Deployment and Performance of Infrastructure to Assist Vehicular Collaborative Sensing

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***Abstract*—To enable situational awareness for automated driving in intelligent transportation systems (ITS), it is envisioned that vehicles will be equipped with sensors, and possibly perform collaborative sensing amongst themselves. Unfortunately such sensing is subject to obstructions, e.g., other vehicles, and the performance can be poor when the penetration of collaborating vehicles is low. A possible solution is to deploy sensing and communication capable infrastructure, e.g., road side units (RSUs) and base stations (BSs), to assist collaborative sensing. This paper explores the performance of infrastructure assisted sensing of roads under various deployment schemes. Our analytical results show that deploying RSUs at intersections and at even spacings is most efficient in covering the roads while cellular based sensors may subject to building obstructions and should be located along roads working as RSUs. RSUs located above the vehicles can have 100% coverage of vehicles once the communication range is large enough to reach relevant sensors. Infrastructure provides a second advantage in providing a dynamic view of the road and thus better coverage over time. Such benefit from sensing temporal diversity is shared by vehicles moving in the opposite direction, yet collaborating with such vehicles involves more challenging V2V communication given the high relative speed and obstruction unless leveraging V2I relays.**

I. Introduction

Automated driving is expected to be a key element in future intelligent transportation systems (ITS). Vehicles will be equipped with sensors, e.g., cameras and LIDARs, to sense the dynamically changing environment around them. Sensing by vehicles is subject to environmental obstructions, especially neighboring vehicles. Vehicles can perform *collaborative sensing* by exchanging sensor data with neighboring vehicles to sense beyond obstructions. The performance relies on the availability of neighboring collaborative sensing vehicles. Sharing sensor data may also introduce high communication loads which may require infrastructure relaying.

Deploying sensing and communication capable infrastructure can help enhance sensing by providing additional sensor points of view and relaying sensor data. Indeed infrastructure sensors can have better unobstructed view and communication channels, e.g., sensors located above the vehicles are less subject to obstructions, and may require less data to be exchanged, e.g., a vehicle may only need data from several infrastructure nodes v.s. neighboring vehicles.

Contributions. In this paper we study the factors impacting the performance of infrastructure assisted sensing. 1) Infrastructure type, i.e., road side units (RSU) or cellular base station (BS). We show that to achieve the same sensing coverage of roads, it is better to deploy RSUs at road intersections and along roads at even spacings. Unobstructed BSs may cover more roads at high road densities and sensing ranges, yet BSs off the roads may get obstructed by buildings. Cellular based sensors should be located along roads and work like RSUs. 2) RSU deployment and capabilities. We show that RSUs deployed above vehicles are not likely to be obstructed, but require a long communication range or sensor data relaying to deliver data to all vehicles requiring the data. 3) Spatio-temporal diversity of sensing. Infrastructure assisted sensing improves sensing diversity by providing sensor data measured from different points of view. In addition infrastructure can improve sensing coverage by utilizing the temporal diversity caused by object/obstruction movement, e.g., sensors track objects using measurements taken at different times. Collaborating with vehicles driving in the opposite direction also improves sensing spatio-temporal diversity, yet such collaboration may rely on high penetration of collaborative vehicles and introduce high communication costs.

Related work. Infrastructure is considered to be an important component to support automated driving [1][2]. Authors of [3] propose a method to sense the environment using RSU based cameras and vehicles' GPS. An analysis of the performance of infrastructure assisted sensing, e.g., sensing coverage, is however absent. The deployment of RSUs has been studied in [4][5][6], but these work focus on optimizing communication performance of infrastructure.

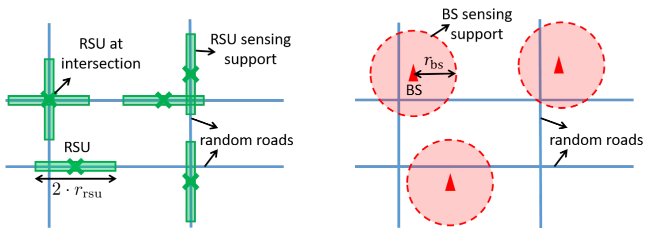
Paper organization. In Section II we compare RSU and cellular based sensing. In Section III we evaluate the performance of RSU assisted collaborative sensing via simulation. We explore the benefits of utilizing sensing temporal diversity in Section IV and conclude the paper in Section V.

