On the performance of cognitive internet-of-vehicles with unlicensed user-mobility and licensed user-activity

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\textbf{A R T I C L E   I N F O}

Article history:
Received 22 December 2017
Revised 18 February 2018
Accepted 15 March 2018
Available online 20 March 2018

Keywords:
Cognitive internet of vehicles (IoV)
Vehicular user mobility
Unlicensed vehicular users
Licensed primary users

\textbf{A B S T R A C T}

Internet of Vehicles (IoV) is regarded as an emerging concept for intelligent transportation cyber-physical systems. Due to the limited number of channels available in IEEE 802.11p DSRC/WAVE standard for vehicular communications, time-critical emergency messages in IoV could suffer from delays. Thus, cognitive radio enabled IoV has potential to overcome this problem, where vehicles (i.e., unlicensed vehicular users as well as unlicensed secondary users) access RF spectrum other than 802.11p spectrum in an opportunistic manner by sensing and identifying the idle channels licensed to primary users without causing any harmful interference to primary users. In cognitive IoV, unlicensed vehicular users rely on spectrum sensing to find idle bands for opportunistic IoV communications. Existing spectrum sensing algorithms either consider low mobility or stationary (no mobility) of unlicensed vehicular users. Furthermore, joint impact of unlicensed vehicular user mobility and primary user activity have not considered while evaluating the performance of spectrum sensing for opportunistic communications. In this paper, we analyze and evaluate the combined impact of unlicensed vehicular user mobility and licensed user activity for cognitive IoV where each vehicle is assumed to be equipped with a wireless device capable of communication and spectrum sensing for wide-band spectrum regime including IEEE 802.11p. We formally study the performance of the proposed approach for cognitive IoV using mathematical analysis by considering a speed of the vehicles, activities of the primary users and distance between licensed and unlicensed users. Then, numerical results obtained from simulations are used to evaluate the performance of the proposed approach. Results show that the unlicensed vehicular user mobility and primary user activity have a higher impact on misdetection probability than that on false alarm probability. Furthermore, communication range, speed, travel direction and distance between unlicensed vehicular users and licensed primary users affect the overlapping time period for spectrum sensing to find idle channels for opportunistic communications. We also study the dynamic spectrum access for opportunistic communications in terms of expected transmission time, achievable per-user rate and expected transmission count for successful communications.

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1. Introduction

Vehicular communications in Internet of Vehicles (IoV) is regarded as a backbone for intelligent transportation systems [1]. IEEE 802.11p standard is proposed for wireless vehicular communications where, out of 7 channels, 1 channel is used as a common control channel and 6 remaining channels are used for actual vehicular data communications. Vehicular communication in IoV helps disseminate the traffic information with an aim of helping to reduce traffic accidents, jams, and cost associated with fuel consumption and lost productivity, to help many infotainment applications, and to help improve the overall traffic management. However, these 7 channels dedicated to vehicular communications could be easily overloaded specially when vehicle density is high such in urban areas or congested areas. Recent studies have shown that the many networks are not fully utilizing their licensed spectrum most of the time [2,3]. However, there is no wireless spectrum left for further development of new wireless services and applications leading the spectrum scarcity [4]. When massive number of vehicles are expected to be communicating with each other and/or to the Internet, IoV is expected to a major contributing factor in spectrum scarcity in the near future.

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https://doi.org/10.1016/j.comnet.2018.03.015
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Dynamic spectrum access in the cognitive radio network is a new paradigm to enhance the spectrum utilization where unlicensed secondary users sense the wireless spectrum to find spectrum opportunities for opportunistic communications without causing any harmful interference to licensed primary users (PUs) [2]. To leverage the opportunistic communications over other channels than IEEE 802.11p channels, unlicensed vehicular users (aka unlicensed secondary users) in cognitive IoV use spectrum sensing to find idle channels (that are licensed to other users such cellular, WiMAX, etc.) to exploit the underutilized licensed spectrum opportunistically for efficient information dissemination in IoV.

