j \in m, j \neq i)$.

The probability $P\left(x_t^j(c) \mid x_t^i(c)\right)$, is shown as follows:

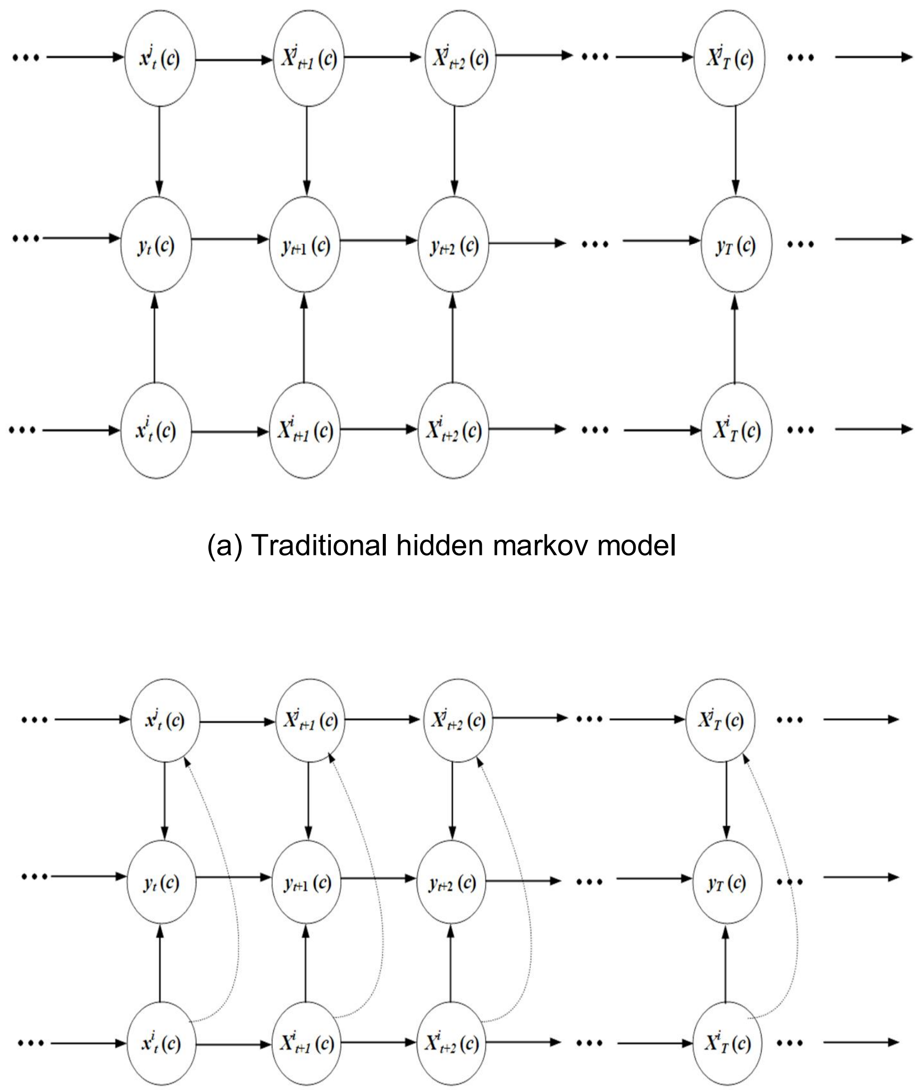
$$P\left(x_t^j(c) \mid x_t^i(c)\right) = \frac{\sum_{t=1,2,\dots} P(x_t^j(c) \mid Y_t(c)) P(x_t^i(c) \mid Y_t(c)) P(Y_t(c))}{\sum_{t=1,2,\dots} P(x_t^i(c) \mid Y_t(c)) P(Y_t(c))} \quad (2)$$

Proof: see Appendix A

We propose a new hidden markov model as shown in Figure. 1 (b). As same as traditional hidden markov model (as shown in Figure. 1 (a)), $x_t^i(c)$, $x_t^j(c)$ are observable states and $y_t(c)$ is hidden states. In proposed hidden markov model, $x_t^i(c)$ is observable states, $x_t^j(c)$ can be considered as hidden states. From this perspective, ith SU is able to predict $x_t^j(c)$.

