Road Traffic Density Estimation For Adaptive Beam Allocation in an ISAC Setup

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Abstract—In this paper, we propose and study a particular use case capable of performing radio-based traffic density estimation for adaptive beam allocation. The proposed scheme explores the synergy between communication and sensing from an Integrated sensing and communication (ISAC) perspective. The traffic density estimation is aided by communication functionality, which involves reusing communication waveforms and utilizing multibeam forming and sweeping techniques. Meanwhile, the sensing outcomes assist in proactively allocating radio beams. There have been accurate traffic monitoring methods relying on a large number of detectors. However, these traditional techniques have some shortcomings, and it is necessary to explore alternative traffic density estimation approaches. In this regard, we exploit orthogonal frequency division multiplexing (OFDM) communication signals of opportunity reflected from targets (vehicles) to estimate the traffic density of a road section by using JensenShannon (JS) divergence and weighted-centroid interpolation based on a few samples of density scenarios. Then, we present a millimeter-wave (mmWave) adaptive beam allocation protocol based on the traffic density estimation to enhance communication coverage for the vehicular users in the area of interest. The simulation results demonstrate that our traffic density estimation can handle a wide range of targets with a relatively low estimation error. In addition, the analysis of the adaptive beam allocation shows that it effectively improves the quality of service (QoS, in terms of outage probability) of the communication system.

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Index Terms—Integrated sensing and communication (ISAC), communication signals of opportunity, traffic density estimation, Jensen-Shannon divergence, mmWave adaptive beam allocation.

I. Introduction

Road traffic monitoring plays an important role in traffic management in the Intelligent Transportation System (ITS). Metrics related to road traffic monitoring include traffic density (defined as number of vehicles per mile), and average speed, etc. The traditional traffic monitoring methods mainly rely on a large number of detectors like cameras, ultrasonic detectors, induction loop detectors, and radar sensors [1]. Such kinds of systems are accurate but exhibit some shortcomings in terms of range and effectiveness as they are easily affected by the environment and bad weather conditions (e.g., fog, rain, etc.). In addition, the cost of deploying these detection/estimation systems is very high, especially with the rapid growth of the metropolis road networks [2]. Therefore, from both application and research perspectives, it is necessary to explore alternative techniques for traffic density estimation, and the radio-based approach is particularly interesting.

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Over the past few years, ISAC has been emerging as a key technology in future wireless systems to support many important applications [3]–[5]. ISAC refers to a design paradigm and enabling technologies, in which sensing and communication systems are integrated to efficiently utilize congested resources [3] by sharing the signal processing algorithms, hardware resources, and spectrum. Thus, it substantially reduces the cost of the hardware and spectrum resources while achieving higher service quality due to the synergy between the communication and sensing. One aspect of ISAC is the reuse of communication waveforms for sensing purpose. Triggered by ISAC, non-collaborative OFDM signals generated from illuminators of opportunity (IoO) can provide an efficient and effective solution to localize, detect, or track targets, which can enable many new use cases such as radio-based road traffic monitoring to help road traffic management in the ITS, and at the same time help the communication system to better allocate its resources proactively. Indeed, communicationassisted sensing and sensing-assisted communication can be achieved in a single ISAC setup [6].

Several research works have developed passive radar sensing techniques by utilizing the signals transmitted from different kinds of IoOs to localize and detect targets. In [7], the authors proposed a multi-target localization and speed estimation scheme by using an OFDM signal transmitted by an IoO. In [8], OFDM signals from a non-collaborative digital video broadcasting-terrestrial (DVB-T) transmitter were used to detect moving targets. Also, some researchers developed road traffic-flow monitoring systems by using noncollaborative DVB-T transmitters [9]. Although the aforementioned systems outperform the traditional traffic monitoring systems in terms of cost and effectiveness, they impose several challenges that need to be addressed. One major concern is that current localization systems either do not provide density information (e.g., [9]), or can only detect a few targets [7], [8], making them incapable of estimating the traffic density of a road section. Moreover, the idea of searching over the whole range-Doppler space to estimate the range and velocity of the targets using the cross ambiguity function requires both large signal bandwidth (for range-resolution [10]) and high power, and also incurs high computational complexity. Finally, pure data-driven traffic estimation models (e.g., machine learning) provides no insight into the physical mechanisms and is less traceable.