To avoid any harmful interference to PUs, spectrum sensing by unlicensed vehicular users is the major step to identify whether the PUs are using their licensed channels or not [3,5]. In cognitive IoV, vehicular users are highly mobile with high speed and the network structure changes very quickly. In the literature, there have been a variety of spectrum sensing methods proposed for cognitive radio networks [3,6–12]. In these existing works, unlicensed users are assumed to be stationary while sensing licensed spectrum and PUs are assumed to be passive during opportunistic transmissions by unlicensed users. Out of most related works, secondary user mobility has been considered in non-cooperative spectrum sensing [6], cooperative spectrum sensing [10], spectrum sensing in the presence of PU mobility [9] and spectrum sensing using random way point model for secondary users in [11] where PUs are not mobile. We note that none of the state-of-the-art methods consider the combined impact of speed of vehicles, primary user ON/OFF activities, PU’s communication range, and secondary user’s sensing range while evaluating the performance of spectrum sensing in cognitive IoV where the speed of the secondary users is in miles/hour.

This paper investigates the joint impact of secondary user-mobility and primary user-activity for spectrum sensing in cognitive IoV where PUs’ communication range, spectrum sensing range and initial distance between licensed and unlicensed users. This paper presents mathematical models using these parameters for false alarm and misdetection probability and expected time duration for overlap for secondary users in cognitive IoV.

In cognitive IoV, each vehicular user is assumed to be equipped with wideband transceiver with a sensing range to sense channels and a transmission range for opportunistic communication. To avoid any harmful interference to licensed PUs and to increase the sensing certainty, secondary user’s transmission range must be shorter than or equal to its sensing range. Furthermore, PU should have their protection range where secondary users are not allowed to use PU’s licensed channels to avoid any harmful interference [3,13]. When a given secondary user and PU are reachable wirelessly, the secondary user will be able to sense the presence of the PU. Otherwise, the secondary user will not be able to sense the PU signal. Furthermore, when secondary user and PU are not mobile, their separation distance does not change over the time. However, when the secondary user is mobile, the sensing range could or could not cover the PU after certain travel time. Speed and direction of vehicular users determine the overlap time duration between vehicular users and PU. Furthermore, the PU’s ON or OFF activity significantly impacts the spectrum sensing for cognitive IoV.

The most important feature of IoV is that users move in the same direction or opposite directions based on the road structure. To find the overlap between sensing range of secondary user and protection range of PU, the distance between these users, which depends on relative speed of these users\(^1\), plays a significant role because distance determines whether a PU is inside the sensing range or not. In this paper, we present a formal analysis for the probability of misdetection and the expected overlap time period by considering sensing range and speed of unlicensed vehicular users, PU’s protection range, and PU’s transmission activities in its channel.

The remainder of the paper is organized as follows. The proposed system model is presented in Section 2 followed by the analysis for combined impact of secondary user-mobility and primary user-activity on spectrum sensing in cognitive IoV in Section 3. Opportunistic communication in cognitive IoV is presented in Section 4. Section 5 has simulation results and discussion. Finally, the paper is concluded in Section 6.

2. System model for cognitive IoV

Without loss of generality, the simplified system model is considered as shown in Fig. 1 that has one unlicensed vehicular user (as a secondary user) with sensing range \(s\) and four road-side primary stations su as TV or WiMAX users to represent PUs with their protection radii \(r\) to study the joint impact of secondary user-mobility and primary user-activity. We note that the formal analysis presented based on this model is directly applicable to multiple secondary users and PUs. In order to make sure that the sensing is performed so as not to interfere during dynamic spectrum access for opportunistic communications, we assume the PU protection range is shorter than the sensing range of the spectrum sensor, that is, \(r \leq s\). In our system model, a vehicular user (i.e., secondary user) in cognitive IoV is mobile and PUs are stationary. Thus, the relative speed between them is the speed of the vehicle. In this setup, the distance between primary and secondary users is a function of distance between them, their relative speed, direction of travel of vehicles, PU’s protection range and the sensing range of vehicular user. For instance, when a vehicular user drives toward a PU, overlap time period is greater than that when a vehicular user drives away from PU.