II. Comparison of RSU and Cellular Based Sensing

We leverage simple stochastic geometry tools to compare the road sensing coverage of two infrastructure sensor deployment schemes: 1) sensors on RSUs placed along roads, and 2) sensors on cellular BSs, randomly placed in space.

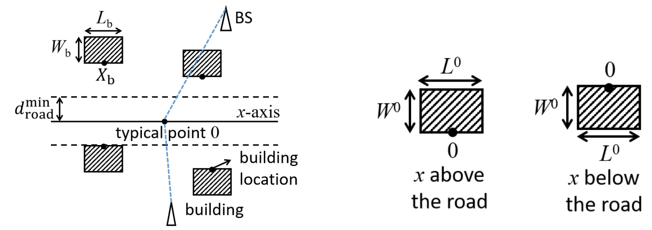
A. System Model

We model the road system using a Manhattan Poisson line process (MPLP) [7] on an infinite 2D plane, see [8][9]. The roads are modeled based on two independent homogeneous



(a) RSU based sensing (b) Cellular based sensing

Fig. 1. Manhattan Poisson line process model for roads. (a) RSU based sensing model, (b) Cellular (BS) based sensing model.



(a) Cellular based sensing (top view) (b) Footprint of a typical building

Fig. 2. (a) Top view of cellular based sensing model under building obstruction (in rural area), $d^{\rm BS,min}_{\rm road} = d^{\rm b,min}_{\rm road} = d^{\rm min}_{\rm road}$. (b) Footprint of a typical building with shape A^0 and located on the same side of road as x.

Poisson point processes (HPPP), $\Psi_x, \Psi_y \subset \mathbb{R}$, along the x-axis and y-axis respectively. At each point of Ψ_x (Ψ_y) there is a vertical (horizontal) line corresponding to a road. We shall initially neglect the width of the roads in this section. The intensities of Ψ_x and Ψ_y, $\lambda^{\rm v}_{\rm road}$ and $\lambda^{\rm h}_{\rm road}$, correspond to the density of vertical and horizontal roads. The total density of roads, and the average length of roads per unit area, are both given by $\lambda_{\rm road} = \lambda^{\rm h}_{\rm road} + \lambda^{\rm v}_{\rm road}$. See Fig. 1 for example.

RSU based sensing: We will assume RSUs are distributed along each road with intensity $\mu_{\rm rsu}$ RSUs/m, resulting in a spatial density $\lambda_{\rm rsu} = \lambda_{\rm road} \cdot \mu_{\rm rsu}$. For simplicity we assume a road can only be sensed by RSUs deployed along the road, i.e., other RSUs are obstructed. RSUs are placed above vehicles and objects on the road and can sense all objects on the road. The sensing support of an RSU is a line segment of length $2 \cdot r_{\rm rsu}$ centered at the RSU. An RSU deployed at an intersection can sense all the roads joining at the intersection. We consider three ways of deploying RSUs: 1) randomly distributed, where RSUs follow HPPP$(\mu_{\rm rsu})$ along each road; 2) evenly spaced, RSUs are deployed along roads at an interval $1/\mu_{\rm rsu}$; 3) RSUs first deployed at intersections, then randomly deployed along roads. The optimal placement of RSUs is beyond the scope of this work, thus we consider the above simple approaches. Placing RSUs at intersections and/or at even spacings would cover roads with fewest RSUs. However in the early stage of deployments, RSUs may be placed at busy road segments first, and subject to environmental limitations, e.g., availability of backbone infrastructure and RSU installation space. The deployment of RSUs may also consider performance of communication, e.g., [4][5][6]. These considerations may bring randomness to RSU placement, and the HPPP model represents a "worst case" deployment with the most randomness. RSU deployments in the real world would likely to be a compromise of these deployment models.

