# On the Joint Impact of SU Mobility and PU Activity in Cognitive Vehicular Networks with Improved Energy Detection

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***Abstract*—Dynamic Spectrum Access (DSA)/Cognitive Radio (CR) systems access the channel in an opportunistic, non-interfering manner with the primary network, thus being a promising approach to solve the problem of spectrum scarcity. Energy Detection, a spectrum sensing technique for DSA/CR systems, is widely used for blind sensing of unused frequency bands due to its non-parametric sensing ability and computationally low complexity. However, spectrum sensing becomes more challenging in Cognitive Vehicular Networks (CVNs) due to Secondary User's (SU's) mobility and often yields a detection performance loss as compared to static scenarios. In order to mitigate the impact of reduced detection performance due to mobility, the usage of an improved version of energy detection technique is proposed in this paper. Usage of Improved Energy Detection (IED) technique in CVNs results more than 10% increment in DSA/CR system performance. In this paper, we study the joint impact of SU's sensing range, PU's protection range and SU's mobility model on the PU Activity using IED technique in CVNs, with detection probability and probability of false alarm as the performance metrics. Also, we derive a closed form expression for the probability of PU being inside SU's sensing range. Based on the proposed framework, numerical results show great agreement with analysis, yielding a superior performance.**

***Index Terms*—Cognitive Vehicular Networks, Improved Energy Detection, Secondary User Mobility, PU Activity**

## I. Introduction

Vehicular networks have emerged as a promising technology for improving road safety and ubiquitous wireless communication services. With rapid development of Intelligent Transport Systems (ITS) and its applications, vehicular networks are facing severe spectrum scarcity [1] and it becomes important to solve the problem efficiently.

In order to support the various applications of Vehicular Networks, the U.S. Federal Communications Commission (FCC) has allocated 75 MHz spectrum in the range of 5.850-5.925 GHz for Dedicated Short Range Communications (DSRC). This spectrum is to be used exclusively for vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. In IEEE 802.11p based vehicular networks, the allocated spectrum consists of 7 channels (6 data channels and 1 service channel), 10 MHz each and 5 MHz is reserved for emergency situations. However, recent research indicates that a crowd of communication nodes in dense traffic can easily exhaust the available spectrum [2], [3] which may result in a havoc due to failure of vehicular networks in such situations. Fortunately, Dynamic Spectrum Access / Cognitive Radio (DSA/CR) systems are envisaged to be a promising and reliable approach to solve this problem. DSA/CR systems aim at increasing the efficiency of spectrum use by allowing unlicensed (secondary) users to opportunistically access licensed spectrum bands temporarily unused by the licensed (primary) users in a non-interfering manner [4].

In DSA/CR systems, various sensing methods [5]-[12] and a variety of spectrum sensing techniques have been proposed in the literature [13]-[16]. However, in most of these works, SUs are assumed to be stationary and PUs are assumed to be idle during SU transmissions. It becomes quite essential in real-life scenarios to consider mobility of SUs and its impact on Primary User's (PU's) activity. In [8], mobility of SUs is considered for analyzing the performance of spectrum sensing and scheduling framework. In [10], a cooperative scenario has been considered and the impact of SU mobility has been studied. Effect of SU's mobility has been studied in [11] using random way-point model, where PUs have been assumed to be stationary. In [17], a joint impact of velocity of vehicles, PU's activities, transmission range of PUs and sensing range of SUs to evaluate the performance of spectrum sensing in CVNs. Different from [17], our work uses IED as the local sensing technique for mobile SUs resulting into nearly 10% increment in detection performance, hence outperforming the state of art results. Also, [17] does not provide a closed form expression for probability of PU being inside SU's sensing range, which has been derived in this paper.

CVNs require a very reliable system characterized by minimal miss-detections and false alarms in order to ensure safety and error-free communication. In this work, we emphasize on improving detection performance by implementing a robust blind sensing technique that overcomes the limitations of Classical Energy Detection (CED).

In this paper, the main contributions can be outlined as follows :

1) A closed form expression for the probability of PU being inside SU's sensing range has been derived considering cases when SU is static as well as mobile.
2) IED technique has been incorporated as the sensing scheme instead of using the CED technique. A detailed analysis of the improvement in performance metrics has been carried out along with a comparison of increase in time and memory complexity of IED and CED, hence proposing the usage of this algorithm for further researches in V2V networks.

The remainder of the paper is organized as follows. Section II describes the network model and spectrum sensing hypothesis, hence formulating the problem statement at hand. Section III describes IED technique and its feasibility in CVNs. Section IV consists of analysis of joint impact of SU mobility and PU activity on spectrum sensing in CVNs with and without mobility. Section V contains Numerical Results simulated in order to show comparison between CED and

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IED algorithms. Section VI concludes the paper outlining the important take-aways from the work and enumerates future scope of this research work followed by acknowledgement and references.

