Predictive Decision-Making for Vehicular Cognitive Radio Networks through Hidden Markov Models

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Abstract—Vehicular networks that require additional spectrum for communication may leverage cognitive radio technology. Towards this aim, the vehicle must select one among several candidate channels for data transmission, with the possibility that other surrounding vehicles may also identify the same spectrum for their use. Such networks are distinguished from their classical, stationary counterparts by high mobility, time-varying, and heterogeneous environment leading to dynamic channel availability. Owing to this changing environment, the history of spectrum usage information may be unavailable to the vehicles at all points on their journey, necessitating blind decision-making. In this paper, we propose a method of spectrum selection without a priori channel information. The main contributions of our work are: (i) we provide a framework to determine, through a Hidden Markov Model, whether a channel is occupied by a licensed user, another cognitive radio enabled vehicle, or if the observed signal fluctuations are due to noise; and (ii) we devise a prediction algorithm to determine which channels are likely to be available within the shortest amount of time. Our approach is verified through a simulation study, and we demonstrate equivalent performance to schemes that use prior history of the channel usage at specific vehicle locations.

I. INTRODUCTION

Vehicular networks are envisaged to enable high bandwidth vehicle-to-vehicle and vehicle-to-roadside infrastructure communication by using licensed frequencies [1]. This technology is poised to realize a host of novel applications from in-vehicle entertainment and enhanced emergency systems for public safety to traffic congestion information access. While spectrum has been reserved in the 5.9 GHz band and its use is specified in the IEEE 802.11p standard for intelligent transportation systems [3], the communication is limited to short-distance inter-vehicular scenarios. Moreover, emerging multimedia and data streaming applications are likely to saturate this band in the near future, necessitating the use of alternate available spectrum. This motivates the new paradigm of cognitive radio vehicular (CRV) networks as a possible solution [1], [2]. CRVs will allow efficient spectrum utilization and identify additional spectrum beyond the constraints of the 5.9 GHz [4]. Here the vehicles are the secondary users (SUs) that access TV white spaces in an opportunistic manner, without causing interference to the stationary roadside TV users as primary users (PUs) within the interference range of the SUs.

One of the key challenges in CR-enabled networks is to perform proper decision-making such as dynamic channel selection. Conventional methods attempt to address this challenge through training-based modeling and prediction by taking advantage of a priori information of channel usage [5], [6]. However, in CRVs, owing to the highly mobile environment, there may not be historical traces of channel usage available to SUs. While exchanging spectrum information with roadside base stations has been considered in [2], there are several practical difficulties involved in high volume data transfers. Moreover, the unknown movement patterns of the vehicles and unpredictable user demands for spectrum make it a challenge to provide requesting SUs with a priori spectrum information. These constraints suggest blind decision-making by SUs, rendering conventional training-based methods of limited value. Furthermore, due to the diverse applications for SUs and PUs, channel occupancy duration shows significant variations between SUs and PUs, accompanied by different levels of transmission powers. This leads to a new challenge of heterogeneity in such networks.

In this paper, we adopt a hidden markov model (HMM)-based approach to perform a realistic decision-making by a typical vehicle, which provides information on an unknown channel state, such as availability of the channel, through observable parameters, such as received signal strength (RSS).

In our approach, through the HMM, first the typical vehicle attempts to infer the type of user occupying each TV channel (state of the channel) at the moment. The next step involves predicting the state of the channels in the near future and performing decision-making, i.e. choosing a free channel that can be used right away or selecting an occupied channel to request in the future. The goal here is to minimize the amount of delay that the typical vehicle experiences before accessing the channel, especially in the case of channel congestion due to the flux of spectrum requests. This in turn has a direct effect on the quality of service and is of paramount importance on delay sensitive applications, such as multimedia streaming and emergency notifications.

The key contributions of our work are summarized as follows:

- Our CRV network architecture incorporates a realistic usage scenario in a dynamic and heterogeneous environment through stochastic modeling and introducing new metrics such as request probability, capture time, and capture delay that are specially designed for such networks.
- Our HMM-based model distinguishes between the states
in which a PU occupies the channel, and the one in which
a SU is doing so. Most previous works that use energy
detection-based sensing assume a single busy state for
these different scenarios. This allows our HMM-based
framework to accurately determine what type of user is
using the channel.