In this paper, we consider an ISAC scheme for both traffic monitoring using OFDM signals of opportunity, and mmWave beam allocation based on traffic sensing. Assume the system is capable of multi-beam forming and sweeping in a cloudradio-access network (C-RAN) [11] which enables centralized processing for communication and sensing cooperatively. With such a configuration, multiple base stations (BSs) can perform (either communication or sensing) cooperatively. We propose a hybrid traffic density estimation technique that combines model-based and data-driven approaches. Then, we present a density-aware and adaptive beam allocation protocol that assigns mmWave beams for the vehicular users in the area of interest. This improves the QoS and enhances the communication coverage. Finally, simulations are conducted to evaluate the proposed scheme. The results indicate that our proposed schemes can efficiently estimate the traffic density and improve the QoS of communication systems using the adaptive beam allocation. Compared to existing radio-based traffic estimation schemes, our proposed method can handle a large number of targets by reusing communication waveforms, without complex processing. *Note that this paper mainly reports preliminary work verified by simulation, providing some insight for future research in this line to consider more sophisticated traffic scenarios. Also, we focus on the basic concept and analysis, assuming some prerequisites, such as mmWave beamforming and beam sweeping, have been met.*

The rest of this paper is organized as follows. Section II presents related work. The system model is presented in Section III. The proposed schemes are described in Section IV. Numerical results are discussed in Section V, followed by conclusions in Section VI.

Major Notations: N_v: Number of vehicles; $Q(x)$: Probability density function (PDF) of a modeled template; $P(x)$: PDF of a testing signal; $p(N_v)$: Distribution of N_v; $q(\epsilon|N_v)$: Conditional distribution of estimation error ϵ; E_{Abs}: Absolute mean square error; E_{Rel}: Relative mean square error; $\bar{P}_{out}$: Outage probability of fixed beam allocation; $\bar{\mathrm{P}}_{out}$: Outage probability of adaptive beam allocation; $\bar{L}$: Mean number of idle beams (fixed beam allocation); $\bar{\mathrm{L}}$: Mean number of idle beams (adaptive beam allocation).

II. Related Work

For active traffic density estimation, the schemes [1], [2] use unmanned aerial vehicle (UAVs) or road side units (RSUs) that are widely deployed. One shortcoming of these approaches is their high implementation and maintenance costs. Also, the UAV-based scheme in [1] requires complicated postprocessing since it uses cameras installed on the UAVs for traffic detection.

For passive sensing techniques, Li et al [7] proposed a passive sensing algorithm to estimate the positions of multiple targets by using OFDM communication demodulated signals. They estimated delay and Doppler by utilizing the sparsity of the demodulation errors and numbers of reflectors. Then, the positions of targets are estimated based on the estimated delayDoppler by using the neural network. The scheme provides accurate estimation using at least 4 receiving BSs, but it can estimate at most 3 targets. Singh et al [12] presented a multi-target detection scheme by using OFDM-Radar to

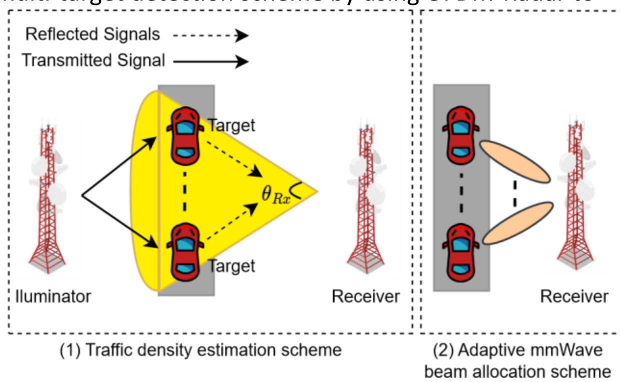

Fig. 1. System architecture of the proposed schemes.

