Integrating Shared Information into the Sensorial Mapping of Connected and Autonomous Vehicles

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Abstract: A connected and autonomous vehicle (CAV) needs to dynamically maintain a map of its environment. Even if the self-positioning and relative localization of static objects (roads, signs, poles, guard-rails, buildings, etc.) can be done with great precision thanks to the help of hd-maps, the detection of the dynamic objects on the scene (other vehicles, bicycles, pedestrians, animals, casual objects, etc.) must be made by the CAV itself based on the interpretation of its low-level sensors (radars, lidars, cameras, etc.). In addition to the need of representing those moving objects around it, the CAV (seen as an agent immersed in that traffic environment) must identify them and understand their behavior in order to anticipate their expected trajectories. The accuracy and completeness of this real-time map, necessary for safely planning its own maneuvers, can be improved by incorporating the information transmitted by other vehicles or entities within the surrounding neighborhood through V2X communications. The implementation of this cooperative perception can be seen as the last phase of perception fusion, after the in-vehicle signals (coming from its diverse sensors) have already been combined. In this position paper, we approach the problem of creating a coherent map of objects by selecting relevant information sent by the neighbor agents. This task requires correctly identifying the position of other communicant agents, based both on the own sensory perception and on the received information, and then correcting and completing the map of perceived objects with the communicated ones. For doing so, the precision and confidence on each information must be taken into account, as well as the trust and latency associated with each source. The broad objective is to model and simulate a fleet of vehicles with different levels of autonomy and cooperation, based on a multi-agent architecture, in order to study and improve road safety, traffic efficiency, and passenger comfort. In the paper, the problem is stated, a brief survey of the state-of-the-art on related topics is given, and the sketch of a solution is proposed.

1 INTRODUCTION

Road traffic accidents cause approximately 1.3 million deaths worldwide per year, and between 20 and 50 million non-fatal injuries (Chen et al., 2019). The promise is that the arrival of *connected and autonomous vehicles* (CAVs) will help to reduce those war-like numbers considerably (Litman, 2020). There are important and growing investments both in industrial and academic research aiming to develop such technologies, and almost all the giants of automobile construction and information technology are involved. The estimated value of this billionaire CAV global market is projected to increase exponentially in the next coming years (Jadhav, 2018). But if this boom is relatively recent, the building blocks for modern autonomous vehicles started to appear several decades ago, with anti-lock brakes, traction control, power assisted steering, adaptive cruise control, etc., when mechanical components have been replaced by electrical, then by electronic successors. Now, as these components are being successfully tied together, along with lidar, radar, cameras, high-definition mapping, pattern recognition, and AI-based control and navigation mechanisms, the car is becoming a kind of thinking machine.

In the literature, it is usual to classify CAVs according to their level of autonomy, ranging from fully manual (level 0 on the SAE taxonomy) to fully automated vehicles (level 5) (Terken and Pfleging, 2020). Due to legal and especially technological limitations,

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no commercial vehicle is currently capable of autonomously performing all the driving tasks without a minimum of supervision, not even the most advanced prototypes. In the perspective of automobile manufacturers, the last level of autonomy should be reached soon, but in fact several locks are still to be lifted before it happens, which include: preparing people and cities for the arrival of new and smart transportation modes, defining a legal and regulatory framework at national and international levels, adapting telecommunication networks to support the amount of data exchanged by CAVs, improving the technology on sensors while reducing costs, and above all, increasing the robustness and reliability of the AI algorithms that control these vehicles.

For safety and fault-tolerant reasons, CAVs must ensure their essential driving capabilities without any communication. However, their behavior can be greatly improved by the possibility of exchanging information with other connected vehicles and road infrastructures in the neighborhood (Sharif et al., 2018). Vehicular ad-hoc networks (VANETs) are spontaneous wireless networks of vehicles, generally organized according to *vehicle-to-everything* (V2X) communication architectures, with the objective of helping navigation and providing diverse roadside services (Sommer and Dressler, 2014). In addition to that *dedicated short-range communication* (DSRC) network, the tendency is that V2X will heavily relay on the 5G cellular network (which allows low latency and large data bandwidths), in a *vehicle-to-network-to-everything* (V2N2X) flavor (Hakeem et al., 2020).

