HMM-based Adaptive Frequency-Hopping Cognitive Radio System to Reduce Interference Time and to Improve Throughput

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Abstract

Cognitive Radio is an advanced enabling technology for the efficient utilization of vacant spectrum due to its ability to sense the spectrum environment. It is important to determine accurate spectrum utilization of the primary system in a cognitive radio environment. In order to define the spectrum utilization state, many CR systems use what is known as the quiet period (QP) method. However, even when using a QP, interference can occur. This causes reduced system throughput and contrary to the basic condition of cognitive radio. In order to reduce the interference time, a frequency-hopping algorithm is proposed here. Additionally, to complement the loss of throughput in the FH, a HMM-based channel prediction algorithm and a channel allocation algorithm is proposed. Simulations were conducted while varying several parameters. The findings show that the proposed algorithm outperforms conventional channel allocation algorithms.

Keywords: Cognitive radio, HMM based channel prediction, frequency-hopping algorithm

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1. Introduction

Cognitive Radio (CR) is a promising technology that has been proposed as a novel means of improving the efficiency of wireless communication systems. Particularly, CR is considered a potential solution to improve spectrum utilization via opportunistic spectrum sharing. A CR network is an intelligent wireless communication system that is aware of its surrounding environment (including aspects such as spectrum utilization, fading conditions, and interference levels). It adapts transmission parameters of the frequency and transmits power by making corresponding changes to its parameters over time. Hence, CRs are considered a promising technology for use with 4G wireless networks or self-organization networks (SON) [1][2][3].

The key idea related to current CR networks is to allow the use of temporarily unused licensed spectrum by a CR under a limitation in which the CR avoids interference to potential primary users in the neighborhood. To work within this limitation, a CR should be capable of spectrum sensing and dynamic frequency selection (DFS)

A spectrum-sensing algorithm detects a vacant channel via a primary system to determine whether or not a certain amount of spectrum is available. DFS algorithms change the transmit frequency of a CR based on the spectrum sensing results. The CR should guarantee accurate sensing and efficient DFS to increase system reliability and performance [2].

In most cases, to achieve accurate spectrum sensing, a CR network has to stop all transmission on the channel. This leads to the aforementioned quiet periods (QP)[4]. Even when sensing accuracy is guaranteed, there are other drawbacks in CR networks related to throughput, latency and undesirable interference [5]. The throughput degradation problem is caused by the lack of transmission during a QP, and undesirable interference stems from the lack of sensing information between QPs.

To the reduce throughput and latency during QP, [6] proposes a double hopping algorithm, which assumes a full duplexing spectrum sensing module. However this algorithm has a hardware complexity.

Additionally, [7] proposes an interference time ratio-based opportunistic spectrum access method. However, it is an incomplete solution which allows a certain level of interference to the primary system.

In this paper, a scheme is proposed to solve the interference problem. A HMM-based channel prediction and selection algorithm is constructed based on a frequency-hopping algorithm.

HMM algorithms are used in a variety of areas in a CR system. In [8], a HMM algorithm is used by the signal classifier using pattern recognition. Sharma, M used the HMM to model the interference temperature dynamics of a primary channel [9]. Secondary nodes use this trained HMM to predict the interference temperature of the channel in future time slots. This model considered channel allocation at the QP period considering future time slot interference temperature. Akbar. I. A proposes dynamically selected different licensed bands for its own use with significantly less interference from and to the licensed users. It is found by predicting the duration of spectrum holes of primary users [10]. Jeon proposed spectrum sensing duration scheduling using HMM [11].

The proposed algorithm achieves the goal of reducing the interference time and increasing the throughput.

The remainder of this paper is organized as follows. In section 2, the proposed system model is introduced. In section 3, the HMM-based channel prediction and DFS algorithm are detailed. In section 4, the simulation results and analyses are given along with a discussion. Finally, the paper is concluded in section 5.

2. System Model

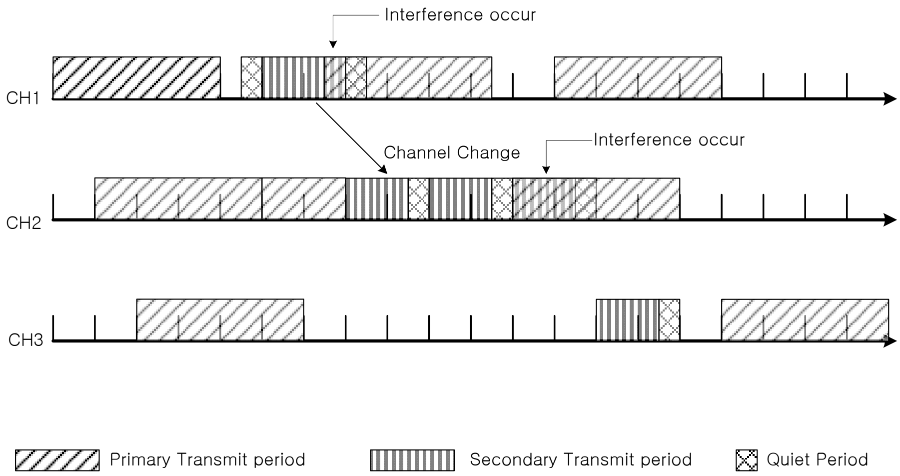


Fig. 1. Cognitive Radio coexistence model

Essentially, a CR network operates so as to coexist with a PU in a frequency channel which is unused by primary system in terms of time and location.