Proposition 2: For the same channel $c\ (c \in m)$, ith SU and jth SU are competitors. If the ith SU

knows its sensing results of the channel c is $x_t^i(c)$, it also can predict the $x_t^j(c)$ what is sensing results of channel c by jth SU. In another word, $x_t^i(c) \to x_t^j(c)$ conforms to hidden markov model.
Proof: see Appendix B



(a) Traditional hidden markov model

(b) The proposed hidden markov model

Figure.1 Traditional and proposed hidden markov model

In proposed hidden markov model, $x_t^j(c)$ can be considered as hidden states and $x_t^i(c)$ is the observed states. We represent proposed HMM as $\boldsymbol{\omega} = \{\mathbf{I}, \mathbf{A}, \mathbf{B}\}$, where $\mathbf{I} = \{I_k\}(k = 0,1)$ is initial state distribution probability of $x_t^j(c)$; $\mathbf{A} = |a_{ij}|$ is the transition matrix; $\mathbf{B}$ is output probability, where $\mathbf{B} = \{b_{ij}\} = P\left(x_t^j(c) \mid x_t^i(c) \right)$.

3.3 HMM-based prediction scheme

The core of proposed HMM-based prediction scheme is: the ith SU can get the prior probabilities of the competitor- jth SU; According to Bayes' theorem, we can obtain Eq. (3) as below

$$P(x_t^i(c) \mid y_t(c)) = \frac{p(x_t^i(c), y_t(c))}{p(y_t(c))} \quad (3)$$

We assume $Q_t(x_t^i(c), y_t(c)) = P(x_t^i(c), y_t(c))$ and submit it to Eq. (3) to obtain Eq. (4)

$$P(x_t^i(c) \mid y_t(c)) = \frac{Q_t(x_t^i(c), y_t(c))}{\sum_{x_t^i(c)=0,1} Q_t(x_t^i(c), y_t(c))} \quad (4)$$

Since

$$\begin{aligned} Q_t(x_t^i(c), y_t(c)) &= \sum P(x_{t-1}^j(c), y_{t-1}(c), x_t^i(c) \mid y_t(c)) \\ &= \sum Q_{t-1}(x_t^j(c), y_{t-1}(c)) \cdot P(x_t^i(c) \mid x_{t-1}^j(c)) \\ &= \sum Q_{t-1}(x_t^j(c), y_{t-1}(c)) \cdot a_{ij} \cdot P(y_t(c) \mid x_t^i(c)) \\ &= P(y_t(c) \mid x_t^j(c)) \sum Q_{t-1}(x_t^j(c), y_{t-1}(c)) \cdot a_{ij} \end{aligned} \quad (5)$$

where, $Q_t(x_t^i(c), y_1(c))$ can be written as $Q_1(x_t^i(c), y_1(c)) = P(x_t^i(c), y_1(c)) = I_k P(y_1(c) \mid x_t^i(c))$, we can obtain $Q_2(x_2^j(c), y_2(c)), Q_3(x_3^j(c), y_3(c)), \ldots, Q_t(x_t^j(c), y_t(c))$.

Hence, we seek to obtain a $x_t^j(c)$ meets Eq. (6) as below:

$$P(x_t^j(c) \mid y_t(c)) = \max_{x_t^j(c) \in \{0,1\}} P(x_t^j(c) \mid y_t(c)) \quad (6)$$

We call this prediction scheme as HMMPS.

3.4 Hidden Markov Prediction-based Non-cooperative Game

To sum up, a new HMM prediction scheme-based non-cooperative game flow chart is shown as below.