- Our model does not rely on a priori measurements or
training algorithms. This implies that no cooperative com-
munication among the users and no precise knowledge of
the channel states in either current or previous time slots
is required.

The rest of the paper is organized as follows: Section II
describes the realistic and dynamic CRV network architecture,
while Section III proposes detailed analytical design of the
HMM and our decision-making algorithm. Results of the
performance evaluation are provided in Section IV. Finally,
Section V concludes our work.

II. NETWORK ARCHITECTURE AND PROBLEM SETUP

As shown in Fig. 1, the vehicular network is composed of
vehicles moving along a highway with roadside infrastructures
such as fixed facilities, houses, etc. existing on the sides of the
highway that may have PUs operating in them. Each vehicle
is provided with both its own position in the highway (by
GPS), as well as the exact location of all roadside PUs (by a
map). Therefore, it is able to measure its distance from them
at each moment. Since in practice the width of the highway
is negligible compared to the distance between vehicles and
roadside infrastructures, the movement path of the vehicles
along the highway is considered to be a straight line. The
process of vehicles entering into the highway is modeled as a
Poisson process with the average arrival rate of \( \lambda \) vehicles per
hour. All vehicles are assumed to be moving with the same
average speed of \( \nu \) miles per hour, while keeping the minimum
safety distance of \( R^m \) miles from each other. According to [7],
the density of vehicles can also be modeled as a Poisson
process with rate \( \gamma = \frac{\lambda}{\nu} \) vehicles per mile.

Regarding CR specifications of our system, \( N_c \) TV channels
with center frequencies \( \{ f_1, f_2, \ldots, f_{N_c} \} \) are accessible by PUs
and opportunistically used by the SUs. Different transmission
powers \( P^{PU} \) and \( P^{SU} \) are assumed for PUs and SUs, respect-
ively, where \( P^{PU} > P^{SU} \). \( G_i^{PU} \) and \( G_i^{SU} \) are defined as
transmission antenna gain for the PUs and SUs, respectively,
and \( G_r \) is the antenna gain of our typical vehicle, which serves
as the receiver in our work to perform the spectrum sensing.
Time is slotted, each slot being 60 seconds. Each channel in a
given time slot can be captured by only one user (either a SU
or a PU), but it can be reused by another user at least \( R^f \) miles
away without causing interference. The value of \( R^f \) is chosen
for the worst case of having a PU transmitting on the smallest
frequency \( f^{min} \) with the assumption that \( RSS^T = -75dBm \)
is the threshold for the interference. Assuming the free space
channel model, we have:

\[
R^f = \sqrt{\frac{P^{PU} G^{PU} G_r (\frac{c}{f^{min}})^2}{4 \pi^2 L(RSS^T)}}
\]  

in which \( c \) is the speed of light and \( L \) is the path loss.

In each time slot, each PU and each SU may request any
of the TV channels with request probability of \( p_{req}^{PU} \) and \( p_{req}^{SU} \)
respectively. Being higher priority users, requesting PUs are
given higher preference over requesting SUs in capturing the
channels. However, within requesting users of the same prior-
ity level, any one user may capture the channel randomly. Each
successful user continues using the channel for a particular
number of time slots according to its application, defined as
the capture time and expressed as \( T^{PU} \) and \( T^{SU} \) for PUs and
SUs, respectively. Capture time of a user is unknown to the
others. However, this metric, with a slight change in definition,
is modeled as an Exponential distribution, with mean values of
\( \tau^{PU} \) and \( \tau^{SU} \) time slots for PUs and SUs, respectively, which
are known by all users. By this definition, capture time is the
prediction of the amount of time remained until the channel
becomes free, given that it is currently in use by a PU or SU.
This modeling is inspired by the inherent difference in the
nature of applications run by PUs and SUs, which suggests
\( \tau^{PU} > \tau^{SU} \), and the choice of Exponential distribution is
meant to be well-reflective of the memoryless nature of this
parameter. This implies that the remaining time for a channel
to become free is independent of the time it has been in use
up to the current moment.

