Multi-Vehicle Tracking and ID Association Based on Integrated Sensing and Communication Signaling

Zhiqin Wang, Kaifeng Han, *Member, IEEE*, Jiamo Jiang, Fan Liu, *Member, IEEE*, and Weijie Yuan, *Member, IEEE*

***Abstract*—The integrated sensing and communication (ISAC) technology, which performs vehicle state sensing and communications simultaneously, has been widely regarded as a key to enable future intelligent vehicular networks. However, the communications information is in general vehicle-specific, which requires the RSU to distinguish vehicle identities (IDs). Conventionally, the vehicles feed back their IDs to the RSU, since they are not contained in the sensing echoes. This letter develops a novel approach for multi-vehicle tracking and ID association using the ISAC signals. In particular, the ID association is done by comparing the similarity of the distributions of estimated and predicted locations based on the Kullback-Leibler divergence (KLD). With the aid of the proposed approach, frequent uplink ID feedback is avoided, leading to a reduced communication overhead as well as latency. We further design a high-efficiency predictive beamforming scheme, which predicts the angular parameters in the following time instant relying on the estimated states. Simulation results show that our proposed scheme can effectively associate different vehicle IDs and improve the communications performance.**

***Index Terms*—Integrated sensing and communication, multi-vehicle ID association, beamforming design.**

I. Introduction

To FULFILL the requirement for the future intelligent vehicle networks, in-network communications and sensing vehicle states are two basic functionalities[1]. On the one hand, the communications between vehicles and roadside infrastructures can provide information for avoiding traffic accidents and congestions. On the other hand, the states, i.e., locations and speeds of vehicles, are critical for several promising applications including autonomous driving and vehicle platooning. However, researches on communications and (radar) sensing are in two parallel ways in the past. As the spectrum resource is become increasingly congested, it is cost inefficient to allocate different resources for both functionalities. With the recent advances of communications and signal processing techniques, it has been shown that the capability of sensing would be integrated with communications, which benefits from dedicated communications and sensing hardware with new waveform design, transmission strategies, and resource allocation [2]. The integrated sensing and communication (ISAC) technology, which aims for integrating both functionalities relying on the same hardware architecture, spectral resources, and signal processing framework, is capable of improving the spectrum efficiency and increasing the overall system throughput [3], [4].

As for the vehicular networks, several pioneering contributions have discussed the integration of sensing into communications [5], [6]. By transmitting a few pilots using the downlink communication signals from the roadside unit (RSU), the vehicles are capable of estimating the corresponding states, which are then fed back to the RSU for enhancing the quality of communications. Obviously, using pilot and frequent feedback will incur a high communication overhead and latency. To address this issue, recent works [7], [8] focused on extracting the vehicle states from the reflected sensing echoes, which have shown advantage of low overhead. In general, the vehicular communications are vehicle-specific, which requires the RSU to have the knowledge of vehicle identities (IDs) before transmitting ISAC signals. As the vehicle ID information is not contained in the sensing echoes, the ID association has become a major challenge for ISAC-enabled vehicular networks. The work of [7] developed a Euclidean distance-based scheme for associating the reflected echoes with the vehicle IDs. However, the Euclidean distance neglects the uncertainties of vehicle locations. The authors of [9] proposed a GPS-aided ID association algorithm which compares the sensed vehicle locations with the ones provided by GPS to associate the IDs. However, it may fail to work when the GPS signal strength is weak. Despite the importance of ID association in ISAC-enabled vehicular networks, this topic is not well investigated.