## II. Problem Formulation and System Model

In this section, we define the Network Model, PU Traffic Model and Signal Model for Spectrum Sensing in detail.

### A. Network Model

The Network Model considered in this paper has been illustrated in Fig. 1. We consider the typical scenario with one vehicle representing SU with sensing range $S$ and multiple PUs with their protection range $R$ (assuming $S > R$ to avoid interference).

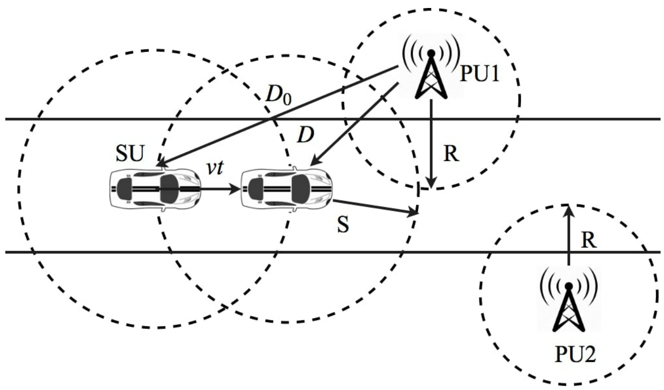


Fig. 1: Network Model

As shown in Fig.1, SU vehicle moves forward on the straight road with velocity $v$ with initial distance between PU and SU being equal to $D_0$. After time $t = t'$, SU vehicle travels a distance equal to $vt'$, altering the instantaneous distance between PU and SU to be equal to $D$. Since, PU is considered stationary in our work, the relative velocity of SU and PU will be equivalent of SU's velocity itself. As evident from Fig.1, the SU's sensing range overlaps with PU's protection range with SU being outside PU's protection range, hence providing spectrum opportunities. This overlap duration creating spectrum opportunities depends on speed and direction of SU, protection range of PU ($R$) and sensing range of SU ($S$).

A joint impact of SU mobility and PU activity on the performance of spectrum sensing in CVNs as in [17] has been considered, but using an improved sensing algorithm. It is essential to note that SUs are not allowed to use PUs' licensed bands under any circumstances [5], [20]. When SU and PU are within each other's ranges, the corresponding SU will be able to sense PU's signals. However, if PU is outside SU's sensing range, SU will not be able to notice existence of PU around it. This scenario becomes more straightforward in non-mobile scenarios, since the distance between static SU and PUs remains unchanged over the course of time. Nonetheless, when SU is mobile (like in CVNs), the PU may fall inside at one instance of time and outside at another, making it's impact significant on the sensing performance. Clearly, the distance between SUs and PUs is a crucial parameter, it being the deciding factor of PU's position with respect to SU's sensing range (inside or outside).

### B. Signal Model for Spectrum Sensing

Based on the two possible scenarios discussed above, let us define two events as follows :

- Event "I" : PU is inside sensing range of SU.
- Event "O" : PU is outside sensing range of SU.

Now, from SU's viewpoint, the channel alternates between two states: "PU as Idle" and "PU as Busy". Hence, we define the conventional binary hypothesis for Event "I" as follows:

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

where, $n(t)$ represents the Additive White Gaussian Noise (AWGN), $h(t)$ represents the sensing channel gain, $x(t)$ denotes the transmitted signal from PU and $y_I(t)$ denotes the signal received at SU given Event "I".

For Event "O", SU solely receives noise regardless of PU's activity (busy or idle). Hence, we formulate the spectrum sensing model for Event "O" as follows:

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

where $y_O(t)$ represents the signal received at SU given Event "O". Here, SU adopts IED instead of CED which will be elucidated in the next section.

## III. Improved Energy Detection in CVNs

In CVN environment, vehicles as communicating nodes move with relatively higher speed compared to nodes in other network environments. Hence, it is necessary to use an algorithm that detects PU activities effectively, minimizing miss-detection and false alarm rate [23]. Therefore, usage of CED as the sensing technique in CVNs is not a wise approach due to its limitations of sensing highly variable signals and instantaneous energy drops.

IED was proposed in order to avoid false alarms or rather reduce their frequency of occurrence as an improvement of Modified Energy Detection (MED) [12]. An additional check is performed by the IED algorithm on the basis of test-statistic of the preceding sensing event. To the best of authors' knowledge, IED has not been used in CVNs, where the usage of such an improved version of non-parametric blind sensing technique can be a blessing to mitigate the reduced performance due to mobility.