We define a set of three different scenarios as unknown
or hidden channel usage states, \( \{ S_1, S_2, S_3 \} \), as follows: At
a given location, a free channel in each time slot is either
captured by a PU (state \( S_2 \)) if at least one PU in \([R^m, R^f]\)
range from the location requests it. It is captured by a SU
(state \( S_1 \)) if no PU and at least one SU in \([R^m, R^f]\) range
from the location requests it, and stays free (state \( S_3 \)) if no
user in \([R^m, R^f]\) range from the location requests it. In order
to obtain observations, each SU measures the RSS on each of
the \( N_c \) TV channel frequencies.

We address the specific problem of choosing the best
available TV channel for a typical vehicle (shown at the center
of the two concentric circles in Fig. 1) moving along the
highway to minimize the delay (i.e. number of time slots)
the vehicle experiences before capturing a free channel, called
capture delay in our work.
We translate the RSS range of each observation class to a distance range in miles between the potential transmitting PU or SU and the typical vehicle assuming the free space channel model. This translation for the lower bound of the $l$th class of observation is done by:

$$R_{lU,min} = \sqrt{\frac{\text{max}\{\text{RSS} - \text{Range} - \text{Margin}\}}{4\pi^2\lambda_o^2}}$$  \hspace{1cm} (2)$$

For calculating the upper bound, $R_{lU,max}$, we simply substitute $O_{\text{max}}$ by $O_{\text{min}}$.

- Number of PUs in $[R_{lU}^m, R_{lU}^r]$ range from the typical vehicle, denoted by $n_{PU}^l$, is found by measuring the PU distances from the typical vehicle given their positions by the map and the vehicle’s position by GPS (see Fig 1). The same approach is used to calculate the number of PUs in the $l$th class range. $[R_{lPU,min}^U, R_{lPU,max}^U]$ from the typical vehicle, denoted by $n_{PU}^l$.  

- The corresponding parameters for SUs are denoted by $n_{SU}$ and $n_{SU}^l$. As no vehicle has exact information about the population and location of other vehicles in the highway, except general stochastic information about their arrival process, it is not possible to calculate exact values of $n_{SU}$ and $n_{SU}^l$. However, estimated values of these parameters, denoted by $\hat{n}_{SU}$ and $\hat{n}_{SU}^l$, respectively, can be calculated using the fact that when density of vehicles follow a Poisson process with rate $\gamma$, then the number of vehicles in any interval of length $x$ miles is also Poisson distributed with parameter $\gamma x$. In our case, $x = 2(R_{lU}^r - R_{lU}^m)$ for $\hat{n}_{SU}$ and $x = 2(R_{lSU,max} - R_{lSU,min}^U)$ for $\hat{n}_{SU}^l$, which covers both the right and the left side directions of the vehicle (Fig. 1). Therefore:

$$\hat{n}_{SU}^l = 2\gamma(R_{lU}^r - R_{lU}^m)$$  \hspace{1cm} (3)$$

$$\hat{n}_{SU}^l = 2\gamma(R_{lSU,max} - R_{lSU,min}^U)$$  \hspace{1cm} (4)$$

- Given that the channel is being used by a user in the current time slot, probability that the same user keeps using it in the next time slot, too, can be calculated using the Exponential distribution assumption:

$$p_{\text{keep}}^U = \text{Prob}(T^U > 1) = e^{-\frac{R_{lSU}^U}{\lambda_o^2}}$$  \hspace{1cm} (5)$$

Hence, probability that the user leaves the channel in the next time slot is:

$$p_{\text{leave}}^U = 1 - p_{\text{keep}}^U$$  \hspace{1cm} (6)$$

- Probability of having no PU requesting a channel in $[R_{lU}^m, R_{lU}^r]$ range from the typical vehicle is calculated as:

$$p_{\text{no-req}}^PU = (1 - p_{\text{req}}^PU)^{n_{PU}}$$  \hspace{1cm} (7)$$

which is based on the fact that the number of requests by PUs follow a Binomial distribution with parameters $n_{PU}$ and $p_{\text{req}}^PU$.

