August 2013
Master's Degree Thesis

Prediction Error Protection for Spectrum Mobility in Cognitive Radio Networks

Graduate School of Chosun University

Department of Computer Engineering

Ivan Christian

Prediction Error Protection for Spectrum Mobility in Cognitive Radio Networks

인지 무선 네트워크에서 스펙트럼 이동성을 위한
예측 방지

August 23, 2013

Graduate School of Chosun University

Department of Computer Engineering

Ivan Christian

Prediction Error Protection for Spectrum Mobility in Cognitive Radio Networks

Advisor: Prof. Sangman Moh, PhD

A thesis submitted in partial fulfillment of the requirements for a Master's degree

April 2013

Graduate School of Chosun University

Department of Computer Engineering

Ivan Christian

크리스티안 이반의 석사학위논문을 인준함

위원장 조선대학교 교수 신 석주 (인)

위 원 조선대학교 교수 강 문수 (인)

위 원 조선대학교 교수 모 상만 (인)

2013 년 5 월

조선대학교 대학원

TABLE OF CONTENT

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Prediction Error Protection for Spectrum Mobility
in Cognitive Radio Networks

Ivan Christian
Advisor: Prof. Sangman Moh, Ph.D.
Department of Computer Engineering
Graduate School of Chosun University

Cognitive radio networks (CRNs) offer a promising solution for spectrum scarcity problem by means of dynamic spectrum access. So long as the secondary user (SU) communication is often interrupted in highly dynamic environments, spectrum mobility is a key feature enabling continuous SU data transmission. Namely, SU performs spectrum handoff by transferring ongoing communication to a vacant channel. Meanwhile, various channel status prediction algorithms in CRNs have been proposed to predict channel availability. However, the algorithms predict imperfectly and may cause interference for incumbent users, especially when the prediction output may be used immediately to access the channels as in the spectrum mobility.

In this thesis, we analyze the prediction error aspect of the particular hidden Markov model-based channel status prediction algorithm. Then, we propose a policy to suppress the interference caused by prediction errors. Namely, we examine the reliability of the current state, and we impose new state transition probability values if the current state is unreliable for prediction. Simulation results show that the proposed policy can effectively decrease interference without

compromising prediction accuracy. Furthermore, we conduct a feasibility study by using the enhanced prediction algorithm in spectrum mobility. We conclude that, although we may be able to meet the channel status prediction requirements of spectrum mobility under particular situations, the long term prediction using single-step-ahead channel status prediction algorithm is still a challenge.

한 글 요 약

인지 무선 네트워크에서 스펙트럼 이동성을 위한 예측 방지

크리스티안 이반
지도 교수: 모상만
컴퓨터공학과
대학원, 조선대학교

인지 무선 네트워크는 다이나믹 스펙트럼 접속을 통해 스펙트럼 부족 문제에 대한 유용한 솔루션을 제공한다. 2차 사용자 통신은 다이나믹 환경에서 빈번하게 중단될 수 있으므로, 스펙트럼 이동성은 2차 사용자 통신의 연속성을 가능하게 하는 핵심 기능이다. 즉, 2차 사용자는 진행 중인 통신을 유휴 채널로 전환함으로써 스펙트럼 핸드 오프를 수행한다. 한편, 인지 무선 네트워크에서의 다양한 채널 상태 예측 알고리즘은 채널 가용성을 예측하기 위해 제안되었다. 그러나 알고리즘들은 불완전하게 예측하고, 스펙트럼 이동에서처럼 예측 결과를 채널 접근을 위해 즉각적으로 사용하는 경우에는 현 사용자에게 간섭을 일으킬 수 있다.

본 논문에서는 특정 은폐 마코프 모델 기반의 채널 상태 예측 알고리즘의 예측 오차를 분석하고, 예측 오류로 인한 간섭을 억제하는 방안을 제안한다. 즉, 현 상태의 신뢰성을 평가하고 현 상태의 예측 신뢰성이 낮으면 새로운 상태 천이 확률 값을 부여한다. 시뮬레이션 결과에 의하면, 제안된 방안이 예측 정확성을 손상시키지 않고 효과적으로

간섭을 줄일 수 있다. 또한, 향상된 예측 알고리즘을 스펙트럼 이동성에 사용함으로써 구현 타당성을 분석한다. 구현 타당성 분석에 따르면, 특정 상황에서 스펙트럼 이동성의 채널 상태 예측 요구사항을 충족할 수 있지만, 1 단계 채널 예측 알고리즘을 이용한 장기적 예측은 해결해야 할 도전 과제임을 알 수 있다.

I. INTRODUCTION

A. Introduction to Cognitive Radio Networks (CRNs)

Rapid development of wireless networking technology has raised a large demand for spectrum band. Whereas the number of devices utilizing unlicensed industrial, scientific, and medical (ISM) band is growing, the allocated spectrum remains the same. This spectrum scarcity problem happens because the current static spectrum allocation policy used by governmental agencies is unable to accommodate the growing bandwidth demand. In fact, exclusively allocated licensed spectrum bands whose availability varies both spatially and temporally, are proved to be underutilized. Meanwhile, a large portion of spectrum in UHV and VHF range will become available in the future upon completing the transition to digital TV [1]. This so-called TV white space calls large interest because radio frequency of the respective spectrum bands has a number of advantageous characteristics that would open numerous new wireless applications in the future.

CRNs are attractive solutions to overcome the spectrum scarcity problem. By enabling dynamic spectrum access (DSA), CRNs can maximize the use of bandwidth resource without changing well-established regulation of spectrum allocation. Here, CRNs introduces the user priority concept in spectrum band utilization [2, 3]. Namely, users consist of primary users (PUs) and secondary users (SUs), each of which corresponds to the conventional devices of licensed networks and the cognitive radio (CR) enabled devices of unlicensed networks, respectively. SUs can use the licensed spectrum bands as long as PUs are absent (i.e., opportunistically). However, if PUs arrive to claim any of the licensed channels back, the SUs have to vacate them immediately and allow PUs to utilize it. After PUs leave the licensed channel, it becomes available again for SUs.

Meanwhile, various artificial intelligence (AI) algorithms have been widely proposed for various applications in CRNs, one type of which is channel status prediction algorithms. The primary objective of such algorithms is to exploit the temporally unutilized licensed spectrum bands by predicting the future availability of licensed channels based on the past channel status observation. Such prediction algorithms have been proposed for some core functionalities in CRNs, such as spectrum sensing and spectrum mobility. In spectrum sensing, channel status prediction is used to predict which channel is the most likely to be available, and the prediction output is used to make a list of channels, which is sorted based on the likelihood of channel availability. Hence, the probability of finding vacant licensed channels can be significantly increased if SUs sense the channels by following the list instead of sensing them in a random or predefined order [4]. In spectrum mobility functionality, channel status prediction is useful to determine when SUs should migrate from the currently-used licensed channel. Thus, accurate prediction helps SUs to do smooth spectrum handoff, which causes very little interference to PU networks, whenever PUs reclaim the channel.

B. Instantaneous Spectrum Access

Spectrum access is the act of accessing unused licensed channels by SUs. It can be categorized into two scenarios. First, SUs do *out-of-band spectrum sensing* periodically in order to list down the unused licensed channels and to develop the channel status statistics. Then, the *out-of-licensed-band spectrum access* scenario happens when the SUs access any unused licensed channels in the beginning of data transmission. Second, while data transmission is taking place, SUs do *in-band spectrum sensing* in regular basis in order to detect the arrival of any PUs in the channel. Then, the *in-licensed-band spectrum access* scenario happens when the SUs have to access another unused licensed channels immediately because PU is detected in the licensed channel in use. Note that we use the spectrum sensing terminologies to explain the spectrum access scenarios to avoid misunderstanding.