Test-statistic as defined for CED, measures the energy received on a primary band during an observation interval and declares the PU's state as busy if the measured energy is greater than a predefined threshold $\lambda$, or idle otherwise [24].

$$\mathcal{T}_i(y_i) = \sum_{n=1}^{N} |y_i(t)|^2 \tag{3}$$

Using Central Limit Theorem assuming large number of samples:

$$\mathcal{T}_i(y_i) \sim \begin{cases} \mathcal{N}(N\sigma_n^2, 2N\sigma^4), & H_0 \\ \mathcal{N}(N(\sigma_s^2 + \sigma_n^2), 2N(\sigma_s^2 + \sigma_n^2)^2), & H_1 \end{cases} \tag{4}$$

where, $\mathcal{T}_i(y_i)$ indicates test-statistic of current sensing event, $\sigma_s^2$ denotes signal power and $\sigma_n^2$ denotes noise power. Therefore, $SNR = \frac{\sigma_s^2}{\sigma_n^2}$. N indicates degrees of freedom ($N = 2$ for vehicular networks [17]). Now, let $\lambda$ denote the predefined threshold which provides a basis for deciding upon idleness or busyness of the channel, $\mathcal{T}_{i-1}(y_{i-1})$ denote test-statistic of previous sensing event and $\mathcal{T}_i^{avg}(\mathbf{T}_i)$ denote the average of previous $P$ test-statistics. Improved Energy Detection says that:

- When $\mathcal{T}_i(\mathbf{y}_i) < \lambda$ and $\mathcal{T}_i^{avg}(\mathbf{T}_i) > \lambda$, the condition $\mathcal{T}_{i-1}(\mathbf{y}_{i-1}) > \lambda$ indicates that $\mathcal{T}_i(\mathbf{y}_i) < \lambda$ may result because of an instantaneous energy drop. In such case, hypothesis $\mathcal{H}_1$ must be considered.
- On the contrary, the condition $\mathcal{T}_{i-1}(\mathbf{y}_{i-1}) < \lambda$ suggests that $\mathcal{T}_i(\mathbf{y}_i) < \lambda$ may have occurred due to the channel release. In such a case hypothesis $\mathcal{H}_0$ must be the decision of CR.

The additional usage of $\mathcal{T}_i^{avg}(\mathbf{T}_i)$ unlike in CED algorithm results into reduced miss-detections for highly variable signals where various consecutive sensing events may be affected by instantaneous energy drops.

## IV. Joint Impact of SU Mobility and PU Activity

In this section, the impact of SU mobility on PU activity is thoroughly investigated. Considering two common performance metrics false alarm probability and miss-detection probability, performance analysis has been carried out.

### A. Probabilities of Events I and O

In this section, we formulate a closed form expression of events "I" and "O".

Initially, we start assuming that the SU and PUs are stationary, hence having a fixed separation between them. The probability distribution of the distance between SU and PU separated by distance $D$ is assumed to follow log-normal distribution given by [21] as follows:

$$F_D(d) = \frac{1}{2}\Big[1 + erf\Big(\frac{d-\mu_d}{\sigma_d}\Big)\Big] \tag{5}$$

where, $erf$ denotes the error function, $erf(x) = \frac{2}{\sqrt{\pi}}\int_0^x e^{-t^2}\mathrm{d}t$, $\mu_d$ and $\sigma_d$ denote mean and standard deviation of distance between PU and SU respectively. Similarly, we can obtain the probability distribution of sensing range $(S)$, $F_S(s)$ and protection range $(R)$, $F_R(r)$. Now, as mentioned earlier, spectrum opportunities exist when distance between PU and SU is lesser than sensing range of SU but greater than protection range of PU. Mathematically as given in [17],

$$\begin{aligned} Pr(I) &= Pr(R < D \leq S) \\ &= F_S(s) - F_R(r) \\ &= \frac{1}{2}\Big[erf\Big(\frac{s-\mu_s}{\sigma_s}\Big) - erf\Big(\frac{r-\mu_r}{\sigma_r}\Big)\Big] \end{aligned} \tag{6}$$

where, $\mu_s$ and $\sigma_s$ represent mean and standard deviation of sensing range and $\mu_r$ and $\sigma_r$ represent mean and standard deviation of protection range. Then, to compute the probability of Event "O", we can simply subtract the probability of Event "I" from 1, considering the fact that Events "I" and "O" are mutually exclusive and collectively exhaustive events.

$$Pr(O) = 1 - Pr(I) \tag{7}$$

To the best of authors' knowledge, the literature does not contain a closed form expression for $Pr(I)$ while considering mobility. As given in [22], the speed distribution of vehicles in free flow state is a Gaussian distribution. Using the theory of random variables, we obtain distribution of time $T = \frac{D}{V}$ which evaluates to a lognormal distribution.