separate the direction of arrivals (DOAs) reflected from targets, but it can only detect up to 2 targets. Bartoletti et al [13] proposed a counting targets scheme using OFDM signals that can count up to 5 targets. However, it requires the positions of the targets to be known for the receiver. Tulay et al [14] proposed passive traffic sensing scheme using dedicated shortrange communications (DSRC) signals transmitted from an RSU. The scheme uses radio signal fingerprinting and machine learning for traffic density. However, it suffers from outage due to environmental changes and requires a large dataset for accurate classification.

III. System Model

A. System Architecture

We consider one transmit BS (IoO), a receive BS, and a number of vehicles on a road section. As shown in Fig. 1, the BS transmits an OFDM signal to illuminate a road section, then the reflected signals are received by another receive BS to estimate the traffic density on the illuminated road section. Note that multiple BSs can be employed and the illuminated road section depends on the beamwidth of the transmit and receive antennas; for instance, both transmit and receive antennas cover one mile of the road section, and the main beam angle θ_{Rx} is equal to 30°.

Based on the estimated traffic density, the receive BS dedicates its antenna modules to form multiple beams aimed to serve all vehicles within the road section. We assume that each vehicle is served by a single beam at most.

B. Signal Model

Consider an OFDM transmitter that maps bits into a sequence of QAM symbols, which are converted into N_s parallel streams. Each one of N_s symbols from the serial-to-parallel conversion is carried by a different subcarrier [10]. Let $X_l[m]$ denotes the lth transmit symbol of the mth subcarrier, where $l = 0,1,\ldots,\infty$ and $m = 0,1,\ldots,N_c-1$. Then, the OFDM baseband signal can be represented as:

$$x(t) = \sum_{n=0}^{N_s-1}\sum_{m=0}^{N_c-1} c_{m,n}\, e^{-j2\pi m\Delta f(t-nT_s)} \cdot g(t) \quad (1)$$

where N_s is the number of OFDM symbols, N_c is the number of OFDM subcarriers, $c_{m,n}$ is the communication information

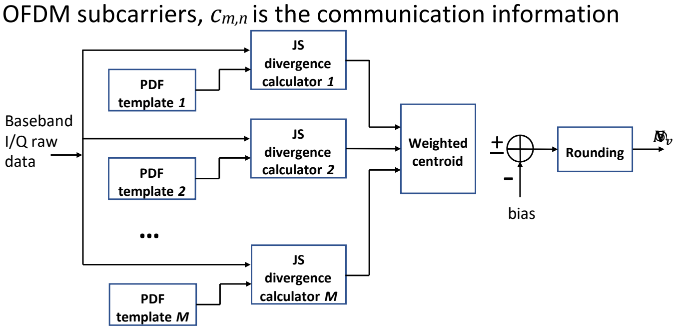

Fig. 2. Architecture of proposed traffic density estimator.

modulated on the mth subcarrier and nth OFDM symbol, Δf is the subcarrier spacing between OFDM symbols, $g(t)$ is the impulse response of the raised cosine shaping filter [10]. Then, the transmitted passband OFDM signal can be expressed as:

$$\tilde{x}(t) = x(t)\, e^{j2\pi f_c t} \quad (2)$$

where f_c is the carrier frequency.

Assume the number of vehicles is N_v in the illuminated road section, which all can be considered as targets. Each target has a radar cross section (RCS) (σ_v dB) and an average speed s_v km/h for $v = \{0,\cdots,N_v-1\}$. Then, the received signal at the receive antenna can be expressed as:

$$y(t)= \sum_{v=0}^{N_v-1}\sum_{n=0}^{N_s-1}\sum_{m=0}^{N_c-1} \sigma_v\, c_{m,n}\, e^{j2\pi f_c(t-\tau)} \cdot e^{-j2\pi m\Delta f(t-\tau)}\, g(t) + n(t) \quad (3)$$

where $n(t)$ is the additive white Gaussian noise (AWGN).