Apart from the periodic spectrum sensing, SUs do instantaneous spectrum sensing just before SUs access the unused licensed channel of choice. This procedure is necessary to protect PUs from interference due to channel status obsolesce. However, in in-licensed-band spectrum access scenario, any SU activities in the licensed channel in use may cause interference to the PUs in the same licensed channel, because they will translate to the undesirable handoff latency. In fact, spectrum sensing is considered the most time-consuming task among those performed during spectrum handoff phase. Therefore, by removing the instantaneous spectrum sensing task out of the spectrum handoff phase, we can significantly reduce the handoff latency thus also reduce the interference to PUs. Furthermore, we define *instantaneous spectrum access* as immediate in-licensed-band spectrum access without doing instantaneous spectrum sensing. Various spectrum handoff strategies in relation with handoff latency are discussed further in Chapter II-B.

C. Problem Statement

Nevertheless, prediction errors are unavoidable part of any channel status prediction algorithms due to the limitation of the algorithms to model channel activities. Moreover, the effects of prediction errors are different for each application. In spectrum sensing applications, the prediction is used only for finding any available channels before actually accessing the channel. In spectrum mobility applications, the prediction may be used for instantaneous spectrum access. Hence, whereas prediction error in spectrum sensing only wastes SU resources without giving interference to PUs, that in spectrum handoff both wastes the resources of SUs and may cause severe interference to PUs if the prediction is not reliable. Thus, it is desirable if we could suppress interference to PUs (due to prediction error) without reducing the prediction accuracy, especially in instantaneous spectrum access scenario.

D. Research Objectives

Our main objective in this thesis is twofold. First, we would like to decrease the interference to PU by suppressing the occurrence of false negative errors of the SUs' channel prediction algorithm. Since the appropriate policy is algorithm-specific, we focus on solving this problem in a particular algorithm. Namely, we propose a PU protection policy which is able to reshape the prediction error profile of a single-step-ahead channel status prediction algorithm. Simulation results show that our proposed policy can effectively decrease the interference to PUs (due to prediction errors) up to 40%, while maintaining the same prediction accuracy level of the original algorithm. Second, we study the feasibility of applying the enhanced algorithm for supporting a smooth spectrum handoff mechanism in spectrum mobility functionality. Namely, we use the enhanced algorithm to do long term (i.e., multi-steps-ahead) prediction, which is of necessity in proactive spectrum handoff strategy. Nevertheless, based on the simulation result, we eventually conclude that such long term prediction is still a challenge.

E. Thesis Layout

The rest of the thesis is organized as follows. First, in Chapter II, we give a brief explanation about the various spectrum handoff strategies in spectrum mobility, and we present the existing channel status prediction algorithms. In Chapter III, we discuss our channel status prediction algorithm of choice, analyze the prediction error, present measurement metrics, and explain the proposed PU protection policy in detail. In Chapter IV, the effectiveness of the PU protection policy is evaluated and discussed. In Chapter V, we study the feasibility of extending the enhanced algorithm for long term prediction in proactive spectrum handoff strategy. Finally, the conclusions of the thesis are given in Section VI

II. RELATED WORKS

A. Spectrum Handoff Strategies

Spectrum mobility is one of the core functionalities in CR which gives spectrum agility feature to the network. The primary objective of spectrum mobility is to perform seamless channel switchover while sustaining performance of ongoing SU communication. The process of changing the channels is called spectrum handoff. Normally SU does three main tasks in spectrum handoff: spectrum sensing, handoff decision, and channel switching. The order of task execution is interchangeable according to the spectrum handoff strategy adopted by SUs. Handoff phase is defined as a period of time from the occurrence of a handoff triggering event to the time when SU can resume its data transmission. Any tasks which take place during the handoff phase will contribute to the length of handoff phase (i.e., handoff latency), which is translated into interference to PU.

Spectrum handoff strategies are characterized by identifying when spectrum sensing and handoff are performed with regard to handoff triggering event occurrence. Spectrum sensing can be done either before or after spectrum handoff triggering events happens, and so can be handoff action [5]. The combination of the two parameters above, gives four spectrum handoff strategies: non-handoff, pure reactive handoff, pure proactive handoff, and hybrid handoff strategy [6]. These cases are shown in Figure 1.

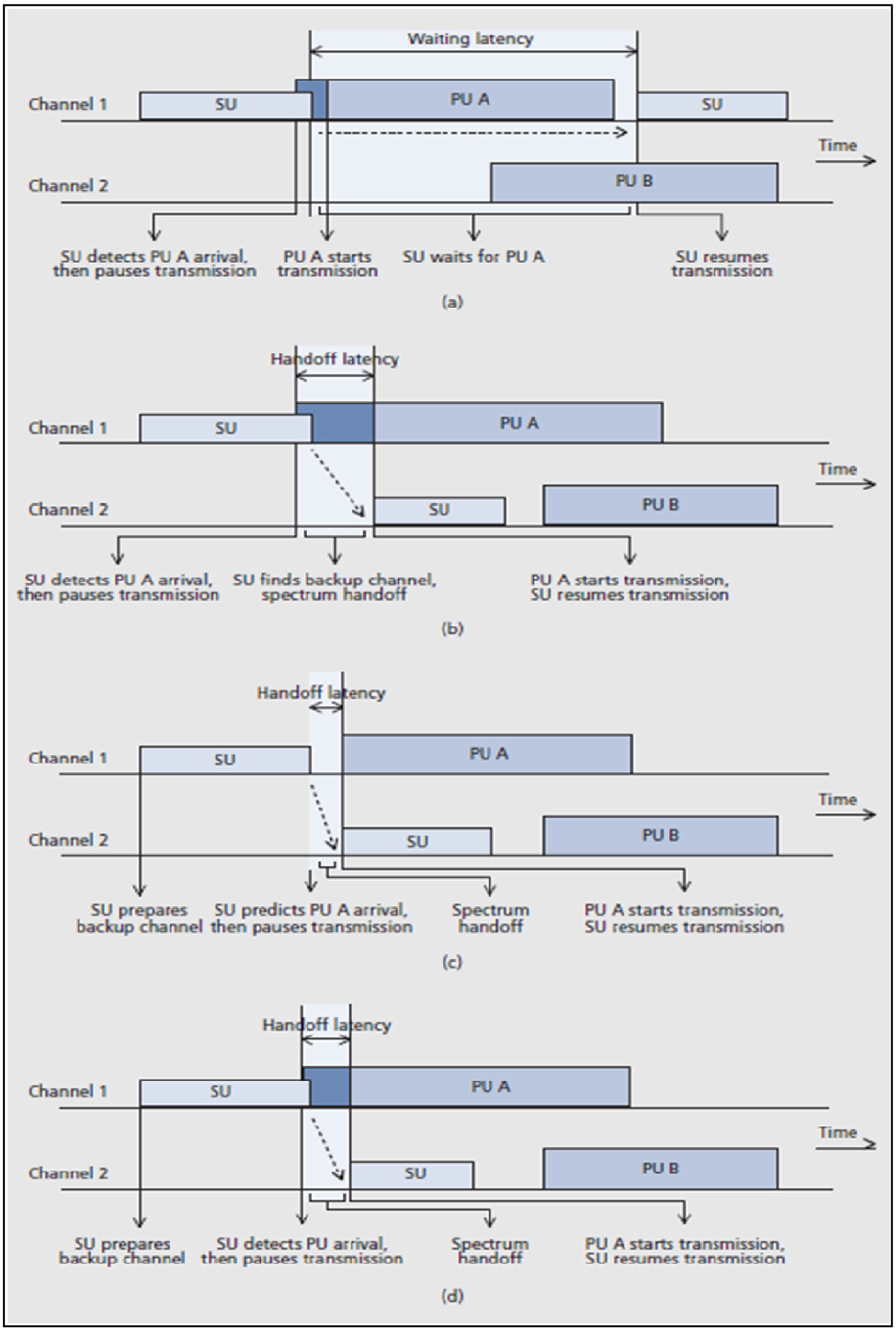


Figure 1. Spectrum handoff strategies: (a) non-handoff; (b) pure reactive handoff; (c) pure proactive handoff; and (d) hybrid handoff.