As shown in Fig.1, SU vehicle travels a distance $vt'$ in time $t = t'$. Hence, the final distance between PU and SU at any time $t$ is $D_0 + vt$, where $D_0$ denotes initial distance between PU and SU at time $t = 0$. The closed form expression of probability of PU being inside SU's sensing range (considering SU mobile) is as follows:

$$Pr(I) = \frac{1}{2}\Bigg[erf\Bigg(\frac{\frac{S-D_0}{v} - \mu_t}{\sigma_t}\Bigg) - erf\Bigg(\frac{\frac{R-D_0}{v} - \mu_t}{\sigma_t}\Bigg)\Bigg] \tag{8}$$

$$Pr(O) = 1 - Pr(I) \tag{9}$$

See Appendix A ■

### B. False Alarm and Miss Detection Probabilities

False Alarm means that SU makes a decision that "PU is busy", while actually the "PU is idle", which leads to wastage of spectrum resource. Accordingly, false alarm probability $P_f^{CED}$ as follows [11]:

$$\begin{aligned} P_f^{CED} &= Pr(R_E > \lambda|H_0)Pr(OFF) \\ &= Pr(R_E > \lambda|H_0, I)Pr(I)Pr(OFF) \\ &\quad + Pr(R_E > \lambda|H_0, O)Pr(O)Pr(OFF) \\ &= Pr(f|I)Pr(OFF) \end{aligned} \tag{10}$$

where, $\lambda$ denotes the decision threshold, $R_E$ denotes the energy of the received signal, $Pr(I)$ and $Pr(O)$ denotes inside and outside probabilities as formulated in (8) and (9) and $Pr(OFF)$ indicates that PU is actually idle (i.e. in OFF state). Also, $Pr(f|I)$ denotes the conditional false alarm probability given that PU is inside SU's sensing range. Evidently, $P_f$ remains unchanged with change in values of sensing and protection ranges which is supported by numerical results.

Miss-detection is defined as SU making a decision of "PU is idle" when actually "PU is busy", hence creating interference to the PU. Mathematically, miss-detection probability $P_m$ can be denoted as [11]:

$$\begin{aligned} P_m^{CED} &= Pr(R_E \leq \lambda|H_1)Pr(ON) \\ &= Pr(R_E \leq \lambda|H_1, I)Pr(I)Pr(ON) \\ &\quad + Pr(R_E \leq \lambda|H_1, O)Pr(O)Pr(ON) \\ &= Pr(ON)[Pr(m|I)Pr(I) + Pr(m|O)Pr(O)] \end{aligned} \tag{11}$$

Here, $Pr(m|I)$ and $Pr(m|O)$ denotes the conditional miss-detection probability given that PU is inside and outside SU's sensing range respectively.

In terms of Q-function, $Pr(m|I)$ and $Pr(f|I)$ can be expressed as:

$$\begin{aligned} Pr(m|I) &= 1 - Pr(R_E > \lambda|H_1, I) \\ &= 1 - Q\Bigg(\frac{\lambda - \mu_{i|H_1,I}}{\sigma_{i|H_1,I}}\Bigg) \end{aligned} \tag{12}$$

$$\begin{aligned} Pr(f|I) &= Pr(R_E > \lambda|H_0, I) \\ &= Q\Bigg(\frac{\lambda - \mu_{i|H_0,I}}{\sigma^2_{i|H_0,I}}\Bigg) \end{aligned} \tag{13}$$

where, $\mu_{i|H_0,I} = N\sigma_n^2$, $\mu_{i|H_1,I} = N(\sigma_s^2 + \sigma_n^2)$, $\sigma^2_{i|H_0,I} = 2N\sigma_n^4$ and $\sigma^2_{i|H_1,I} = 2N(\sigma_s^2 + \sigma_n^2)^2$. Hence, by substituting (8), (9), (12) and (13) into (11), we obtain miss-detection probability using CED as follows:

$$P_d^{CED} = 1 - Pr(ON)\Big[Pr(m|I)Pr(I) + Pr(m|O)Pr(O)\Big] \tag{14}$$

Substituting (12), (8) and (9), we obtain the closed form expression for $P_d^{CED}$ as follows:

$$P_d^{IED} = P_d^{CED} + P_d^{CED}\big(1 - P_d^{CED}\big) \cdot Q\Bigg(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\Bigg) \tag{15}$$

Similarly,

$$P_{fa}^{IED} = P_{fa}^{CED} + P_{fa}^{CED}\big(1 - P_{fa}^{CED}\big) \cdot Q\Bigg(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\Bigg) \tag{16}$$