Cellular based sensing: BSs are modeled as randomly located on the 2D plane, e.g., follow an HPPP with intensity $\lambda_{\rm BS}$ [7][10]. We assume a BS's sensing support is a disc with radius $r_{\rm BS}$ centered at the BS, see Fig. 1b. We model BSs as being subject to building obstructions – see the 3D model shown in Fig. 2a. Consider a typical location, 0, on a typical horizontal road, i.e., the x-axis. We neglect other roads and the results for vertical roads would be similar. The locations of BSs follow an HPPP$(\lambda_{\rm BS})$ on

$$D_{\rm BS} = (-\infty, \infty) \times \left((-\infty, -d^{\rm BS,min}_{\rm road}) \cup (d^{\rm BS,min}_{\rm road}, \infty)\right), \quad (1)$$

i.e., the minimum distance from BSs to the center of road is $d^{\rm BS,min}_{\rm road}$ (e.g. width of road and sidewalk). The height of BSs is $h_{\rm BS}$. Buildings are the only obstructions. Each building is associated with a location $X_{\rm b} \in \mathbb{R}^2$ and a 3D shape modeled by a random cuboid parametrized by $A_{\rm b} = (L_{\rm b}, W_{\rm b}, H_{\rm b})$, where $L_{\rm b}, W_{\rm b}, H_{\rm b} \in \mathbb{R}^+$ correspond to the length, width and height of the cuboid. The side corresponding to $L_{\rm b}$ is assumed to be parallel to the road. The location of the building, $X_{\rm b}$, is at the center of the side closest to the road. See Fig. 2. We assume the shape of buildings are independent and identically distributed, and independent of the locations of the buildings. The locations of buildings follow HPPP$(\lambda_{\rm b})$ on

$$D_{\rm b} = (-\infty, \infty) \times \left((-\infty, -d^{\rm b,min}_{\rm road}) \cup (d^{\rm b,min}_{\rm road}, \infty)\right), \quad (2)$$

i.e., the minimum distance from the side of a building to the road is $d^{\rm b,min}_{\rm road}$. The location 0 can be viewed by a sensor at location x if it falls in the sensing range of the sensor and there are no buildings obstructing the LOS sensing channel. Our random obstruction model is roughly appropriate for sparse suburban/rural areas where building densities are low and buildings can be approximated as randomly distributed.

We shall examine the *coverage of roads*, i.e., the proportion of roads covered by at least one sensor, under different sensor deployment schemes given road density $\lambda_{\rm road}$ and sensor spatial density $\lambda_{\rm rsu}$ (and building density $\lambda_{\rm b}$).

B. RSU Based Sensing Coverage

Randomly distributed RSUs (RSU random). On each road, the coverage of RSUs follows a 1D Poisson Boolean process [11]. RSUs on each road follow an HPPP with intensity $\mu^{\rm rand}_{\rm rsu} = \lambda_{\rm rsu}/\lambda_{\rm road}$, each covering a road segment of length $2 \cdot r_{\rm rsu}$. It follows that the number of RSUs covering a typical location, $N^{\rm rand}_{\rm rsu}$, is Poisson with mean $\mathrm{E}[N^{\rm rand}_{\rm rsu}] = \mu^{\rm rand}_{\rm rsu} \cdot (2 \cdot r_{\rm rsu})$. The coverage of road is thus given by

$$p^{\rm rsu,rand}_{\rm cover}(\lambda_{\rm rsu}, r_{\rm rsu}, \lambda_{\rm road}) = \mathrm{P}(N^{\rm rand}_{\rm rsu} > 0) = 1 - e^{-\frac{\lambda_{\rm rsu}}{\lambda_{\rm road}} \cdot 2 \cdot r_{\rm rsu}}. \quad (3)$$

Evenly spaced RSUs (RSU even). The distance between two neighboring RSUs is $\frac{1}{\mu^{\rm even}_{\rm rsu}} = \frac{\lambda_{\rm road}}{\lambda_{\rm rsu}}$, thus the proportion of road covered is easily shown to be

$$p^{\rm rsu,even}_{\rm cover}(\lambda_{\rm rsu}, r_{\rm rsu}, \lambda_{\rm road}) = \min\left\{1, 2 \cdot r_{\rm rsu} \cdot \frac{\lambda_{\rm rsu}}{\lambda_{\rm road}}\right\}. \quad (4)$$