To be able to drive autonomously, a CAV needs to dynamically construct and update a map of its environment: based on its low-level sensors (radars, lidars, cameras, etc.), the agent represents the objects around (identity, position), their current trajectories (speed, direction, acceleration), and supposed itineraries (road driving steps) (Arnold et al., 2019). In addition to identifying the roads and lanes, and estimating its self-position with centimeter precision, the map of detected moving objects is necessary for planning the CAV trajectory and for choosing adapted maneuvers. An accurate perception of the surrounding environment is necessary to ensure a reliable behavior, which implies transforming sensory data into semantic information. 3D object detection is a fundamental function of this perceptual system.

Supposing that standard and common communication protocols should be established among different car constructors and road traffic authorities, CAVs will be able to constantly share their own perceptions with other surrounding agents, communicating their high-level updated map of detected objects and

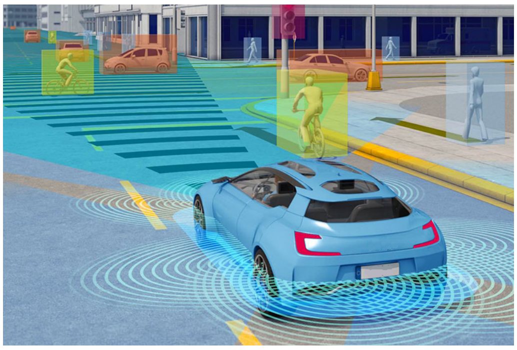

Figure 1: The image represents a CAV perceiving its surrounding environment. Based on its low level sensors (cameras, radars, lidars, etc.) and hd-maps, the vehicle identifies roads, lanes, and its own position on the street, and projects a map with the objects perceived in the scene and their respective trajectories.

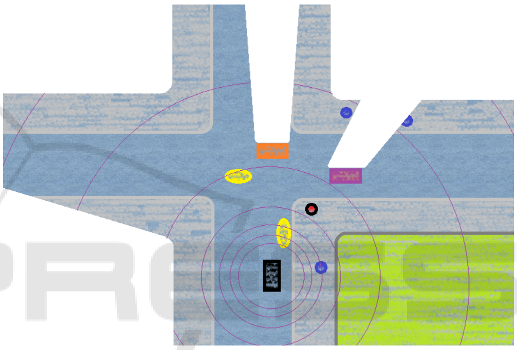

Figure 2: The vehicle and the neighbor entities that it can detect and identify, given the range of its sensors and its field of view.

corresponding estimated dynamics. Another alternative is the transmission of low-level signals, with the drawback of requiring both very large (then expensive) data transfer bandwidth, and intense processing effort of the ego-vehicle to interpret its own sensors and, in addition, the other agents communicated signals. Since self-driving is a real-time safety-critical decision problem, and a CAV needs to be able to answer rapidly to unexpected events, the possibility of adopting the first alternative (sharing high-level information) should be preferred.

In this paper, we approach the problem of creating a coherent map of objects by selecting relevant and reliable information given by the neighbor agents. The task implies to correctly identify the position of other communicant agents based both on the own sensory perception and on communicated geolocation information, then correcting and completing the projected scene based on matching the objects (perceived and communicated), and eventually finding the unperceived ones. This procedure can offer two advan-

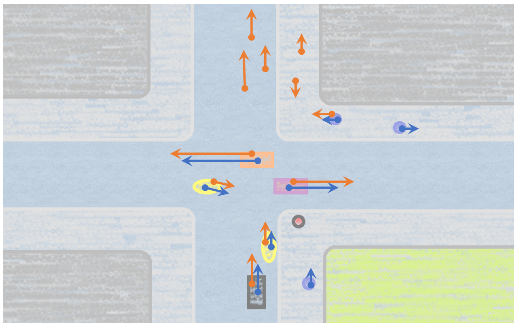

Figure 3: The image represents the map of objects projected by a CAV, where the blue arrows indicate the positions and trajectories of objects estimated by the agent, and the orange arrows, the ones communicated by another agent in the neighborhood. This information can be used, if trusted, to improve the precision of the map, and to anticipate the presence of unperceived objects.

tages: increasing the precision of the reconstructed map of objects by correcting the estimated positions, and also helping to incorporate non-detected objects. This functioning is exemplified in Figures 1 to 3.

