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Value-Anticipating V2V Communications for Cooperative Perception

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Abstract— **The growing penetration of on-board communication units is enabling intelligent vehicles to share their sensor data with cloud computing platforms as well as with other vehicles. Although this unlocks the possibility of a variety of emerging applications, the massive amount of data traffic in vehicular networks is expected to pose a big challenge in the long term. In this paper, we shed light on the potential of *value-anticipating networking* to tackle this issue. A vehicle sending a piece of information first anticipates the value of that information for potential receivers. When the network is congested, the sender may defer or even cancel transmissions of less valuable information, so that important information can be delivered to receivers more reliably. We investigate the applicability of this concept to cooperative perception, where vehicles exchange processed sensor data over vehicle-to-vehicle (V2V) networks to collaboratively improve coverage and accuracy of environmental perception. Through simulations based on realistic road traffic, we show that value-anticipating V2V communications can significantly improve the performance of cooperative perception under heavy network load.**

I. Introduction

Vehicular networks have been recognized as a key driver in the evolution of intelligent vehicles. Connectivity to network infrastructures allows vehicles to leverage the powerful computational resources of cloud and edge computing platforms. An increasing number of vehicles are equipped with a rich set of on-board sensors, which generate a massive amount of data on the road. The cloud- and edge-based analysis of such vehicle-generated sensor data is a promising enabler of a wide variety of services, ranging from generation and maintenance of high-resolution road maps to cloud-assisted intelligent driving [1]. Connectivity among vehicles is another important aspect that unlocks the potential of a different class of promising applications. A typical example is cooperative perception, where vehicles share sensor data with each other over vehicle-to-vehicle (V2V) networks to perceive road objects beyond their own sensors' fields of view. Both types of emerging services are expected to increase data traffic in vehicular networks by multiple orders of magnitude. The excessive load on the network would increase the risk that important data packets are delayed or even lost, potentially leading to serious safety threats.

The concept of *value-anticipating networking* can be a promising solution to this problem [2]. When a vehicle attempts to send information (*e.g.*, sensor data) over vehicular networks, it first anticipates the *value* of each piece of information from the perspective of potential receiver(s). Although the actual value is unknown until the information is received and interpreted by the receivers, the sender vehicle may leverage a generic value model and its own knowledge about road and network conditions to infer the value that the information can be expected to deliver to the receivers. Based on the anticipated value of information, the sender may defer or even cancel transmissions of less valuable information to save network resources, which eventually helps deliver valuable information more reliably.

In this paper, we investigate the potential of value-anticipating networking and its applicability to cooperative perception. Although radio channels in the dedicated ITS band do not have enough bandwidth for vehicles to exchange raw sensor data such as camera images, some recent research work has shown the feasibility of using DSRC/ITS-G5 networks to periodically broadcast digest information such as types, positions, and dynamic state of perceived road objects [3]. However, sending information about all of the road objects that are detected by on-board sensors may still cause high network load, especially in a dense urban environment with a large number of vehicles and other road "objects" (*e.g.*, pedestrians). The high load on the radio channel would likely lead to packet loss and large communication latency, potentially degrading accuracy and timeliness of vehicles' perception of road objects. Our *value-anticipating cooperative perception* framework copes with this problem by intelligently selecting information to be sent at each transmission opportunity. Vehicles include the information about each perceived road object into a data message only if its anticipated value is more than a pre-defined threshold for at least one vehicle within the communication range. We employ an information theory approach to quantify the expected value of information.

Through a simulation study based on realistic road traffic, we show that value-anticipating V2V communications can significantly improve the performance of cooperative perception under heavy network load.

II. Related Work

A. Cooperative Perception

Some recent work has proved that sharing sensor data among neighboring vehicles over vehicular networks helps them reliably detect the surrounding road objects. Günther et al. [4] proposed a data message format, called *Environmental Perception Message*, for exchanging perception information among vehicles. The message consists of three key components: (i) position and dynamic state of the sender vehicle, (ii) fields of view of on-board sensors, and (iii) perception information of road objects. The perception information is

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represented by position, type, size and dynamic state of each object, which can be estimated by analyzing the vehicle's own sensor measurements. While there are also other variants of message format, we collectively call them *Cooperative Perception Messages* (CPMs) in this paper.