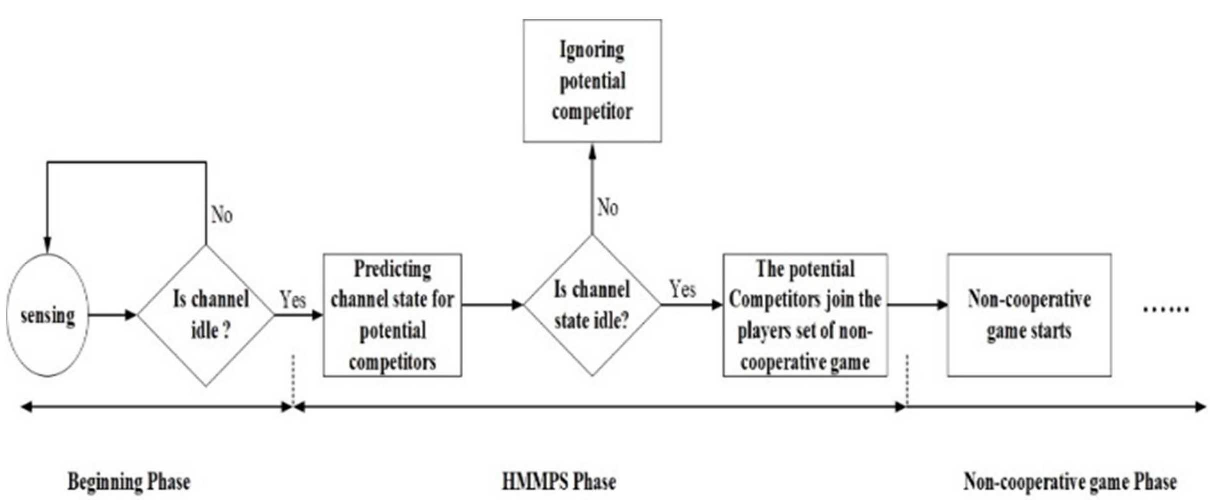


Figure. 2 The flow chart of proposed HMM-based non-cooperative

4. Simulation

In this section, we investigate the behavior of proposed the new HMM prediction scheme-based non-cooperative game (HMMPS-based non-cooperative game) via simulation. The parameter values can be found in [5].

Figure 3 shows the comparison of SU transmitter power between the HMMPS-based non-cooperative game and non-cooperative game without prediction scheme. Since, the SU predict the competitors' spectrum sensing results; if sensing results of competitors are predicted as 0, in which means the competitors will not join the non-cooperative game, the SU will not pay much for accessing the channel usage. In here, the pay of SU is SU power, actually. Hence, SUs who are in the HMMPS-based non-cooperative game need less power compare to the non-cooperative game without HMMPS.

As Figure. 3 shown, the prior need less power than latter. Moreover, according to , the utility (bits per joule) of prior is higher than latter. Figure. 4 shows this conclusion as well. From Figure 4, we can find that the utility of SUs' who are in the HMMPS-based non-cooperative game is significantly higher than the SUs who are in the common non-cooperative game.

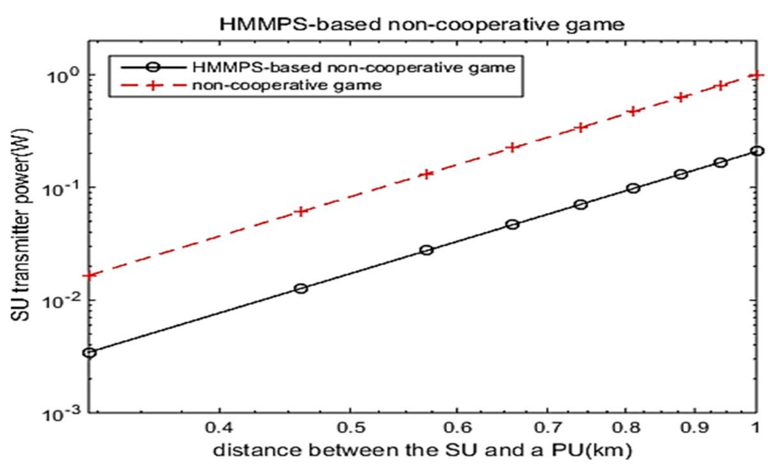


Figure. 3 The comparison of SU transmitter power between HMMPS-based non-cooperative game and non-cooperative game

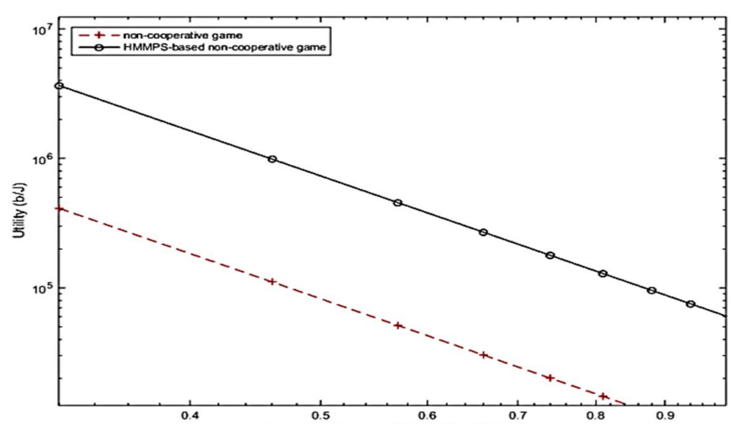


Figure. 4 The comparison of SUs' utility between HMMPS-based non-cooperative game and non-cooperative

Figure 5 show comparison of PU transmitter power between the HMMPS-based non-cooperative game and non-cooperative game without prediction scheme. Due to an SU i dynamic adaptive power control based competitors spectrum sensing results in HMMPS-based. The PU transmitters also only need to spend power because they can know the SU active or not via prediction scheme.

