Weighted Cooperative Spectrum Sensing for Cognitive Vehicular Networks

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***Abstract*—With the rapid development of intelligent transportation systems, vehicular devices are getting connected with each other. However, this leads to the problem of spectrum scarcity. Dynamic spectrum access (DSA)/cognitive radio (CR) has emerged as an effective solution to solve the problem of inefficient spectrum utilization. Spectrum sensing is the key in DSA/CR system. In cognitive vehicular networks (CVNs), spectrum sensing becomes more complex and challenging and that often leads to a loss in performance detection. Due to the effect of channel fading/shadowing and due to secondary user (SU) mobility, individual SUs may not be able to detect the existence of primary user (PU). In this paper, we propose a weighted cooperative spectrum sensing (weighted-CSS) framework for accurate detection of PU in CVNs. The weights are calculated from the probability of PU being inside the SU's sensing range and SU being outside the PU's protection range (inside probability). The calculated weight for SU indicates the reliability in the signal received by SU. The framework contains two stages. In the first stage, inside probability is calculated at each SU and the inside probability and the energy signal received from PU are sent to a base station (BS). In the second stage, BS assigns a weight to each SU based on the inside probability and makes a decision by combining the information received from SUs. Numerical results indicate that, on an average, the proposed framework performs $\approx$ 15% better than the conventional local spectrum sensing.**

***Index Terms*—Cognitive vehicular networks, weighted cooperative spectrum sensing, secondary user mobility.**

I. Introduction

The intelligent transportation system (ITS) is an important part to revolutionize the traditional vehicle into the digital automated vehicle. Numerous vehicles are getting connected to the internet through vehicle-to-anything (V2X) communication technologies [1]. As communication technologies are getting integrated with vehicular networks it will improve the transportation safety and traffic management system.

With rapid development of ITS and its applications, vehicular networks are facing severe spectrum scarcity [2] and it becomes important to solve the problem efficiently. The U.S Federal Communication Commission has allocated 75MHz spectrum bandwidth at 5.9-GHz for dedicated short-range communication. This spectrum is only used for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. However, recent studies indicate that in dense traffic scenario, allocated spectrum can get exhausted [3], which may result in congestion for vehicular communications.

Dynamic spectrum access / cognitive radio (DSA/CR) has been introduced as a revolutionary solution to the problem of spectrum scarcity. DSA/CR aims at better utilization of spectrum by allocating frequency spectrum dynamically instead of static allocation. Spectrum sensing is the key in DSA/CR systems. If the primary user (PU) is idle, then DSA/CR system allows the secondary users (SUs) to temporarily access the frequency channels of PUs without creating any harmful interference to PUs [4].

In literature, various spectrum sensing methods and techniques have been proposed. However, most of them assume SU to be stationary or with low mobility. In [5], [6], authors investigated the impact of SU mobility on the spectrum sensing performance. In [7], the authors have proposed an improved energy detection algorithm to study the impact of SU mobility on detection performance in cognitive vehicular network (CVN). In [8]–[10] authors have analysed the performance of energy detection considering arbitrarily correlated dual antenna receiver and correlated multi-antenna receiver for mobile cognitive user. While, other relevant works can be found in [11], [12]. However, all the previous works considered a single user scenario. While, in case of CVN, due to the effect of multipath fading and shadowing, spectrum sensing becomes more complex and challenging and thus decision taken by individual SU can not be reliable. To overcome this, cooperative spectrum sensing approach has been adapted in the literature which exploits the benefit of spatial diversity among SUs [13]–[16].

However, using only cooperative spectrum sensing will not solve the problem because SU will only be able to correctly receive the signal transmitted by PU if the PU is inside the sensing range of SU. Moreover, as SUs are mobile, the distance between PU and SU will be time varying. As a result, PU may fall inside the sensing range of SU at one instance and outside at another instance. Thus, if at any instance PU falls outside the sensing range of SU, then, SU is unable to notice the existence of PU and, irrespective of the signal transmitted by PU, SU will only receive noise. To overcome this, we devise an approach where each SU is assigned a weight which indicates the reliability of the information provided by the SU. These weights are calculated from the probability that the PU is inside the sensing range of SU and SU is outside the protection range of PU (inside probability).