- \textbf{Lemma 1:} Probability of having no SU requesting a channel in $[R_{lU}^m, R_{lU}^r]$ range from the typical vehicle is calculated as:

$$p_{\text{no-req}}^{SU} = e^{-n_{SU}^l x p_{\text{req}}^{SU}}$$  \hspace{1cm} (8)$$
Proof of this lemma is provided in Appendix A.

- Probability of having at least one user (either SU or PU) requesting a channel in \([R^m, R^n]\) range from the typical vehicle is simply:

\[
p^{\text{at-least-one-req}}_U = 1 - p^{\text{no-req}}_U
\]

- We denote the number of PUs and SUs requesting a channel in the \(l\)th class range from the typical vehicle by \(n^{\text{PU}}_{l,\text{req}}\) and \(n^{\text{SU}}_{l,\text{req}}\) respectively. It is impossible to find the exact value of these parameters due to the lack of exact information about the number of SUs, and also the probabilistic nature of both SUs’ and PUs’ requests. Approximating, we have:

\[
n^{\text{PU}}_{l,\text{req}} \approx n^{\text{PU}}_l \times p^{\text{PU}}_{\text{req}}
\]

\[
n^{\text{SU}}_{l,\text{req}} \approx n^{\text{SU}}_l \times p^{\text{SU}}_{\text{req}}
\]

Now we design the HMM parameters \(\pi, A,\) and \(B\) for the typical vehicle that needs a channel. As mentioned before, we specify vector \(\pi\) empirically after an initial run of simulation described in Section IV, from which we identify the statistics of channel states over a period of time. Our typical vehicle is provided with this vector as initial information.

For deriving the elements of the matrices \(A\) and \(B\), we (i) allow PUs to capture the channel with higher priority over SUs, and (ii) view these elements as conditional probabilities as follows:

\[
a_{ij} = P_{\text{Prob}}(S^{k+1}_m = j | S^k_m = i)
\]

\[
b_{i,l} = P_{\text{Prob}}(O^k_m = l | S^k_m = i)
\]

Therefore, elements of matrices \(A\) and \(B\) are calculated as:

\[
a_{1,1} = p^{\text{keep}}_\text{SU} + (p^{\text{PU}}_\text{leave} \times p^{\text{PU}}_{\text{at-least-one-req}})
\]

\[
a_{1,2} = p^{\text{PU}}\text{leave} \times p^{\text{PU}}_{\text{at-least-one-req}}
\]

\[
a_{1,3} = p^{\text{PU}}\text{leave} \times p^{\text{SU}}_{\text{req}} \times p^{\text{SU}}_{\text{at-least-one-req}}
\]

\[
a_{2,1} = p^{\text{PU}}\text{leave} \times p^{\text{SU}}_{\text{ req}} \times p^{\text{PU}}_{\text{at-least-one-req}}
\]

\[
a_{2,2} = p^{\text{PU}}\text{keep} + (p^{\text{PU}}_\text{leave} \times p^{\text{PU}}_{\text{at-least-one-req}})
\]

\[
a_{2,3} = p^{\text{PU}}\text{leave} \times p^{\text{SU}}_{\text{req}} \times p^{\text{SU}}_{\text{at-least-one-req}}
\]

\[
a_{3,1} = p^{\text{SU}}_{\text{at-least-one-req}} \times p^{\text{PU}}_{\text{at-least-one-req}}
\]

\[
a_{3,2} = p^{\text{SU}}_{\text{at-least-one-req}}
\]

\[
a_{3,3} = p^{\text{SU}}_{\text{ req}} \times p^{\text{SU}}_{\text{at-least-one-req}}
\]

\[
b_{1,l} = \frac{n^{\text{SU}}_l}{\sum_{i=1}^{N_o} n^{\text{SU}}_i} \quad l = 1, \cdots, N_o
\]

\[
b_{2,l} = \frac{n^{\text{PU}}_{l,\text{req}}}{\sum_{i=1}^{N_o} n^{\text{PU}}_i} \quad l = 1, \cdots, N_o
\]

\[
b_{3,l} = \begin{cases} 0 & l = 1, \cdots, N_o - 1 \\ 1 & l = N_o \end{cases}
\]