See Appendix B ■

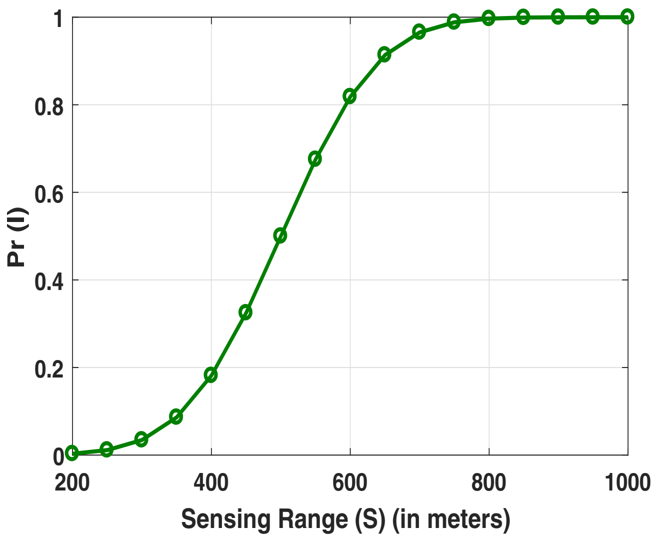


Fig. 2: Probability of PU being inside SU's sensing range vs various values of sensing range, ($R = 100m, v = 20kmph$)

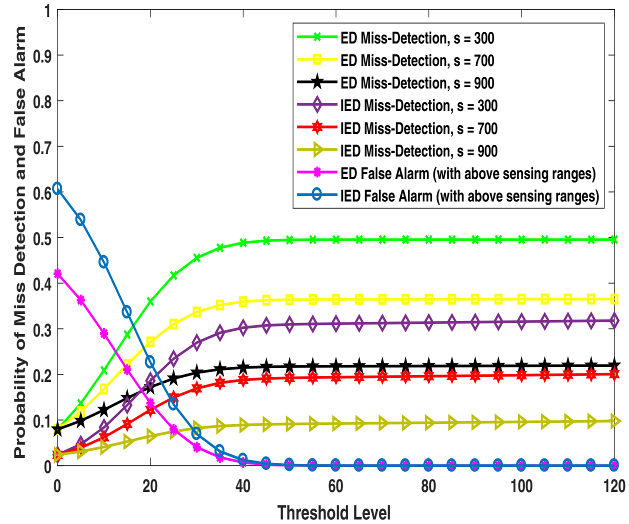


Fig. 3: Probabilities of Miss-Detection and False Alarm vs Various Sensing Ranges and Thresholds ($R = 100m, D = 200m, S = \{300m, 700m, 900m\}, v = 40kmph, M = 1, P = 3, Pr(ON) = 0.5, Pr(OFF) = 0.5$)

In the expression of $\mu_{avg}$ and $\sigma_{avg}$ given in Appendix B, $P$ indicates number of previous sensing events considered and $M$ indicates number of sensing events where a primary signal is actually present such that $M \in [0, P]$.

As evident from (15), the value of detection probability will increase significantly. However, it is worth noting that IED algorithm improves at the cost of increase in false alarm probability, however, such an increase in false alarm is not as significant as the improvements demonstrated by Fig.6 in numerical results section.

## V. Numerical Results

In this section, corroboration to the theoretical framework discussed above has been provided. A comparison between CED and IED algorithm has been demonstrated highlighting superiority of using IED algorithm in CVNs. The expressions for probabilities of false alarms and miss-detection as in (10) and (11) have been extensively tested.

In Fig.2, plot for variation of probability of PU being inside SU's sensing range, $Pr(I)$, for different values of sensing range has been demonstrated. According to IEEE 802.11p DSRC standards, the maximum value of sensing range is 1000 meters [25]. Here, we take the value of protection range, $R = 100$ meters and since $S > R$, we vary the value of $S$ from 200 to 1000 meters. As expected, the probability of inside ($Pr(I)$) increases with increase in sensing range ($S$).

In Fig.3, the effect of SU Mobility on trade-off between false alarm probability $P_f$ and miss-detection probability $P_m$ is evaluated using (10) and (11). Also, a comparison between ED and IED algorithms has been demonstrated. Here, we consider that the velocity of SU vehicle remains unchanged for a single sensing event. Also, $Pr(ON) = Pr(OFF) = 0.5$. As anticipated, the value of false alarm increases for IED algorithm as a cost of paying for reduced miss-detection probability for V2V scenarios. Evidently, we can observe a trade-off between miss-detection probability and false alarm rate for both CED and IED algorithms. For instance, consider threshold $\lambda = 20$, $P_m^{CED} = 0.3598$, $P_m^{IED} = 0.1862$, $P_f^{CED} = 0.1371$ and $P_f IED = 0.2263$. Clearly, results show that lower threshold level results in higher false alarm probability, but lower miss-detection probability.