In this letter, we aim for solving the multi-vehicle tracking and ID association problem using ISAC signaling. In particular, the RSU transmits multi-beam ISAC signals to vehicles, which are reflected by the vehicles and acquired by the RSU. From sensing echoes, the RSU can extract the delays, Dopplers, as well as the angles and then estimate the locations and speeds of different vehicles. Next, the future locations of vehicles can be predicted using the states, which are used for a high-efficiency predictive beamforming design. To distinguish the IDs of different vehicles, we resort to the Kullback-Leibler divergence (KLD) as the measure to characterize the similarity of the densities of predicted location and estimated location at the same time instant. The optimal ID association can then be given by minimizing the KLD. The main benefits of the proposed algorithm are on two folds. First, the vehicles can reduce the frequency for feeding back

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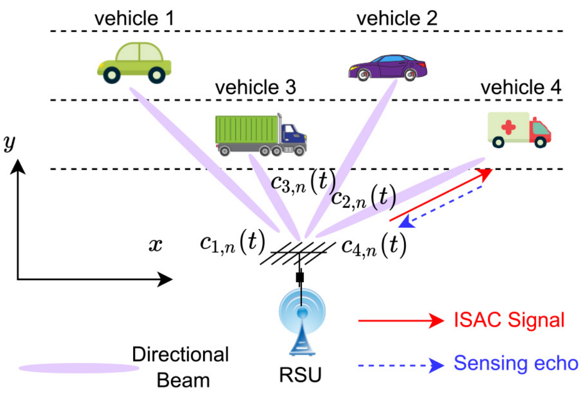

Fig. 1. Vehicular network model.

their IDs and the occupation of the uplink channels. Second, the predictive beamforming design allows the RSU to use the whole downlink blocks for transmitting data information. Moreover, we notice that the Doppler corresponding to communication channel is half of the Doppler shift associated wit the sensing channel. Therefore, the Doppler spread can be compensated at the RSU side to reduce the communication receiver complexity at the vehicle side. Consequently, both the communication overhead and latency can be significantly reduced, which is vital for the future intelligent vehicular networks.

Notations: The term $\mathbb{C}^{N\times M}$ denotes a complex space of dimension $N \times M$; $(\cdot)^{\mathrm{T}}$, $(\cdot)^{-1}$, and $(\cdot)^{\mathrm{H}}$ denote the transpose, the inverse, and the Hermittian operators, respectively; $\|\cdot\|$ denotes the norm of a vector; $\hat{x}$ and $\bar{x}$ denote the estimated and predicted values of variable x; $\mathbb{E}[x]$ denotes the expectation of x; $\propto$ denotes equity up to a constant.

II. System Model

A. Signal Model

As shown in Fig. 1, we consider a vehicular network consisting of K vehicles moving along the road, which is parallel to the x-axis. The RSU is located at $\mathbf{s}_0 = [x_0, y_0]^{\mathrm{T}}$ and the location for the k-th vehicle (with vehicle ID k) at time instant n is $\mathbf{s}_{k,n} = [x_{k,n}, y_{k,n}]^{\mathrm{T}}$, where $x_{k,n}$ and $y_{k,n}$ are the coordinates on x-axis and y-axis, respectively. The RSU is operating at the millimeter wave (mmWave) band and is mounted with an N_t uniform linear array (ULA) for signal transmission as well as an N_r ULA for echo acquisition. Each vehicle is equipped with N_v antennas for receiving the ISAC signals. At each time instant, the RSU sends a multi-beam ISAC signal to all vehicles, denoted by

$$\mathbf{x}_n(t) = \mathbf{W}_n \mathbf{c}_n(t), \tag{1}$$

where $\mathbf{c}_n(t) = [c_{1,n}(t), \ldots, c_{k,n}(t)]^{\mathrm{T}}$ is the original signals to K vehicles, $\mathbf{W}_n \in \mathbb{C}^{N_t\times K}$ is the beamforming matrix, whose k-th column is

$$\mathbf{w}_{k,n} = \sqrt{\frac{1}{N_t}}\mathbf{a}(\theta_{k,n}), \tag{2}$$

which steers the beam to the indented direction $\theta_{k,n}$. The p-th element in the steering vector $\mathbf{a}(\theta)$ is $e^{-j\pi(p-1)\cos\theta}$.