In calculating \(b_{3,l}\), we seek the probability of having a user in the \(l\)th class range from the typical vehicle transmitting over the channel, while we assume that the channel is in free state (S3) meaning that no user in \([R^m, R^n]\) range from the typical vehicle is using the channel. This leads us to the conclusion that there is either one out-of-range user or no user occupying the channel. We have designed our observation class boundaries such that when translated to distance values, the last \(N_o\) class includes the out-of-range parts of the highway \((< R^m \text{ and } > R^n)\). Therefore, when the channel is in free state, any RSS reading will definitely fall in the \(N_o\) class.

B. Prediction

We next predict the channel state in the next time slot, from the viewpoint of the typical vehicle. As no previous channel state information is available to the typical vehicle, we cannot use the classical methods of decoding in HMM, such as the Viterbi algorithm. Instead, we only use RSS value read in the current time slot and the HMM designed in the above approach. Assuming that the current time slot observation falls into the \(l\)th class, first, we estimate the channel state in the current time slot for the \(m\)th TV channel using matrix \(B\) as:

\[
S^k_m = \arg\max_{i \in \{1,2,3\}} b_{i,l}
\]

Then we predict the channel state in the next time slot by matrix \(A\) as:

\[
S^{k+1}_m = \arg\max_{j \in \{1,2,3\}} a_{S^k_m,j}
\]

This calculation is repeated for all the \(N_o\) TV channels.

C. Decision-Making

The final step is to decide what would be the best TV channel according to the above prediction. Our aim is to minimize capture delay for the typical vehicle. Therefore, in the \(k\)th time slot, channels are classified based on their predicted state for the \((k + 1)\)th time slot into three sets \(C_{k+1}^1\), \(C_{k+1}^2\), and \(C_{k+1}^3\), with \(|C_{k+1}^i|\) denoting the cardinality of the \(i\) set. The subscript of each set denotes the predicted state. For channel selection, the highest priority is given to the free channels listed in \(C_{k+1}^3\), followed by channels in use by a SU listed in \(C_{k+1}^1\), and finally those in use by a PU listed in \(C_{k+1}^2\). The rationale behind giving higher priority to the channels in use by SUs over those in use by PUs is the longer average capture time of PUs. This incurs more waiting time for accessing the channel for the typical vehicle. Among channels with the same priority level, we use random selection.

Fig. 3 summarizes the steps of the proposed algorithm in a flowchart.
We simulate the CRV network in MATLAB. We consider a scenario in which vehicles move along a 30 mile highway with the parameter values given in Table I. As mentioned in Section III, the initial decision for some parameters of HMM such as vector $\pi$, size and the values of observation set is based on an initial run of the simulation. We call our proposed algorithm Analytical HMM-based Decision-Making (A-HMM-DM).

IV. EVALUATION

We simulate the CRV network in MATLAB. We consider a scenario in which vehicles move along a 30 mile highway with the parameter values given in Table I. As mentioned in Section III, the initial decision for some parameters of HMM such as vector $\pi$, size and the values of observation set is based on an initial run of the simulation. We call our proposed algorithm Analytical HMM-based Decision-Making (A-HMM-DM).

Given the fact that no previous work considers the concepts of capture time and capture delay, we compare the performance of our proposed algorithm with three different incarnations of A-HMM-DM that are all based on a common set of architectural assumptions. The three approaches selected for comparison with A-HMM-DM are:

- Simulation-designed HMM-based Decision-Making (S-HMM-DM): In this method the design of the HMM (matrices $A$ and $B$) is completely based on statistics extracted from a previous run of the simulation, which provides us with a sequence of observations and their associated states over a relatively long period of time (over 3500 time slots). As mentioned before, no vehicle is assumed to have access to such a data history, making this method an ideal case where SUs have omniscient knowledge of the past. We expect this method to outperform any other method with limited or no history information.