IV. Proposed Solution and Analysis

Fig. 2 shows a conceptual architecture of the proposed traffic density estimator that will be explained in Subsection. IV-A. With the knowledge of traffic density, mmWave beam can be allocated accordingly to optimize system performance proactively.

A. Road Traffic Density Estimation

Density estimation is performed in two phases: 1) modeling of probability density function (PDF) templates, and 2) estimation. In the first phase, M probability density function (PDF) templates are generated based on experiments. The second phase includes two steps, i.e., weight (divergence) calculation based on JS-divergence [15], and density calculation using weighted-centroid method. The JS-divergence is a measure which describes the distance between two probability density distributions $P(x)$ and $Q(x)$ for data x, hence providing a way to compare the statistical characteristics of different received radio signals. Given measured datasets of the received radio signals, we calculate the PDF templates using Kernel density estimation (KDE) [16].

In the template preparation phase, experiments are conducted for specific values of N_v. With a dataset of received echo signal y_j's, the estimated PDF is computed as follows:

$$Q(x) = \frac{1}{Kh}\sum_{j=1}^{K} \mathcal{K}\left(\frac{x-y_j}{h}\right) \quad (4)$$

where K is a non-negative kernel function (e.g., normal) and h is a smoothing factor. The same way is used to generate M PDF templates: $Q^{(1)}(x),\ldots,Q^{(M)}(x)$. Similarly, in the estimation phase, we obtain the measured PDF $P(x)$ for the unknown number of vehicles. Then, the JS-divergence between $P(x)$ and $Q^{(i)}(x)$ is calculated as follows:

$$JS(P(x)||Q^{(i)}(x)) = \frac{1}{2}KL(P(x)||\mathcal{M}(x)) + \frac{1}{2}KL(Q^{(i)}(x)||\mathcal{M}(x))$$
$$\mathcal{M}(x) = (1/2)(P(x)+Q^{(i)}(x)) \text{ and } KL(P(x)||\mathcal{M}(x)) \quad (5)$$

where is the Kullback-Leibler (KL) divergence between distributions $P(x)$ and $\mathrm{M}(x)$, and the KL-divergence is given by:

$$KL(P(x)||\mathcal{M}(x)) = \sum_{j=1}^{K} P(x_j)\ log_2 \frac{P(x_j)}{Q(x_j)} \quad (6)$$

Note that the JS-divergence is a smoothed version of the KL-divergence, and it is preferred since it is bounded $0 \leq JS(P(x)||\mathcal{M}(x)) \leq 1)$ no matter what N_v is, and symmetric so that the distance is independent of the order of the two PDFs under test.

With M JS-divergence values obtained in the first step of estimation phase, the weighted-centroid-based traffic density estimate is given by

$$\tilde{N}_v = \frac{\sum_{i=1}^{M} N_v^{(i)} * JS\left(P\|Q^{(i)}\right)}{\sum_{i=1}^{M} JS\left(P\|Q^{(i)}\right)} - \mathcal{B}(N_v) \quad (7)$$

where $\mathrm{B}(N_v)$ is the bias between the actual and estimated number $\tilde{N}_{v,s}$: of targets, which can be

$$\mathcal{B}(N_v) = \frac{1}{S}\sum_{s=1}^{S}(\tilde{N}_{v,s} - N_v)$$

estimated based on S measurements

(8)

B. Beam Allocation Protocols

In this phase, we make use of our proposed traffic density estimation scheme to enhance the QoS of the communication system. Specifically, we propose an adaptive beam allocation protocol that enables the BS to reserve antenna modules and assign mmWave beams based on the estimated number of vehicles. Two beam allocation scenarios are considered: (*i*) fixed beam allocation and (*ii*) adaptive beam allocation.