In order to deploy cooperative perception at scale, it is important to take the limitations of network capacity into account. A possible approach to cope with the network load is to introduce a decentralized congestion control (DCC) mechanism, which dynamically adjusts the frequency of message transmissions based on the network load. Günther et al. [3] investigated the feasibility of leveraging the standard DCC mechanisms [5] for adaptive transmissions of CPMs. Their simulation results show that DCC allows CPMs to coexist with Cooperative Awareness Messages (CAMs) in the ITS-G5 network. However, the simulations do not consider non-vehicle road objects, which brings additional perception information into CPMs. Coping with such a large number of road objects is still an open challenge.

B. *Value-Anticipating Networking*

Value of information is an emerging concept to prioritize network traffic to facilitate efficient utilization of limited network resources. Bisdikian et al. [2] characterized the value of information in wireless sensor networks by multiple attributes including trust (*e.g.*, reputation of the information source), usefulness (*e.g.*, novelty, relevance, and timeliness) and convenience (*e.g.*, format compatibility, etc.). Basagni et al. [6] applied a similar concept to underwater wireless sensor networks for submarine surveillance and monitoring.

Some other prior work has also considered value of information in vehicular networks. The ETSI standard on Cooperative Awareness services has a dedicated mechanism to trigger the generation of a new message [7]. In the standard, each vehicle is basically supposed to generate a CAM at time intervals determined by the DCC mechanism. Besides the scheduled message generation, vehicles may also generate a new CAM if the dynamic state of the transmitting vehicle has changed more than a pre-defined threshold since the last message generation. It can be seen as a possible embodiment of value-anticipating networking, since such a significant change in the state would be often hard to predict and thereby constitute valuable information for receivers. Huang et al. [8] proposed a mechanism to dynamically adjust power and time intervals of beacon message transmissions. Each vehicle predicts the expected error of the vehicle's own position from the neighboring vehicles' points of view, and determines the probability of transmitting a beacon message at each transmission opportunity based on the expected error. The existing mechanisms above are designed for the transmission of Basic Safety Messages (BSMs) or CAMs, which contain the sender vehicle's own position and dynamic state. None of the existing solutions can be directly applied to cooperative perception applications, where vehicles exchange perception information about the surrounding road objects for data fusion.

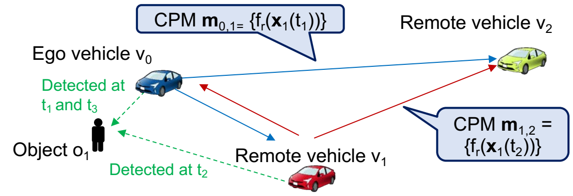

Fig. 1. Example of CPM content selection problem

III. Problem Formulation

A. *Basic Assumptions*

Let $\mathcal{V}$ denote the set of all the vehicles in the environment. We assume that a subset of vehicles $\mathcal{V}' \subseteq \mathcal{V}$ are equipped with both on-board sensors (*e.g.*, radar, lidar, camera, etc.) and a hardware unit for V2V communications. At each time step t, a vehicle $v_i \in \mathcal{V}'$ perceives a set of road objects $\mathcal{O}_{i,t}$ by its on-board sensors, and generates a *perception record* for each of the detected objects $o_j \in \mathcal{O}_{i,t}$. We define the perception record as a probability distribution $f_r(\boldsymbol{x}_j(t))$ about *state* $\boldsymbol{x}_j(t)$ of the object, since sensor measurements usually contain a certain amount of uncertainty. The state $\boldsymbol{x}_j(t)$ of an object o_j can be characterized by one or a set of feature(s), such as type, position, speed, size and/or visual appearance of the object. For simplicity of discussion, we define the state $\boldsymbol{x}_j(t)$ by a vector consisting of the 2-dimensional position $[x_j(t), y_j(t)]$ and speed $[\dot{x}_j(t), \dot{y}_j(t)]$ of the detected object. We assume that vehicles' on-board sensors can measure the position of each perceived object with a random measurement noise, which follows a Gaussian distribution. The assumption of Gaussian noise makes it possible to simply describe the perception record $f_r(\boldsymbol{x}_j(t))$ by the mean $\boldsymbol{z}_j(t)$ and the covariance matrix $R_j(t)$ of the distribution. At the end of each time step t, $v_i \in \mathcal{V}'$ broadcasts a *Cooperative Perception Message* (CPM) $\boldsymbol{m}_{i,t}$ that contains the position and the dynamic state (*e.g.*, speed, acceleration, orientation, etc.) of the ego vehicle v_i as well as all or a subset of the perception records. The duration of each time step is either constant or dynamically adjusted by an underlying congestion control mechanism.