Fig. 1 depicts the operation of a CR network. The CR system observes spectrum utilization via its spectrum sensing functionality. If a given channel is a vacant spectrum channel, meaning that it is unused by a primary system, a CR user can transmit bursts. Otherwise, the CR user cannot transmit bursts. Additionally, the CR user stops transmitting when primary burst transmission suddenly appear in the channel.

As shown in **Fig. 1**, the CR system uses CH1 at the starting time while periodically sensing CH1 usage of primary users via QP. When a primary burst appears on CH1, the CR system stops transmission on CH1 and changes to another spectrum channel (in this case, to CH2). Even when the CR is capable of accurate spectrum sensing, interference can occur during CR data transmission periods as a result of non-contiguous spectrum sensing.

Fig. 2 represents an interference situation between a primary burst and a CR burst.

A CR system burst consists of T_{HP} (Hopping time period), T_D (Data burst period), and T_{QP} (Quiet period). The primary system starts its transmission burst with T_{pri} at a given time t using the same channel M. Upon the primary transmission starting time t, which is located between the end of T_{QP} and the end of T_D, interference occurs for the duration of T_D when the maximum interference time can be defined as T_D. Here interference time means total overlap time between primary data burst and CR data burst when the primary system and CR system access the same frequency channel.

If a primary system is occupying the channel, interference does not occur because the CR system detect primary system at the T_{QP} and then CR system does not access channel M.

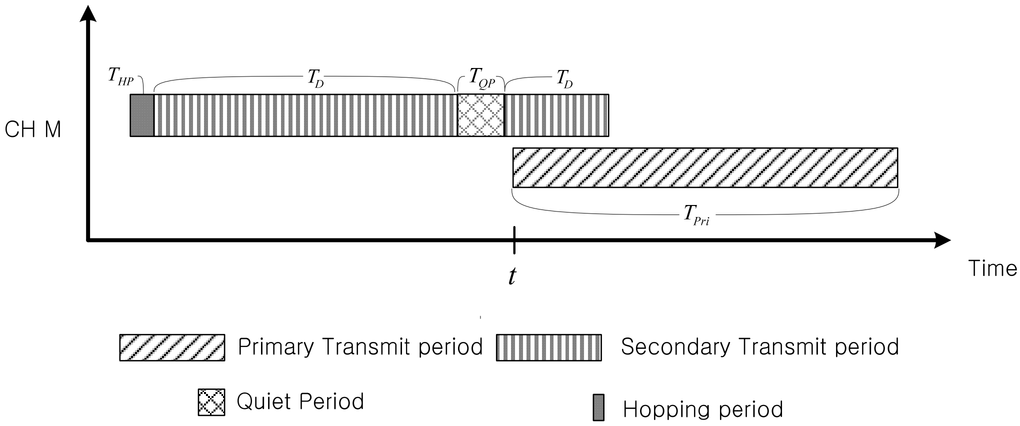


Fig. 2. Interference situation in cognitive radio

When the number of generated bursts is assumed to follow a Poisson distribution, the probability of no primary burst during a QP can be defined by the following equation (1) [12]:

$$P_{b\_QP} = \frac{e^{-\lambda_p T_{QP}} (\lambda_p T_{QP})^0}{0!} \tag{1}$$

Here λ_p is the arrival rate of primary system.

Additionally, the probability that least one primary burst exists during T_D can be defined by the following equation (2):

$$P_{P\_T_D} = 1 - e^{\lambda_p (T - T_{QP})} \tag{2}$$

From the two equations above, the interference probability of a CR and a primary system can be defined as

$$P_{\text{interference}} = e^{-\lambda_p t_{QP}} (1 - e^{-\lambda_p (T - T_{QP})}) \tag{3}$$

Accordingly, the expected value of the interference can be derived by the following equation (4):

$$\mathrm{E}\{I\} = T_D P_{\text{int}\,erference} = T_D e^{-\lambda_p T_{QP}} (1 - e^{-\lambda_p (T - T_{QP})}) \tag{4}$$

In accordance with the above equation (4), the amount of interference $\mathrm{E}\{I\}$ depends on the length of T_D and arrival rate λ_p assuming the same value of T_{QP}.

Assuming that the arrival rate λ_p is fixed, it is necessary to reduce T_D to reduce the amount of interference time. Therefore, the FH algorithm avoids interference better than the long burst transmission algorithm because it has a short data transmission period.

Similarly, system throughput can be defined by the following equation (5):

$$\text{Throughput} = T - T_{QP} - T_{hop} - \mathrm{E}\{I\} = T - T_{QP} - T_{hop} - T_D e^{-\lambda_p T_{QP}} (1 - e^{-\lambda_p (T - T_{QP})}) \quad (5)$$

According to the equation (5) above, the disadvantages of the long burst transmission algorithm are throughput degradation caused by a QP and an increase in the interference time ratio caused by QP duration mismatches.

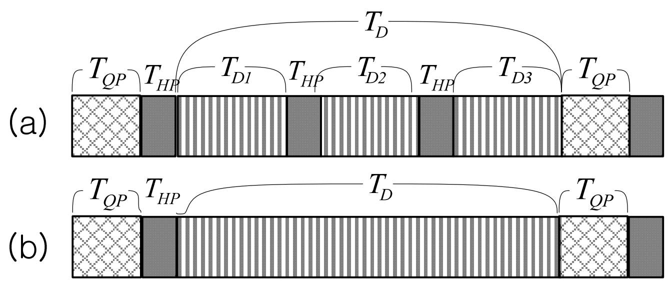
In order to overcome the drawbacks of long burst transmission algorithm, the FH algorithm is proposed here. This algorithm changes the operation frequency channel frequently using divided small-hopping bursts.