We assume that the BS assigns beams based on requests made by some active vehicles and these requests follow the Poisson arrival model [17]. Note that the beam alignment is out of scope of this paper and it can be done based on the location information of each vehicle, which can be obtained with the use of available positioning technologies during the requests process. Consider that the service requests arrival form a Poisson process with a mean arrival rate $\lambda = \alpha \cdot \tau$, where α is the number of packets transmitted in the time interval τ, and $\lambda > 0$. Then, the success probability of the BS to serve the vehicles using N_B mmWave beams can be expressed as:

$$P_{suc}(N_B|N_v) = \sum_{r \leq N_B} \frac{(N_v\lambda)^r \ e^{-N_v\lambda}}{r!} \tag{9}$$

where r is the number of requests per vehicle. Note that to achieve successful communication for the active vehicles, the beam assignment should satisfy the constraint $r \leq N_B$. If the probability that r exceeds the number of beams N_B, this is known the outage probability which can be represented as:

$$P_{out}(N_B|N_v) = \sum_{r > N_B} \frac{(N_v\lambda)^r \ e^{-N_v\lambda}}{r!} \tag{10}$$

Two beam allocation schemes are considered in this paper. Let us start with the fixed beam allocation scheme. In this scenario, a fixed number of beams N_B is reserved to serve the vehicles, where N_B can be chosen based on historical traffic data and it should not exceed the maximum number of beams N_{max} that BS can support. The outage probability $\bar{P}_{out}$ can be expressed as:

$$\bar{P}_{out} = \textstyle\sum_{N_v} p(N_v) P_{out}(N_B|N_v) \tag{11}$$

and the mean number of idle (not used) beams $\bar{L}$ is given by:

$$\bar{L} = \sum_{N_v} p(N_v) \sum_{r \leq N_B} \frac{(N_v\lambda)^r \ e^{-N_v\lambda}}{r!} \cdot (N_B - r) \tag{12}$$

Note that the fixed beam allocation scenario does not provide flexibility and imposes coverage problems when the number of vehicles is greater than the number of reserved beams. Therefore, we propose an adaptive beam allocation, which alleviates the problems of the fixed beam allocation.

For the adaptive beam allocation scheme, we introduce a control parameter $a(N_v+\epsilon)$ that is a pre-defined offset function (or look-up table) for adjusting allocation level as N_v changes. Practically, there must be a ceiling for resource availability. The ceiling can be represented by $min\left(N_{max}, N_v + \epsilon + a(N_v + \epsilon)\right)$, where $\epsilon = \tilde{N}_v - N_v$ is the estimation error. The corresponding conditional outage probability (conditioned on N_v) is as follows:

$$\mathcal{P}_{out}(N_v) = \sum_{\epsilon} q(\epsilon|N_v) \ P_{out}\big(min(N_{max}, N_v + \epsilon + a(N_v + \epsilon))|N_v\big) \tag{13}$$

where $q(\epsilon|N_v)$ is a conditional distribution of estimation errors. Note that the term $P_{out}\, min(N_{max}, N_v + \epsilon + a(N_v + \epsilon))|m)$ in (13) represents the adaptivity of our beam allocation scheme, which is achieved by selecting the minimum value between N_{max} and $N_v + \epsilon + a(N_v + \epsilon)$. Then, we have the outage probability of the adaptive scheme:

$$\bar{P}_{out} = \sum_{N_v} p(N_v)\ \mathcal{P}_{out} \tag{14}$$

Finally, the mean number of idle beams (conditioned on N_v) can be expressed as:

$$\mathcal{L}(N_v) = \sum_{\epsilon} q(\epsilon|N_v) \sum_{r \leq N_B} \frac{(N_v\lambda)^r \ e^{-N_v\lambda}}{r!} \cdot \Big[min\Big(N_{max}, N_v + \epsilon + a(N_v + \epsilon)\Big) - r\Big] \tag{15}$$

and, the mean number of idle beams is:

$$\bar{L} = \sum_{N_v} p(N_v)\ \mathcal{L}(N_v) \tag{16}$$

V. Quantitative Assessment

A. Simulation Setup

We evaluate traffic density estimation and adaptive beam allocation performances through Matlab Simulation, assuming a geometrical-based single-bounce channel model and known path loss. Assume an IoO located at (-700, -50) m and a receive BS located at (2500, 40) m. The IoO and the receive BS beamwidths intersect to cover a road section of one mile length. For simplicity without loss of major road traffic behavior, assume the road section has one lane[1]. We consider the transmitted signal as an mmWave OFDM signal with N_c = 1024 subcarriers, and f_c = 28 GHz. For pulse shaping, a raised-cosine filter with a roll-off factor of 0.25 is utilized.