The ISAC signals are reflected by the vehicles and the echoes can be acquired at the RSU. For the echo reflected by the vehicle k, we have the following expression as[1]

$$\mathbf{y}_{k,n}(t) = \beta_{k,n}\mathbf{b}(\theta_{k,n})\mathbf{a}^{\mathrm{H}}(\theta_{k,n})\mathbf{x}_{k,n}(t-\tau_{k,n})e^{j2\pi\gamma_{k,n}t} + z(t), \tag{3}$$

where $\beta_{k,n}$, $\tau_{k,n}$, and $\gamma_{k,n}$ denote the reflection coefficient, the propagation delay, and the Doppler shift, respectively. The vector $\mathbf{b}(\theta_{k,n}) \in \mathbb{C}^{N_r\times 1}$ denotes the receive steering vector. The term $z(t)$ is the additive noise, which obeys a Gaussian distribution of zero mean and variance σ^2.

Due to the fact that the echoes have no information of the vehicle IDs, we use a new index i for denoting the i-th echo received by the RSU. Based on the received echo $\mathbf{y}_{i,n}(t)$ at time instant n, the RSU is capable of performing matched filtering by using a bank of delayed and Doppler shifted version of the transmitted signals $c_{i,n}(t)$, see, e.g., [11]. Assuming that the delay τ and Doppler γ can be tuned to the delay and Doppler corresponding to the i-th echo, we can express the estimates of τ_i and γ_i as

$$\hat{\tau}_{i,n} = \tau_{i,n} + n_\tau = \frac{2\|\mathbf{s}_0 - \mathbf{s}_{i,n}\|}{c_s} + n_\tau, \tag{4}$$

$$\hat{\gamma}_{i,n} = \gamma_{i,n} + n_\gamma = \frac{2v_{i,n}f_c\cos\theta_{i,n}}{c_s} + n_\gamma, \tag{5}$$

where c_s denotes the signal propagation speed, $v_{i,n}$ denotes the speed of the i-th target at time n, $\theta_{i,n}$ denotes the angle of target i relative to the RSU, f_c and c denote the carrier frequency and the signal propagation speed, respectively. The Gaussian noise terms n_τ and n_γ are with zero means, whose variances σ_τ^2 and σ_γ^2 are scaled by the accuracy of sensing detection. Having the delay and Doppler estimates in hand, we can write the received signal as

$$\mathbf{r}_{i,n} = G\beta_{i,n}\mathbf{b}(\theta_{i,n})\mathbf{a}^{\mathrm{H}}(\theta_{i,n})\mathbf{w}_{i,n} + \mathbf{z}_{i,n}, \tag{6}$$

where the constant G denotes the matched filter gain.

B. Vehicle State Model

As the vehicles are moving on the road, their states will evolve with time. In particular, the state transition function for vehicle location can be written as

$$\mathbf{s}_{k,n+1} = \mathbf{s}_{k,n} + [v_{k,n}, 0]^{\mathrm{T}}\Delta t, \tag{7}$$

where Δt denotes the duration of a single time instant. As for the evolution of angle $\theta_{k,n}$, it can be approximated by

$$\theta_{k,n+1} = \theta_{k,n} + \frac{v_{k,n}\Delta t\sin\theta_{k,n}}{\|\mathbf{s}_0 - \mathbf{s}_{k,n}\|}, \tag{8}$$

when the variation of the range distance is negligible in a single time instant.

C. Communications Model

For massive antenna systems operated in the mmWave band, the channel model to the k-th vehicle is generally line of sight (LoS) dominated,[2] which is given by

$$\mathbf{H}_{k,n}(t) = h_{k,n}\mathbf{f}(\theta_{k,n})\mathbf{a}^{\mathrm{H}}(\theta_{k,n})e^{j2\pi\nu_{k,n}t}, \tag{9}$$

[1] Here we employ the asymptotical property of the massive antenna system such that the echoes reflected by different vehicles can be distinguished [10]. Thus, no inter-beam interference exists.