For convenience, the case of long burst transmission is called QP-based algorithm in the remaining chapters.

3. Proposed DFS algorithm with HMM-based channel prediction

3.1 Proposed Frequency-Hopping Algorithm

Fig. 3 depicts the FH transmission burst. A FH transmission burst is divided into small-hop bursts consisting of several instances each of T_{HP} and T_D. The CR system senses available channels during a QP. During each data transmission period, the CR system can transmit over a separate frequency channel, implying that the data transmission period channel of the CR using the same frequency channel is shorter than the QP-based algorithm. Hence, the interference time is reduced when using the FH-based algorithm compared to when the QP-based algorithm is used. This can be expressed by equation (4). However, adopting a FH DFS algorithm directly can be problematic.



(a) FH-based algorithm transmit burst (b) QP-based algorithm transmit burst

Fig. 3. Comparison of FH and QP-based algorithm

First, the FH-based algorithm should have the hopping sequence defined for frequency hopping. The FH-based algorithm operates to change the frequency at T_{Dx} during the entire period of T_D. Therefore, the CR System must have its hopping sequence defined for the operating frequency before a transmit operation can begin during a QP. The authors of one recent study [6] assume that a full duplex sensing operation senses another frequency channel, which excludes operation frequency channel utilization during the data transmission period. However, this approach leads to other types of overhead, such as an additional receiver for spectrum sensing, sensing information, occasional frequency allocation information and other types.

Therefore, this paper proposes the pre-allocation of the frequency channel for each hopping period (T_{Dx}) at the beginning of data transmission period (T_D) using a prediction algorithm which utilizes post-spectrum sensing information. To realize this method, this paper uses a frequency channel utilization prediction algorithm based on HMM. The issue of throughput reduction is also a concern. According to equation (5), the FH-based algorithm has weaker throughput performance than the QP-based algorithm under a small arrival rate λ, as the FH-based algorithm increases the redundancy time due to the numerous frequency-hopping periods. Actually the CR system allocates a frequency channel before data burst transmission. However, if a primary burst appears during a CR data transmission period at the CR operation frequency channel, interference occurs between the CR and primary system. If we can predict whether the primary system occurs during the CR data transmission period, we can decide on a more efficient operation channel considering the above situation. This might show an advantage in interference time compared with a QP-based algorithm, because the CR change operation frequency channel is dynamically based on HMM-based prediction results. Additionally, there can be an advantage in throughput compared with an FH-based algorithm because throughput is reduced by the T_{HP} of the CR system through prediction of the idle length of the primary system.

In order to solve this problem, an adaptive FH algorithm is proposed. This algorithm changes the number of hops during the data transmission period using the predicted channel state information. This is described in detail in the remaining part of Chapter 3.

3.2 HMM Model Based on Channel State

As discussed earlier, the proposed algorithm uses a channel prediction algorithm based on HMM.

A Hidden Markov Process (HMP) is a doubly stochastic process in which the generation of observation symbols depends on the emission properties of the states. The underlying process is a finite-state homogeneous Markov chain. This process is not observable and is often referred to as the regime. The second process is a sequence of conditionally independent random variables given the Markov chain. At any given time, the distribution of each random variable depends on the Markov chain only through its value at that time. This distribution is time-invariant and it may be a member of any parametric family. The sequence of conditionally independent random variables is often referred to as the observation sequence [13].

In this paper, the Hidden Markov Model (HMM) is defined based on the Channel State Information (CSI) and next channel state is predicted based on the estimated parameter and allocated optimal channel which minimizes the interference time ratio to the primary system.

Mathematically, the HMM-based *pth* channel state can be defined as $\Gamma_p = (A_p, B_p, \pi_p)$, where A_p is the state transition probability distribution, which can be defined as follows:

$$A_p = \{a_{p,ij}\}, \quad 1 \le i, j \le N \text{ with}$$

$$a_{p,ij} = \Pr(q_{p,t} = s_{p,j} \mid q_{p,t-1} = s_{p,i}),\ 0 \le a_{p,ij} \le 1 \text{ and } \sum_{j=1}^{N} 0 \le a_{p,j} \le 1 \tag{6}$$

Here, $s_{p,1}, s_{p,2},....s_{p,N}$ denotes N different states and $q_{p,t}$ is the actual state of time t. And i, j denotes *ith* and *jth* state and N means total number of states.
Additionally, B is the observation symbol probability distribution, which can be defined as

$$B_p = \{b_{p,i}(v_{p,k})\}, \qquad 1 \le i \le N, \quad 1 \le k \le K$$

with $b_{p,j}(v_{p,k}) = \Pr(v_{p,k} at\ t \mid q_{p,t} = s_{p,j})$. $0 \le b_{p,j}(v_{p,k}) \le 1$ and $\sum_{j=1}^{N} 0 \le b_{p,j}(v_{p,k}) \le 1$ and $V_p = \{v_{p,1}, \cdots v_{p,k} \cdots, v_{p,K}\}$ represent the symbol observation values. Here K means total number of observations.