Since the CAV network constitutes an open connected environment, the possible presence of non-cooperative or even malicious agents, which send incorrect data, cannot be ignored. In this case, the trust on the source, and the confidence on the information must be considered. When several connected agents receive and interpret the same signals, a possible solution to that issue is estimating reliability by measuring local inconsistencies. In the rest of the paper, Section 2 presents the validation strategy, Section 3 exposes an overview on the state-of-the-art, Section 4 introduces the proposed solution, and Section 5 concludes the paper.

2 VALIDATION

Once reliable CAVs will be available, it will be essential to study how a fleet will be able to interact in order to maximize collective safety, passenger comfort, and produce intelligent mobility. Indeed, it is important to identify the underlying barriers to human acceptability of CAVs (Fraedrich and Lenz, 2016), in order to ensure the proper deployment of this new mode of transportation. Between humans, in a context of road interaction, body and facial cues are sent back and mutually interpreted. A CAV will not provide humans with such clues, making it more difficult for them to understand the decisions made by the AI and to adopt appropriate behavior.

In this work, we would like to include this ergonomic dimension into the evaluation of the proposed model, tackling two complementary objectives: (*i*) to study the problem of coordinating a collective of VACs in mixed traffic; (*ii*) to study their acceptability and appropriation by the various human road users with whom those VACs interact. The use of an immersive simulation tool is an acceptable alternative (Sovani, 2017) to perform preliminary tests with humans. For this work, a physical simulator integrating the SCANeR Studio software (Fig. 4) will be used to implement our validation tests. SCANeR Studio is one of the high-end simulators currently available, implementing microscopic traffic simulation, such as SUMO (Lopez et al., 2018), GAMA (Taillandier et al., 2019), or MATISSE (Torabi et al., 2018). The platform simulates object detection tasks performed by the CAV, artificially introducing imprecision, false-detection, and confidence estimates, like shown in Fig. 5.

Figure 4: CompactSim, using SCANeR Studio (AVS), adapted to simulate the situation where a human is transported by a CAV.

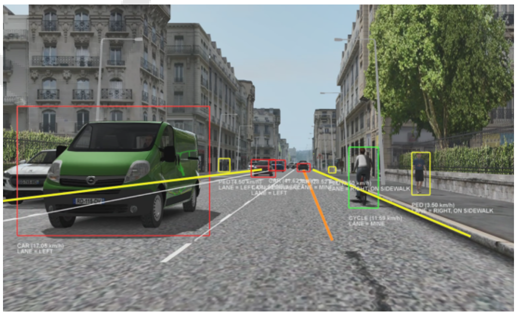

Figure 5: Self-positioning, object and road detection, endowed by the SCANeR Studio simulation platform.

In this way, in addition to classic metrics (Friedrich, 2016) into which the performance of the proposed model is compared to the performance of road traffic without it, considering average time-travel, and average number of dangerous or damaging events (accidents, emergence breaks, etc.), the proposed model will also be tested through the use of simulation to perform ergonomic experiments with humans transported by VACs in order to measure and understand the situations and behaviors that can cause discomfort or fear. From the results of these experiences, machine-human communication strategies can be proposed, tested, then validated using the simulator, with the aim of explaining the actions taken by the AI and thus promoting acceptability. Moreover, this human evaluation of the system as a whole can enable a subjective metric to compare the efficiency of different cooperation strategies.

3 STATE-OF-THE-ART

The exchange of local sensing information with other vehicles or infrastructures via wireless communications by which the perception range can be extended or augmented up to the boundary of connected vehicles is called *cooperative perception*. It can provide oncoming traffic information beyond the line-of-sight and field-of-view of the ego-vehicle, helping the CAV on its decision making and planning tasks by improving vehicle awareness on the road, which can promote safer and smoother autonomous driving (Kim et al., 2015). The recent literature is rich in examples of the use of cooperative perception applied to self-driving problems, and an exhaustive survey is not in the scope of this paper. Instead of it, we would like to present in this section some illustrative samples.