In this context, we propose a weighted cooperative spectrum sensing (weighted-CSS) framework for CVNs in a centralized environment. For simplicity, we consider the interweave spectrum sharing paradigm. The framework is divided into two stages. In the first stage, the inside probability is calculated for each SU. There are two methods for calculating the inside probability: 1) using the distribution of the distance between PU and SU, and 2) using the coordinates of the SU. The detailed analyses for both methods are given. In the second stage, the received signal from PU, along with inside probability, will be sent to the base station (BS) by each SU using dedicated channel in an orthogonal manner. At BS, a weight for each SU is calculated using the inside probability. To take the effect of SU mobility into account, the sensing information from a SU that has higher inside probability is assigned with a higher weight. In decision making at BS, the contribution of the sensing information of the SUs having low inside probability will be negligible. By combining all the information received from SUs, BS reaches a decision and informs all the SUs about it.

The main contributions of this paper are threefold and can be summarized as follows:

- Firstly, distance distribution based and coordinates based method for calculating inside probability are analyzed.
- Secondly, an algorithm for assigning weights to each SU at BS is proposed. The assigned weight indicates the reliability of sensing information received from that SU.
- Lastly, performance analysis is carried out to analyze false alarm and miss detection probabilities for the proposed weighted-CSS framework and verified by simulations. Numerical results indicate that, on an average, the proposed framework performs $\approx 15\%$ better than the conventional local spectrum sensing.

The remainder of this paper is organized as follows. In Section II network model is defined. Section III contains the proposed weighted cooperative spectrum sensing framework and its analysis. Numerical and simulation results are explained in Section IV. Finally, concluding remarks are presented in Section V.

II. Network model

The network model considered for modelling SU mobility is illustrated in Fig. 1. M mobile SUs are considered where S_i is the sensing range of ith SU, v_i is the velocity for $i = 1 \dots M$ and one stationary PU with protection range (R). To avoid any harmful interference, the sensing range of SU is considered to be greater than or equal the to protection range of the PU. The initial distance between PU and SU$_i$ is D_0^i and after some time t, SU$_i$ moves distance $v_i t$ and at that time the distance between PU and SU$_i$ changes to D_t^i.

For any SU to detect a PU, it is necessary that the PU is within the sensing range of SU otherwise SU will not be able to notice the existence of PU. It is also important to note that the PU has a protection range where SUs are not allowed to access bands at any cost [4]. Thus, spectrum sharing is only possible when PU is inside the sensing range of SU and SU is outside the protection range of PU. The time varying distance D_t^i between PU and any SU$_i$ at any time moment determines

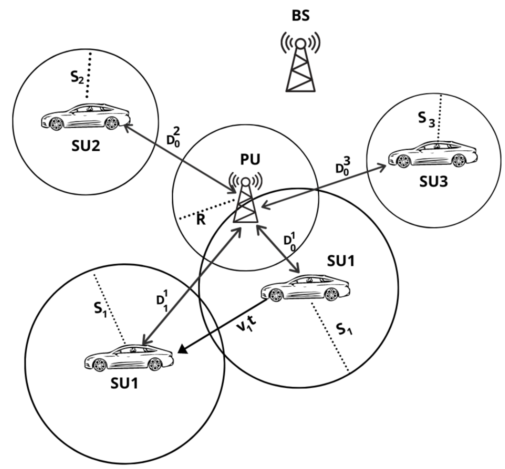

Fig. 1: Considered Network Model

whether the SU will be able to notice the PU and correctly receive the transmitted signal energy. In this context, we define following two events:

- Event "I": PU being inside the sensing range of SU and SU being outside the protection range of PU
- Event "O": PU being outside the sensing range of SU

Note that, at any time, if the SU is inside the protection range of PU ($D_t^i \leq R$) then, SU will be able to detect the PU. But in this case even if PU is idle, SU is not allowed to access PU band at any cost [4]. That is why for event "I", we are only considering the area in which SU can detect PU and transmit if channel is free.