For spectrum sensing, signal from PUs should be checked whether the PU is active or not in given time and location. PU’s activities in the channel are represented by two state birth-death process with ON and OFF states [15]. At the mobile secondary user, the received signal \(r_\ell(t)\) can be represented as (1) and can be detected using two hypotheses, \(H_0\) representing only noise being present in the channel and \(H_1\) representing PU being present in a given channel as

\[
r_\ell(t) = \begin{cases} n(t), & \text{if } H_0 : \text{PU absent} \\ h t_\ell(t) + n(t), & \text{if } H_1 : \text{PU present}, \end{cases}
\]

(1)

where \(t_\ell(t)\) is the transmitted signal by PU, \(h\) is the channel gain, and \(n(t)\) is the additive white Gaussian noise at the mobile secondary user. After sampling of the received signal, the energy detection can be used to distinguish two hypotheses for identifying whether the PU is absent or active in a given channel as

\[
R_\ell = \frac{1}{W} \sum_{n=0}^{W-1} |r_\ell(n)|^2 \mathbb{I}_{H_1} - \lambda_E \mathbb{I}_{H_0}.
\]

(2)

where \(W\) is the sensing window length and \(\lambda_E\) is a decision threshold for energy based PU signal detection approach [16].

Definition 1. When the hypothesis \(H_0\) is true then either there is no PU within the sensing range or PU is inactive within the sensing range \(s\). Thus the PU ‘absent’ event is defined as the \(\alpha\) event.

Definition 2. When a channel is used by the primary user and secondary user detects a PU signal in a given channel (i.e., hypothesis \(H_1\)), this PU ‘busy’ event is represented as the \(\beta\) event.
3. Formal analysis for secondary user-mobility and primary user-activity on spectrum sensing

This section investigates formal analysis to evaluate the impact of secondary user-mobility and primary user ON/OFF activity in terms of probability of misdetection of spectrum opportunities and the expected overlapping time duration between secondary and primary users when the secondary user is mobile [112]. Note that when unlicensed secondary user mis-detects that the primary user is absent when PU is actually present, secondary user cause harmful interference to PUs. Thus misdetection probability is more important than false alarm since false alarm does not lead to harmful interference to PUs.

Based on Definitions 1 and 2, we formally analyze the event $\alpha$ (PU ‘absent’ in a given channel) and the event $\beta$ (channel ‘busy’ or used by PU) and state/prove the following propositions.

**Proposition 1.** For a separation distance $D$ between a secondary user and PU, the condition for the PU being inside the sensing range of the secondary user is $r < D \leq S$. The probability for the event $\beta$, that is, $\Pr(B)$, the probability that the PU is inside the sensing range of secondary user and the secondary user detects that the PU is present in a given channel, is

$$\Pr(B) = \frac{1}{2} \left[ \text{erf} \left( \frac{S - \mu_v}{\sigma_v \sqrt{2}} \right) - \text{erf} \left( \frac{r - \mu_r}{\sigma_r \sqrt{2}} \right) \right].$$  \hspace{1cm} (3)

Note that the $\Pr(B)$ in (3) does not consider secondary user mobility. Thus, when secondary user mobility is considered, the $\Pr(B)$ is

$$\Pr(B) = \int_{\frac{r - \mu_r}{\sigma_r \sqrt{2}}}^{\frac{S - \mu_v}{\sigma_v \sqrt{2}}} \int_{\frac{v - \mu_v}{\sigma_v \sqrt{2}}}^{0} \frac{1}{2\pi \sigma_v} \exp \left( -\frac{(v - \mu_v)^2}{2\sigma_v^2} \right) \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{(v - \mu_v)^2}{2\sigma_v^2} \right) dv \, dt. \hspace{1cm} (4)$$

Then, the probability of a given PU being outside of the sensing range of a secondary user, that is the probability for the event $\alpha$, $\Pr(A)$, is

$$\Pr(A) = 1 - \Pr(B).$$ \hspace{1cm} (5)

**Proof.** Both probabilities $\Pr(A)$ and $\Pr(B)$ depend on the distribution function of separation distance between a PU and mobile secondary user. As shown in Fig. 1, the PUs are protected within the radii of $r$ where no secondary users are allowed to use PUs’ licensed channels used by PUs in a given location and time. When both secondary user and primary users are static, the probability distribution of a overlap between sensing range of secondary users and protection range of PUs separated by a distance $d$ is log-normal which can be expressed as [17]

$$F_r(d=r) = \int_{-\infty}^{r} \frac{1}{\sigma_r \sqrt{2\pi}} \exp \left( -\frac{(z - \mu_r)^2}{2\sigma_r^2} \right) dz = \frac{1}{2} \left[ 1 + \text{erf} \left( \frac{r - \mu_r}{\sigma_r \sqrt{2}} \right) \right].$$ \hspace{1cm} (6)

where $\text{erf}(\cdot)$ is an error function, $\mu_r$ is the mean value and $\sigma_r$ is the standard deviation value of the protection range of the PU.