Several overviews on the state-of-the-art concerning CAVs have been published recently, such as (Yurtsever et al., 2020; Marcillaud et al., 2020; Cavazza et al., 2019), concerning a domain that is evolving fast. Roughly speaking, current CAV research on cooperative models focus on two different sets of problems: (a) managing the flow of vehicles to maintain a smooth traffic, and (b) road and lane trajectory coordination. The first topic concerns meso and macro-traffic organization, and approaches problems such as the reduction of the average travel time, reduction of congestion, reduction of consumption, itinerary re-planing to balance traffic density, etc. The second topic concerns maneuvers such as overtaking, lane merging, roundabout merging, road intersection crossing, etc.

Traffic jams and slowdowns are problems that concern several cities in the world, and several studies focus on the use of CAVs and learning mechanisms to reduce them (Barthelemy and Carletti, 2017; Mouhcine et al., 2018), both based on local data (low volume of communication shared among near agents), and on global (city-scale) data (diffused by central traffic authorities) (Marcillaud et al., 2020). The presence of accidents, obstacles, or blocked vehicles reduces the number of available lanes, which can also lead to traffic jams. If the vehicles can communicate and take into account such events during their decision processes, disseminating the information and coordinating actions, such jams can be reduced (Kordonis et al., 2020).

Another particular approached problem concerns reducing shock waves using communication. A *shock wave* is often the result of exceptional actions, such as emergency braking (Marcillaud et al., 2020), which can cause slowdowns and increase traffic density. The occurrence of shock waves can be reduced with the help of multiagent coordination (Vaio et al., 2019). CAV agents use the information exchanged with neighbor vehicles to adapt their speed and maneuvers. More generally, anticipating events also enables to avoid accidents, save fuel, and reduce car wear (Kamal et al., 2015b).

Many slowdowns and jams are caused by the presence of intersections with dense traffic, which put vehicles in conflict, increasing the chances of having an accident (Marcillaud et al., 2020). To avoid collisions, intersections are regulated by traffic rules and infrastructures that determine priority. However, in case of heavy traffic, the distribution of vehicles at intersections can also be uneven, causing slowdown and stress. Through the use of intelligent coordination, CAV agents can decide to change route (Lin and Ho, 2019), allowing a better distribution of vehicles over the different possible itineraries, or even influence the behavior of traffic lights.

Vehicle-intersection coordination (Kamal et al., 2015a; Gaciarz et al., 2015) allows to obtain a more fluid traffic and to reduce fuel consumption. Each CAV optimizes its trajectory after accepting its passage order. When well-coordinated, the number of situations into which the vehicles must stop at intersection can be greatly reduced. As a traffic light in an intersection controls the flow of vehicles in the axes, anticipating the state of an intersection managed by a traffic light helps to avoid unnecessary stops and intensive braking. Communicating traffic lights can inform when they will change their states, allowing the CAVs to anticipate those events and then adapt their actions (Almannaa et al., 2019). At limit, given certain conditions, traffic light-free intersection control can be envisioned, only based in communication and intelligent coordination (Zhang et al., 2020).

Another situation that a CAV must be able to handle is lane merging, which requires fine speed adaption to the other vehicles. The merging zone of two lanes may be managed through infrastructure (Rios-Torres and Malikopoulos, 2017) or by self-organization (Wang et al., 2018; Mosebach et al., 2016). If a CAV detects other vehicles, it slows down and calculates a trajectory to cross the merging point without collision. The involved vehicles can communicate their intentions in order to better coordinate their actions.

The work presented in (Vasic et al., 2016) introduces an overtaking decision algorithm for networked intelligent vehicles based on cooperative tracking and sensor fusion. The ego-vehicle is equipped with lane keeping and lane changing capabilities, and with a forward-looking lidar sensor which feeds a tracking module that detects other vehicles, such as the vehicle that is to be overtaken (leading) and the oncoming traffic. Based on the estimated distances to the leading and the oncoming vehicles and their speeds, a risk is calculated and a corresponding overtaking decision is made. The performance of that overtaking algorithm, in which it fuses object estimates received from the leading car, which also has a forward-looking lidar, overcomes the case when the ego-vehicle only relies on its own individual perception.