From the perspective of the SU, the channel alternates between two states: idle (no activity) and busy (occupied). The PU channel activity can be modeled by two state birth-death process [7]. Thus, for spectrum sensing we define binary hypothesis for Event "I" as follows:

$$y_I(t) = \begin{cases} n(t), & H_0 \\ h(t)x(t) + n(t), & H_1 \end{cases} \tag{1}$$

For Event "O" SU only receives noise regardless of the state of PU. In this scenario the hypothesis turns into following scenario:

$$y_O(t) = n(t), \quad H_0, H_1 \tag{2}$$

where $y_I(t)$ is the signal that SU receives given Event "I". $x(t)$ denotes the transmitted PU signal, $n(t)$ is the additive white Gaussian noise (AWGN), $h(t)$ represents channel gain, $y_O(t)$ is the signal that SU receives given Event "O".

III. Proposed Weighted Cooperative spectrum sensing

A. Inside probability analysis

In this section, the inside probability for each SU ($\Pr^i(I)$) is derived using distance distribution and using SU's coordinates. Detailed analysis of methods is presented below:

1) Distance distribution method: The inside probability can be derived using the cumulative distribution function of the distance D^i between stationary PU and mobile SU$_i$. Now according to [6] the cumulative distribution function of the distance between static PU and mobile SU can be assumed as log-normal distribution i.e.

$$F_D^i(d^i) = \frac{1}{2}\left[1 + \text{erf}\left(\frac{d^i - \mu_d^i}{\sigma_d^i\sqrt{2}}\right)\right] \tag{3}$$

where, erf$(\cdot)$ denotes the error function, μ_d^i and σ_d^i denote the mean and standard deviation of distance between static PU and mobile SU$_i$. Similarly, cumulative distribution function for sensing range of SU$_i$ and protection range of PU can be defined. As discussed earlier, SU will be only able to detect PU and transmit (if possible), when the distance D^i, between the SU$_i$ and PU, is between PU's protection range (R) and SU$_i$'s sensing range (S_i). Thus, we can write probability of event "I" for SU$_i$ as [7]:

$$\begin{aligned} \Pr^i(I) &= \Pr(R < D^i \leq S_i) \\ &= \Pr\left(R < D_0^i + v_i t \leq S\right) \\ &= \Pr\left(\frac{R - D_0^i}{v_i} < t \leq \frac{S_i - D_0^i}{v_i}\right) \end{aligned} \tag{4}$$

According to [17], SU velocity can assumed to be Gaussian distributed. The distance between PU and SU is assumed to be log-normal distributed, using theory of random variable, distribution of time can be derived as log-normal distribution [7]. Using this, the above equation can be written as:

$$\begin{aligned} \Pr^i(I) &= F_T^i\left(\frac{S_i - D_0^i}{v_i}\right) - F_T^i\left(\frac{R - D_0^i}{v_i}\right) \\ &= \frac{1}{2}\left[\text{erf}\left(\frac{\frac{S_i - D_0^i}{v_i} - \mu_t^i}{\sigma_t^i\sqrt{2}}\right) - \text{erf}\left(\frac{\frac{R - D_0^i}{v_i} - \mu_t^i}{\sigma_t^i\sqrt{2}}\right)\right] \end{aligned} \tag{5}$$

where D_0^i is the initial distance between PU and SU, μ_t^i and σ_t^i are the mean and standard deviation of time distribution, S_i is the SU's sensing range, R is the PU's protection range, v_i is the SU's velocity.

2) Coordinates method: The probability of Event "I" can be also calculated for each SU using the coordinates of the mobile SU. Here, SU coordinates are generated using random way-point mobility model, in which SU can move randomly in a fixed square area with its velocity and it is assumed that PU is fixed at center. A sufficiently large ($\approx 10^6$) number of SU coordinates are generated. Now, for each SU coordinates, the Euclidean distance from PU[1] is calculated. From this distance and using the definition of inside probability ($R < D_i < S_i$), we can calculate the inside probability. Assuming we have total K coordinates for SU$_i$ and those are denoted by $[(x_1, y_1), (x_2, y_2), ..., (x_k, y_k)]$, the PU coordinates are denoted as (x, y), then using Algorithm 1, the inside probability for SU$_i$ can be calculated.

[1]The position of PU can be estimated using channel state information which may be available in CVN over control and broadcast channels.