At the receiver side, assume the received signals are reflected from vehicles with RCSs σ_v following the uniform distribution U$\sim$[1,11] based on the experiments reported in [18], the vehicles' average speed is s_v = 96.5 km/h, and the separation distance between vehicles is a random number between [10-15] m. Each reflected echo includes 41374 I/Q samples mixed with noise such that the signal-to-noise ratio

(SNR) is 2.7 dB. Four PDF templates for N_v=2, 20, 50 and 100 are considered and they are modeled based on synthetic datasets generated using simulation. The major simulation parameters used in the system evaluation of this paper are summarized in Table I.

TABLE I

SETTING OF MAJOR SIMULATION PARAMETERS.

Parameter	Value	Parameter	Value
# of subcarriers N_c	1024	RCS σ_v	U~[1,11]
Carrier frequency f_c	28 GHz	Vehicles sep. dist.	10-15 m
SNR	2.7 dB	Average speed s_v	96.5 km/h
# of PDF templates M	4	# of iterations	20
# of Fix. beams N_B	15	# of Adapt. beams N_{max}	17

For evaluating the adaptive beam allocation, two additional schemes, i.e., fixed allocation and unlimited allocation, are considered as benchmarks. We run the traffic density estimation scheme 20 times and record the estimated number of vehicles $\tilde{N}_v$ and the estimation error ϵ in each step. This data will be used to evaluate the outage probability and mean number of idle beams as described in Subsection V-B.

B. Simulation Results

Fig. 3 shows the estimated PDF of the received signals for different numbers of vehicles, suggesting that the PDF is close to Gaussian and the standard deviation of the received signal increases as the number of vehicles increases.

The four JS-divergence values for a ground true of 35 vehicles are given in Table II, and the weighted centroid estimator leads to an estimate $\tilde{N}_v$ = 36 which is very close to the true number N_v = 35. The estimation performance is evaluated in mean square error (MSE) conditioned on the number of vehicles N_v. Specifically, the total absolute and relative MSEs conditioned on N_v can be calculated as follows:

$$\mathcal{E}_{Abs(\mathcal{S}|N_v)} = \sqrt{\sum_{\epsilon\in\mathcal{S}} \epsilon^2 \; q(\epsilon|N_v)} \tag{17}$$

$$\mathcal{E}_{Rel(\mathcal{S}|N_v)} = \frac{\mathcal{E}_{Abs(\mathcal{S}|N_v)}}{N_v} \tag{18}$$

where error set S refers to "all" (i.e., all possible values for error ϵ), $\epsilon < 0$ or $\epsilon > 0$. If the PDF of N_v, $p(N_v)$, is known, then we have unconditional MSEs:

$$\bar{\mathcal{E}}_{Abs(\mathcal{S})} = \sum_{N'_v} p(N'_v)\mathcal{E}_{Abs(\mathcal{S}|N'_v)} \tag{19}$$

$$\bar{\mathcal{E}}_{Rel(\mathcal{S})} = \frac{\mathcal{E}_{Abs(\mathcal{S})}}{N_v} \tag{20}$$

The unconditional average estimation errors are given in Table III, assuming N_v is uniformly distributed over [5,20]. Fig. 4 shows the estimation errors conditioned on N_v. Note that in general the estimation bias $B(N_v)$ is not zero and we may intentionally leave it as it is. One can see from Fig. 4 that the negative relative error $\bar{E}_{Rel(-)}$ is smaller compared to the positive relative errors $\bar{E}_{Rel(+)}$, which means the estimator most likely outputs a number $\tilde{N}_v$ greater than the true number N_v. This biased estimation tends to request slightly more mmWave beam allocation to reduce the outage probability.