[2] In the scenarios of non-LoS (NLoS) channel, NLoS identification and mitigation scheme can be used, e.g., [12], [13].

where $h_{k,n} = \sqrt{\frac{c}{4\pi f_c \|\mathbf{s}_0 - \mathbf{s}_{k,n}\|^2}}$ denotes the channel gain, $\mathbf{f}(\theta_{k,n}) \in \mathcal{C}^{N_v \times 1}$ denotes the receive steering vector at the vehicle side, $\nu_{k,n}$ is the Doppler shift associated with the communications channel, which is theoretically equal to half of the round-trip Doppler $\gamma_{k,n}$. After downlink signaling transmission, the vehicle adopts a receive beamformer $\mathbf{g}_{k,n}$ for maximizing the signal-to-noise ratio (SNR) gain. Consequently, the received signal at the *k*-th vehicle is given by

$$y_{k,n}(t) = h_{k,n} e^{j2\pi\nu_{k,n}t} \mathbf{g}_{k,n}^{\mathrm{H}} \mathbf{f}(\theta_{k,n}) \mathbf{a}^{\mathrm{H}}(\theta_{k,n}) \mathbf{w}_{k,n} c_{k,n}(t) + \omega(t), \quad (10)$$

where $\omega(t)$ denotes the additional Gaussian noise with power spectral density (PSD) N_0.

D. ID Association Problem

From the sensing echoes, the RSU is capable of inferring the delays and Dopplers corresponding to all vehicles, which enables various location-based services. Nevertheless, from the communications perspective, the communications information is vehicle-specific, which can not be extracted from the sensing echoes. Thus, there is a need to associate the vehicle IDs with all sensing echoes reflected by the vehicles. For ease of exposition, we make the following basic assumptions: 1) All vehicles can be detected at the RSU; 2) Each vehicle produces only one reflected echo; 3) Each reflected echo is associated with only one vehicle.

Given the above assumptions, our goal is to find the optimal scheme that pairs the vehicle ID *k* and the echo index *i*, expressed as

$$(i,k)^* = \arg\min_{(i,k)} \; M_{i,k} \quad (11)$$

$$s.t. \; \sum_i \mathbb{I}_{i,k} = 1 \quad (\mathrm{C1})$$

$$\sum_k \mathbb{I}_{i,k} = 1, \quad (\mathrm{C2})$$

where $\mathbb{I}_{i,k} \in \{0,1\}$ is the association indicator and $M_{i,k}$ is a metric to measure the 'distance' of *i* and *k* in measure space.[3]

III. Multi-Vehicle Tracking and ID Association via ISAC Signals

In this section, we present a new scheme for multiple vehicle tracking and ID association using ISAC signals. Our goal is to associate the vehicle IDs as well as to determine the vehicle states from the reflected echoes.

A. Vehicle State Estimation

Assuming that at the initial time instant $n = 0$, the RSU has the knowledge of the locations as well as the speeds of all *K* vehicles.[4] To extract the angle $\theta_{i,n}$ from the received echo $\mathbf{r}_{i,n}$, we first estimate the reflection coefficient $\beta_{i,n}$, given by

$$\hat{\beta}_{i,n} = \frac{\xi}{c_s \hat{\tau}_{i,n}}, \quad (12)$$

where ξ is the radar cross section (RCS) of the vehicle. Next, Eq. (6) yields the likelihood function $p(\mathbf{r}_{i,n}|\theta_{i,n})$ and the angle $\theta_{i,n}$ can be obtained by maximizing $p(\mathbf{r}_{i,n}|\theta_{i,n})$. As the resolution for the angular parameter relies on the size of antenna array. The maximum likelihood estimator can be expressed as

$$\hat{\theta}_{i,n} = \arg\max_{\theta_{i,n}\in\mathbf{\Theta}} p(\mathbf{r}_{i,n}|\theta_{i,n}), \quad (13)$$

where $\mathbf{\Theta}$ denotes the set containing all possible values of $\theta_{i,n}$.