Algorithm 1: Inside Probability

Input: PU protection range (R),
SU sensing range (S_i),
PU coordinates (x, y),
SU coordinates $[(x_1, y_1), (x_2, y_2), ..., (x_k, y_k)]$

for $z \leftarrow 1$ **to** K **do**
  distance[z]=$\sqrt{(x_z - x)^2 + (y_z - y)^2}$
  if *$R \leq$ distance[z] $\leq S_i$* **then**
    count(Event "I")=count(Event "I")+1
  end
end
$\Pr^i(I)$=count(Event "I")/K

B. Decision making at BS

In this section, we explain how BS makes a final decision about channel status. First a weight assignment algorithm (see Algorithm 2) is introduced which assigns weight to each SU based on its inside probability. The basic idea behind the proposed weight assignment algorithm is that the higher the inside probability, the higher the confidence we have on the sensing information received from that SU.

Algorithm 2: Proposed weight assignment algorithm

Input: $\Pr^i$(I) for i =1,...M
for $i \leftarrow 1$ **to** M **do**
  $w_i = Pr^i(I) / \sum_{k=1}^{M} Pr^k(I)$
end

Here w_i is the calculated weight for each SU, the output signal received at BS is $Y = \sum_{i=1}^{M} w_i \cdot y_i$. The final decision is made by comparing Y to a threshold. Here y_i is the energy signal sent by SU$_i$. As y_i are assumed to be i.i.d. Gaussian random variable and w_i is constant, we can say that Y also follows Gaussian distribution i.e.

$$Y \sim \begin{cases} \mathcal{N}\left(\sum_{i=1}^{M} w_i \cdot E(y_i|H_0), \sum_{i=1}^{M} w_i^2 \cdot \text{Var}(y_i|H_0)\right) & H_0 \\ \mathcal{N}\left(\sum_{i=1}^{M} w_i \cdot E(y_i|H_1), \sum_{i=1}^{M} w_i^2 \cdot \text{Var}(y_i|H_1)\right) & H_1 \end{cases} \tag{6}$$

C. Performance of the proposed scheme

Now, the false alarm probability (P_f) of the proposed weighted-CSS scheme can be derived as:

$$\begin{aligned} P_f &= \Pr\left(Y > Th|H_0\right) \\ &= Q\left(\frac{Th - E\left(Y|H_0\right)}{\sqrt{\text{Var}\left(Y|H_0\right)}}\right) \end{aligned} \tag{7}$$

where, $E(Y|H_0) = \sum_{i=1}^{M} w_i \cdot E(y_i|H_0)$ and $\text{Var}(Y|H_0) = \sum_{i=1}^{M} w_i^2 \cdot \text{Var}(y_i|H_0)$ are conditional mean and variance of Y respectively and Th represents decision threshold.

Similarly, the miss detection probability (P_{md}) of the proposed weighted-CSS scheme can be derived as:

$$\begin{aligned} P_{md} &= \Pr\left(Y \leq Th|H_1\right) \\ &= 1 - Q\left(\frac{Th - E\left(Y|H_1\right)}{\sqrt{\text{Var}\left(Y|H_1\right)}}\right) \end{aligned} \tag{8}$$

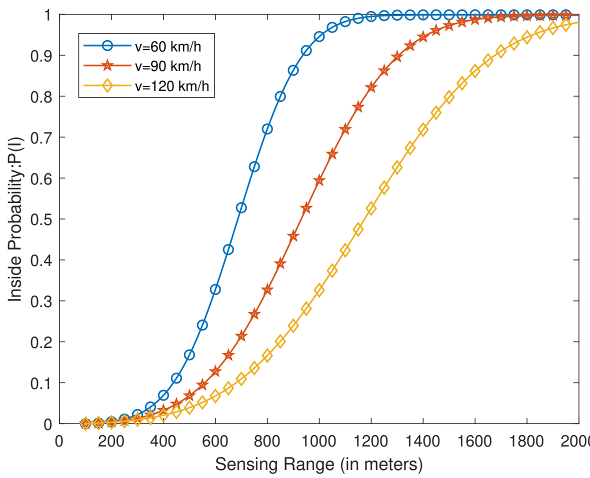

Fig. 2: Inside probability (R=100m, D_0^i=200m)