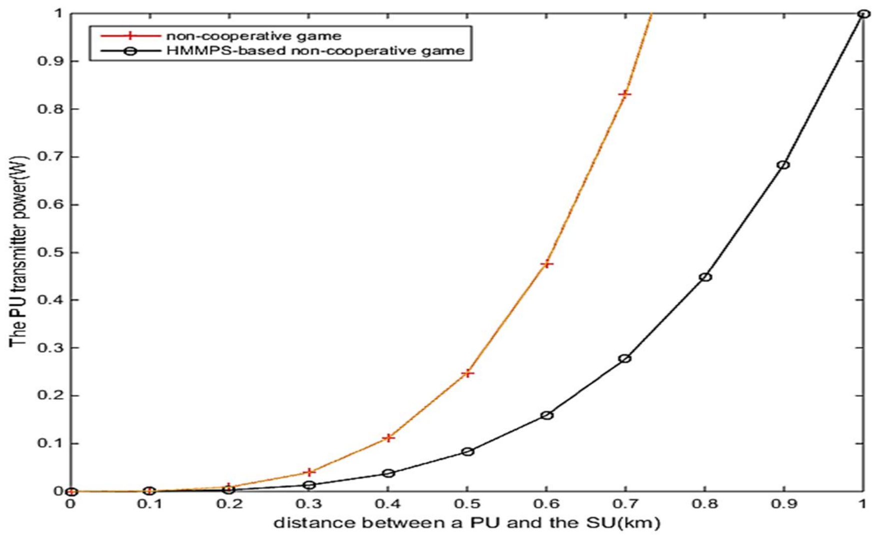


Figure. 5 The comparison of PUs transmitter between HMMPS-based non-cooperative game and non-cooperative game

5. Conclusion

In this paper, we proposed a new hidden Markov model prediction scheme for the non-cooperative game in cognitive radio networks. In this prediction scheme, for a SU, where competitors' spectrum sensing results are predicted rather than channel states. The non-cooperative game achieves the complete information game via such prediction scheme. Comparing to without such prediction scheme, it improves the power and utility efficiency of the SU. Furthermore, it also improves the power efficiency of the PU.

Appendix A

According to condition probability theorem, we can obtain Eq. (1) as follows

$$P\left(x_t^j(c) \mid x_t^i(c)\right) = \frac{P(x_t^j(c), x_t^i(c))}{P(x_t^i(c))} \tag{1}$$

And according to Bayes theorem

$$P(x_t^j(c) \mid x_t^i(c)) = \frac{P(x_t^i(c) \mid x_t^j(c))P(x_t^j(c))}{P(x_t^i(c))} \tag{2}$$

we can rewrite by the whole probability formulate as fellow:

$$P\left(x_t^j(c), x_t^i(c)\right) = \sum_{t=1,2,\ldots} P(x_t^j(c), x_t^i(c) \mid Y_t(c)) \tag{3}$$

$$P(Y_t(c))P(x_t^i(c)) = \sum_{t=1,2,\ldots} P(Y_t(c))P(x_t^i(c) \mid Y_t(c)) \tag{4}$$

ith SU, jth SU and channel c is mutual independence. Hence, Eq. (2) can be rewritten as

$$P(x_t^i(c) \mid x_t^j(c)) = \frac{\sum_{t=1,2,...} P(x_t^i(c), x_t^j(c) \mid Y_t(c))P(Y_t(c))}{\sum_{k=0,1} P(Y_t(c))P(x_t^i(c) \mid Y_t(c))}$$
$$= \frac{\sum_{t=1,2,...} P(x_t^j \mid Y_t(c))P(x_t^i(c) \mid Y_t(c))P(Y_t(c))}{\sum_{t=1,2,...}^{T} P(x_t^i(c) \mid Y_t(c))P(Y_t(c))} \quad (5)$$

The proof is ended.