$\pi_{p,i}$ is the initial state of given the HMM, which can be defined as follows: $\pi_{p,i} = \Pr(q_{p,1} = i)$. It is possible to define the channel state information to observe sequence $V_p = \{v_1, \cdots, v_K\}$ $v_k \in \{0,1\}$ in the proposed model, where V_p is the *pth* CSI which defines a vacant (0) or a busy (1) observation.

3.3 HMM Parameter Estimation Via Baum-Welch Algorithm

Only the observation sequence is known, implying that the channel state observation data must be determined to obtain the history of the spectrum sensing results. Hence, the model parameter for each channel must be determined based on the channel state observation to predict the future channel state [14]. To estimate model parameter Γ_p, the Baum-Welch (BW) algorithm is used. The BW algorithm is an iterative procedure using a locally maximized $\Pr(V_p \mid \Gamma_p)$ under a chosen value of Γ_p. In order to estimate the HMM parameter, $\xi_p(i, j) = \Pr(q_{p,t} = s_{p,i}, q_{p,t+1} = s_{p,j} \mid V_p, \Gamma_p)$ is initially defined. $\xi_p(i, j)$ can be rewritten with a conditional probability, as follows:

$$\xi_p(i, j) = \frac{\alpha_{p,t}(i) a_{p,ij} b_{p,j}(v_{p,t+1}) \beta_{p,t+1}(j)}{P(V_p \mid \Gamma_p)} \tag{7}$$

Here, $\alpha_{p,t}(i)$ is a forward variable which can be defined as $\alpha_{p,t}(i) = \Pr(v_{p,1} v_{p,2} ... v_{p,T}, q_{p,T} = s_{p,i} \mid \Gamma_p)$, and $\beta_{p,t}(i)$ is a backward variable which is defined as $\beta_{p,t}(i) = \Pr(v_{p,t+1} v_{p,t+2} .... v_{p,T} \mid q_{p,T} = s_{p,i}, \Gamma_p)$. Additionally, the probability of being in state $s_{p,i}$ at time t is defined via the following equation (8):

$$\delta_{p,t}(i) = \sum_{j=1}^{N} \xi_{p,t}(i, j) \tag{8}$$

The model parameter Γ_p can be obtained using following equation (9)(10) based on the above parameter. Additionally,

$\pi_{p,i}$ = the expected frequency (number of times) of being in state $s_{p,i}$ at time (t=1)= $\delta_{p,1}(i)$

$$\hat{a}_{p,ij} = \frac{\text{expected number of transitions from state } s_{p,i} \text{ to state } s_{p,j}}{\text{expected number of transitions from state } s_{p,i}} = \frac{\sum_{t=1}^{T-1} \xi_{p,t}(i,j)}{\sum_{t=1}^{T-1} \delta_{p,t}(i)} \quad (9)$$

$$\hat{b}_{p,j}(v_k) = \frac{\text{expected number of time in state j and observing symbol } v_k}{\text{expected number of times in state } j} = \frac{\sum_{t=1,\ s.t.Ot=v_k}^{T} \delta_{p,t}(j)}{\sum_{t=1}^{T} \delta_{p,t}(j)} \quad (10)$$

3.4 Channel State Prediction and DFS Algorithm

The current state of each channel must be known for the channel prediction procedure. This can be determined by the well-known Viterbi algorithm, which maintains the probability and the previous node of the most probable path coming to each state i at time *t*.

The initial path probability and path node can be defined by the following equation (11):

$$\begin{aligned} &\varphi_{p,1}(i) = \pi_{p,i} b_{p,i}(v_1) \ : \ \text{initial path probability} \\ &\psi_{p,1}(i) = 0 \ : \ \text{path node} \end{aligned} \quad (11)$$

Here, the path probability refers to the probability of selecting the given path from the initial state, and the path node indicates the previous state, which has the maximum probability apart from the destination output probability as part of the path probability.

Recursion is determined until the current time *t* via the following equation (12) to find the most likely path:

$$\begin{aligned} &\varphi_{p,t+1}(j) = \max_{1 \le i \le N} \varphi_{p,t}(i) a_{p,ij} b_{p,j}(v_{p,t+1}) \\ &\psi_{p,t+1}(j) = \arg\max_{1 \le i \le N} \varphi_{p,t}(i) a_{p,ij} \end{aligned} \quad (12)$$

The termination condition can be defined via the following equation (13):

$$\begin{aligned} &\Pr(\text{optimum path}) = \max_{1 \le i \le N} \varphi_{p,T}(i) \\ &q_{p,T}^{\ *} = \arg\max_{1 \le i \le N} \varphi_{p,T}(i) \end{aligned} \quad (13)$$

The Viterbi algorithm is used to complete path back tracing to select the optimal path. The path back tracing equation is $q_{p,t}^{*} = \psi_{p,t}(q_{p,t+1}^{*})\quad t = T-1,......1$. Based on the estimated current state, the next channel status can be predicted.

The estimated HMM parameter of each channel can be described as follows:

$$\Gamma_p = (A_p, B_p, \pi_p) \tag{14}$$

Fig. 4 represents the channel allocation algorithm based on the estimated channel state model Γ_p.

It is necessary to find the probability in which the primary system uses an unoccupied channel at the next time period. This is determined by the following equation (15):

$$C_{Idle,p,t+1} = \Pr(0 = v_{p,t+1} \mid \Gamma_p, \pi_{p,t}) = \max(a_{p,t,t+1}) b_{p,t}(v_{p,t} = 0) \tag{15}$$

The above equation (15) refers to the probability that the *pth* channel is idle at the given time t+1.