Given the estimates of the delay and angle corresponding to the *i*-th target, its location can be inferred by the RSU as

$$\hat{\mathbf{s}}_{i,n} = \mathbf{s}_0 + \frac{c_s \hat{\tau}_{i,n}}{2} \cdot \left[\sin\hat{\theta}_{i,n}, \cos\hat{\theta}_{i,n}\right]^{\mathrm{T}}. \quad (14)$$

Obviously, the positioning error of target *i* depends on the estimation accuracy of $\hat{\tau}_{i,n}$ and $\hat{\theta}_{i,n}$. In general, the accuracy of delay estimation can be characterized by [14]

$$\sigma_\tau \cong \frac{1}{2B\sqrt{2\mathrm{SNR}}}, \quad (15)$$

where *B* and SNR denote the signaling bandwidth and signal-to-noise ratio, respectively. As for the angle estimation, its mean squared error is bounded by the Cramer-Rao lower bound (CRB) [15], which is given by

$$\sigma_\theta \geq \frac{1}{\mathbf{j}^{\mathrm{T}}\mathbf{D}\mathbf{j}}, \quad (16)$$

where $\mathbf{j}$ is the Jacobian vector, formulated as

$$\mathbf{j} = [\frac{\partial r_{i,n}^1}{\partial\theta_{i,n}}, \ldots, \frac{\partial r_{i,n}^{N_r}}{\partial\theta_{i,n}}]^{\mathrm{T}}, \quad (17)$$

and $\mathbf{D} = \frac{1}{\sigma_z^2}\mathbf{I}$. According to Mellin transformation, the *n*-th order moment of the product of two independent variables satisfying

$$\mathbb{E}[(xy)^n] = \mathbb{E}[x^n]\mathbb{E}[y^n]. \quad (18)$$

Therefore, we can determine the covariance matrix $\mathbf{V}_{i,n}$ for the location of the *i*-th target based on Eq. (14).[5] Moreover, the speed of the *i*-th target can be estimated using the Doppler estimate $\hat{\gamma}_{i,n}$, expressed as

$$\hat{v}_{i,n} = \frac{c_s \hat{\gamma}_{i,n}}{f_c \cos\hat{\theta}_{i,n}}. \quad (19)$$

B. Predictive Transmit Beamforming Design

Having obtained the estimated location as well as the speed, the RSU is capable of further predicting the location of the *i*-th target in the following instant using the state transition model (see Eq. (7)),

$$\bar{\mathbf{s}}_{i,n+1} = \hat{\mathbf{s}}_{i,n} + [\hat{v}_{k,n}, 0]^{\mathrm{T}}\Delta t. \quad (20)$$

As the state evolution model is generally associated with a transition noise, the predicted location of the *i*-th target is with

[3] It should be note that the choice $M_{i,k}$ is not limited to any specific measure spaces. For example, the work of [7] considered the use of Euclidean distance for $M_{i,k}$. In our work, we restrict $M_{i,k}$ in probability space to better characterize the similarity of two distributions.

[4] The vehicle states can be estimated by using the scanning mode of the RSU or by vehicle uplink feedback.

[5] Note that the cosine and sine functions involve nonlinear transformation. Here we resort to Taylor series for determining the second-order moments of $\sin\theta_{i,n}$ and $\cos\theta_{i,n}$ given σ_θ. The calculations are straightforward and not included here due to space limitation.

uncertainty σ_m^2. According to Eq. (8), the angular parameter at time $n+1$ can be predicted as

$$\bar{\theta}_{i,n+1} = \hat{\theta}_{i,n} + \frac{\hat{v}_{i,n}\Delta t \sin\hat{\theta}_{i,n}}{\|\mathbf{s}_0 - \hat{\mathbf{s}}_{i,n}\|}. \tag{21}$$

The predicted angle $\bar{\theta}_{i,n+1}$ can then be used for designing the transmit beamformer $\mathbf{w}_{i,n+1}$ before transmitting the data information. Compared with the conventional scheme which utilizes several pilots for beam pairing, our proposed beamforming design extracts the beam directions from the echoes, which enables the use of whole downlink block for data transmission. As a result, both the communication overhead and latency can be reduced.