Similarly, for secondary users with a sensing range, one can express

$$F_s(s) = \frac{1}{2} \left[ 1 + \text{erf} \left( \frac{s - \mu_s}{\sigma_s \sqrt{2}} \right) \right],$$ \hspace{1cm} (7)

where $\mu_s$ is the mean value and $\sigma_s$ is the standard deviation value of the sensing range of secondary user.

For a separation distance $D$ between a PU and secondary user, the necessary condition for the PU with protection range $r$ being inside the sensing range of secondary users $S$ is $r < D \leq S$. Then, the probability, $\Pr(B)$, for the event $\beta$, that the PU lies inside the sensing range of secondary user is expressed as

$$\Pr(B) = \Pr(r < D \leq S) = F_s(s) - F_r(r) = \frac{1}{2} \left[ \text{erf} \left( \frac{s - \mu_s}{\sigma_s \sqrt{2}} \right) - \text{erf} \left( \frac{r - \mu_r}{\sigma_r \sqrt{2}} \right) \right].$$ \hspace{1cm} (8)

which proves the (3).

As mentioned, the $\Pr(B)$ in (7) does not consider secondary user mobility which is analyzed below. The speed of vehicles in free flow stage is a Gaussian distribution [18,18,19] with minimum speed $v_{min} = \mu_v - 3\sigma_v$ and maximum speed $v_{max} = \mu_v + 3\sigma_v$, the probability density function can be expressed as [17]

$$g_v(v) = \frac{f_v(v)}{\int_{v_{min}}^{v_{max}} f_v(v) \, dv},$$ \hspace{1cm} (9)

where $f_v(v)$ is Gaussian probability density function with a average speed $\mu_v$ and standard deviation $\sigma_v$, that is,

$$f_v(v) = \frac{1}{\sigma_v \sqrt{2\pi}} \exp \left( -\frac{(v - \mu_v)^2}{2\sigma_v^2} \right) \hspace{1cm} (10)$$
Then, the probability density function \( g_v(v) \) can be rewritten as
\[
g_v(v) = \frac{2f_v(v)}{\text{erf} \left( \frac{v_{\text{max}} - \mu_v}{\sigma_v \sqrt{2}} \right) - \text{erf} \left( \frac{v_{\text{min}} - \mu_v}{\sigma_v \sqrt{2}} \right)}. \tag{9}
\]

Then, the expected value of speed for secondary user is expressed as
\[
E[V] = \bar{v} = \int_{v_{\text{min}}}^{v_{\text{max}}} v g_v(v)dv. \tag{10}
\]

Next, for a given vehicle with its initial speed \( \bar{v}(0) \), the instantaneous speed \( v(t) \) at time \( t \) can be expressed as
\[
v(t) = \bar{v}(0) + \int_{0}^{t} a(y)dy, \tag{11}
\]
where \( a(y) \) is the acceleration of a vehicle at time \( y \). Using [11], the distance traveled by a given vehicle for a given time interval \([0, t]\) is defined as
\[
D_w(t) = \int_{0}^{t} v(y)dy. \tag{12}
\]
Thus, using (12), each vehicle can compute its distance traveled in time period \( t \). The vehicular user can check whether a PU is reachable or not after certain time \( t \) by using distance traveled in a given time interval, its initial speed, its acceleration and the protection range of the PU. Then, the distance between the mobile secondary user and stationary PU for the interval \([0, t]\), where the secondary user is approaching PU and initial separation distance between them was \( D \), is computed as
\[
D_e = |I(su) \times D_w(t) + D|,
\]
where \( I(su) \in \{-1, 1\} \), i.e., if vehicular user is approaching PU, then \( I(su) = -1 \), and if the vehicular user is moving away from PU, then \( I(su) = 1 \). We can easily derive the probability density function of the random variable time \( t = \tau \) as
\[
f_\tau(t) = \int_{0}^{\bar{v}} f_v(|I(su) \times D_w(t) + D|) f_v(v)dv. \tag{13}
\]
Then, we can further derive the probability of event \( \beta, Pr(B) \), with respect to secondary user’s velocity \( v \) as
\[
Pr(B) = Pr(\tau < |I(su) \times D_w(t) + D|) \leq S = \int_{-\infty}^{\bar{v}} \int_{-\infty}^{\bar{v}} f_\tau(t)dt
\]
\[
= \int_{-\infty}^{\bar{v}} \int_{-\infty}^{\bar{v}} \frac{1}{\sqrt{2\pi}\sigma_v} \exp \left[ - \frac{(v - \mu_v)^2}{2\sigma_v^2} \right] dvdt. \tag{14}
\]
which proves (4).