B. *Formulation of the CPM Content Selection Problem*

In this section, we define a content selection problem, referring to the simple example scenario in Fig. 1. The example contains an ego vehicle v_0 and two remote vehicles v_1 and v_2 in v_0's communication range. The ego vehicle detected an object o_1 at time t_1 by its on-board sensors, and broadcast a CPM $\boldsymbol{m}_{0,1}$ that included a perception record about object o_1. After a while, the ego vehicle received a CPM $\boldsymbol{m}_{1,2}$ from a remote vehicle v_1, which also included a perception record about the same object o_1 generated by v_1 at time t_2. Then at time t_3, the ego vehicle v_0 detected object o_1 by its on-board sensors again. Our key research question in this work is *whether the ego vehicle v_0 should include the new perception record about object o_1 in its CPM for the next transmission opportunity*. The new perception record may not be so valuable for the remote vehicle v_1, since it recently detected object o_1 by its own sensors. Even though the position of object o_1 may have changed since time t_2, the remote vehicle v_1 may leverage a generic motion prediction model to extrapolate the position of object o_1 for a short period of time. However, the value of the information from the remote vehicle v_2's perspective could be different from that of v_1. We assume that due to long distance and/or occlusion by other road objects, vehicle v_2 has not detected o_1 by its sensors. Furthermore, due to lossy wireless channels, the remote vehicle v_2 might have failed to receive either or both of $\boldsymbol{m}_{0,1}$ and $\boldsymbol{m}_{1,2}$. If both CPMs were not available at v_2, the new perception record would be valuable for this receiver.

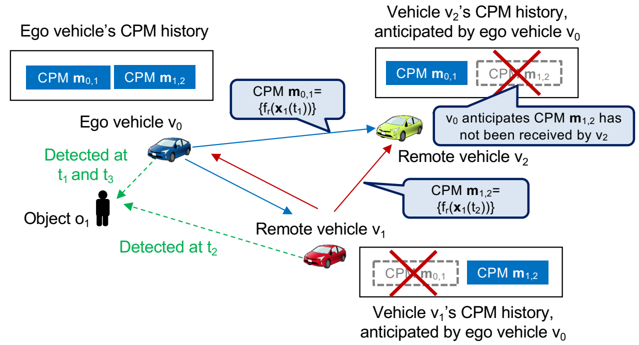

Fig. 2. Example of prior knowledge anticipation

IV. Value-Anticipating Cooperative Perception

A. Design Overview

Our basic policy on content selection is to include a perception record into the next CPM only if the anticipated value of the information is more than a pre-defined threshold for at least one remote vehicle in the communication range. In order to anticipate the value of information, the ego vehicle maintains the following three types of lists:

- *Neighbor list*: positions of connected vehicles in $\mathcal{V}'$ within the ego vehicle's communication range. The list can be updated based on CPMs that the ego vehicle has received over the recent time window W. We empirically set W to 3 seconds in this paper.
- *CPM history*: a list of CPMs that the ego vehicle has *obtained* (*i.e.*, has either generated by itself or received from remote vehicles) over the recent time window W.
- *Anticipated CPM histories of remote vehicles*: lists of CPMs that neighboring vehicles are expected to have obtained over the window W (see Sec. IV-B for details).