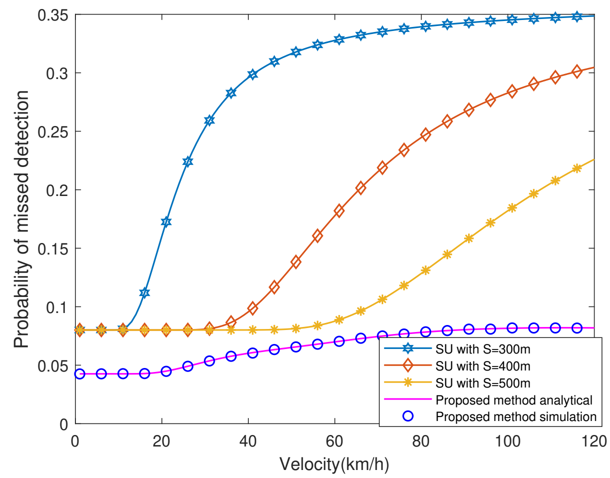

Fig. 4: Comparison of miss detection probability using conventional method and proposed method weighted-CSS (S=[300, 400, 500]m, D_0^i=[200, 220, 240]m R=100m, $\Pr(ON)$=0.5 and $\Pr(OFF)$=0.5)

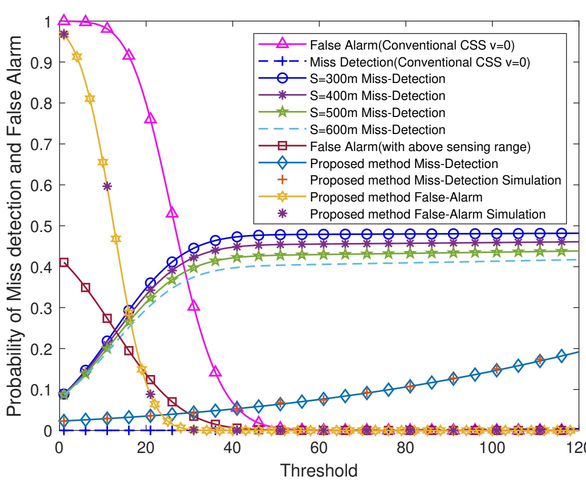

Fig. 3: Comparison of false alarm and missed detection probability (S=[300, 400, 500, 600]m, D_0^i=[210, 220, 230, 240]m, v_i=[25, 30, 35, 40]m/s, R = 100m)

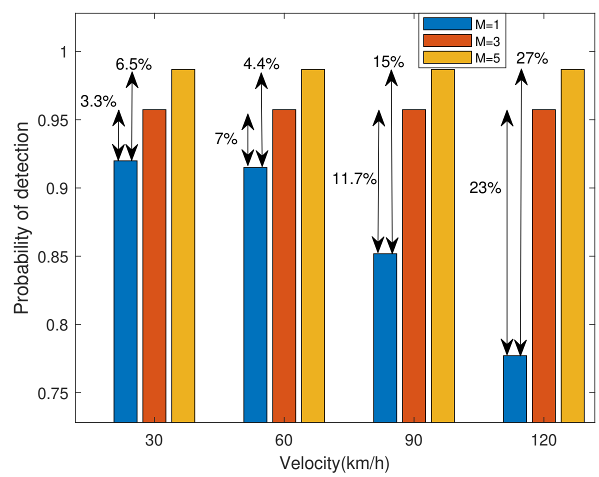

Fig. 5: Comparison of gain in detection probability using conventional method and proposed weighted-CSS at different velocities ($\Pr(ON)$=0.5 and $\Pr(OFF)$=0.5)

where, $E(Y|H_1) = \sum_{i=1}^{M} w_i \cdot E(y_i|H_1)$ and $\mathrm{Var}(Y|H_1) = \sum_{i=1}^{M} w_i^2 \cdot \mathrm{Var}(y_i|H_1)$ are conditional mean and variance of Y respectively.

IV. Numerical and simulation results

In this section, simulation results are presented to corroborate the proposed spectrum sensing framework. For SU mobility simulations, random way-point mobility model is used with PU being fixed at center. Approximately 10^6 random way-points are generated. These random way-points are treated as the coordinates of mobile SU and for each way-point its distance from PU is obtained. Using this distance, the inside probability for that SU is calculated. In the same manner, inside probability is calculated for all SUs.