In Fig.4, the variation of miss-detection probability ($P_m$) for both CED and IED versus SU velocity (in km/h) has been plotted, where PU protection range, $R = 100$ meters, initial separation between PU and SU, $D = 200$ meters and SU's sensing ranges ($S = 300, 700$ meters) using (11). Also, 4 provides a comparison for two cases where $Pr(OFF) > Pr(ON)$, such that $Pr(OFF) = 0.75, Pr(ON) = 0.25$ and $Pr(OFF) = 0.60, Pr(ON) = 0.40$ for ED and IED. Evidently, there is a significant decrease in $P_m$ for IED as compared to CED. For instance, consider SU velocity, $v = 40$ km/h, $S = 300$ meters, $Pr(ON) = 0.25$ and $Pr(OFF) = 0.75$, we get $P_m^{CED} = 0.1169$ and $P_m^{IED} = 0.0318$. Moreover, it is worth noting that the probability of miss-detection increases with increase in $Pr(OFF)$, keeping sensing range constant. For example, consider SU velocity $v = 40$ km/h, sensing range $S = 300m$, $Pr(ON) = 0.25$ and $Pr(OFF) = 0.75$, we get $P_m^{CED} = 0.1227$ and $P_m^{IED} = 0.0340$, whereas, for $Pr(ON) = 0.40$ and $Pr(OFF) = 0.60$, we get $P_m^{CED} = 0.0962$ and $P_m^{IED} = 0.0245$, clearly showing that the latter $P_m$ are quite smaller than earlier. Similarly, probability of miss-detection decreases with increase in value of sensing range, keeping $Pr(ON)$ and $Pr(OFF)$ constant, which is as expected.

Similarly, in Fig.5, the variation of $P_m$ for both CED and IED versus SU velocity (in km/h) has been analyzed. Here, we consider different values of $Pr(ON)$ and $Pr(OFF)$ such that $Pr(ON) > Pr(OFF)$, taking values $Pr(ON) = 0.60, Pr(OFF) = 0.40$ and $Pr(ON) = 0.75, Pr(OFF) = 0.25$. Miss-detection probability decreases with increase in $Pr(ON)$ for same sensing range $S$. For example, consider SU velocity, $v = 40$ km/h, $S = 300$ meters, $Pr(OFF) = 0.25$ and $Pr(ON) = 0.75$, we get $P_m^{CED} = 0.0476$ and $P_m^{IED} = 0.0102$, whereas taking $Pr(ON) = 0.60, Pr(OFF) = 0.40$, we get $P_m^{CED} = 0.0684$ and $P_m^{IED} = 0.0159$. Similarly, with increase in value of sensing range, the value of $P_m$ increases for constant value of $Pr(ON)$ and $Pr(OFF)$.

In Fig.6, we analyze the overall percentage gain in detection probability obtained by leveraging IED in lieu of CED for different velocities. As evident, a significant percentage improvement is achieved simply by changing the local sensing technique at SU vehicle. For SU velocity, $v = 60kmph$, a gain of approximately 10% is obtained at a minimal cost explained

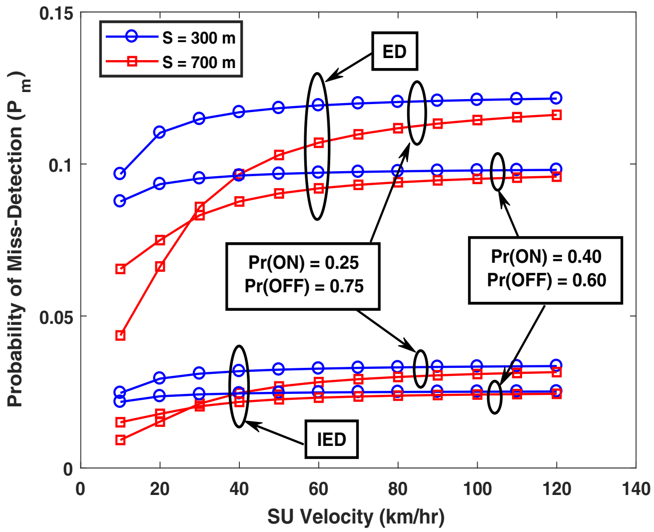


Fig. 4: Comparison of Miss-detection probabilities using CED and IED for different values of SU velocities with different sensing ranges for cases when $Pr(OFF) > Pr(ON)$, ($Pr(ON) = \{0.25, 0.40\}, Pr(OFF) = \{0.75, 0.60\}, R = 100m, D = 200m, S = \{300m, 700m\}, M = 1, P = 3$)