The CR system can select channel with the highest probability of an idle state. However, this is not an optimal channel, even if the given channel has the highest idle probability, as the channel state can change at the next time period t+2. Thus, a high idle probability channel as well as feasible idle time duration must be determined during the channel hopping time.

It is necessary to determine the probability that a primary system uses an unoccupied channel while the CR system transmits data. This can be described by the equation (16) below.

$$C_{Idle,p,H_T} = \Pr(0 = v_{p,t}, v_{p,t+1}, \cdots v_{p,H_T} \mid \Gamma_p, \pi_{p,t}) = \prod_{t=1}^{T} a_{p,t,t+1} b_{p,t}(v_{p,t} = 0) \tag{16}$$

In this equation, $\pi_{p,t}$ is defined by the following equation (17):

$$\pi_{p,t} = \arg\max_{1 \le t \le T} \pi_{p,t-1} a_{p,t-1,t} \tag{17}$$

In order to define a hopping sequence, the maximum throughput at each channel must be determined. This is done using the following equation (18):

$$\mathbf{HS} = \arg\max_{p \in \mathbf{HS}V} \left(\sum_{t=H_{T1}}^{H_{TL}} C_{idle,p,t} T_D - LF_t \right) \quad where \;\; LF = \begin{cases} LF = 0 & p_t = p_{t-1} \\ LF = HD & p_t \neq p_{t-1} \end{cases} \tag{18}$$

In this equation (18), **HS** denotes the hopping sequence vector, where the length is identical to the total number of hops L; **HSV** denotes all combinations of hops; T_D is the data transmission period at each hopping period, and LF is a loss factor caused by frequency hopping.

According to the above equation (18), The CR system selects the hopping sequence with the maximum expected throughput. If the given channel p has high interference probability, it causes a reduction in the throughput; hence, the CR system does not select channel p. Moreover, if the selected channel state at time period t+1 differs from the channel state at time t, the throughput is reduced due to the change in the channel state. Therefore, the CR system may select a hopping sequence with low interference probability and a low channel change frequency.

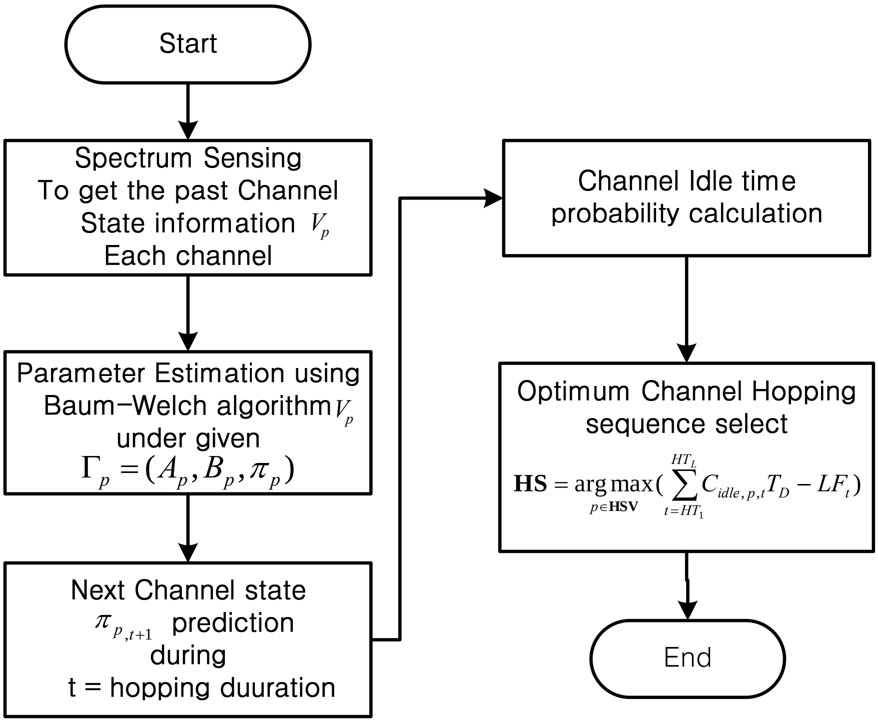


Fig. 4. Block diagram of the proposed FH-based DFS algorithm

Throughput of the proposed algorithm can be analyzed using equation (5). In equation (5) the whole cognitive system period T and Quiet period duration T_{QP} is a fixed value which is system-defined. Thus, influence parameters to the performance are interference period $\mathrm{E}\{I\}$ and redundant time slot of the frequency change T_{hop}. Here, expectation value of the interference can be defined by the following equation when we assume Poisson distribution.

$$\mathrm{E}\{\mathrm{I}\} = (1 - \zeta_{HMM})(1 - e^{-\lambda_p (T_{Di})}) T_{Di} \tag{19}$$

where T_{Di} is i^{th} data transmission duration and ζ_{HMM} is accuracy of the HMM prediction.

It is difficult to evaluate accuracy of the HMM prediction mathematically. If accuracy is perfect, expectation of the interference converges to 0.

T_{hop} means total frequency change time. If a primary data burst appears during secondary data transmission duration $2T_{Di}$, our proposed algorithm changes operation frequency. It can represent equation (20) assuming perfect prediction accuracy.

$$T_{hop} = \sum_{i=1}^{M} T_{HP}(1 - e^{-2\lambda_p T_{Di}}) \tag{20}$$

where T_{HP} is frequency change redundancy duration.