RSUs at intersections along with randomly distributed RSUs (RSU inter). In MPLP, the road intersections on a horizontal road follow $\mathrm{HPPP}(\lambda^{\mathrm{v}}_{\mathrm{road}})$, thus the spatial density of intersections is $\lambda_{\mathrm{inter}} = \lambda^{\mathrm{h}}_{\mathrm{road}} \cdot \lambda^{\mathrm{v}}_{\mathrm{road}}$. If $\lambda_{\mathrm{rsu}} \leq \lambda_{\mathrm{inter}}$, we assume each intersection has a probability $\lambda_{\mathrm{rsu}}/\lambda_{\mathrm{inter}}$ of having an RSU and there are no RSUs off intersections. If $\lambda_{\mathrm{rsu}} > \lambda_{\mathrm{inter}}$, each intersection has an RSU and in addition each road has randomly distributed RSUs with linear density $\mu^{\mathrm{rand}}_{\mathrm{rsu}}$, where $\mu^{\mathrm{rand}}_{\mathrm{rsu}}$ is such that the total RSU spatial density is λ_{rsu}. The coverage of horizontal roads is given in the following theorem.

Theorem 1. *Under the above RSU deployment at road intersections in MPLP, the coverage of horizontal roads is,*

$$p^{\mathrm{rsu,inter,h}}_{\mathrm{cover}}(\lambda_{\mathrm{rsu}}, r_{\mathrm{rsu}}, \lambda^{\mathrm{h}}_{\mathrm{road}}, \lambda^{\mathrm{v}}_{\mathrm{road}}) = \begin{cases} 1 - e^{-\frac{\lambda_{\mathrm{rsu}}}{\lambda^{\mathrm{h}}_{\mathrm{road}}}\cdot(2\cdot r_{\mathrm{rsu}})}, & \text{if } \lambda_{\mathrm{rsu}} \leq \lambda^{\mathrm{h}}_{\mathrm{road}} \cdot \lambda^{\mathrm{v}}_{\mathrm{road}} \\ 1 - e^{-\mu^{\mathrm{total}}_{\mathrm{rsu}}\cdot(2\cdot r_{\mathrm{rsu}})}, & \text{otherwise,} \end{cases} \quad (5)$$

where

$$\mu^{\mathrm{total,h}}_{\mathrm{rsu}} = \frac{\lambda_{\mathrm{rsu}} + (\lambda^{\mathrm{v}}_{\mathrm{road}})^2}{\lambda^{\mathrm{h}}_{\mathrm{road}} + \lambda^{\mathrm{v}}_{\mathrm{road}}}. \quad (6)$$

The proof again results from Boolean processes and is omitted due to space limits. By symmetry, the coverage of vertical roads is given by $p^{\mathrm{rsu,inter,h}}_{\mathrm{cover}}(\lambda_{\mathrm{rsu}}, r_{\mathrm{rsu}}, \lambda^{\mathrm{v}}_{\mathrm{road}}, \lambda^{\mathrm{h}}_{\mathrm{road}})$.

C. Cellular Based Sensing Coverage

Cellular coverage without obstructions (cellular unobstructed). The 2D sensing supports of unobstructed BSs follows a simple 2D Boolean process [11], which results in a coverage:

$$p^{\mathrm{BS}}_{\mathrm{cover}}(\lambda_{\mathrm{BS}}, r_{\mathrm{BS}}) = 1 - e^{-\lambda_{\mathrm{BS}}\cdot\pi\cdot r^2_{\mathrm{BS}}}. \quad (7)$$

Cellular coverage under obstruction (cellular obstructed). Denote by $A^0 = (L^0, W^0, H^0)$, where $L^0, W^0, H^0 \in \mathbb{R}^+$, a typical random cuboid having the same distribution as buildings. For a BS located at x, we denote by $E(x, A^0) \subseteq \mathbb{R}^2$ the footprint, i.e., the region occupied reference to the location of the building, of a typical building of shape A^0 located on the same side of the road as x, see Fig. 2b. The average number of BSs sensing a typical location 0 is characterized in the following theorem.