Then, the probability of event \( \alpha \) can be calculated as
\[
Pr(A) = 1 - Pr(B), \tag{15}
\]
which proves (15). Thus, (7), (14) and (15) prove the Proposition 1.

Furthermore, from (7), we can see that \( Pr(B) \) depends on sensing range of vehicular user, velocity of the vehicular user and initial distance between the PU and vehicular user, and protected radius of PU.

Proposition 2. The probability of misdetection that depends on sensing range of vehicular user, protection range of PU, velocity of vehicular user and energy detection threshold is given by
\[
Pr(\text{miss}) = Pr(R_E \leq \lambda_E | H_0, B)Pr(B)Pr_{\text{(ON→OFF)}} + Pr(\lambda_E \leq R_E | H_0, A)Pr(A)Pr_{\text{(OFF→ON)}}, \tag{16}
\]
where
\[
Pr(R_E \leq \lambda_E | H_1, B) = 1 - Pr(R_E > \lambda_E | H_1, B)
= 1 - Q \left( \frac{\lambda_E - E(R_E | H_1, B)}{\sqrt{\text{Var}(R_E | H_1, B)}} \right), \tag{17}
\]
and
\[
Pr(R_E \leq \lambda_E | H_0, A) = 1 - Pr(R_E > \lambda_E | H_0, A)
= 1 - Q \left( \frac{\lambda_E - E(R_E | H_0, A)}{\sqrt{\text{Var}(R_E | H_0, A)}} \right), \tag{18}
\]
with \( E(R_E | H_0, A) = n(\sigma_{\text{noi}}^2) \) and \( \text{Var}(R_E | H_0, A) = 2n(\sigma_{\text{noi}}^2)^2 \).

Proof. Without loss of generality, PUs being active and idle are exponentially distributed with parameters \( \alpha \) and \( \beta \) respectively [20]. Then, the probabilities of PU being present/active and absent/idle are, respectively, represented by \( p_P \) and \( p_a \) and are given as
\[
p_P = \frac{\alpha}{\alpha + \beta}, \quad p_a = \frac{\beta}{\alpha + \beta}. \tag{19}
\]
The probability \( Pr_{\text{(OFF→ON)}} \) is used to denote that the given PU during current sensing period \( t \) is ON, which was OFF/idle during the previous sensing period.

Similarly, the probability \( Pr_{\text{(ON→OFF)}} \) is used to denote the channel will be used by the PU during current sensing period \( t \) which was also ON/active during previous sensing period. With this information, the probability \( Pr_{\text{(OFF→ON)}} \) can be expressed as
\[
Pr_{\text{(OFF→ON)}} = p_P - p_P e^{-(\alpha + \beta)t}. \tag{20}
\]
Similarly, the probability \( Pr_{\text{(ON→OFF)}} \) can be expressed as
\[
Pr_{\text{(ON→OFF)}} = p_a + p_a e^{-(\alpha + \beta)t}. \tag{21}
\]
Then, by considering secondary user mobility and primary user activity for probability of mistestion on spectrum sensing, \( Pr(\text{miss}) \), can be expressed as follows
\[
Pr(\text{miss}) = Pr(R_E \leq \lambda_E | H_1, B)Pr(B)Pr_{\text{(ON→OFF)}} + Pr(\lambda_E \leq R_E | H_1, A)Pr(A)Pr_{\text{(OFF→ON)}}, \tag{22}
\]
where \( R_E \) is the energy of the received signal at the target user in (2), \( \lambda_E \) is the threshold, and \( Pr(B) \) and \( Pr(A) \) are, respectively probabilities of PU being inside and outside the sensing range of the secondary user. The probabilities \( Pr(R_E \leq \lambda_E | H_1, B) \) and \( Pr(\lambda_E \leq R_E | H_1, A) \) represent the conditional probability of misdetection for the event \( \beta \) and event \( \alpha \) respectively. To find these conditional probabilities \( Pr(R_E \leq \lambda_E | H_1, B) \) and \( Pr(\lambda_E \leq R_E | H_1, A) \), we used energy detection given in (2) to find whether there is PU signal present or not [15,16]. The energy of the signal is compared against the threshold and decision is made based on (2).