Based on the anticipated CPM histories of remote vehicles, the ego vehicle infers each remote vehicle's prior knowledge about the state of an object of interest $o_j \in \mathcal{O}_{i,t}$, as will be discussed in Sec. IV-C. Finally, we define the value of each perception record based on the *relative information entropy* it will likely deliver to each potential receiver, and select the contents of the next CPM based on the anticipated value of information. The detailed definition of the value of information will be discussed in Sec. IV-D.

B. Anticipating the CPM Histories of Remote Vehicles

The first step of the content selection process is to anticipate pieces of information already available at potential receivers. We define the potential receivers by a set of remote vehicles that are within the ego vehicle's communication range, and thereby included in its neighbor list. Due to the limited communication range and potential packet loss, some remote vehicles may not have obtained CPMs that the ego vehicle has obtained over the recent time window, and vice versa. Consequently, each vehicle in the neighbor list often has different sets of information about each object of interest. A straightforward approach to cope with the heterogeneity would be to have remote vehicles notify the ego vehicle of a set of CPMs they have successfully received in the past. However, this would be undesirable, since the notification incurs additional communication overhead, easily spoiling the benefit of value-anticipating networking. In order to anticipate CPM histories of remote vehicles without explicitly asking their prior knowledge, the ego vehicle introduces a conservative assumption that each remote vehicle has obtained only a subset of CPMs in the ego vehicle's own CPM history. When the ego vehicle obtains a new CPM $\boldsymbol{m}_{i',t}$, it first puts the CPM into its own CPM history. In addition, the ego vehicle also puts the obtained CPM to each remote vehicle v_i's *anticipated* CPM history only with a certain probability $p_{i' \to i}(t)$. Note that the anticipated CPM histories of remote vehicles are also maintained by the ego vehicle itself. If a remote vehicle v_i is a sender of the new CPM (*i.e.*, $i = i'$), we set the probability $p_{i' \to i}(t)$ to 1 because it is obvious that v_i holds its own CPM message. Otherwise, $p_{i' \to i}(t)$ is a real number between 0 and 1 depending on the level of network congestion, distance between a sender and a receiver vehicle, etc.

Fig. 2 shows an example of this anticipation process for the scenario in Fig. 1. The ego vehicle v_0 has obtained two CPMs over the recent time window, and both of them are kept in its own CPM history. Based on the neighbor list and the ego vehicle's CPM history, v_0 anticipates a list of CPMs available in CPM histories of remote vehicles v_1 and v_2. The ego vehicle v_0 expects that the first CPM $\boldsymbol{m}_{0,1}$ would have been successfully received by v_1 and v_2 with probabilities $p_{0\to 1}(t_1)$ and $p_{0 \to 2}(t_1)$, respectively. In this example, v_0 anticipates that $\boldsymbol{m}_{0,1}$ was received by v_2, while it did not reach v_1. Since the second CPM $\boldsymbol{m}_{1,2}$ was sent by the remote vehicle v_1, it is trivial to anticipate that v_1's CPM history contains $\boldsymbol{m}_{1,2}$. Thus $\boldsymbol{m}_{1,2}$ is put into v_1's anticipated CPM history with probability 1. On the other hand, the CPM $\boldsymbol{m}_{1,2}$ is added to v_2's anticipated CPM history only with probability $p_{1 \to 2}(t_2)$.

C. Anticipating the Remote Vehicle's Prior Knowledge

Based on the anticipated CPM histories of remote vehicles, the ego vehicle infers each remote vehicle's knowledge about the state of an object of interest $o_j \in \mathcal{O}_{i,t}$. We employ a Kalman filter for this inference process. The Kalman filter is widely applied to object tracking systems, as it helps mitigate the impact of measurement errors by iteratively fusing the predicted state based on a pre-defined motion model and measurements at each time step.