For adaptive beam allocation, we simply define the control parameter $a(N_v + \epsilon)$ as follows:

$$a(N_v + \epsilon) = max\Big(0, round\big(\gamma * (N_v + \epsilon)\big)\Big) \tag{21}$$

where γ is a positive real constant (γ = 0.0001 has been chosen in the simulation), and $round(\,)$ is the rounding function. In Fig. 5, the outage probabilities of strategies are calculated

[1]More realistic conditions, such as multi-lane road section, will be considered in our future work.

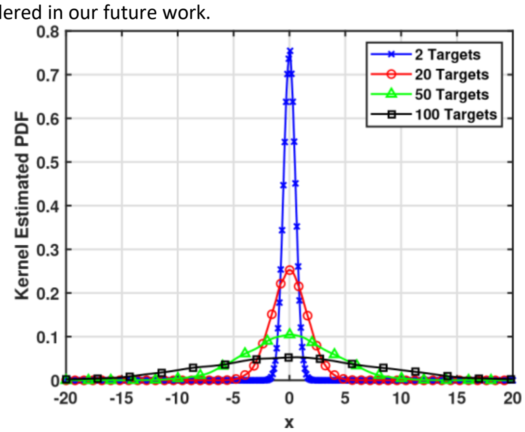

Fig. 3. Estimated PDF of the received signal at different numbers of targets.

TABLE II

JS-DIVERGENCES BETWEEN THE PDF TEMPLATES AND A TESTING SIGNAL PDF OF 35 VEHICLES.

Number of vehicles	2	20	50	100
JS-divergence	0.8000	0.2482	0.1849	0.4926

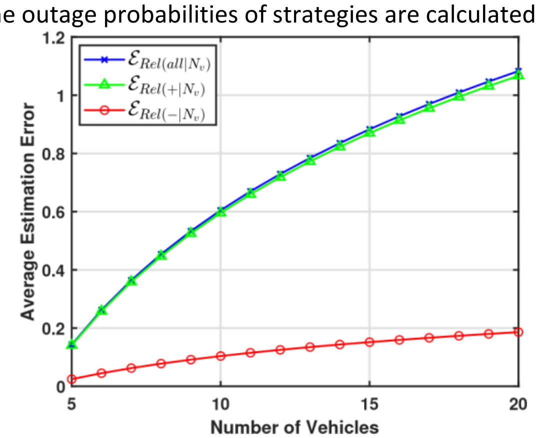

Fig. 4. Average relative estimation errors over N_v.

TABLE III

ESTIMATION ERRORS AVERAGED OVER $N_v \in [5,20]$.

$\bar{E}_{Abs(all)}$	$\bar{E}_{Rel(all)}$	$\bar{E}_{Abs(+)}$	$\bar{E}_{Rel(+)}$	$\bar{E}_{Abs(-)}$	$\bar{E}_{Rel(-)}$
11.441	1.083	11.271	1.067	1.967	0.186

for different numbers of vehicles N_v and packet arrival rates λ, assuming uniform distribution of $N_v \in [5,20]$. For the fixed-allocation benchmark scheme, $N_B = 15$ is selected. For the adaptive allocation with ceiling (N_{max}), the number of reserved beams is equal to $min(N_{max}, N_v+\epsilon+a(N_v+\epsilon)$, and the number of reserved beams could reach up to $N_{max} = 17$, while for the adaptive allocation without ceiling (another benchmark scheme), the number of reserved beams is equal to $N_v + \epsilon + a(N_v + \epsilon)$.