C. Multi-Vehicle ID Association

To associate echo index i and vehicle ID k, we resort to the Kullback-Leiber divergence (KLD) for measuring the similarity of target i and vehicle k in probability space. In particular, the KLD of two arbitrary density functions of the same variable x is given by

$$\mathbb{D}[p|q] = \int p(x)\ln\frac{p(x)}{q(x)}\mathrm{d}x. \tag{22}$$

Therefore, the multi-vehicle ID association problem can be formulated by finding the pair of densities $p(\mathbf{s}_{i,n+1}) = p(\mathbf{s}_{i,n+1}|\bar{\mathbf{s}}_{i,n+1})$ and $q(\mathbf{s}_{i,n+1}) = p(\mathbf{s}_{i,n+1}|\hat{\mathbf{s}}_{k,n+1})$, corresponding to the predicted and estimated locations, respectively. In the above two subsections, we have derived the uncertainties of $\bar{\mathbf{s}}_{i,n+1}$ and $\hat{\mathbf{s}}_{k,n+1}$. Hence, both $p(\mathbf{s}_{i,n+1}|\bar{\mathbf{s}}_{i,n+1})$ and $p(\mathbf{s}_{i,n+1}|\hat{\mathbf{s}}_{k,n+1})$ can be written in Gaussian forms and their KLD is given by

$$\begin{aligned}\mathbb{D}_{i,k} \propto \int &\exp\left((\mathbf{s}_{i,n+1}-\bar{\mathbf{s}}_{i,n+1})^{\mathrm{T}}\frac{1}{\sigma_m^2}\mathbf{I}(\mathbf{s}_{i,n+1}-\bar{\mathbf{s}}_{i,n+1})\right)\\ &\left[\left((\mathbf{s}_{i,n+1}-\bar{\mathbf{s}}_{i,n+1})^{\mathrm{T}}\frac{1}{\sigma_m^2}\mathbf{I}(\mathbf{s}_{i,n+1}-\bar{\mathbf{s}}_{i,n+1})\right)\right.\\ &\left.-\left((\mathbf{s}_{i,n+1}-\hat{\mathbf{s}}_{k,n+1})^{\mathrm{T}}\mathbf{V}_{i,n}^{-1}(\mathbf{s}_{i,n+1}-\hat{\mathbf{s}}_{k,n+1})\right)\right]\mathrm{d}\mathbf{s}_{i,n+1}. \end{aligned} \tag{23}$$

Remark: The optimal association of all K detected targets and vehicle IDs can be determined by solving the following problem

$$(i,k)^* = \arg\min_{i,k}\sum_{(i,k)}\mathbb{D}_{i,k}, \tag{24}$$

under the constraints (C1) and (C2). Note that $\mathbb{D}_{i,k}$ can be expressed in a quadratic form, as the integration in (23) gives out the conditional expectations of $p(\mathbf{s}_{i,n+1}|\bar{\mathbf{s}}_{i,n+1})$. Hence, the above optimization problem can be solved using standard solvers [16].

Compared to the scheme based on Euclidean distance [7], the proposed vehicle ID association approach can exploit the estimation uncertainty, which is robust to the randomness during the movement of the vehicles. As shown in Fig. 2, for the classic scheme, the vehicle ID feedback has to be done at each time instant to ensure the reliability of vehicle-specific information transmission. On the contrary, for the proposed algorithm, after feeding back the vehicle IDs at the initial stage, the RSU will track the vehicles and associate their IDs simultaneous based on the ISAC echoes in the following time instants. As a result, the frequency of using uplink channel dedicated for ID feedback can be reduced.