As discussed in Sec. III-A, we define a state vector of an object o_j at each time t_k by a vector consisting of position $[x_j(t_k), y_j(t_k)]$ and speed $[\dot{x}_j(t_k), \dot{y}_j(t_k)]$ of the object:

$$\boldsymbol{x}_j(t_k) = [x_j(t_k), y_j(t_k), \dot{x}_j(t_k), \dot{y}_j(t_k)]^T. \tag{1}$$

For simplicity of discussion, we assume that the motion of an object during a time period from t_{k-1} to t_k can be modeled as a linear equation as follows:

$$\boldsymbol{x}_j(t_k) = F(t_k)\boldsymbol{x}_j(t_{k-1}) + \boldsymbol{w}_j(t_k) \tag{2}$$

where

$$F(t_k) = \begin{bmatrix} 1 & 0 & t_k - t_{k-1} & 0 \\ 0 & 1 & 0 & t_k - t_{k-1} \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

and $\boldsymbol{w}_j(t_k)$ is a process noise that follows a Gaussian distribution $\mathcal{N}(\mathbf{0}, Q_j(t_k))$.

Since we assume that vehicles can measure the positions of the surrounding road objects by their on-board sensors, a measurement $\boldsymbol{z}_j(t_k)$ can be represented as:

$$\boldsymbol{z}_j(t_k) = H\boldsymbol{x}_j(t_k) + \boldsymbol{v}_j(t_k) \tag{4}$$

where

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{5}$$

and $\boldsymbol{v}_j(t_k)$ is a Gaussian measurement noise that follows $\mathcal{N}(\mathbf{0}, R_j(t_k))$. Thus a perception record is defined by a Gaussian distribution $f_r(\boldsymbol{x}_j(t_k)|\boldsymbol{z}_j(t_k), R_j(t_k)) = \mathcal{N}(\boldsymbol{z}_j(t_k), R_j(t_k))$ which is parameterized by the measurement $\boldsymbol{z}_j(t_k)$ and its uncertainty $R_j(t_k)$.

In order to infer a remote vehicle v_i's prior knowledge on an object o_j's state, the ego vehicle first extracts all the perception records $f_r(\boldsymbol{x}_j(t))$ about object o_j from v_i's anticipated CPM history. Let $\{f_r(\boldsymbol{x}_j(t_1)|\boldsymbol{z}_j(t_1), R_j(t_1)), f_r(\boldsymbol{x}_j(t_2)|\boldsymbol{z}_j(t_2), R_j(t_2)), \ldots, f_r(\boldsymbol{x}_j(t_n)|\boldsymbol{z}_j(t_n), R_j(t_n))\}$ denote the list of perception records that v_i is expected to have obtained, where t_k denotes the time when the k-th CPM was obtained. The ego vehicle uses the history of perception records as input to estimate o_j's state at the current time t_{n+1} as well as the corresponding uncertainty. Let $\hat{\boldsymbol{x}}(t_k|t_{k'})$ denote the estimated state of o_j at time t_k based on the perception records obtained at or before time $t_{k'}$. We first initialize the estimated state $\hat{\boldsymbol{x}}_j(t_0|t_0)$ to $[0,0,0,0]^T$ and its covariance matrix (*i.e.*, uncertainty) $P_j(t_0|t_0)$ to $\sigma_0^2\boldsymbol{I}_{4\times4}$, where σ_0 is an arbitrary large value and $\boldsymbol{I}_{4\times4}$ is the 4×4 identity matrix. For each perception record obtained at time t_k, the ego vehicle predicts object o_j's state based on the estimated state at the previous time step t_{k-1} and the motion model in Eq. (2):

$$\hat{\boldsymbol{x}}_j(t_k|t_{k-1}) = F(t_k)\hat{\boldsymbol{x}}_j(t_{k-1}|t_{k-1}). \tag{6}$$

The uncertainty P_j about object o_j's state is also updated accordingly as:

$$P_j(t_k|t_{k-1}) = F(t_k)P(t_{k-1}|t_{k-1})F(t_k)^T + Q(t_k) \tag{7}$$

Subsequently, the ego vehicle corrects the predicted state based on the perception record at time t_k:

$$\hat{\boldsymbol{x}}_j(t_k|t_k) = \hat{x}_j(t_k|t_{k\ \ 1}) + K(t_k)\left(\boldsymbol{z}_j(t_k) - H\hat{x}_j(t_k|t_{k\ \ 1})\right) \tag{8}$$

where the Kalman gain $K(t_k)$ is defined as:

$$K(t_k) = P_j(t_k|t_{k\ \ 1})H^T\left(R(t_k) + HP(t_k|t_{k\ \ 1})H^T\right)^{\ \ 1}. \tag{9}$$