High-definition (HD) maps are essential for the safe operation of CAVs. They allow a CAV to determine its exact position in real time, ensuring self-localization, helping to detect fixed objects and terrain details by matching collected data and stored data. It liberates the CAV to concentrate its efforts on detecting the dynamic objects on the scene. GPS, radar, ultrasonic technology, and normal cameras combine with lidar sensors to create a centimeter accurate 3D image, required for safe navigation. An additional semantic layer is superimposed onto the 3D image. Semantic maps include information such as lane boundaries, speed limits, turn restrictions, and stopping points (Badue et al., 2021).

Like the human perception, which relies on different senses (vision, hearing, touching, etc.), a CAV needs to fuse data provided by different sources for obtaining coherent information. The sensors that equip a CAV work in a collaborative way: the analysis of a specific sensor could not be sufficient to make a decision and should be coupled with the analysis of other sources. A lidar sensor, for example, is good at calculating distances, but cannot see colors. A video camera would bring this missing information to lidar. In a general scheme, the interaction between several sensors can occur at different stages of the process (Elmenreich and Leidenfrost, 2008): point, feature, or detected object level, like shown in Fig. 6. Comprehensive reviews of the state-of-the-art of CAV perception technology concerning sensing, localization and mapping methods can be read in (Van Brummelen et al., 2018; Rosique et al., 2019; Hu et al., 2020).

Depending on the configuration, data from different sources can be fused in complementary, competitive, or cooperative combinations (Elmenreich and Leidenfrost, 2008). A fusion is called complementary if the information are independent, but can be combined in order to create a more complete model of the environment, providing a spatially or temporally extended view. Generally, fusing complementary data can be made by addition, or juxtaposition (e.g. the employment of multiple cameras to build up a 360 degrees picture of the environment). Competitive fusion is used for fault-tolerant systems, where each sensor delivers independent measurements of the same target, providing redundant information. In this case, a more robust information can be achieved by correcting erroneous sources (e.g. reduction of noise by combining two overlaying camera images). Finally, cooperative fusion provides an emerging view of the environment by combining non redundant information, but the result is sensitive to inaccuracies coming from any of the sources (i.e. the combined model can present decreased accuracy and reliability).

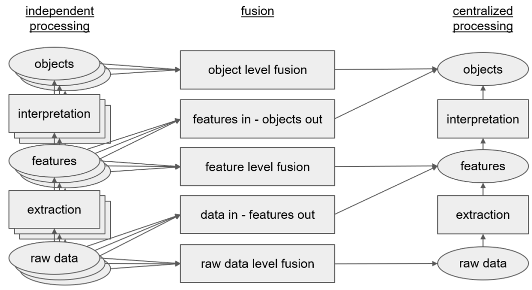

Figure 6: The fusion of data coming from different sensors can present interactions from the low to the high-level analysis (Elmenreich and Leidenfrost, 2008).

4 PROPOSED APPROACH

Exchanging information is necessary to implement cooperation between vehicles. In this work, we are not searching to integrate data from the raw sensors of other cars, but rather high-level information: e.g. the presence of a pedestrian or a vehicle in an invisible segment, emergency braking impossible to detect locally, etc. Communication can significantly improve vehicle perceptive capabilities, working as an additional sensing, combining information collected from multiple cars in a cooperative perspective.

However, extracting good information from the data communicated by other agents can be challenging as the agent may receive uncertain information from unknown agents (Cholvy et al., 2017). One solution is, based on a priori trusted information, to rank the agents and representing reliability through a total

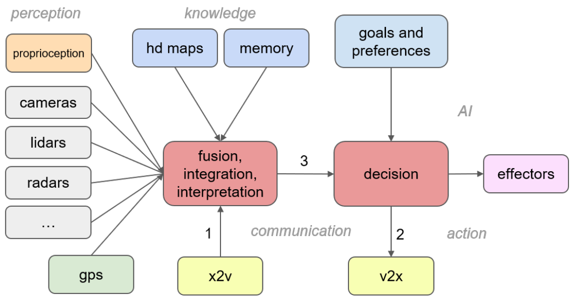

Figure 7: Diagram of modules which compound a connected and autonomous vehicle.