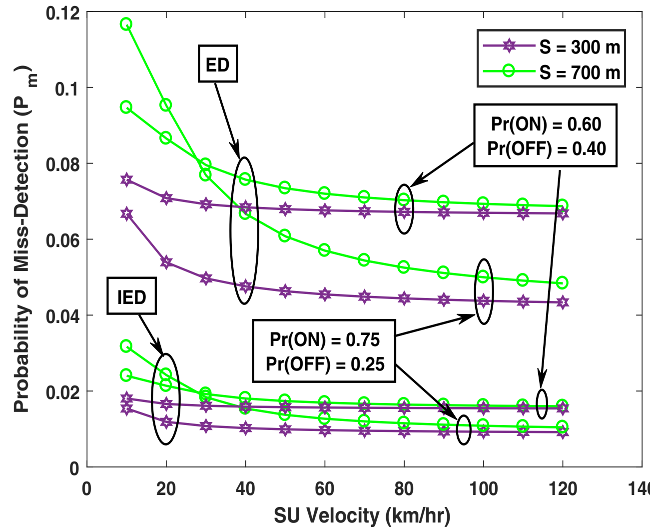


Fig. 5: Comparison of Miss-detection probabilities using CED and IED for different values of SU velocities with different sensing ranges for cases when $Pr(ON) > Pr(OFF)$ ($Pr(OFF) = \{0.25, 0.40\} Pr(ON) = \{0.75, 0.60\}, R = 100m, D = 200m, S = \{300m, 700m\}, M = 1, P = 3$)

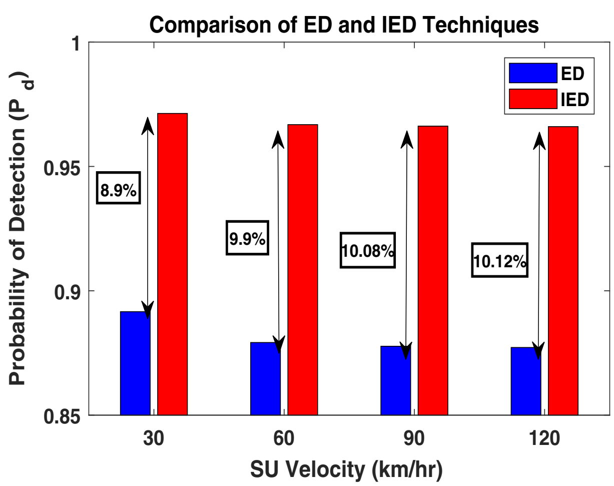


Fig. 6: Percentage gain comparison of CED and IED Techniques in terms of detection probabilities for different velocities, $Pr(ON) = 0.25$, $Pr(OFF) = 0.75$, $R = 100m$, $S = 300m$, $D = 200m$, $M = 1$, $P = 3$

in the next paragraph.

The comparison of computational cost in case of CED and IED can be explained as follows: The computation of $\mathcal{T}_i(\mathbf{y}_i)$ requires $N$ multiplication operations and $N-1$ sum operations, which, however, is required in both algorithms. Apart from that, IED algorithm computes $\mathcal{T}_i^{avg}(\mathbf{T}_i)$, which carries out $P-1$ sum operations and one division operation, performs two additional comparisons (lines 9 and 10). Furthermore, for each channel sensed by the CR, IED algorithm has a requirement of memory to store the last $P-1$ test statistic values. However, the increase in the computational cost for IED algorithm can be considered as negligible, as compared to various conventional methods such as covariance-based detectors [28] or cyclostationary feature detectors [26], [27], which requires comparatively more computationally complex computations.

## VI. Conclusion and Future Work

In this paper, the joint impact of SU mobility and PU activity has been investigated leveraging the superiority of IED technique. As discussed in the paper, IED overcomes limitations of CED technique, yielding an extraordinary improvement in system performance. We also derived a closed form expression for probability of event "I" and "O", which is used further to formulate the expressions of miss-detection and false alarm probabilities. Experimental results corroborate the theoretical analysis. At the end, the percentage gain of approximately 10% obtained by using IED technique for V2V networks clearly demonstrates its superiority. Future work for this paper would include incorporating dense traffic scenarios, or networks with multiple PUs and SUs operating in a cooperative manner using this improved algorithm.


## VII. Acknowledgement

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## Appendix A
## Derivation of Inside Probability, $Pr(I)$

$$
\begin{aligned}
Pr(I) &= Pr(R < D \leq S) \\
&= Pr(R < D_0 + vt \leq S) \\
&= Pr\Big(\frac{R - D_0}{v} < t \leq \frac{S - D_0}{v}\Big) \\
&= F_T\Big(\frac{S - D_0}{v}\Big) - F_T\Big(\frac{R - D_0}{v}\Big) \\
&= \frac{1}{2}\Big[erf\Big(\frac{\frac{S-D_0}{v} - \mu_t}{\sigma_t}\Big) - erf\Big(\frac{\frac{R-D_0}{v} - \mu_t}{\sigma_t}\Big)\Big]
\end{aligned}
$$

where, $F_T(t)$ is the Cumulative Distribution Function (CDF) of lognormal distribution as discussed in Section IV.