In Fig. 2, the plot for inside probability as a function of the sensing range for single SU is shown. Results shown in Fig. 2 are calculated analytically using (5) and the Monte-Carlo simulations are performed using the coordinates method. We observe that as sensing range is increased from 0m to 2000m, as expected the inside probability increases. We can also observe that for a particular value of sensing range, inside probability increases when the velocity of the SU decreases. This can be understood as with a higher SU velocity, the PU will be quickly outside the SU's sensing range and that leads to decrease in inside probability.

In Fig. 3, the impact of SU mobility on false alarm and miss detection probabilities is demonstrated. Here, we have assumed that during one sensing period, SU velocity remains unchanged. The noise variance is randomly generated with 0 mean and variance of 1. Also, the channel status is set as $\Pr(ON)$=0.5 and $\Pr(OFF)$=0.5. Here, the comparison between conventional false alarm and miss detection probability for single mobile SU and proposed method is given, where the conventional false alarm and miss detection probability are calculated using [7, equation (10) and (11)] with SU having sensing range=[300, 400, 500, 600]m with velocity=[25, 30, 35, 40]m/s and initial distance=[210, 220, 230, 240]m. On the other hand, false alarm and miss detection are calculated using proposed method using equation (7) and (8) respectively with M=4 and for the same sensing range, same velocities and same initial distance as mentioned above. We can observe that false alarm error obtained using proposed method is increased at a cost of significantly reduced probability of miss detection. However, if we select a decision threshold around 20, then the best combination of both false alarm and miss detection can be obtained.

In Fig. 4, the plot of probability of miss detection as a function of the velocity is illustrated. Here, the comparison between conventional miss detection probability for single mobile SU with the proposed method is demonstrated. Miss detection for single SU is calculated from [7, equation (11)] with SU having sensing ranges=[300, 400, 500]m, initial distance=[200, 220, 240]m with $\Pr(ON)$=0.5 and $\Pr(OFF)$=0.5. On the other hand, miss detection probability is calculated using (8) for M=3 with same sensing range and same initial distance as mentioned above. The operating threshold is taken such that $P_f = P_{md}$. We can observe that as SU's velocity increases, the miss detection probability increases. This can be understood as with a higher SU velocity, PU will be quickly outside the SU's sensing range and that will lead to SU having a higher chance of missing PU's signal. As we can clearly see, the miss detection calculated using proposed method gives better performance compared to performance obtained using conventional method for single SU.

In Fig. 5, the gain obtained in detection probability is shown. Detection probability is calculated as $P_d = 1 - P_{md}$. Here, M=1 represents the conventional detection probability calculated for single SU with S=700m with initial distance=200. M=3 represents the detection probability calculated using proposed method for 3 SUs with sensing range=[650, 600, 650]m with initial distance=[210, 200, 210]m. M=5 represents the detection probability calculated using proposed method for 5 SUs with sensing range=[600, 650, 700, 650, 600]m with initial distance=[250, 210, 200, 210, 250]m. We can observe that as we are adding new SUs in the system, though the new added SUs have low sensing range and high initial distance compared to the previous one, we are still able to obtain better detection performance. If we compare the detection performance for $M = 1$ and $M = 3$, an average gain of 13% is obtained. And with $M = 5$, on average we are able to obtain gain of 17%.

V. Conclusions

In this paper, we have proposed a weighted-CSS framework for CVNs. We use coordinate method to compute the inside probability of SU, which is usually not considered in the state of the art schemes. We then propose an algorithm to assign weights to each SU based on the computed inside probability. Furthermore, a comprehensive performance analysis is carried out for the proposed weighted cooperative spectrum scheme. Our analysis and analytical results were confirmed and validated by the Monte-Carlo simulations. For modelling SU's velocity, random way-point mobility model is used. Numerical results indicate that, on an average, the proposed framework performs $\approx 15\%$ better than the conventional local spectrum sensing. Our future work includes the analysis for finding optimal number of SUs that will take part in spectrum sensing, and extending to a scenario where both PU and SUs are mobile.

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