For a given secondary user with the event \( \beta \), the conditional probability \( Pr(R_E \leq \lambda_E | H_1, B) \) can be written using Q(\_) function as follows
\[
Pr(R_E \leq \lambda_E | H_1, B) = 1 - Pr(R_E > \lambda_E | H_1, B)
= 1 - Q \left( \frac{\lambda_E - E(R_E | H_1, B)}{\sqrt{\text{Var}(R_E | H_1, B)}} \right), \tag{23}
\]
where \( E(R_E | H_1, B) = n(\sigma_{\text{noi}}^2 + \sigma_{\text{sig}}^2)^2 \) with \( n = 2 \) degree of freedom in vehicular network and \( \text{Var}(R_E | H_1, B) = 2n(\sigma_{\text{noi}}^2 + \sigma_{\text{sig}}^2)^2 \) for noise variance \( \sigma_{\text{noi}} \) and received signal variance \( \sigma_{\text{sig}} \) [11]. Similarly, for the event \( \alpha \), the conditional probability \( Pr(\lambda_E \leq R_E | H_1, A) \) can be written as follows
\[
Pr(R_E \leq \lambda_E | H_0, A) = 1 - Pr(R_E > \lambda_E | H_0, A)
= 1 - Q \left( \frac{\lambda_E - E(R_E | H_0, A)}{\sqrt{\text{Var}(R_E | H_0, A)}} \right), \tag{24}
\]
where \( E(R_E | H_0, A) = n(\sigma_{\text{noi}}^2)^2 \) and \( \text{Var}(R_E | H_0, A) = 2n(\sigma_{\text{noi}}^2)^2 \).

Which proves the Proposition 2.
Based on misdetection probability in (22), the probability of successful detection can be computed as $Pr(\text{success}) = 1 - Pr(\text{miss}).$

Note that based on our analysis there is no significant impact of speed of vehicular secondary user and PU activity on false alarm. Due to this reason and the space limitation, formal mathematical analysis and numerical results are not included in the paper.

**Proposition 3.** The expected overlap time duration between PU and mobile secondary user is

$$E(T) = \frac{1}{E(V)} \int_0^\infty \frac{1}{\sqrt{2\pi \sigma_v^2}} \left[ \exp \left\{ \frac{-(v-\mu_v)^2}{2\sigma_v^2} \right\} \right]^2 dv,$$

(25)

**Proof.** For the expected velocity $E(V)$ and PU’s sensing range $s$, the expected value of overlapping time duration $T$ available between stationary PU and mobile secondary user can be computed as

$$E[T] = \frac{s}{E(V)}.$$  

(26)

The Eq. (26) does not consider the impact of initial distance between PU and the vehicular, and assumes that the PU and vehicular user are within the communication range of each other at the beginning. However, the expected time duration depends jointly on the sensing range of the secondary user, the initial distance between PU and vehicular user, and the speed of the vehicular user. Thus, the overlapping time duration $T$ is a random variable with a probability density function in (13) and its expected value can be computed as

$$E(T) = \int_0^T t f_T(t) dt.$$  

(27)

By substituting (13) into (27), we get the expected overlapping time duration as

$$E(T) = \int_0^\infty \frac{1}{\sqrt{2\pi \sigma_v^2}} \left[ \exp \left\{ \frac{-(v-\mu_v)^2}{2\sigma_v^2} \right\} \right]^2 dv,$$

(28)

where $T = (S - D)/\nu$. This proves the Proposition 3.