Theorem 2. *Under our obstruction model, the number of BSs sensing a typical location 0, $N^{\mathrm{o}}_{\mathrm{BS}}$, has mean*

$$\mathrm{E}[N^{\mathrm{o}}_{\mathrm{BS}}] = \lambda_{\mathrm{BS}} \cdot \int_{D_{\mathrm{BS}} \cap b(0, r_{\mathrm{BS}})} e^{-\mathrm{E}[N_{\mathrm{b}}(x)]} dx, \quad (8)$$

where

$$\mathrm{E}[N_{\mathrm{b}}(x)] = \lambda_{\mathrm{b}} \cdot \mathrm{E}_{A^0}\left[\left|(l_{0,\rho(A^0)\cdot x} \oplus \check{E}(x, A^0)) \cap D_{\mathrm{b}}\right|\right], \quad (9)$$

is the expected number of buildings blocking the BS at x, $b(0, r_{\mathrm{BS}})$ is a disc centered at 0 with radius r_{BS} $l_{0,\rho(A^0)} \cdot x$ is the line segment between 0 and $\rho(A^0) \cdot x$, $\rho(A^0) = \min(1, \frac{H^0}{h_{\mathrm{BS}}})$, $\oplus$ is the Minkowski sum [11], $\check{E}(x, A^0) = \{y | -y \in E(x, A^0)\}$.

The proof follows by Campbell's theorem [11] and is omitted due to space limits. If λ_{BS} and λ_{b} are small, the sensing channels between 0 and BSs can be approximated as independent. $N^{\mathrm{o}}_{\mathrm{BS}}$ then follows a Poisson distribution with the same mean and the coverage is given by

$$p^{\mathrm{BS,o}}_{\mathrm{cover}}(\lambda_{\mathrm{BS}}, r_{\mathrm{BS}}, \lambda_{\mathrm{b}}) = 1 - e^{-\mathrm{E}[N^{\mathrm{o}}_{\mathrm{BS}}]}. \quad (10)$$

Building density model. $p^{\mathrm{BS,o}}_{\mathrm{cover}}$ depends on λ_{b}, not λ_{road}. In fact building density is positively correlated with road density, e.g., over 0.6 correlation [12], thus in this work we will use a very simple model for building density, i.e.,

$$\lambda_{\mathrm{b}} = c \cdot \lambda_{\mathrm{road}}, \quad (11)$$

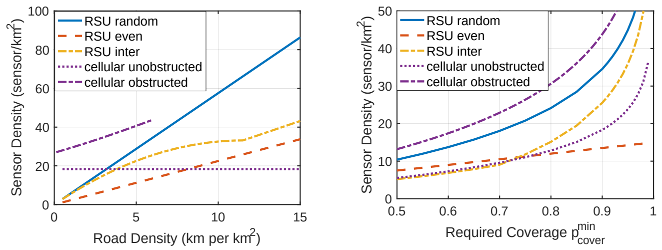
where c is a constant such that $\lambda_{\mathrm{b}} = \frac{1}{400} / \mathrm{m}^2$ at $\lambda_{\mathrm{road}} = 6\,\mathrm{km}$ per km^2. The actual relationship is more complicated and we use this simple model to study the scaling of cellular coverage qualitatively.