Our proposed algorithm has a better performance. However, the proposed algorithm is more complex because of HMM training and prediction algorithm. Complexity of the proposed algorithm is influenced by HMM complexity. HMM complexity consists of a forward variable $\alpha_{p,t}$ and a backward variable $\beta_{p,t}$ decision complexity and Baum-Welch algorithm complexity. HMM complexity is represented in **Table 1** [15].

Table 1. Complexity analysis

Parameter	Number of multiplication
Complexity of forward algorithm	NTK(M2+D)
Complexity of backward algorithm	NTK(M2+D)
Complexity of Baum-Welch algorithm	NTKM2D

Here N means number of states, T is number of observation, K is the total number of transitions divided by the total number of states, M means dimension of the observation vector and D is maximum number of observations for a sing transition.
In our model, M is 2(0,1) and D is 1. Therefore complexity of our algorithm can be defined as 14NTK. This means HMM complexity is influenced by the number of states and observations. This has an effect on HMM prediction accuracy.

4. Simulation Environment and Results

As the performance of the proposed algorithm is affected by the accuracy of the HMM prediction, performance is analyzed based on these aspects.

To evaluate the performance of the proposed scheme, a computer simulation was run using the parameters in **Table 2** below.

Table 2. Simulation parameters

Parameters	Variable
The maximum number of states for HMM	8 states and 20
Primary burst length T_{pri}	8, 20 time slots
Secondary burst length at each hopping duration H_T	3 time slots
Number of hopping	4, 8(12, 24 time slots)
Number of CR users	3 users and 5 users
Total test timeslots	10000 time slots

Primary burst generation probability Distribution	Poisson distribution $\lambda = 0.03 \sim 0.1$

The evaluation parameter is defined by the following equation (21)(22)

$$\text{Interference time prob.} = \frac{T_{interference}}{T_{test}} \tag{21}$$

$$\text{Throughput prob.} = \frac{T_{suc}}{T_{test}} = \frac{T_{test} - T_{QP} - T_{interferenc} - T_{hopping}}{T_{test}} \tag{22}$$

Here, $T_{interference}$ is the total number of time slots of the interference occurrence, T_{test} is the total number of test time slots, T_{suc} is the number of successful data transmission time slots, T_{QP} is the QP time slot, and $T_{hopping}$ is the redundant time slot of the frequency change.

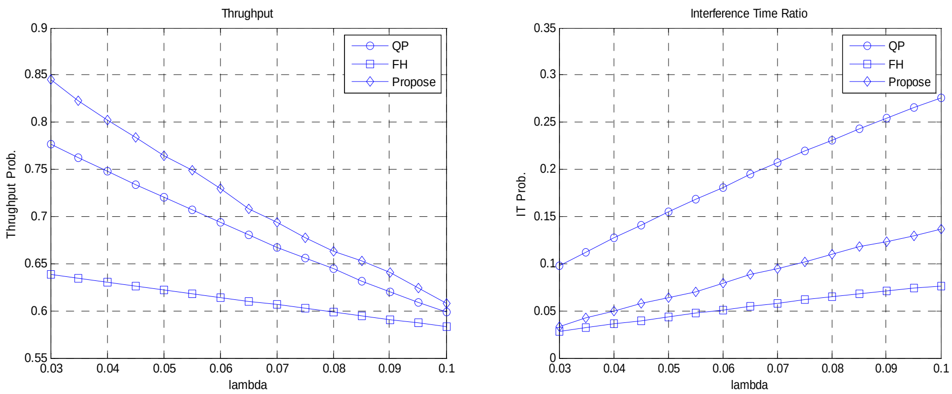


Fig. 5. Performance comparison QP, simple FH, proposed algorithm
(HMM State = 8, number of hops = 8, CR users = 3, primary bursts = 8)

Fig. 5 shows the performance of the proposed algorithm. This result was simulated under HMM State 8, with 8 hops, 3 CR users and a primary burst length of 8.

The proposed algorithm shows good throughput performance compared to the simple FH algorithm and QP-based algorithm. However, the interference time probability values are not as good as those of the FH algorithm. The proposed hopping sequence selection algorithm is based on the throughput equation (18). Therefore, it has more weight compared to that inherent in an interference reduction procedure. However, throughput probability partially includes interference probability. Therefore, the overall performance including interference is better compared to the other two algorithms.

Fig. 6 shows the performance of the proposed algorithm under various HMM states. Generally, an HMM state has larger values than the minimum non-transition section. For example, the simulation result in **Fig. 6** shows 20 time slot primary bursts. Therefore, the HMM state should be defined as 20 states to obtain an accurate prediction result. As shown in **Fig. 6**, a model with 20 states shows better performance compared to a model with 8 states. In addition, due to the inaccurate prediction in the high λ case, the performance is worse than the QP-based algorithm. However, the interference probability is nearly identical because the interference performance is dominated by the FH algorithm.