1. Non-handoff Strategy

In non-handoff strategy, SU keeps staying in original channel and being idle until the channel becomes free again. In other words, SU selects the current licensed channel as the next target channel. After PU leaves the licensed channel, SU resumes the data transmission again. The major disadvantage of this approach is that it causes high waiting latency to SU because the delay is as long as PU is active in the corresponding channel, not to mention that the time is badly wasted during SU waiting period.

2. Pure Reactive Handoff Strategy

In pure reactive handoff strategy, SU applies reactive spectrum sensing and reactive handoff action approach. That is to say, SU performs all spectrum handoff tasks during the handoff phase. The advantage of this approach is that SU can get an accurate target channel since instantaneous spectrum sensing is done in the most relevant spectrum environment. Nevertheless, it comes at a cost of longer handoff latency. Since SU performs spectrum sensing after detecting the handoff event, spectrum sensing becomes the major delay in the handoff process.

3. Pure Proactive Handoff Strategy

In pure proactive handoff strategy [7, 8], SU uses proactive spectrum sensing and proactive handoff action approach. SU performs spectrum sensing to find a backup target channel before a handoff triggering event happens. Based on the knowledge of PU traffic model, SU is able to predict PU arrival so that SU evacuates the channel beforehand. That is to say, SU only executes channel switching during the handoff phase. There are several advantages in using pure proactive strategy. First, handoff latency can be very short because everything can be planned in advance. Second, the possibility of multiple spectrum handoffs can be minimized by considering future target channel usage when selecting backup target channel. However, the drawback of this strategy is that backup target channel can remain obsolete. There is a chance that prepared backup channel is already occupied by other users at handoff time. In addition, accurate PU traffic model is of necessity. Poor prediction may badly degrade the overall spectrum mobility performance.

4. Hybrid Handoff Strategy

Hybrid handoff strategy combines pure reactive and pure proactive strategy by applying proactive spectrum sensing and reactive handoff action [9, 10]. Target channel selection is prepared beforehand or during SU data transmission while spectrum handoff is performed after a handoff triggering event happens. That is to say, SU excludes spectrum sensing task from the handoff phase. Hybrid handoff strategy is a reasonable compromise between pure reactive and pure proactive strategy. Faster spectrum handoff time can be achieved as spectrum sensing time is not performed during the handoff process. However, target channel can stay obsolescent as it does in pure proactive approach.

From the PUs' point of view, proactive spectrum handoff is the most preferred strategy because it causes the least interference to PUs. Thus channel status prediction algorithm is required for adopting this approach.

B. Channel Status Prediction Algorithms

Several works related to channel status prediction in CRNs have been proposed. In [11], a linear regression model with a sigmoid function is proposed to characterize channel activities and predict future channel occupancy. Various artificial intelligence techniques has been proposed for the applications of CRNs [12], among which hidden Markov model (HMM) is a suitable candidate for prediction task. In [13], the first attempt of using HMM to predict channel occupancy was made. In [14], a Markov-based channel prediction algorithm (MCPA) is proposed to model channel usage pattern to support a proactive spectrum handoff mechanism in which the forward-only Baum-Welch algorithm is used as an online training method. However, the prediction accuracy of those algorithms is not given. A similar approach has been proposed in [15], where the hidden Markov model (HMM) algorithm is used to predict the next channel status. However, the prediction accuracy suffers in non-deterministic traffic patterns. In [16], partially observable Markov decision process is proposed to minimize the delay due to spectrum sensing in reactive spectrum handoff strategy. In [17], a multilayer perceptron (MLP) based neural network is used to reduce the spectrum sensing energy by channel status prediction. Furthermore, the performance of the MPL algorithm is compared with that of the MCPA algorithm in terms of false negative errors and overall prediction errors [18], but no attempt is made to reduce the false negative errors that dominate overall prediction errors. In [19], the known-state sequence hidden Markov model (KSS-HMM) algorithm is proposed for a spectrum sensing application. The performance and prediction accuracy of the algorithm is evaluated and compared with the conventional HMM algorithm, but the false negative errors still dominate the false positive errors.

III. PU PROTECTION POLICY

Since the appropriate policy to suppress the occurrence of false negative errors of channel prediction algorithm is algorithm-specific, we focus our effort on the KSS-HMM algorithm. It is said that the KSS-HMM algorithm has much lower computation complexity than the conventional HMM algorithm with comparable prediction accuracy performance.

A. Known-State Sequence Hidden Markov Algorithm

1. Basic Assumptions

We consider that a channel has a Poisson arrival rate, in which the duration of busy status follows a geometric distribution. Let us assume that spectrum sensing is done periodically. A timeslot is defined as the interval between two consecutive spectrum sensing periods. The busy and idle channels are coded as binary values of "1" and "0", respectively. This binary stream is fed to a channel status prediction algorithm for predicting the channel status at future timeslot. Furthermore, the algorithm operates either at a learning phase or at a prediction phase. In the learning phase, the model parameters are updated and, in the prediction phase, the channel status of the next timeslot is predicted.

2. Structure of Algorithm

KSS-HMM is a channel status prediction algorithm whose state transition at each timeslot is logically transparent. Figure 2 shows the states diagram of the KSS-HMM algorithm, which is comprised of positive and negative states, each of which

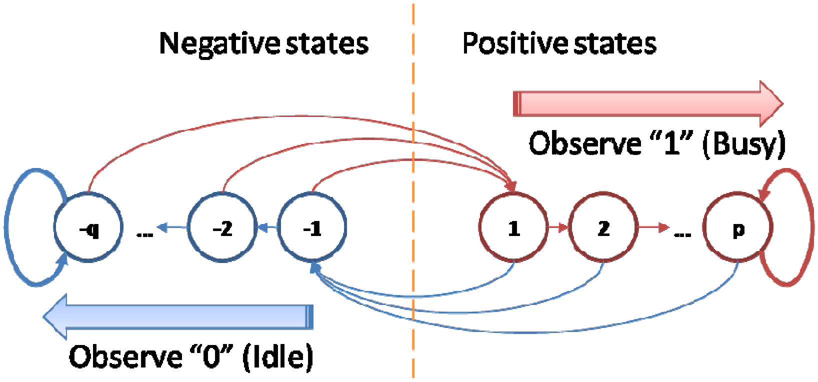


Figure 2. State transition of the original KSS-HMM algorithm.

indicates consecutive busy and idle status of the channel, respectively. Each state is connected to another by probability values. Nevertheless, there are only two possible transitions on each state, which correspond to two non-zero probability values toward the next states. At each timeslot, the algorithm has to update its current state based on the current input. Therefore, the state sequence progression of the KSS-HMM algorithm is tractable, which makes it easy to analyze and adjust. Note that an instance of the KSS-HMM algorithm only corresponds to one channel. Thus, the number of instances of the algorithm is as many as the number of channels observed.