Note that in order for a mobile secondary user to be able to sense the PU signal correctly, the value of $E(T)$ in (28) should be greater than or equal to sensing time $W$ in (2), that is, $E(T) \geq W$. Otherwise, the secondary user would not have enough time to collect sufficient signal samples to make a correct decision.

### 4. Opportunistic communication in cognitive IoV

Once the idle channel is found, vehicular users (secondary users) access idle channel for opportunistic communications. For a given channel, the expected data rate $R_n$ for a given channel $n$ based on the achievable data rate $R_e$ (e.g. 11 Mbps, 24 Mbps, 54 Mbps) and the probabilities of channel being used by PU $P_{ON \rightarrow ON}$ and $P_{OFF \rightarrow ON}$ can be expressed as

$$R_n = R_e(1 - P_{OFF \rightarrow ON})(1 - P_{ON \rightarrow ON}).$$  

(29)

Then, the data rate per vehicular user for $N_n$ total number of vehicular users can be computed as

$$R_{n}^1 = \frac{R_n}{N_n}.$$  

(30)

Note that $N_n$ can be estimated based on the periodic broadcast status message in IoV [22]. When multiple channels are idle, a given vehicular user selects the channel which offers the highest data rate and satisfies its required data rate ($R^1$) as

$$c = \arg \max_n R_{n}^1, \quad \forall n, \quad \text{subject to} \quad R_{n}^1 \geq R^1.$$  

(31)

For instance, when a vehicular user can use 802.11p channels (which offers maximum of 27 Mbps data rate) when no channel opportunities are available. However, when there are channel opportunities in other bands than 802.11p and all 802.11p channels are already overcrowded, vehicular users could switch to the other channels that offer higher data rate such as TV or WiMAX channels if available.

Because of the error in transmission, each vehicular user may have to retransmit the information. The expected retransmission count, that is the average number of retransmissions needed to transfer a packet successfully, can be estimated as [23]

$$T_c = \sum_{m=1}^{\infty} m p_m^{m-1} (1-p_f) = \left[ \frac{1}{1-p_f} \right].$$  

(32)

where $[\cdot]$ is a ceiling operator. The $p_f$ is the probability of failure with $p_e$ and $p_u$ as transmission error in downlink and uplink transmissions respectively, that is

$$p_f = 1 - (1-p_e)(1-p_u).$$  

(33)

When failure probability $p_f=1$, the $T_c$ in (32) is very large that implies that retransmission will be done for very long time. Along the line of [24], we can express the expected successful data delivery time in terms of $T_c$ for data of size $D_S$ bits with a data rate $R_{n}^1$ as

$$T_f = T_c \cdot \frac{D_S}{R_{n}^1}.$$  

(34)

### 5. Performance evaluation

This section presents the simulation scenarios and numerical results obtained from simulations to corroborate our theoretical analysis presented in previous sections. Vehicular user (or secondary user) is considered to be mobile and each vehicular users has its sensing range. The residential base stations or access points are considered to be PUs and each PU has its protection range where secondary users are not permitted to use PUs’ active channels.

First, we plotted the variation of probability $Pr(B)$ vs. the sensing range for a given protection range of PU $r = 110$ meter as shown in Fig. 2. The maximum sensing range of secondary user is considered to be the same as the maximum range in IEEE 802.11p...
DSRC standard for vehicular networks [25]. We observed that the probability $Pr(B)$ increases with the sensing range as shown in Fig. 2.

Second, we plotted the variation of probability of mis-detection $Pr(\text{miss})$ versus the speed of mobile secondary user where a given PU's protection range $r = 110$ meter, initial separation distance between PU and secondary user $D = 200$ meter and secondary user's sensing ranges ($s = 250, 500, 750$ and $1000$ meter) as shown in Fig. 3. The probability PU being ON, $PU_{ON \rightarrow ON}$ from $0.30$ to $0.60$ to $0.90$ to see how PU's OFF → ON activity impacts the performance of mis-detection. In Fig. 3, we observed that the probability $Pr(\text{miss})$, decreased when the sensing range of the secondary user increased for a given $PU_{ON \rightarrow ON}$ value. However, the probability of mis-detection increased when the speed of the mobile secondary user increased for a given $PU_{OFF \rightarrow ON}$ value. In other words, a faster speed resulted in a higher probability of mis-detection as the fast speed made PU be outside the secondary user's sensing range quickly resulting in the higher chance of misdetection of PU's signal. We also observed that when the probability of PU being active during sensing period (when it was idle in previous sensing period) increased from $0.3$ to $0.60$ to $0.9$, the probability of misdetection increased by approximately $10\%$ for each case with secondary user's speed higher than $40$ km/hr as shown in Fig. 3. This happens since PU was idle in previous sensing period and it is expected to be idle during current sensing period with given probability but it is not idle which results in higher mis-detection probability for a given sensing range.