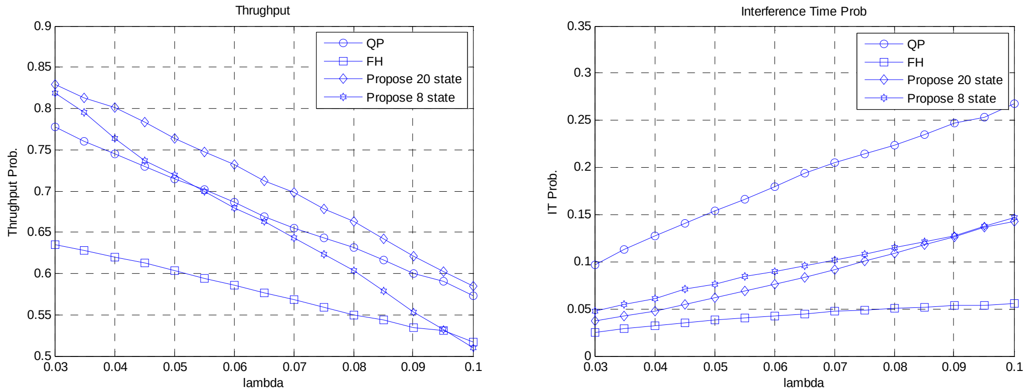


Fig. 6. Performance comparison of QP, simple FH, the proposed algorithm (HMM State = 8 and 20, number of hops = 8, CR users = 3, primary bursts = 20)

Fig. 7 shows the performance of the proposed algorithm with different hopping periods.

It was deemed necessary to compare how far into the future the proposed method can predict. The simulation parameters were set as follows: 8 for H_t (24 time slots) and 4 for H_t (12 time slots). Through this simulation, the performance was found to degrade continually in this case. This is associated with the reliability of past observation sequences. Moreover, the interference probability degrades only slightly, as the interference performance is dominated by the length of the hopping duration (the time slot) and not the amount of hopping time.

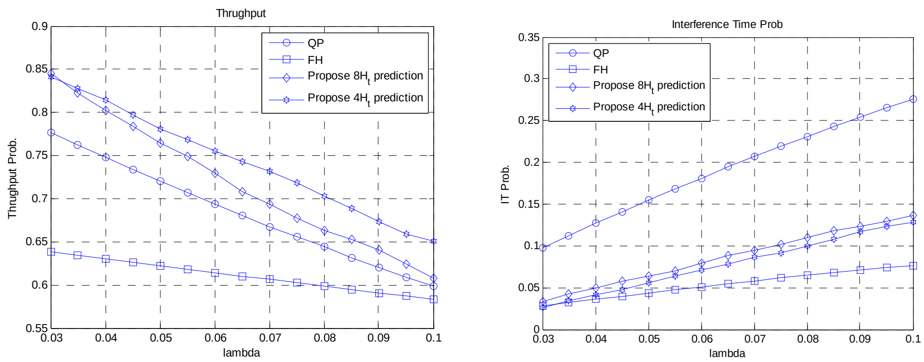


Fig. 7. Performance comparison of QP, simple FH, the proposed algorithm (HMM State = 8, number of hops = 4,8, CR users = 3, primary bursts = 8)

Fig. 8 shows the performance of the proposed algorithm with different numbers of CR users. The results show better performance compared to the conventional FH- and QP-based algorithms. One interesting finding is that the conventional FH performance and the result after a change of the QP-based method are very similar in terms of the throughput performance. This shows that the FH algorithm is feasible with a high density of users. Accordingly, the performance gap is larger than the case with three CR users in the results shown in **Fig. 5** between the proposed algorithm and the conventional algorithm.

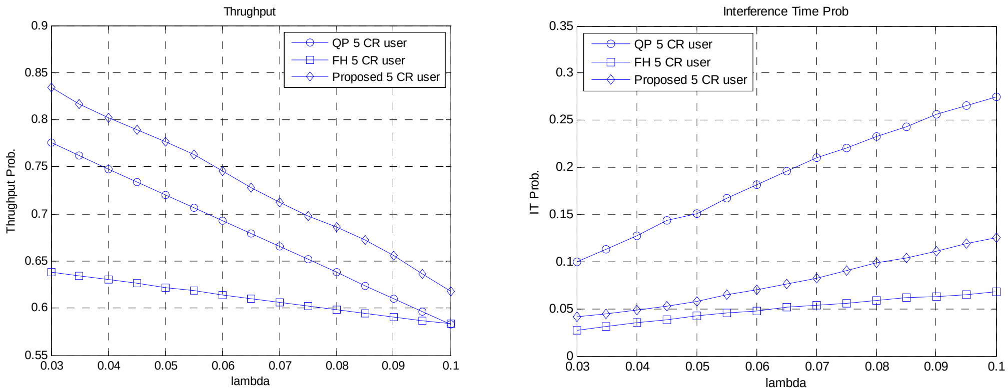


Fig. 8. Performance comparison of QP, simple FH, the proposed algorithm
(HMM State = 8, number of hops = 8, CR users = 5, primary bursts = 8)