3. Learning Method

The KSS-HMM algorithm models the channel activities using the number of negative and positive states and the probability of receiving an input of "1" and "0" at each state. These parameters are periodically updated during the learning process using a frequentist approach. In the beginning of the learning phase, the algorithm starts with one positive state and one negative state with either of the states being the current state. If the last current state is the positive state, observing input "1" or

"0" transfers the current state to the next positive state or to the lowest negative state, respectively. The opposite transitions happen when the last current state is the negative state, where it is transferred to the lowest positive state or to the next negative state upon observing an input of "1" or "0", respectively. If the destined state does not exist, the model expands itself by adding the necessary state. Hence, the number of states during the prediction phase grows dynamically by as much as the occurrence of consecutive "1" and "0" inputs in the learning phase.

On every state transition, the corresponding state transition count is incremented. Let a_{ij} and Φ_{ij} denote the state transition probability from current state i to next state j, and the transition count from current state i to next state j that has been observed, respectively. Then the state transition probability value at each state is calculated as follows:

$$a_{ij} = \frac{\Phi_{ij}}{\sum_j \Phi_{ij}} \tag{1}$$

Furthermore, let $P(0|S_i)$ and $P(1|S_i)$ denote the probability of observing channel status idle and busy at the next timeslot, given the current state S_i, respectively. Then, the probability that the channel is busy or idle in the next timeslot is given by:

$$a_{ij} = \begin{cases} P(0|S_i) & , \ if\ i,j < 1\ and\ i \geq 1, j < 1 \\ P(1|S_i) & , \ if\ i,j \geq 1\ and\ i < 1, j \geq 1 \end{cases} \tag{2}$$

The duration of the learning process determines the prediction accuracy level that can be achieved by the algorithm, assuming that the channel usage remains unchanged during the prediction phase. In this thesis, we consider the prediction performance of the KSS-HMM algorithm after sufficient learning period.

B. Performance Metrics

Prediction error is a mismatch between the channel status predicted by the algorithm at the current timeslot and the sensed channel status at a later timeslot. It is classified further into false positive and false negative errors. The former happens when the algorithm predicts the channel to be busy but it turns out to be idle while the latter happens when the algorithm predicts the channel to be idle but it turns out to be busy.

Let ε_P and ε_N be the number of false positive errors and false negative errors, respectively. Then, the total number of prediction errors ε_T is the summation of ε_P and ε_N. For performance evaluation, we introduce new metrics to exhibit the composition of false positive and false negative errors over the total prediction errors. The false positive error ratio, *FPER*, and the false negative error ratio, *FNER*, are defined as follows.

$$FPER = \frac{\varepsilon_P}{\varepsilon_T} \tag{3a}$$

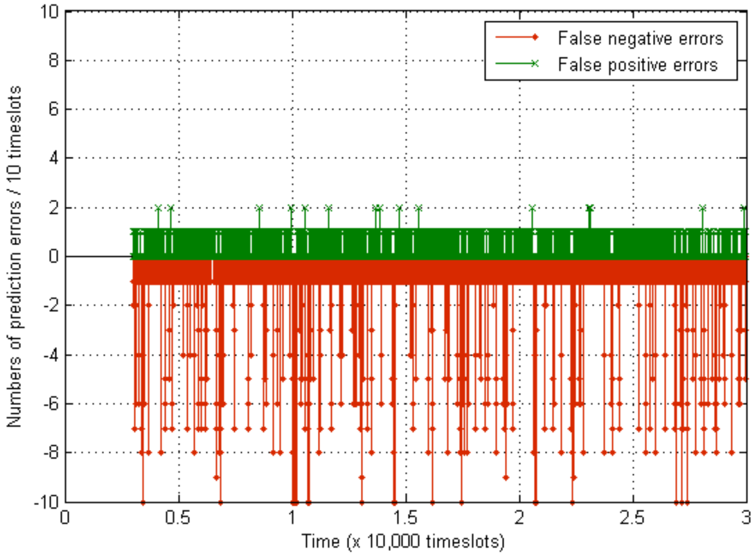
$$FNER = \frac{\varepsilon_N}{\varepsilon_T} \tag{3b}$$

That is, we normalize the false positive errors and false negative errors over the total number of prediction errors to get *FPER* and *FNER*, respectively. Note that the summation of both ratios equals to 1, which is the normalized value of the total number of prediction errors with itself.

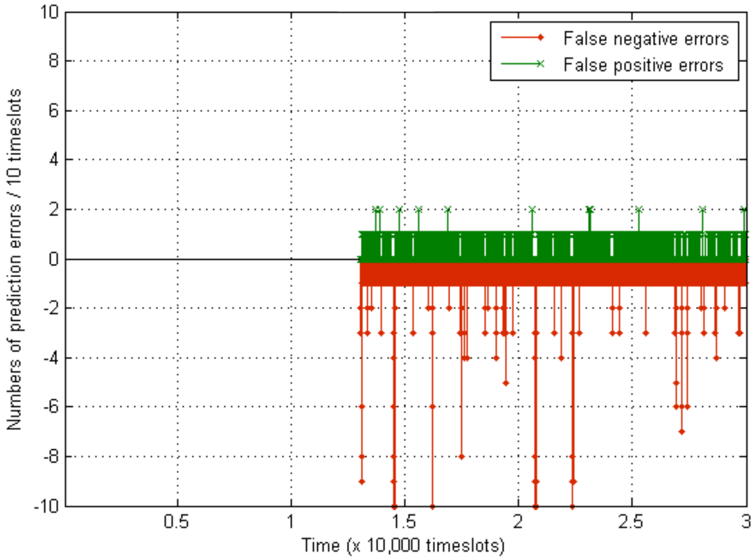
C. Prediction Error Analysis

We identify that prediction error of any channel status prediction algorithms may come from model limitations and model inaccuracies. Every algorithm has a limitation which originates from the structure itself. In case of the original KSS-HMM algorithm, it does not have a memory component to remember the pattern sequences of channel usage and it relies on the duration of channels being busy and idle statistics. As a result, it cannot predict when a channel status transition is going to take place. This vulnerability, however, can only be fixed by changing or modifying the algorithm. On the other hand, an insufficient learning process causes model inaccuracies in capturing the channel activities statistics, which, in turn, leads to prediction errors. Unlike prediction errors due to model limitations, errors due to model inaccuracy can be reduced by updating the model through a learning process.

Figure 3 shows prediction error profiles of the original KSS-HMM algorithm if the prediction error is enumerated and classified into false positive and false negative error every ten timeslots in the prediction phase. We compare the outline of false positive and false negative errors over the simulation time between the KSS-HMM algorithm with an insufficient learning process and that with an excessively long learning process. It shows that the false positive and negative errors due to model limitations happen quite evenly during the prediction phase, while those due to model inaccuracies tend to diminish as the learning process continues. On top of this, it is obvious that false negative errors dominate the overall prediction error amount for the two cases.



(a)



(b)

Figure 3. Prediction error profile of the original KSS-HMM algorithm with (a) insufficient learning process, and (b) excessively long learning process.

D. Protection Policy

1. State Classification

The probability values heavily rely on the state transition samples space that was observed during the learning process. The transition probabilities of states with a large number of samples have greater relevancy to the channel usage statistics rather than those of states with just a few samples. Therefore, based on the number of samples that construct the probability values, we classify the states into well-trained states and under-trained states. Let PU protection factor Φ_{TH} be the minimum number of state transition samples that a state is expected to have to construct the state transition probability values. The states with Φ_{TH} state transition samples fall into well-trained states, and the other states are classified as under-trained states. Well-trained states are said to have relevant state transition probability values to the channel usage statistics. On the contrary, the state transition probabilities of under-trained states are irrelevant to the channel usage statistics and, thus, their usage in channel status prediction is unreliable and leads to unnecessary prediction errors. This error can be avoided by applying a prediction policy that controls the occurrence of false negative errors.