- Maximum-Likelihood-designed HMM-based Decision-Making (ML-HMM-DM): Similar to the previous method, we design the HMM using the same data history but based on Maximum-Likelihood estimation [8] of matrices $A$ and $B$ instead of the statistics.

- Homogeneous Analytical HMM-based Decision-Making (HA-HMM-DM): This method is an incomplete version of our method, which follows all the steps except that it assumes the same request probability for both PUs and SUs (i.e., $P_{reqPU} = P_{reqSU}$) and also the same mean value for capture time (i.e., $\tau_{SU} = \tau_{PU}$). We expect a performance penalty due to this simplification.

Performance evaluation is done from two different aspects: HMM Accuracy and Capture Delay as follows:

A. HMM Accuracy

Using designed HMM in each method, we find the most likely sequence of states for a given test sequence of observations based on the Viterbi algorithm [8]. Fig. 4 shows the accuracy of HMM in terms of the percentage of correctly estimated states versus the length of the test sequence for a given channel. The results validate our claim that our proposed algorithm is almost as accurate as the two history-based methods (S-HMM-DM and ML-HMM-DM) without having access to training data, achieving around 70% accuracy. However, HA-HMM-DM suffers from a slight degradation in accuracy for higher sequence lengths, which occurs as this scheme does not include request probability and capture time. We also see that the length of the test sequence has almost no effect on the results, which proves the stability of our model. It should be noted that the limited performance, even for the history-based methods, is due to the probabilistic nature of the system and the limited capability of HMMs in prediction.
As another metric to evaluate the accuracy, we consider the success rate of the typical vehicle in estimating the channel state over its travel along the highway. Fig. 5 shows this metric for one channel. It is seen that the two history-based methods achieve a slightly better estimation than analytical ones and acceptable accuracy of over 70% is achieved for all four methods.

Using a prediction-based algorithm, best channel is selected. Results reveal that our HMM matches the accuracy of classical approaches implemented in our network architecture that use a priori training data. Thus, our method is applicable for a larger set of scenarios, where this training data is not available. The observed channel access delay is significantly reduced, compared with random selection of channels, and similar to those methods which benefit from available training data.

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APPENDIX A: PROOF OF LEMMA 1

Proof. We have \( n^{SU} \sim \text{Poisson}(\hat{n}^{SU}) \), each of them requesting a channel with probability \( p^{SU}_{req} \). Thus, the joint probability of having \( n^{SU} \) users in \([R^m, R^l]\) range from the typical vehicle, and having none of them requesting a channel is calculated as follows:

\[
\begin{align*}
\text{Prob}(n^{SU}, no - req) &= \text{Prob}(no - req|n^{SU})\text{Prob}(n^{SU}) \\
&= (1 - p^{SU}_{req})^n^{SU} e^{-\hat{n}^{SU}}(\hat{n}^{SU})^{n^{SU}} \frac{n^{SU}}{n^{SU}} \\
&= e^{-\hat{n}^{SU}}(\hat{n}^{SU}(1 - p^{SU}_{req})^{n^{SU}})
\end{align*}
\]

(28)

Therefore, using Bayes’ theorem, the desired probability is:

\[
\begin{align*}
p^{SU}_{no - req} &= \sum_{n^{SU}=1}^{\infty} \text{Prob}(n^{SU}, no - req) \\
&= \sum_{n^{SU}=1}^{\infty} e^{-\hat{n}^{SU}}(\hat{n}^{SU}(1 - p^{SU}_{req})^{n^{SU}}) \\
&= e^{-\hat{n}^{SU}}P^{SU}_{req}
\end{align*}
\]

\[
(29)
\]

V. CONCLUSION

In this paper, we investigate how to ensure that a typical vehicle is able to identify the occupants of a set of channels, estimate the duration of future unavailability of them, and then use them opportunistically in a CRV network. A realistic network architecture is proposed and modeled by a novel analytical HMM that defines possible states of a channel as being occupied by a PU, a SU, or none of them, and RSS values resulting from their transmissions as observations.

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