## Appendix B
## Derivation of Probability of Detection for Improved Energy Detection

As discussed earlier, Improved Energy Detection (IED) technique depends on current test-statistic $\mathcal{T}_i(y_i)$, previous test-statistic $\mathcal{T}_{i-1}(y_{i-1})$ and average for previous $P$ test-statistics $\mathcal{T}_i^{avg}(\mathbf{T}_i)$, we re-write the average test-statistics as:

$$\mathcal{T}_i^{avg}(\mathbf{T}_i) = \frac{1}{P}\sum_{p=0}^{P-1}\mathcal{T}_{i-P+p}(y_{i-P+p})$$

For large number of sensing events, we can assume that $\mathcal{T}_i^{avg}(\mathbf{T}_i)$ to follow Gaussian distribution according to Central Limit Theorem.

$$\therefore \mathcal{T}_i^{avg}(\mathbf{T}_i) \sim \mathcal{N}(\mu_{avg}, \sigma_{avg}^2)$$

Now, in order to compute $\mu_{avg}$ and $\sigma_{avg}^2$, we define $M$ as number of sensing events (out of previous $P$ sensing events) where primary signal was actually present, i.e $M \in [0, P]$.

When channel is idle: $\mu_{i|H_0} = N\sigma_n^2$ and $\sigma_{i|H_0}^2 = 2N\sigma_n^4$. Similarly, when channel is busy: $\mu_{i|H_1} = N(\sigma_s^2 + \sigma_n^2)$ and $\sigma_{i|H_1}^2 = 2N(\sigma_s^2 + \sigma_n^2)^2$.

Hence, the probability of occurrence of any event can be written as:

$$Pr(i) = Pr(busy) + Pr(idle)$$

where '+' denotes the logical OR condition, considering the fact that both the events are mutually exclusive in nature. Further, as per the definition of $M$, DSA/CR system (in SU vehicle) remains busy for $M$ sensing events and idle for $P-M$ sensing events.

$$\begin{aligned}\mu_{avg} &= \frac{M}{P}\mu_{i|H_1} + \frac{P-M}{P}\mu_{i|H_0} \\ &= \frac{M}{P}N(\sigma_s^2 + \sigma_n^2) + \frac{P-M}{P}N\sigma_n^2\end{aligned}$$

$$\begin{aligned}\sigma_{avg}^2 &= \frac{M}{P^2}\sigma_{i|H_1}^2 + \frac{P-M}{P^2}\sigma_{i|H_0}^2 \\ &= \frac{M}{P^2}2N(\sigma_s^2 + \sigma_n^2)^2 + \frac{P-M}{P^2}2N\sigma_n^4\end{aligned}$$

Now, as per the definition of $P_d^{IED}$:

$$\begin{aligned}P_d^{IED} =& Pr(\mathcal{T}_i(y_i) > \lambda)_{H_1} + Pr(\mathcal{T}_i(y_i) \le \lambda)_{H_1} \\ &\times Pr(\mathcal{T}_i^{avg}(\mathbf{T}_i))_{H_1} \cdot Pr(\mathcal{T}_{i-1}(y_{i-1}) > \lambda)_{H_1}\end{aligned}$$

According to the definition, $Pr(\mathcal{T}_i(y_i) > \lambda)_{H_1}$ and $Pr(\mathcal{T}_{i-1}(y_{i-1}) > \lambda)_{H_1}$ denote detection probability $P_d^{CED}$, $Pr(\mathcal{T}_i(y_i) \le \lambda)_{H_1}$ denotes miss-detection probability $P_m^{CED} = 1 - P_d^{CED}$ and $Pr(\mathcal{T}_i^{avg}(\mathbf{T}_i))_{H_1}$ denotes $Q(\frac{\lambda - \mu_a vg}{\sigma_{avg}})$.

$$\therefore P_d^{IED} = P_d^{CED} + P_d^{CED} \cdot (1 - P_d^{CED}) \cdot Q\Big(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\Big)$$

Similarly, we derive the expression for $P_{fa}^{IED}$:

$$\therefore P_{fa}^{IED} = P_{fa}^{CED} + P_{fa}^{CED} \cdot (1 - P_{fa}^{CED}) \cdot Q\Big(\frac{\lambda - \mu_{avg}}{\sigma_{avg}}\Big)$$

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