2. Formal Statement of the Proposed Policy

Let S be a set of all possible states in KSS-HMM algorithm. Let S_P and S_N be the set of all positive states and negative states, respectively. Let i be the current state and j be the next possible state. Then the proposed policy is mathematically stated as follows.

$$\forall i \in S\colon a_{ij} = \begin{cases} \frac{\Phi_{ij}}{\sum_j \Phi_{ij}} & if\ \left(\sum_j \Phi_{ij} \geq \Phi_{TH}\right) \\ 0.5 < P_{ovr} < 1 & if\ \left(\sum_j \Phi_{ij} < \Phi_{TH}\right) \wedge (j \in S_P) \\ (1 - P_{ovr}) & if\ \left(\sum_j \Phi_{ij} < \Phi_{TH}\right) \wedge (j \in S_N) \end{cases} \quad (4)$$

The main idea of our proposed policy is to assume that the channel is always busy if the state transition probabilities are unreliable, and it is simply explained as follows.

i. Determine whether the current state falls into either well-trained or under-trained categories.

ii. For under-trained states, protect PUs from interference by overriding the state transition probability toward a positive state by P_{ovr} and the state transition probability toward a negative state by $(1 - P_{ovr})$, where the value of P_{ovr} should be greater than 0.5 (i.e., $0.5 < P_{ovr} \leq 1$).

iii. For well-trained states, use the transition probability of the state to make prediction of channel status.

IV. PERFORMANCE EVALUATION

A. Simulation Environment

We do the simulation using Matlab 7.11.0 (R2010b). The simulation parameters are summarized in Table 1. First, we set a default value for parameter Φ_{TH} to 40 based on our experimental observation. It will be shown in Chapter IV-C that this assumption is a practical choice. We choose the biased probability value P_{ovr} of 0.9. Furthermore, we prepare seven datasets with mean arrival time T (i.e., $1/\lambda$, where λ is the parameter of Poisson distribution) of 10, 12, 14, 16, 18, 20, and 22 timeslots. For each dataset, we generate 30,000 binary sequence samples that follow the geometric distribution. We assume that the average durations of a channel being busy and idle are equal for each interval of PU arrival (i.e., mean traffic intensity equals 0.5). Note that success probability p parameter of the geometric distribution is determined dynamically for each PU arrival time instance.

Table 1. Simulation parameters

PU protection factor Φ_{TH}	0 - 300 samples (default: 40)
Biased probability value P_{ovr}	0.9
Number of datasets	7 datasets
Number of samples per dataset	30,000 binary samples
Mean PU arrival time T	10, 12, 14, 16, 18, 20, 22 timeslots
Mean traffic intensity	0.5

B. Simulation Results and Discussion

We evaluate the performance of the original algorithm and the enhanced algorithm in terms of prediction error ratios, given the binary input streams with various mean arrival times. Figure 4 shows that the prediction error of the original algorithm is dominated by false negative errors; that is, the *FNER* is above 60% in all cases, which means that the prediction errors cause interference to PUs for all datasets. By applying the proposed PU protection policy, the enhanced algorithm has reduced the *FNER* up to 40%. In contrast to *FNER*, the enhanced algorithm has higher degree of *FPER* than the original algorithm, as it is shown in Figure 5. It means that there is more spectrum opportunity loss than before. Nevertheless, the prediction error profile of the enhanced algorithm is preferable in instantaneous spectrum access application, because the SU activities becomes less harmful to PU.

Furthermore, we also compare the prediction accuracy level as shown in Table 2. It shows that the original algorithm has slightly better accuracy than the enhanced one for datasets with a mean arrival time of 10 to 18 timeslots, while the opposite happens for datasets with a mean arrival time of 20 and 22 timeslots. However, since the difference is just a matter of 1-2%, we can say that both cases achieve the same level of prediction accuracy and the variation of the prediction accuracy is insignificant. In summary, at a given PU protection factor Φ_{TH}, our proposed PU protection policy successfully protects PUs from interference caused by prediction errors without losing significant prediction accuracy.

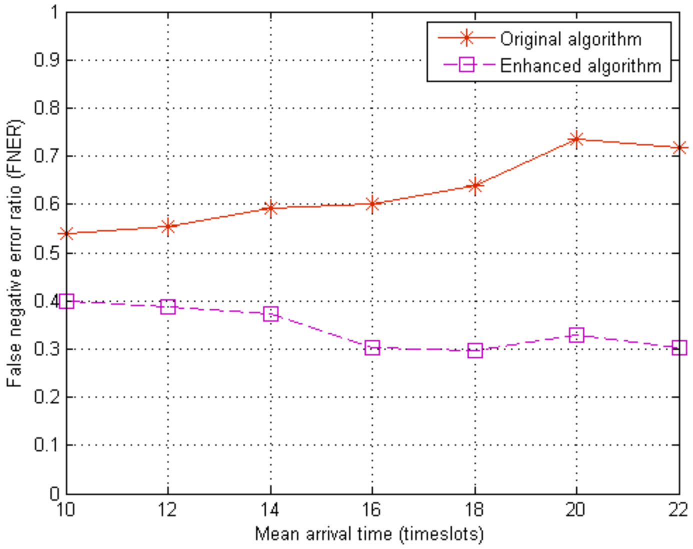


Figure 4. False negative error ratio (FNER) of the original and enhanced algorithm.

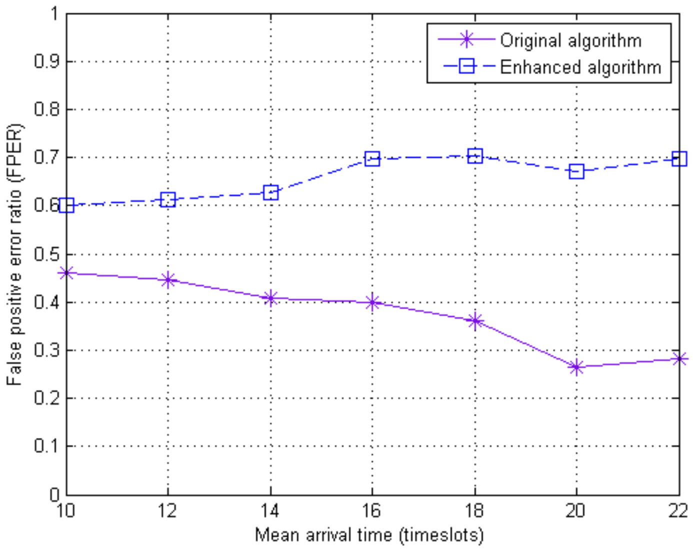


Figure 5. False positive error ratio (FPER) of the original and enhanced algorithm.

Table 2. Prediction accuracy of the original and the enhanced algorithm.