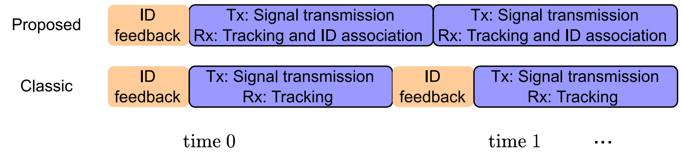

Fig. 2. Transmission block structure comparison.

D. Sensing-Assisted Downlink Communications

The sensing information can be used for receive beamforming and compensating channel effects.

Assuming that the predicted angle at time $\bar{\theta}_{k,n+1}$ has been contained in the ISAC signal to vehicle k at time instant n, the k-th vehicle can therefore formulate the receive beamforming, i.e.,

$$\mathbf{g}_{k,n+1} = \mathbf{f}(\bar{\theta}_{k,n+1}), \tag{25}$$

without estimating the relative angular parameter. In addition to predicting the beam direction, as already discussed in [7], we observe that the sensing parameters can be even used for predicting the downlink channels. In general, the Doppler shift will significantly degrade the communications performance from the communications perspective [17]. Observed by the fact that the Doppler γ corresponding to the sensing channel is a round-trip Doppler while the Doppler ν associated with the communication channel is the one-way parameter, we can use the estimated speed $\hat{v}_{k,n}$ for predicting the one-way Doppler shift at time $n+1$. It is capable of compensating the Doppler shift of the communication channel at the RSU. Similarly, as the location of vehicle k can be predicted by the RSU at time $n+1$, the RSU can predict the channel path loss factor $h_{k,n+1} = \sqrt{\frac{c}{4\pi f_c\|\mathbf{s}_0-\mathbf{s}_{k,n+1}\|^2}}$ as well. As a result, all channel information can be acquired without use of dedicated pilots, showing the benefits of employing ISAC signals in the future intelligent vehicular networks.

To evaluate the communications performance, we consider the sum achievable rate of all vehicles at a single time instant n, which is given by

$$R_n = \sum_{k=1}^{K}\log(1+\mathrm{SNR}_{k,n}), \tag{26}$$

where $\mathrm{SNR}_{k,n}$ denotes the receive SNR at the k-th vehicle, which is expressed as

$$\mathrm{SNR}_{k,n} = \frac{p_{k,n}|h_{k,n}\mathbf{g}_{k,n}^{\mathrm{H}}\mathbf{f}(\theta_{k,n})\mathbf{w}_{k,n}\mathbf{a}^{\mathrm{H}}(\theta_{k,n})|^2}{N_0}, \tag{27}$$

where $p_{k,n}$ is the transmitted signal power. If the predicted beam direction is aligned with the actual angle, the SNR is maximized, resulting in the maximum achievable rate.

IV. Simulation Results

Let us consider a network with 8 vehicles moving on the two-lane road. For simplicity, the location of RSU is fixed at $[0,0]^{\mathrm{T}}$ and the road is parallel to the x-axis with coordinate 10 m on the y-axis. The initial positions of the vehicles are randomly generated on the road with 10 m minimum spacing. The RSU is equipped with an $N_t = 64$ transmit ULA and an $N_r = 64$ receive ULA and is operating in the mmWave band with carrier frequency $f_c = 30$ GHz. We assume that the transmit and receive arrays are sufficiently isolated and will not interfere with each other. The speeds of vehicles follow a truncated Gaussian distribution with mean 20 m/s and standard