D. Comparisons of Different Sensor Deployment Schemes

We will focus on the MPLP model, yet analysis of other road models, e.g., (non-random) Manhattan grid model [**?**], and Poisson line process [13], would be similar. The metric we study is the *minimum sensor spatial density* required to achieve a target coverage, $p^{\min}_{\mathrm{cover}}$. $r_{\mathrm{rsu}} = r_{\mathrm{BS}} = 200\,\mathrm{m}$, and we let $\lambda^{\mathrm{h}}_{\mathrm{road}} = \lambda^{\mathrm{v}}_{\mathrm{road}}$. For obstructed cellular sensing model, we assume buildings have the same dimensions, $l_{\mathrm{b}} = l_{\mathrm{b}} = 14\,\mathrm{m}$, $h_{\mathrm{b}} = 3\,\mathrm{m}$. The BS height is $h_{\mathrm{BS}} = 15\,\mathrm{m}$. $d^{\mathrm{BS,min}}_{\mathrm{road}} = d^{\mathrm{b,min}}_{\mathrm{road}} = 10\,\mathrm{m}$, i.e., the width of two $3.5\,\mathrm{m}$ lanes and $3\,\mathrm{m}$ sidewalk. Fig. 3a illustrates the required sensor density to achieve $p^{\min}_{\mathrm{cover}} = 90\%$ as one varies the road density, e.g., from sparse rural to dense urban areas. We only present result of obstructed cellular based sensing for small road densities, i.e., $\lambda_{\mathrm{road}} \leq 6\,\mathrm{km} / \mathrm{km}^2$. In dense urban areas, the buildings are taller and fill the city blocks separated by roads, making it difficult for a BS to have a good LOS coverage of streets which are one block away. For better sensing coverage, cellular based sensors would need be located on the sides of the buildings next to roads, which then becomes similar to our assumptions on RSU placement. In this setting, the performance of sensing would then be similar to that of RSUs but perhaps placed at a larger height. Fig. 3b exhibits the required sensor density for different $p^{\min}_{\mathrm{cover}}$ at $\lambda_{\mathrm{road}} = 6\,\mathrm{km} / \mathrm{km}^2$.

Benefit of placing RSUs at intersections. Deploying RSUs at intersections can double the coverage benefit per RSU, i.e. coverage along two roads so the required sensor density is reduced, see the difference between 'RSU random' and 'RSU inter' in Fig. 3a. As λ_{road} increases, we have more intersections to place RSUs thus the benefit keeps increasing. At high road densities, e.g., $\lambda_{\mathrm{road}} \geq 11\,\mathrm{km} / \mathrm{km}^2$, deploying RSUs only at (some of) the intersections is enough to cover the roads and the required RSU density is reduced by half.

Randomly v.s. evenly spaced RSUs. If RSUs are distributed at even spacings, there is no overlap among the sensing supports of RSUs thus $\lambda^{\mathrm{even,min}}_{\mathrm{rsu}} < \lambda^{\mathrm{rand,min}}_{\mathrm{rsu}}$. Furthermore the sensor densities in random deployments is proportional to $-\log(1 - p^{\min}_{\mathrm{cover}})$ and go to infinity as $p^{\min}_{\mathrm{cover}} \to 1$. In evenly



(a) Sensor density at different road densities

(b) Sensor density for different coverage requirements

Fig. 3. (a) Minimum sensor density to achieve 90% coverage at different road densities λ_{road}. (b) Minimum sensor density for different $p_{\text{cover}}^{\min}$ at road density $\lambda_{\text{road}} = 6\,\text{km per km}^2$.

spaced deployments, the sensor density increases linearly with $p_{\text{cover}}^{\min}$ and is bounded. Deploying RSUs at even spacings and at intersections would in principle minimize the required RSU density. However the distance between intersections is not necessarily a multiple of the sensing range, thus overlap between RSUs might be inevitable. Optimal deployment of RSUs will thus depend on the actual road topology.

RSU based sensing v.s. cellular based sensing. If BSs are unobstructed, the required sensor density does not scale with λ_{road}. Furthermore the required sensor density is proportional to $1/r_{\text{BS}}^2$ in cellular based sensing while proportional to $1/r_{\text{rsu}}$ in RSU based sensing. The sensor density and associated cost in cellular based sensing could be smaller than RSU based sensing when road density and sensing range are high. When BSs are subject to building obstructions, however, the required sensor density increases with building density, which is positively correlated with road density, and cellular based sensing thus may not be more efficient than RSU based sensing, see 'cellular obstructed' in Fig. 3. As we have discussed, cellular based sensing in dense urban area may only cover the roads surrounding the BSs and work similar to RSUs.