Mean arrival time (timeslots)	Original algorithm (%)	Enhanced algorithm (%)
10	86.1601	85.1547
12	87.6580	86.6257
14	88.1418	87.5829
16	89.1223	87.0850
18	89.3719	87.1051
20	87.5398	88.8995
22	88.5630	90.0227

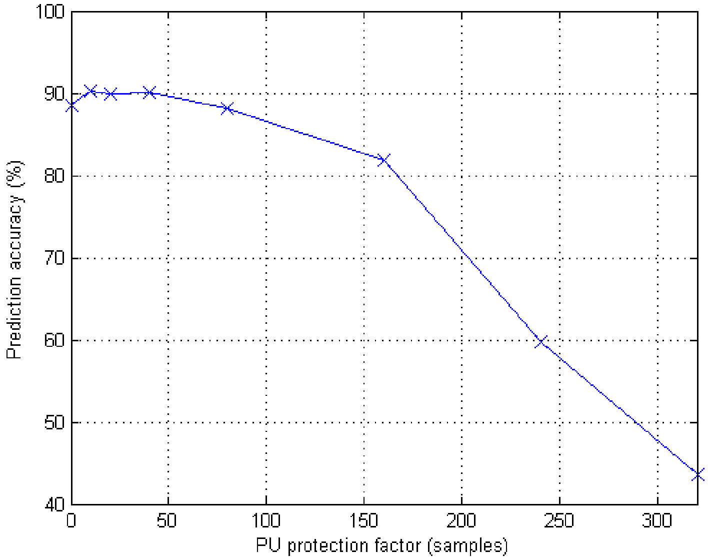
C. Optimum Value of PU Protection Factor

The PU protection factor Φ_{TH} holds a central role in our proposed policy in that it determines the degree of protection against false negative errors while also affecting the prediction accuracy to some extent. Therefore we run another simulation session using the dataset which has a mean arrival time of 22 timeslots to observe the effect of PU protection factor Φ_{TH} on the prediction accuracy level and prediction error ratios.

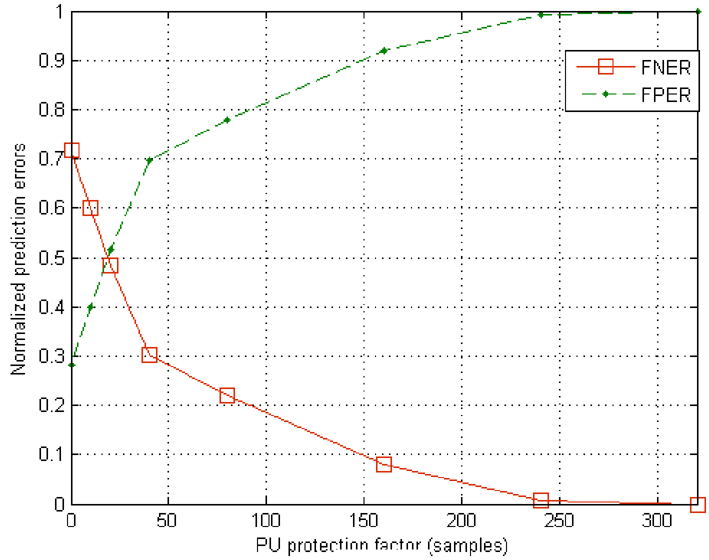
Figure 6 shows the dynamic of prediction accuracy together with its corresponding prediction error ratios as we vary Φ_{TH} from 0 to 320, given that the maximum number of samples that any states may have after undergoing the optimum learning process is 270 samples. Prediction accuracy remains stable at its optimum level for small values of Φ_{TH}. However, it starts to decrease at a Φ_{TH} of 50 and continues to drop as we further increase the value of Φ_{TH}. On the contrary, the *FNER* tends to drop exponentially as Φ_{TH} is increased while the corresponding *FPER* starts soaring. It means that the greater the value of Φ_{TH}, the more protection the PUs will get, but at the same time, the greater the spectrum opportunity loss the SUs will experience. In the most extreme case, a Φ_{TH} of 320 gives total protection to PU at the cost of very low prediction accuracy.

Therefore, we are most interested in the range of Φ_{TH} where the prediction accuracy remains stable. Specifically, we can control *FPER* and *FNER* while keeping the prediction accuracy high by setting Φ_{TH} in the range of 0 to 50. At 0 of Φ_{TH}, it aggressively utilizes spectrum opportunities but, at 50 of Φ_{TH}, it is more courteous toward PUs because the interference to PUs is at the lowest point while the spectrum opportunity loss of SUs is at the highest one. Recalling the simulation result in Chapter IV-B, it is confirmed that the default value of Φ_{TH} is still within the practical range. We can strike a balance between the two extremes at 25 of Φ_{TH}, where both the spectrum opportunity loss of SUs and the interference to PUs are around at the same level.

In summary, the optimum value of PU protection factor Φ^{*}_{TH} depends on the maximum interference temperature allowed at a particular licensed channel. For a channel with a stringent requirement, Φ^{*}_{TH} is 50, since SUs access the channel in a less intrusive manner and thus give the least interference to PUs. Nevertheless, if the requirement is more tolerable, Φ^{*}_{TH} is 25, since it maximizes the spectrum opportunity utilization while keeping the interference to PUs at the lowest possible level.



(a)



(b)

Figure 6. Effect of the enhanced algorithm with varying PU protection factor Φ_{TH}: (a) protection accuracy and (b) prediction error ratios.

V. FEASIBILITY OF LONG TERM PREDICTION

A. A Need for Long Term Prediction

A smooth channel switching using proactive spectrum handoff strategy in spectrum mobility is highly desirable in spectrum mobility. There are at least two issues regarding the channel status prediction algorithm in the application of spectrum mobility. First, the prediction accuracy is of utmost importance due to the nature of the application. That is, it is desirable if handoff latency can be made as short as possible to avoid further interference to PUs [20]. Since spectrum sensing is considered as a time-consuming process, SUs might not check the current availability of the target channel by re-sensing the channel during spectrum handoff to save time. Instead, SUs rely solely on prediction output to directly access the channel. Thus, we need a channel status prediction algorithm that offers high prediction accuracy so that the chance that the target channel is available at spectrum handoff time is still high even without spectrum sensing.

Second, prediction beyond the next timeslot is also desirable in spectrum handoff to avoid the occurrence of multiple spectrum handoffs in one data transmission session. In a situation where the prediction horizon of the algorithm is limited to single-step-ahead (i.e., short term) instead of multiple-steps-ahead (i.e., long term), the duration of future channel availability cannot be predicted beforehand. Therefore, if only the channel status can be predicted more than the next timeslot, then target channel that is more likely to be available during data transmission can be selected, and the probability of multiple spectrum handoff can be reduced.

The enhanced KSS-HMM algorithm is a potential candidate for this purpose, because not only does it achieve high prediction accuracy, but it also protects PUs from interference due to prediction errors, as discussed in Chapter IV. However, since the algorithm is originally designed for single-step-ahead prediction, the method for multi-step-ahead prediction needs to be developed. In this chapter, we study the feasibility of using the enhanced algorithm to do multi-steps-ahead prediction.

B. Multi-steps-ahead Prediction

Assuming that the observed input is an independent event (i.e., the occurrence of input at a timeslot does not affect the occurrence of input at other timeslots), at a given *n*-steps-ahead prediction horizon, the probability of having $q_1, q_2, \ldots, q_n$ consecutive channel status in the next n timeslots is calculated using the chain rule formula:

$$P(q_1, q_2, \cdots, q_n | S_0) = \prod_{k=1}^{n} P(q_k | S_{k-1}) \quad (5)$$

where $P(q_k|S_{k-1})$ denotes the probability of having channel status q_k at state S_{k-1}.

After calculating the probability of a total of *2n* output combinations, the algorithm selects the greatest value as the prediction output. In our simulation we only consider a prediction horizon up to $n=5$.