Next, we considered different values of $PU_{ON \rightarrow ON}$ and plotted the variation of probability of mis-detection versus the velocity of secondary user with different sensing ranges as shown in Fig. 4. We observed that when $PU_{ON \rightarrow ON}$ increased from $0.3$ to $0.60$ to $0.9$, the mis-detection probability increased for a given velocity as shown in Fig. 4. When $PU_{ON \rightarrow ON}$ is greater than $PU_{OFF \rightarrow ON}$, the mis-detection probability is decreasing for increasing velocity of the secondary user as shown in Fig. 4. Furthermore, from both Figs. 3 and 4, we observed that when probability $PU_{OFF \rightarrow ON}$ is greater than or equal to the probability $PU_{ON \rightarrow ON}$, the probability of mis-detection increased.

Then, we plotted the variation of expected overlapping duration per epoch versus the secondary user's speed as shown in Fig. 5. In this scenario, we considered the protection range of PU $r = 110$ meter, an initial separation distance between PU and secondary user $D = 200$ meter, and secondary user's sensing range $s = 1000$ meter for reference plot in Fig. 5. The secondary user's sensing range was varied as $s = 250, 500, 750$ and $1000$ meter. In Fig. 5, we observed that the expected overlapping duration per epoch decreased with increasing speed for a given sensing range and it increased with increasing sensing range of the secondary user. This can be interpreted as, for higher sensing range, the PU has a higher possibility to fall into the secondary user's sensing range for longer overlapping time duration. Furthermore, from Fig. 5, we observed that the expected overlapping time using (26) was highest since it assumes that initial separation distance between PU and the secondary user is equal to the sensing range of the secondary user, and PU and the secondary user are assumed to be within the communication range of each other at the beginning.

Next, for performance evaluation of dynamic spectrum access for opportunistic communication, we plotted the variation of per-user data rate for vehicular users vs. the number of vehicular users as shown in Fig. 6. The per-user data rate decreases when a number of user in IoV increases because of sharing of the same channel.
Then, we plotted the variation of expected transmission time vs the achievable data rate for given number of vehicles and probability of transmission failure as shown in Fig. 7. We observed that expected transmission time decreases with the increasing achievable data rate for given number of users and probability of failure as shown in Fig. 7. Expected transmission time is highest (or lowest) when more (or less) vehicles are present and highest (or lowest) probability of transmission failure.

Finally, we plotted the variation of expected transmission count versus the probability of transmission failure as shown in Fig. 8. We observed that when transmission failure increases, the expected transmission count increases exponentially and when failure probability $p_f$ is 1, transmission count reaches to infinity which means there will be no successful transmission of the packet.

6. Conclusion

In this paper, we have studied the combined impact of secondary user mobility and primary user activity for dynamic spectrum access in cognitive IoV. Formal analytical model for the probability of mis-detection for spectrum sensing and expected overlapping time duration per epoch for mobile secondary users are derived. Furthermore, expected transmission time and count for retransmission in case of packet delivery failure are derived based on the operating condition of the network. Performance of the proposed formal models are evaluated using numerical results obtained from Monte Carlo simulations. We found that when the speed of the vehicles increased, the probability of mis-detection increased (but no significant impact on false alarm) and the expected overlapping time duration per epoch (between mobile secondary user and stationary PU) decreased. Opportunistic communications in cognitive IoV can enhance the overall network performance by disseminating the information in a timely manner.

Acknowledgments

This work was supported in part by the U.S. National Science Foundation (NSF) under grants CNS-1658972 and CNS-1650831, and by the U.S. Department of Homeland Security (DHS) under grant award number, 2017ST000003. However, any opinion, finding, and conclusions or recommendations expressed in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the funding agencies. The authors would like to thank T. Amin for the discussions on the presented topic.

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