The covariance matrix P_j is also updated as follows:

$$P_j(t_k|t_k) = (I - K(t_k)H)\,P_j(t_k|t_{k-1}) \tag{10}$$

Once the prediction and correction steps are executed for all the perception records in the anticipated CPM history of remote vehicles, the ego vehicle applies the final prediction step to derive the estimated state $\hat{\boldsymbol{x}}_j(t_{n+1}|t_n)$ and the covariance matrix $P(t_{n+1}|t_n)$ at the current time step t_{n+1} based on Eqs. (6) and (7), respectively. We regard the Gaussian probability distribution $\mathcal{K}_{pri}(\boldsymbol{x}_j(t_{n+1})|\hat{\boldsymbol{x}}_j(t_{n+1}|t_n), P(t_{n+1}|t_n)) = \mathcal{N}\left(\hat{\boldsymbol{x}}_j(t_{n+1}|t_n), P(t_{n+1}|t_n)\right)$ as remote vehicle v_i's anticipated prior knowledge on object o_j's state from the ego vehicle's perspective. The ego vehicle v_0 repeats the inference process above for all the pairs of objects $o_j \in \mathcal{O}_{0,t}$ and remote vehicles v_i in its neighbor list.

D. Content Selection based on Value of Information

If the remote vehicle v_i receives the new perception record $f_r(\boldsymbol{x}_j(t_{n+1})|\boldsymbol{z}_j(t_{n+1}), R_j(t_{n+1}))$, v_i could use Eqs. (8) and (10) to further update its knowledge. Let $\mathcal{K}_{pos}\left(\boldsymbol{x}_j(t_{n+1})|\hat{\boldsymbol{x}}_j(t_{n+1}|t_{n+1}), P(t_{n+1}|t_{n+1})\right)$ denote v_i's posterior knowledge about object o_j's state in the case that the ego vehicle decides to include the new perception record into its next CPM. We define the value of the new perception record ν_i for the remote vehicle v_i by the *relative information entropy* of the posterior knowledge $\mathcal{K}_{pos}$ with respect to the prior knowledge $\mathcal{K}_{pri}$ as:

$$\nu_i = \int_{-\infty}^{\infty} \mathcal{K}_{pos}\left(\boldsymbol{x}_j(t_{n+1})\right) \cdot \log \frac{\mathcal{K}_{pos}\left(\boldsymbol{x}_j(t_{n+1})\right)}{\mathcal{K}_{pri}\left(\boldsymbol{x}_j(t_{n+1})\right)} d\boldsymbol{x}_j(t_{n+1}) \tag{11}$$

The ego vehicle includes the perception record $f_r(\boldsymbol{x}_j(t_{n+1})|\boldsymbol{z}_j(t_{n+1}), R_j(t_{n+1}))$ into the next CPM only if ν_i is larger than a pre-defined threshold θ for at least one remote vehicle in its neighbor list.

V. Simulation

We have conducted a simulation study to identify the feasibility of value-anticipating cooperative perception.

A. Simulation Scenario

We use the Luxembourg SUMO Traffic (LuST) scenario [9] to simulate a realistic road environment in Luxembourg. The LuST scenario models 24 hours of vehicle mobility across a 11 km × 13 km city region based on real statistics of traffic volume. The scenario contains various types of vehicles (*e.g.*, cars, buses, etc.) with different sizes, while the road geometry and shapes of buildings are extracted from OpenStreetMap. These features enable realistic simulations of occlusions of the sensors' fields of view. We define a

Fig. 3. Simulation field and region of interest

region of interest with the size of 300 m $\times$ 300 m at one of the road intersections in the city center, as indicated by a red square in Fig. 3. In order to avoid a boundary effect, where vehicles around the edge of the region tend to have a lower number of neighbors, we simulate sensor measurements and CPM transmissions of all the connected vehicles within a 500 m range beyond the region boundary. All the simulations are performed during a 30-second time frame starting at 8 a.m., when the road is heavily congested with commuters.