In addition, we also derive the theoretical estimation of the prediction accuracy value as we increase the prediction horizon. Let $P_1(acc)$ be the probability that the single-step-ahead prediction is accurate. Then, applying the same chain rule, the probability that the *n*-steps-ahead prediction is accurate $P_n(acc)$ is given by:

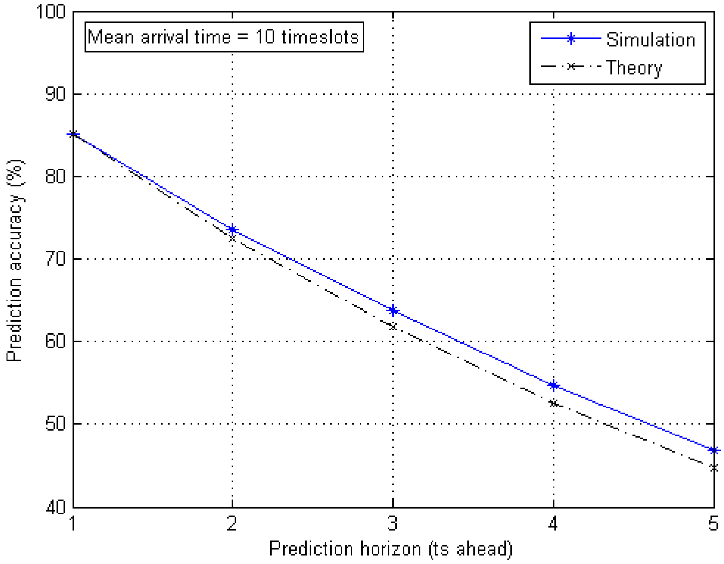
$$P_n(acc) = (P_1(acc))^n \quad (6)$$

C. Simulation Results and Discussions

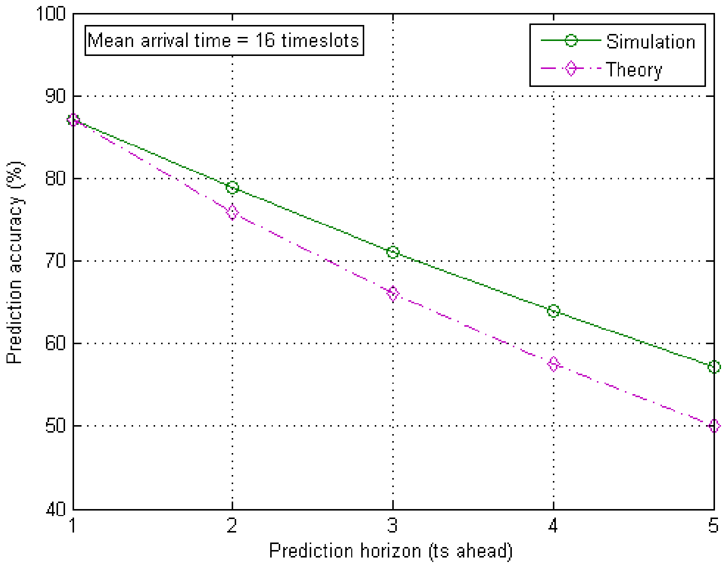
We continue our simulation using three scenarios, each of which has mean arrival time of 10, 16 and 22 timeslots, respectively. Keeping all other parameters the same as the previous simulation, we vary the prediction horizon from 1 up to 5 timeslots ahead at each scenario and plot them in graphs as depicted in Figure 7 and Figure 8.

Simulation results show that, in general, the prediction accuracy level resulting from the simulation follows the corresponding theoretical estimation value. That is, the prediction accuracy level tends to drop around 7-12% as we increase the prediction horizon. This trend reflects the main drawback of using a single-step-ahead algorithm for multi-steps-ahead prediction in that the error occurs at one prediction step and propagates to the next prediction step. However, the decrease of prediction accuracy becomes less as the prediction step is goes further.

We notice that for all prediction steps, the scenarios with relatively long mean arrival time tend to result in higher prediction accuracy than those with shorter ones. This trend is the effect of prediction errors due to model limitations. Since datasets with long mean arrival times have less frequent channel status transitions than those with shorter arrival times, prediction error is also less likely to happen, which results in slightly higher prediction accuracy. In addition, we can estimate the worst prediction accuracy level of prediction horizon of interest using (6). Observing the first scenario, the prediction accuracy of each prediction horizon is very close to its theoretical value and the performance is the lowest among the other scenarios. Therefore, having the prediction accuracy for single-step-ahead, we can estimate the worst performance from the theoretical value and we can expect that the actual performance might be better, especially in channels with relatively long mean arrival times.

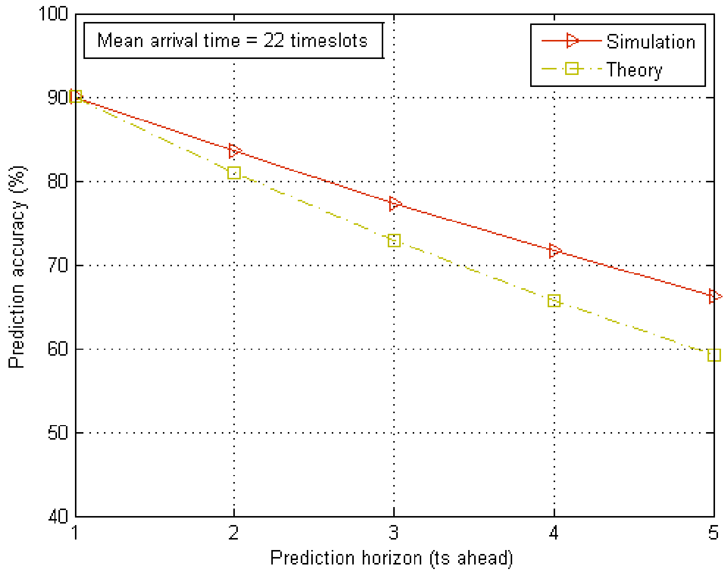


(a)



(b)

Figure 7. Prediction accuracy of the enhanced KSS-HMM algorithm in multi-steps-ahead prediction for mean arrival times of (a) 10 and (b) 16, and (c) 22 timeslots.



(c)

Figure 8. (continued) Prediction accuracy of the enhanced KSS-HMM algorithm in multi-steps-ahead prediction for mean arrival times of (a) 10, (b) 16, and (c) 22 timeslots.

Furthermore, assuming that as much as 75% prediction accuracy is considered to be the minimum acceptable prediction accuracy in spectrum handoff applications, the prediction horizon for which the algorithm can predict with satisfactory accuracy varies according to the channel usage statistics. That is, when PU arrival time on a channel is relatively long, then channel status can be predicted for a longer prediction horizon with satisfactory accuracy. However, when the PU arrival time tends to be short, then the prediction horizon becomes short as well. Our simulation result illustrates this situation. Namely, at a given minimum expected accuracy of 75%, the enhanced algorithm can be used to predict up to 3 steps ahead when the mean arrival time of the channel is 22 timeslots. However, the prediction horizon is shorten to 2-steps-ahead or even to single-step-ahead when the mean arrival times of the channels are 16 and 10 timeslots, respectively.

Therefore, if we further assume that it takes 1 timeslot to complete the whole spectrum handoff process, then the enhanced algorithm can definitely meet the first requirement because it always achieves more than 75% prediction accuracy for single-step-ahead prediction. However, it can only meet the second requirement conditionally depending on the channel activities statistic.

VI. CONCLUSIONS

The applications of channel status prediction algorithms for instantaneous spectrum access in CRNs have raised a new issue: the interference with PUs of the licensed channels due to channel status prediction errors. In this thesis, we propose a PU protection policy, which is a specific solution for a KSS-HMM channel status prediction algorithm, for reducing the negative effects of prediction errors. Simulation results show that our proposed policy can effectively reduce interference due to prediction errors while maintaining the same level of prediction accuracy of the original algorithm. Furthermore, we conduct feasibility analysis by applying the enhanced algorithm in spectrum mobility applications. We conclude that, although we may be able to meet the channel status prediction requirements of spectrum mobility under particular situations, the long term prediction using single-step-ahead channel status prediction algorithm is still a challenge.