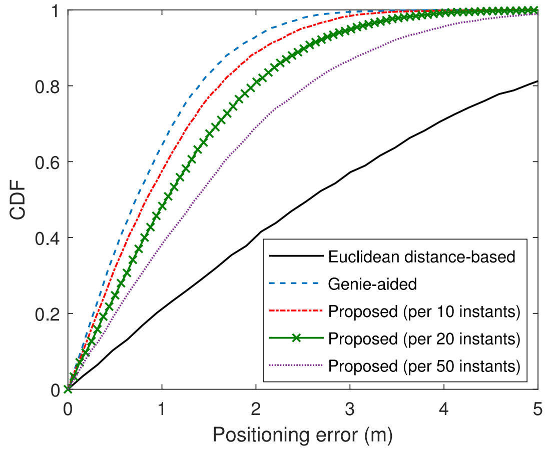

Fig. 3. CDF of the positioning error.

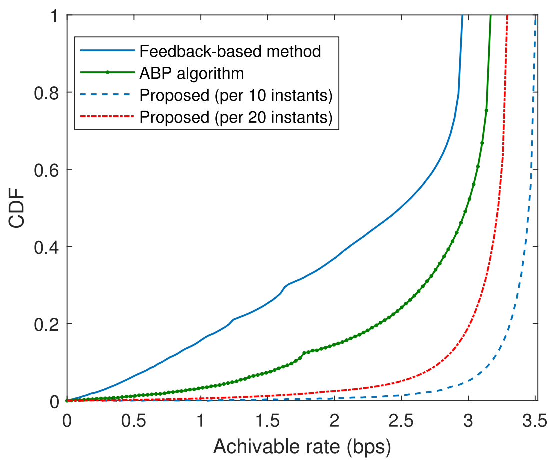

Fig. 4. CDF of the achievable rate.

deviation 5 m/s within the range of [0, 40] m/s.[6] The duration for each time instant is $T = 0.02\ s$. The noise terms are set with standard deviations of $\sigma_z = 1$ and $\sigma_m = 0.2$ m. The SNR gain for sensing matched filtering is $G = 10$.

In Fig. 3, we compare the cumulative distribution function (CDF) of the positioning error for different schemes. The genie-aided method which demands the vehicles to feedback their IDs to the RSU at each time instant has the best performance, since all detected vehicles can be perfectly associated with their IDs. Our proposed algorithm can almost attain the performance of the genie-aided scheme while reducing the frequency for ID feedback to once for every 10/20 time instants. As a benchmark scheme, the Euclidean distance-based ID association scheme will suffer from performance loss due to the ignorance of the estimation uncertainty. Through the simulation results, we can see our proposed algorithm can accurately track the vehicles and associate their IDs in the network using ISAC signaling.

In Fig. 4, the CDF of the sum achievable rate of all time instants for different algorithms is illustrated. It should be noted that if the vehicle is not correctly associated with its ID, the communications rate is 0. The performance of approximate beam pairing (ABP) scheme [18] and communications pilot-based scheme with perfect ID association is plotted as a benchmark. We can observe that our proposed algorithm significantly outperform the communications pilot-based algorithm even with one ID feedback for every 20 instants. This is because the proposed algorithm relying on ISAC signals can adopt the whole downlink block as pilots, compare to one or two pilots for the communications pilot-based scheme, resulting in higher accuracy for the angle tracking. Moreover, the proposed algorithm performs better than the ABP scheme, since the ABP may fail to work when the angular parameter experience large variation in two consecutive time instants.

[6]We consider a Gaussian distribution because that in most cases, the vehicle speeds will not much higher or much lower than the road required speed.

V. Conclusion

In this letter, we proposed an ISAC signaling based multi-vehicle tracking and ID association scheme for the future intelligent vehicular networks. With the help of sensing capability, the RSU can extract the states of the vehicles at the current time instant, which can enhance the downlink communications and reduce the overhead as well as communications latency. We further developed a KLD-based scheme for associating the detected vehicles with vehicle IDs, which guarantees the reliability of vehicle-specific communications and reduces the frequency of uplink ID feedback. Simulation results demonstrate the effectiveness and superiority of the proposed approach for multi-vehicle tracking and association.

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