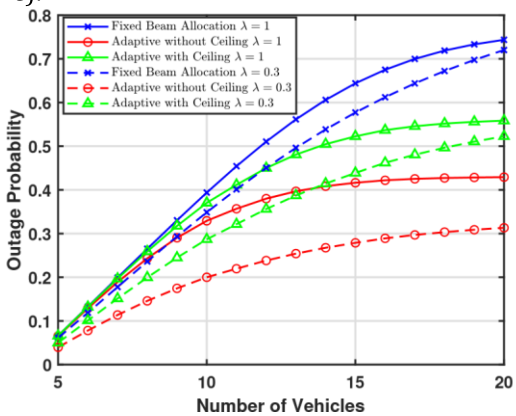

Fig. 5. Outage probability comparison based on number of vehicles.

From the comparison results we can conclude that, compared to the fixed allocation, our adaptive schemes suffer from less outage, which improves the QoS accordingly, thanks to the adaptivity backed up by the real-time traffic density estimation.

Finally, let us evaluate the level of resource waste using the mean number of idle beams ($\bar{L}$ and $\bar{L}$) as a metric. As shown in Fig. 6, the two adaptive schemes perform similarly, indicating that a resource ceiling does not necessarily impact the level of resource waste; and compared to the fixed strategy, they vary

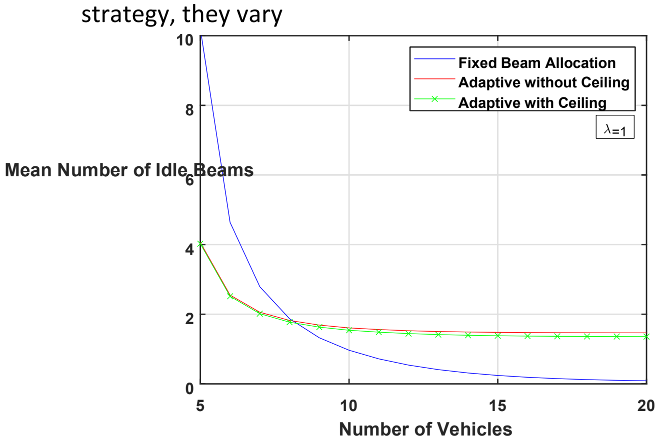

Fig. 6. Mean number of idle beams comparison at different numbers of vehicles.

less as the number of vehicles changes. Interestingly, there is a turning point at $N_v = 8$, and the adaptive schemes outperform over the fixed counterpart when $N_v < 8$; as N_v increases, both of the adaptive schemes approximately exhibit a small constant level of idleness. Note that the overall beam allocation performance is measured by both outage and idleness, and it can be stated that as the number of vehicles increases, the adaptive schemes perform significantly better than the fixed strategy at a minor penalty of $\bar{L} \approx 1.3$.

TABLE IV

COMPARISON OF TRAFFIC DENSITY ESTIMATION SCHEMES.

	Radiobased	# of cars	Bad Weather	Dyn Env.	Complexity
[1]	×	large	×	√	high
[14]	√	large	√	×	high
Ours	√	large	√	√	low

VI. CONCLUSIONS

An ISAC use case with synergy between communication and sensing is conceptually demonstrated. The traffic density estimator combines both model-based and data-driven approaches. It makes use of Jensen-Shannon divergence and weighted-centroid interpolation, requiring no huge effort on labeling and training, nor complex processing like deep learning. The traffic density estimation scheme provides passive sensing for a large number of targets, while the adaptive beam allocation enhances communication in terms of connectivity and QoS for the vehicular users within the covered road section. The simulation results suggests that the density estimation could deal with a large number of targets with a relatively low estimation error. Moreover, the performance comparison shows that the adaptive beam allocation outperforms over the fixed beam allocation by reducing the outage probability and guaranteeing service to detected vehicles. Table IV shows major difference between our scheme and traffic density estimation methods given in [1], [14], though it is not possible to make quantitative comparison. In addition to incorporating adaptive beam allocation, our scheme can adapt to bad weather conditions and dynamic environment, and has low complexity. For future work, the estimation and beam allocation performances will be further studied, considering more sophisticated scenarios, including multi-lane, realistic road traffic conditions and ground clutter.

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