III. RSU Assisted Collaborative Sensing

In this section we use numerical simulation to evaluate the performance of RSU assisted collaborative sensing, i.e., vehicles sense the surrounding environment based on sensor data from collaborative other sensing vehicles and RSUs.

We consider a typical freeway scenario as described in [14], see Fig. 4. There are three lanes in each direction, and the lane width is $4\,\text{m}$. RSUs are distributed at even spacings, d_{rsu}, along one side of the road. The distance from RSUs to the side of road is d_{road}. RSU sensing range is r_{rsu}. Vehicles are modeled as rectangular cuboids. Each vehicle has an independent probability p_s to be a collaborative sensing vehicle, equipped with a sensor, e.g., LIDAR, mounted on the central top. We refer to p_s as the *penetration ratio*. Vehicles have the same sensing range as RSUs. A vehicle is sensed if *any* part of the vehicle is sensed. We denote by *region of interest* the region a vehicle need to sense, and refer to the objects (vehicles) overlapping with the region of interest as *objects of interest*. Denote by s the velocity of vehicles, the region of interest is the region of lanes in same direction within

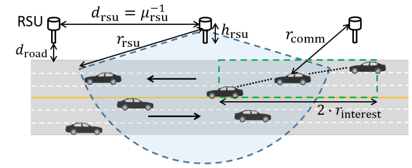


Fig. 4. Collaborative sensing with infrastructure.

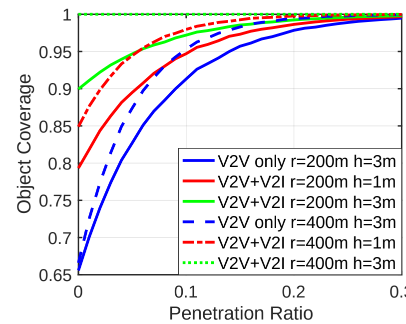


Fig. 5. Object coverage for different communication ranges r_{comm}: $200\,\text{m}$, $400\,\text{m}$, and different RSU heights h_{rsu}: $1\,\text{m}$, $3\,\text{m}$. 'V2V': sensing with vehicles in same direction; 'V2I': sensing with RSUs.

range $r_{\text{interest}} = 10 \cdot s$, i.e., vehicles require a $10\,\text{sec}$ prediction of the lanes in the same direction – vehicles moving in the same direction are more relevant. We further assume vehicles collaborate with *all* collaborative sensing vehicles moving in the *same* direction within communication range r_{comm} since the communication links to these vehicles are more stable. For collaboration with RSUs, we assume vehicles can get sensor data from RSUs within range r_{comm}. Half of vehicles are randomly selected to be sedans $4.8\,\text{m} \times 1.8\,\text{m} \times 1.5\,\text{m}$ (length $\times$ width $\times$ height), while the other half are SUVs $5\,\text{m} \times 2\,\text{m} \times 1.8\,\text{m}$. Taller vehicles may obstruct and impact the sensing coverage of RSUs located at lower heights. Vehicles of different height see different obstruction fields and thus have different sensing coverage. Vehicles are randomly located in the lanes and moving at constant speed $s = 20\,\text{m}\,/\,\text{sec}$, the lane density of vehicles is $\mu_{\text{vehicle}} = \frac{1}{2 \cdot s} = 0.025$ vehicles$/\,\text{m}$, e.g., the average gap between two neighboring vehicles in the same lane is $2\,\text{sec}$. The metric we use is *object coverage*, i.e., the proportion of objects of interest which are sensed via collaborative sensing.

Fig. 5 exhibits how object coverage of a sensing vehicle scales with the penetration of collaborative vehicles. RSUs are evenly distributed at even spacings $d_{\text{rsu}} = 400\,\text{m}$ and the sensing range of RSUs and vehicles are $200\,\text{m}$. The RSUs cover the whole road without gap when there is no obstruction. The sensing by a single vehicle is not satisfactory, e.g., 65% object coverage without collaboration (0 penetration). The object coverage increases with the penetration ratio, yet the coverage is still limited at low penetrations, i.e., the early stage of automated driving. Collaborative sensing with RSUs provides 100% coverage of objects of interest when RSUs are located above vehicles and the communication range is long enough, i.e., vehicles can receive all relevant sensor data if $r_{\text{comm}} \geq r_{\text{interest}} + r_{\text{sensor}}$, see 'V2V + V2I r =