We assume that 50% of the vehicles are equipped with sensors and a hardware unit for V2V communications, and generate a CPM every 100 ms.

In this simulation study, we evaluate the performance of cooperative perception in terms of *object tracking errors* of connected vehicles. Every second, each connected vehicle attempts to estimate the current positions of all the road objects within its communication range. We employ the Kalman filter designed in Sec. IV-C for each connected vehicle to estimate and extrapolate the positions of the road objects based on the history of CPMs that it has obtained over the recent time window W. We define the object tracking error as the distance between the estimated position and the actual position of each object. As a baseline, we also evaluate a straightforward cooperative perception system where connected vehicles include all the perception records into CPMs regardless of their value of information.

B. Sensor Model

In order to simulate sensor measurements by connected vehicles, we implemented the sensor occlusion model of [4] into our simulator. The model assumes that each connected vehicle is equipped with two radar sensors, each of which has a fan-shaped field of view with a radius of 80 m and a horizontal angular coverage of 60 degrees. Each radar sensor is installed at the center of the front and rear bumpers, such that the vehicle can detect objects ahead as well as behind. All the road objects in the simulation are modeled as polygons. A vehicle is modeled as a rectangle, where the length and width of individual vehicles are derived from a SUMO simulation scenario. A sensor can detect a remote object in its field of view if at least one corner point of the remote object is within the line-of-sight of the sensor.

We assume that a connected vehicle detecting an object can measure its position. The measured object position is assumed to include a random noise, which follows a zero-mean Gaussian distribution with a covariance matrix $\sigma_r^2 \boldsymbol{I}_{2\times 2}$. The parameter σ_r is affected by two separate factors: (i) an error in the absolute position of the ego vehicle (*e.g.*, GPS error) and (ii) a relative position error of the remote object with respect to the ego vehicle's position (*i.e.,* errors caused by radar measurements). The SAE J2945/1 standard [10] requires a positioning system used to generate Basic Safety Messages to keep the 1-sigma absolute error within 1.5 m under the presence of line-of-sight to satellites. On the other hand, automotive-grade radars typically have a range resolution in the order of centimeters. Assuming that the absolute position error of the ego vehicle is a dominant factor, we set the parameter σ_r to $1.5/\sqrt{2}$ m to simulate the 1-sigma absolute error of 1.5 m.

C. V2V Communication Model

For V2V communications, we employ a simple channel model with a communication range of 300 m and an interference distance of 500 m. We assume that a CPM is successfully delivered to neighboring vehicles within the communication range with the following probability $p(t) = \exp(-\lambda s/\gamma\tau)$ where λ the number of vehicles within the interference distance from a sender, s is the average message size of CPMs, γ is the data rate of V2V communications and τ is the transmission interval of CPMs. We set γ to 6 Mbps based on the data rate of DSRC and ITS-G5 networks, while τ is set to 100 ms as discussed in Sec. V-A. The parameters λ and s dynamically vary over time depending on road traffic and the number of perception records included into CPMs, respectively. In order to avoid the boundary effect, we approximate λ by the average density of connected vehicles in the region of interest over the last 100 ms, multiplied by the area of an interference region. Similarly, we approximate s by the average size of CPMs that are transmitted by the connected vehicles in the region of interest during the recent 100 ms window as $s = s_h + \overline{n}s_r$, where s_h is the header size, $\overline{n}$ is the average number of perception records included in a CPM and s_r is the size of a perception record. In the following evaluation, we set s_h to 8 bytes based on the DSRC standard, while the constant s_r is set to 20 bytes assuming that each perception record contains at least a timestamp, 2-dimensional position measurement and a covariance matrix. We also assume that connected vehicles can accurately estimate the packet reception probability based on their own channel load measurements.