Appendix B

We describe truth states space and observed states with $\mathbf{S}$ and $\mathbf{O}$, which are denoted as $\mathbf{S} = \{y_t(c) = k\}(k = 0,1;\ c \in m)$ and $\mathbf{O} = x_t^i(c) \in \{x_1^i(c), x_2^i(c), x_3^i(c), ..., x_t^i(c)\}(t = 1,2,...;\ 1 \le i \le N; c \in m)$, respectively. We can obtain Eq. (4) as follow

According to contingent probability definition:

$$P\left(x_t^i(c) \mid x_{t-1}^i(c), x_{t-2}^i(c), ..., x_1^i(c)\right)$$
$$= P\left(y_t(c) \mid x_{t-1}^i(c), x_{t-2}^i(c), ..., x_1^i(c)\right) P\left(y_t(c) \mid y_{t-1}(c), y_{t-2}(c), ..., y_t(1)\right) P\left(x_t^i(c) \mid y_t(c)\right) \quad (1)$$

Base on Bayes' rule, Eq. (1) can be rewritten as below.

$$P(x_t^i(c) \mid x_{t-1}^i(c), x_{t-2}^i(c), ..., x_1^i(c))$$
$$= \frac{P(x_{t-1}^i(c), x_{t-2}^i(c), ... \mid y_{t-1}(c))}{P(x_{t-1}^i(c), x_{t-2}^i(c), ..., x_1^i(c))} \cdot$$
$$P(y_{t-1}(c)) \cdot P(y_t(c) \mid y_{t-1}(c), y_{t-2}(c), ..., y_1(c)) \cdot p(x_t^i(c) \mid y_t(c))$$
$$= \frac{P\left(y_{t-1}(c), x_{t-1}^i(c)\right) P(x_{t-2}^i(c), x_{t-3}^i(c), ..., x_1^i(c) \mid y_{t-1}(c), x_{t-1}^i(c))}{P(x_{t-2}^i(c), x_{t-3}^i(c), ..., x_1^i \mid x_{t-1}^i(c))P(x_{t-1}^i(c))} \cdot \quad (2)$$
$$P(y_t(c) \mid y_{t-1}(c), y_{t-2}(c), ..., y_1(c)) \cdot P(x_t^i(c) \mid y_t(c))$$
$$= \frac{P(y_{t-1}(c), x_{t-1}^i(c))P(x_{t-2}^i(c), x_{t-3}^i(c), ..., x_1^i(c) \mid x_{t-1}^i(c))}{P(x_{t-2}^i(c), x_{t-3}^i(c), ..., x_1^i(c) \mid x_{t-1}^i(c))P(x_{t-1}^i(c))} \cdot$$
$$P(y_t(c) \mid y_{t-1}(c), y_{t-2}(c), ..., y_1(c)) \cdot P(x_t^i(c) \mid y_t(c))$$

In [13], it demonstrated that $Y_t(c) = \{y_1(c), y_2(c), ..., y_t(c)\}(t = 1,2,...)$ fits a Markov model. Therefore, we can obtain Eq. (3) as follows:

$$P(x_t^i(c) \mid x_{t-1}^i(c), x_{t-2}^i(c), ..., x_1^i(c))$$
$$= P(y_{t-1}(c) \mid x_{t-1}^i(c))P(y_t(c) \mid y_{t-1}(c))P(x_t^i(c) \mid y_t(c)) \quad (3)$$
$$= P(x_t^i(c) \mid x_{t-1}^i(c))$$

We draw a conclusion that $\mathbf{O}$ is a Markov chain due to Eq. (3) is with Markov property. We assume output probabilities matrix $\mathbf{\Lambda}$,

$$\mathbf{\Lambda} = \left| P\left(o = x_t^j(c) \mid o = x_t^i(c)\right) \right|$$
$$= \sum_{j \ne i, j=1}^{m} \sum_{i=1}^{m} P(y_t^i(c) \mid x_t^i(c))P(y_t^j(c) \mid y_t^i(c))P(x_t^j(c) \mid y_t^j(c)) \quad (4)$$

where $y_t^i(c), y_t^j(c)$ is the truth states of channel c for ith and jth SU .

In addition, the proof in Appendix A, we can know as below

$$P(x_t^i(c) \mid x_t^j(c)) = \frac{\sum_{t=1,2,\ldots} P(x_t^i(c), x_t^j(c) \mid Y_t(c)) P(Y_t(c))}{\sum_{k=0,1} P(Y_t(c)) P(x_t^i(c) \mid Y_t(c))}$$

$$= \frac{\sum_{t=1,2,\ldots} P(x_t^j \mid Y_t(c)) P(x_t^i(c) \mid Y_t(c)) P(Y_t(c))}{\sum_{t=1,2,\ldots}^{T} P(x_t^i(c) \mid Y_t(c)) P(Y_t(c))}$$

Hence, $x_t^i(c) \to x_t^j(c)$ conforms to hidden markov model.

Proof End

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