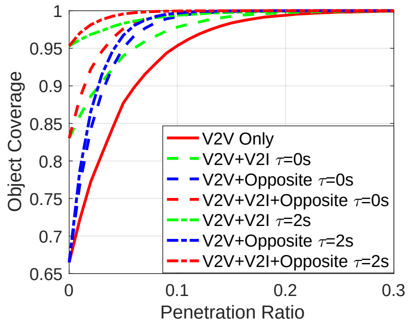


Fig. 6. Object coverage for different tracking window τ and collaboration schemes: 'V2V' with vehicles moving in the same direction; 'V2I' with RSUs; 'Opposite' with vehicles moving in the opposite direction.

$400\,\mathrm{m}\ \ h = 3\,\mathrm{m}$'. We also examine the impact of other factors of RSU deployment, e.g., distance to roadside, the sensing range of RSUs and vehicles, RSU density, etc. Numerical results show these factors have little impact once RSUs are located higher than vehicles, cover the whole road, and have enough communication range.

IV. Spatio-temporal Diversity in Collaborative Sensing

In the previous section we study how collaborative sensing improves coverage for a *snapshot* of the environment by providing spatial diversity in sensing, i.e., sensor data for locations and objects from different points of view. In addition, collaborative sensing can improve sensing performance via utilizing temporal diversity in sensing. Objects in the environment are moving thus the environment is dynamic, e.g., vehicles' regions of interest, blockage fields, and the sensor coverage sets are varying with time. Sensor data measured at different time provides possibly different information regarding the environment, thus sensors can utilize temporal diversity for sensing and tracking of objects in the environment.

Sensors can track the states of objects in the environment, e.g., locations, velocity, acceleration, etc, and thus have a good estimate of the objects even when the sensing of the objects is obstructed for some time. For simplicity we assume an object is tracked by a sensor at t if the object has been sensed in time interval $[t - \tau, t]$, where τ is the maximum time window for reliable tracking without new sensor data. Vehicles in the same direction may provide little temporal diversity as they may move at similar. We consider collaboration with relative mobile sensors: RSUs and/or vehicles in the opposite direction. We use the same simulation assumptions as Section III.

Fig. 6 illustrates the object coverage reliability of collaborative sensing for different collaboration schemes and different τ. The communication range is $r_{\mathrm{comm}} = 500\,\mathrm{m}$, enough to communicate with all relevant sensors, and $h_{\mathrm{rsu}} = 1\,\mathrm{m}$, i.e., RSUs are subject to vehicles' obstruction. Such assumption on h_{rsu} is mainly used to make the sensors subject to obstructions to study the impact of temporal diversity. Sensing coverage increases with tracking window τ, showing temporal diversity can be utilized to improve sensing. Vehicles in the opposite direction may provide more spatial diversity than RSUs, i.e., more collaborative vehicles than RSUs, yet this rely on the penetration ratio and may introduce higher traffic loads. Even if RSUs are subject to obstructions, RSUs utilizing temporal diversity alone can already provide a relative high coverage, e.g., over 95% coverage without collaborating with other vehicles (0 penetration). At the early stage of automated driving, collaborative vehicles in the opposite direction may not present and communication can be costly, while RSUs assisted sensing, possibly utilizing temporal diversity in sensing, can effectively improve sensing coverage.

V. Conclusion

In this paper we show that carefully deployed sensing capable infrastructure has good coverage of roads, and can effectively help vehicles to sense beyond obstructions. However, this would require deployment of sensing and communication capable RSUs regularly along the roads and at intersections, as enabling sensing at existing cellular infrastructure may suffer from obstructions. Furthermore, to share sensor data with all relevant vehicles, long range and high rate V2I/V2V (relay) links are required. One may consider enabling infrastructure to relay sensor data generated by vehicles and infrastructure with neighboring infrastructure via (mmWave) backhaul.

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