D. Simulation Results

Fig. 4 shows the 90th-percentile object tracking errors with the threshold on value of information θ varied from 1 to 10. For the baseline scheme that sends all the perception records regardless of their values, the 90th-percentile tracking error becomes as much as 10.8 m. In other words, 10% of the road objects suffer from large tracking errors beyond 10.8 m or even are not perceived by connected vehicles in the vicinity. This is mainly because CPMs are frequently lost

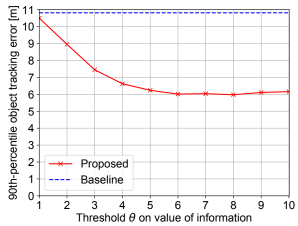

Fig. 4. Object tracking error (90th-percentile)

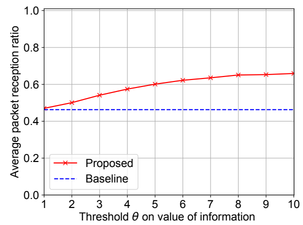

Fig. 5. Packet reception ratio with different value thresholds

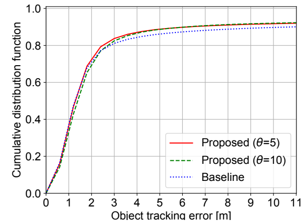

Fig. 6. Cumulative distribution of object tracking errors

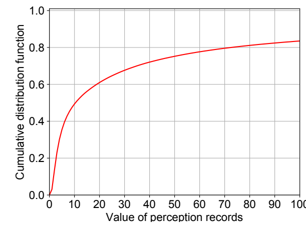

Fig. 7. Cumulative distribution of value of information

due to heavy congestion of the V2V network. In contrast, the value-anticipating communications can reduce such a worst-case error to about 6 m. As each connected vehicle sends only a subset of perception records that are expected to be valuable for potential receivers, the load on the V2V network is mitigated, leading to an improved packet reception ratio. It allows the system to reliably deliver valuable perception records that help reduce object tracking errors of neighboring vehicles. This observation is backed by the results in Fig. 5, which shows the average packet reception ratio with each parameter configuration. With the baseline scheme, the packet reception ratio drops to 46% as the network is overloaded by a huge number of perception records, while the proposed scheme facilitates successful delivery of more CPMs. Note that the packet reception ratio in Fig. 5 can be considered as the worst-case performance, as we use a conservative channel model in this evaluation. In addition, the proposed content selection mechanism can be combined with a decentralized congestion control mechanism to further improve the reliability of message delivery.

In Fig. 4, we can also see that the 90th-percentile object tracking errors of the proposed scheme is suppressed more effectively as we introduce a higher threshold θ on the value of information. This is a natural consequence because the higher θ makes the system filter out the perception records more aggressively, resulting in larger reduction of the network load. Although it helps mitigate worst-case errors, the parameter θ should be carefully chosen because a too high value threshold may discard *moderately* valuable perception records, affecting the overall system performance. Fig. 6 shows cumulative distributions of object tracking errors of the baseline scheme as well as the proposed scheme with $\theta = 5$ and $\theta = 10$. The baseline scheme results in a median object tracking error of 1.3 m. For the proposed scheme with $\theta = 10$, the median tracking error slightly increases to 1.4 m in exchange for a 43% reduction of the 90th-percentile error. On the other hand, with $\theta = 5$, the system achieves the equivalent reduction of 90th-percentile error with no negative impact on the median tracking error. Thus, with appropriate selection of θ, the value-anticipating V2V communications can effectively bound the worst-case object tracking performance without sacrificing the overall system performance. For this simulation scenario, we can also conclude that $\theta = 5$ would be a good trade-off point that effectively reduces the network load while minimizing the risk of filtering moderately valuable perception records.

Finally, we show the cumulative distribution of the value of perception records in Fig. 7. The result implies that a significant fraction of perception records are actually not that beneficial for receivers, and can be filtered out without affecting the performance of environmental perception.

VI. Conclusion

In this paper, we have investigated the feasibility of value-anticipating cooperative perception, where each vehicle intelligently decides which perception records to send over V2V networks based on the anticipated value of the information. Through a simulation study, we have shown that it can significantly improve the performance of cooperative object tracking by vehicles.

While we have mainly focused on *novelty* as a key attribute that constitutes the value of information, in general this value is also affected by multiple other factors such as freshness, relevance, etc. The investigation of other value attributes is an important part of our future work. The applicability to other types of object features (*e.g.*, types and appearance of road objects) will also be investigated in the future.

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