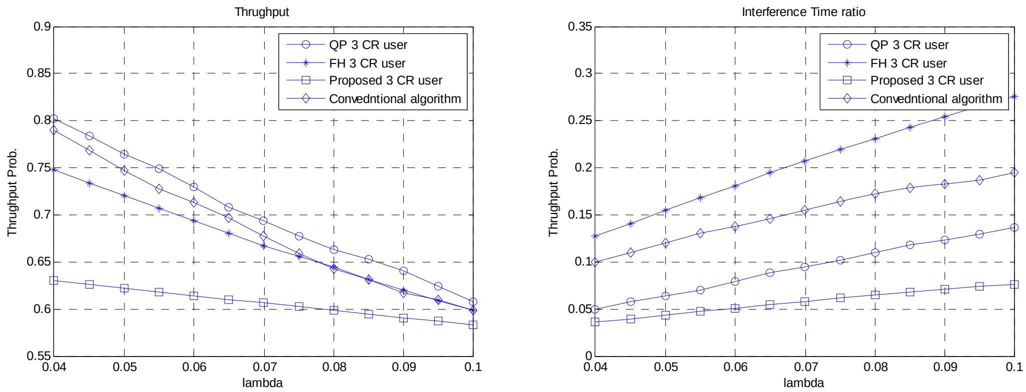


Fig. 9. Performance comparison of QP, simple FH, the proposed algorithm and conventional HMM-based algorithm
(HMM State = 8, number of hops = 8, CR users = 3, primary bursts = 8)

Fig. 9 shows the performance of the proposed algorithm and conventional HMM-based DFS algorithm. We refer to [10] for evaluation of the conventional algorithm. Conventional algorithm estimates HMM model select channel t based on the channel occupancy probability with long bursts. Therefore the case of low primary arrival rate has better performance compared with conventional QP-based algorithms. However, it has a similar performance QP-based algorithm in the high arrival rate case. It is caused by an increase in interference time.

In the case of ITR performance, it is different from a throughput case. ITR performance is better than QP-based algorithm. That's why, if channel occupancy probability is higher than vacant probability, a secondary system cannot access the channel. The secondary system waits until vacant probability is higher than occupancy probability.

5. Conclusion

This study proposes a frequency-hopping channel allocation algorithm using channel prediction based on HMM. The performance was evaluated via a computer simulation. Through the simulation results, performance of the proposed algorithm was verified. This algorithm can reduce interference time performance while improving throughput performance. Particularly, the proposed algorithm results in better performance with a high density of users and a high arrival rate. However, the algorithm results in inaccurate values in the HMM state in poor conditions. Therefore, additional research is necessary, including research related to the estimation of the maximum primary burst length.

References

[1] Sunghwan Sohn, Ning Han, Guanbo Zheng and Jae Moung Kim "Pilot Periodicity Based OFDM Signal Detection Method for Cognitive Radio System," *IEICE Trans. Communication*, vol. E91-B, no. 5, pp. 1644-1647, 2008.

[2] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J.Commun.Mag*, pp. 201-220, 2005.

[3] Ning Han, Sung Hwan Sohn, Jae Moung Kim, "A Blind OFDM Detection and Identification Method Based on Cyclostationarity for Cognitive Radio Application," *IEICE Trans. Communication,* vol. E92-B, no. 6, pp. 2235-2238, 2009.

[4] IEEE, IEEE P802.22™/ DRAFTv1.1 Draft Standard for Wireless Regional Area Networks Part 22: Cognitive Wireless RAN Medium Access Control (MAC) and Physical Layer (PHY) specifications: Policies and procedures for operation in the TV Bands.

[5] Dong Chen, Jiandong Li, Jing Ma, "In-band Sensing without Quiet Periods in Cognitive Radio," in *Proc. of WCNC 2008*, pp. 723-728, 2008.

[6] Daniel Willkomm, Mathias Bohge, Daniel Hollos, James Gross and Adam Wolisz, "Double Hopping: A New Approach for Dynamic Frequency Hopping in Cognitive Radio Network," in *Proc. of Personal, Indoor and Mobile Radio Communications, 2008. PIMRC 2008. IEEE 19th International Symposium*, pp.1-6, 2008.

[7] Rui Min; Daiming Qu; Yang Cao; Guohui Zhong, "Interference avoidance based on multi-step-ahead prediction for cognitive radio," in *Proc. Communication Systems, 2008. ICCS 2008. 11th IEEE Singapore International Conf.*, pp. 227-231, 2008.

[8] Xinying He, Zhimin Zeng, Caili Guo, "Signal Classification Based on Cyclostationary Spectral Analysis and HMM/SVM in Cognitive Radio," in ICNTMA pp. 309-312, 2009.

[9] Sharma, M., Sahoo, A., Nayak, K.D. "Channel modeling based on interference temperature in underlay cognitive wireless networks," in ISWCS 08, pp. 224-228, 2008.

[10] Akbar, I.A.; Tranter, W.H., "Dynamic spectrum allocation in cognitive radio using hidden Markov models: Poisson distributed case," *in Proc. of IEEE Southeast Conf.*, pp. 196-201, 2007.

[11] Wha Sook Jeon; Dong Geun Jeong, "An Advanced Quiet-Period Management Scheme for Cognitive Radio Systems," *Vehicular Technology, IEEE Transactions on*, vol. 59, pp 1242, 2010.

[12] Abramson, N. "The ALOHA System - Another Alternative for Computer Communications," in *Proc. of Fall Joint Computer Conf. (AFIPS)*, vol. 37, pp. 251-285, 1970.

[13] Yariv Ephraim, Neri Merhav, "Hidden Markov Processes," *IEEE Trans. on Information Theory,* vol. 48, No.6, pp. 1518-1569, June 2002.

[14] Rabiner, L.R., "A tutorial on hidden Markov models and selected applications in speech recognition," in *Proc. of the IEEE,* pp. 257-286, 1989.

[15] Carl Mitchell, Mary Harper, and Leah Jamieson, "On Complexity of Explicit Duration HMM's," *IEEE Trans. on speech and audio processing*, vol. 3 no. 3, May. 1995.

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