In order to meet the requirements regardless of the average PU arrival time on a channel, having relatively high prediction accuracy is essential, especially for doing multi-steps-ahead prediction using the single-step-ahead model. For future work, we are going to integrate memory elements into the design of the KSS-HMM algorithm so the prediction error caused by model limitations can be reduced and the prediction accuracy can be increased.

BIBLIOGRAPHY

[1] C.-J. Kim, S.-W. Kim, J. Kim, and C. Pyo, "Dynamic Spectrum Access/Cognitive Radio Activities in Korea," *Proc. of IEEE Symp. on New Frontiers in Dynamic Spectrum*, Apr. 2010.

[2] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "A Survey on Spectrum Management in Cognitive Radio Networks," *IEEE Communications Magazine*, Vol. 46, No. 4, Apr. 2008, pp. 40-48.

[3] I. F. Akyildiz, W.-Y. Lee, and K. Chowdhury, "CRAHNs: Cognitive Radio Ad Hoc Networks," *Ad Hoc Networks*, vol. 7, No. 5, July 2009, pp. 810–36.

[4] H. Kim and K. Shin , "Efficient Discovery of Spectrum Opportunities with MAC-Layer Sensing in Cognitive Radio Networks," *IEEE Transactions on Mobile Computing*, Vol. 7, No. 5, pp. 533-545, May 2008.

[5] L.-C. Wang and C.-W. Wang, "Spectrum Handoff for Cognitive Radio Networks: Reactive-Sensing or Proactive-Sensing?" *Proc. of IEEE Int. Conf. on Performance, Computing and Communications (IPCCC)*, Dec. 2008.

[6] I. Christian, S. Moh, I. Chung, and J. Lee, "Spectrum Mobility in Cognitive Radio Networks," *IEEE Communications Magazine*, Vol. 50, No. 6, pp. 114-121, June 2012.

[7] L. Yang, L. Cao, and H. Zheng, "Proactive Channel Access in Dynamic Spectrum Networks," *Physical Communication (Elsevier)*, Vol. 1, pp. 103-111, June 2008.

[8] Yi Song and Jiang Xie, "Proactive Spectrum Handoff in Cognitive Radio Ad Hoc Networks Based on Common Hopping Coordination," *Proc. of IEEE Conf. on Computer Communications Workshops (INFOCOM 2010*),

pp.1-2, 15-19 March 2010.

[9] C. Cordeiro and K. Challapali, "C-MAC: A Cognitive MAC Protocol for Multi-Channel Wireless Networks," *Proc. of 2nd IEEE Int. Symp. on New Frontiers in Dynamic Spectrum Access Networks (DySPAN 2007)*, Apr. 2007.

[10] G. Ko *et al*., "Channel Management in IEEE 802.22WRAN Systems," *IEEE Communications Magazine*, vol. 48, no. 9,Sept. 2010, pp. 88–94.

[11] S. Yarkan and H. Arslan, "Binary Time Series Approach to Spectrum Prediction for Cognitive Radio," *Proc. of Vehicular Technology Conf. (VTC Fall 2007)*, 30 Sep. - 3 Oct. 2007.

[12] A. He, K.-K. Bae, T. R. Newman, J. Gaeddert, K.-W. Kim, R. Menon, L. Morales-Tirado, J. J. Neel, Y.-P. Zhao, J. H. Reed, and W. H. Tranter, "A Survey of Artificial Intelligence for Cognitive Radios," *IEEE Transactions on Vehicular Technology*, May 2010.

[13] T. Clancy and B. Walker, "Predictive Dynamic Spectrum Access," *Proc. of SDR Forum Technical Conf. (SDR 2006)*, 15 Nov. 2006.

[14] I. A. Akbar and W. H. Tranter, "Dynamic Spectrum Allocation in Cognitive Radio Using Hidden Markov Models: Poisson Distributed Case," *Proc. of IEEE SoutheastCon 2007*, pp.196-201, Mar. 2007.

[15] C.-H. Park, S.-W. Kim, S.-M. Lim, and M.-S. Song, "HMM Based Channel Status Predictor for Cognitive Radio," *Proc. of Asia-Pacific Microwave Conf. (APMC 2007)*, pp.1-4, Dec. 2007.

[16] R. Ma, Y. Hsu, and K. Feng, "A POMDP-Based Spectrum Handoff Protocol for Partially Observable Cognitive Radio Networks," *Proc. of IEEE Wireless Communications and Networks Conf. (WCNC)*, Apr. 2009.

[17] V. K. Tumuluru, P. Wang, D. Niyato, "A Neural Network Based Spectrum Prediction Scheme for Cognitive Radio," *Proc. of IEEE Int. Conf. on Communications (ICC 2010)*, 23-27 May 2010.

[18] V. K. Tumuluru, P. Wang, and D. Niyato, "Channel Status Prediction for Cognitive Radio Networks," *Journal of Wireless Communications and Mobile Computing (WCMC)*, Oct. 2010.

[19] H. Ahmadi, Y. H. Chew, P. K. Tang, and Y. A. Nijsure, "Predictive Opportunistic Spectrum Access Using Learning Based Hidden Markov Models," *Proc. of IEEE 22nd Int. Symp. on Personal Indoor and Mobile Radio Communications (PIMRC 2011)*, pp. 401-405, Sep. 2011.

[20] Y. Zhang, "Spectrum Handoff in Cognitive Radio Networks: Opportunistic and Negotiated Situations," *Proc. of IEEE Int. Conf. on Communications (ICC)*, June 2009.

ACKNOWLEDGEMENTS

First and foremost, I offer my sincerest gratitude to my supervisor Prof. Sangman Moh for his excellent guidance, caring and patience and providing me with comfortable research environment. His sincere encouragement to pursue my master's degree at MCL (Mobile Computing Lab) and his continuous support have been a great assistance to achieve a milestone in my career. Without his help, this thesis would not have been completed. He is the friendliest, easy going and encouraging advisor that anyone could wish for.

I would also like to show appreciation to all members of the thesis examining committee Prof. Seokjoo Shin and Prof. Moonsoo Kang for their valuable advices and insight throughout my research. In addition, I would like to thank Department of Computer Engineering, Chosun University, to provide me the atmosphere to augment my knowledge.

My family members in Indonesia have always supported me with their distant love. The experience of being away from home helps me to realize the value and importance of family. Therefore, I am grateful to them and I would like to dedicate this thesis to my family, especially for my late father Freddy Soebiantoro who passed away 1 month before I started the scholarship program. I would like to thank my mother Lucia I. Mestikawati and my dear brothers Oscar Marino and Eric Yonathan, for their constant prayers during my study. Special thanks goes to my beloved Melia Triani for patiently waiting for me to finish this three-years scholarship program. Your great patience means a lot to me.

During my daily life in Korea, I have been supported by colleagues and cheerful friends. Sunil K. Timalsina is my roommate in Green Village Dormitory and also my first colleague in MCL who becomes a great friend to share research ideas. Christian H. W. Oey is a great mentor in network engineering field and a wonderful colleague in MCL whom I worked the research projects with. Being my roommate in the last two years in Korea, we shared our lives as we were struggling to graduate. Heewook Shin, Seongcheol Park, Myeonghee Lee, Cheolheon Baek, and Su Han support me with many things in MCL. Li Xiang taught me Korean language a lot and assisted me to obtain TOPIK level 4. Rabin Bhusal motivated me a lot to pursue professional certification in network engineering field. My fellow-countrymen Rudi Siagian, Shelly Salim, Karina P. Kim, Ganis Z. Santoso, Yvan Christian, Adrianto Tejokusumo, Rico Hartono, and Irvanda Kurniadi have made my life in Korea more interesting and convenient.

This research was supported by the KGSP (Korean Government Scholarship Program), under the NIIED (National Institute for International Education).