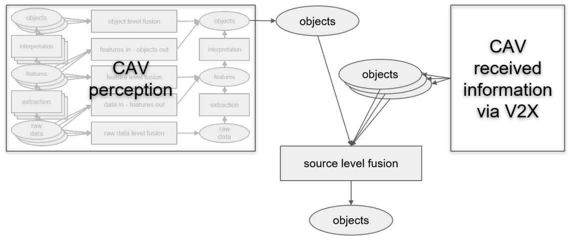

Figure 8: The information coming from different sources must be integrated into the vehicle's model of the scene, creating an additional fusion stage.

preorder. The overall communication set is first evaluated with the help of inconsistency measures. Next, the measures are used for assessing the contribution of each agent to the overall inconsistency of the communication set.

Techniques for merging raw information have been studied extensively. Two different approaches exist: the first one considers sources (i.e. agents) in an equal way and merging techniques such as majority merging, negotiation, arbitration merging or distance-based merging for solving conflicts raised by contradictory information. The second one takes sources reliability into account, providing weights for discounting or ignoring pieces of information whose source is not sufficiently reliable. This factor can be used to weaken the importance of information provided by unreliable sources (Cholvy et al., 2017).

In the proposed approach, a CAV must: (1) integrate the information received via V2X into its own high-level perception of the scene; (2) assess the relevance of the information to be communicated to other vehicles; and (3) send to other vehicles its own intentions, and receive the other vehicles intentions, to coordinate actions. Such elements are shown in Fig. 7. In this paper, we offer a reflection on the first two problems. The first one concerns how can a VAC combine its own perceptual data (interpreted from camera, radar, lidar) with communicated information from multiple nearby cars using self-localization to build an improved perception. Many data can be uncertain and inaccurate. In other words, the problem is how to combine information from multiple agents, given the potential uncertainty and inaccuracy of the information, and based on the trust and reputation accorded to the sources. The second question concerns how critical or important each isolated piece of information from each neighbor vehicle can be in assisting the vehicle, and how the information can be hierarchically set up to provide the critical information to the vehicles, minimizing data transfer.

Even if the industry works with the perspective of sharing raw sensors data from different neighbor vehicles, it can be very complicated for each vehicle to fuse all this data, assessing confidence and trust. The approach proposed in this paper concerns a high-level integration: each CAV realizes its own interpretation concerning self-localization, environment detection, and mobile objects detection, and shares this interpreted information. The bandwidth necessary to do so is then greatly reduced, but the agent must still make choices concerning how the communicated information can be integrated into its own interpretation of the scene, dealing with inconsistency, imprecision, and confidence factors.

One of the difficulties in fusing data from multiple vehicles involves their relative localization. The cars need to be able to know precisely where they are in relation to each other as well to objects in the vicinity. For example, if a single pedestrian appears to different cooperating cars in different positions, there is a risk that, together, they see two pedestrians instead of one. Using directly other cars raw signals is very hard due to the amount of data that must be processed in real time, while the vehicles is in motion and taking decisions. We can list some different sources of positioning information which must be treated in different levels of confidence: (a) my position given by an hd-map, (b) my position given by the gps or deduced from proprioception, (c) my position according to the view of other agents and communicated to me, (d) the position of other vehicles or pedestrians according to my own sensory interpretation, (e) their position according to their own self-positioning methods and communicated to me, (f) the position of other vehicles or pedestrians informed by another VACs or infrastructures.

When detecting a given object j, a set of properties θ_j is also perceived (type, position, direction, speed, etc.), and the agent can assess the confidence on its own detection $w_{0,j}$. From the point of view of the *ego-vehicle* ($i = 0$), and based on the history of recent interactions, a trust measure t_i can be associated to each of the neighbor vehicles i. Then, an aggregation function selects the answer following a simple weighted majority rule, calculated by

$s_j = \sum_{i=0}^{m} t_i \; w_{i,j} \;:\; \forall i, j$, where s_j is the score of candidate answer for object j, and m is the number of vehicles communicating in the considered time.

Those simple scheme can be improved by including the known reputation of the sources on the weighting function, which must be informed by recognized road authorities. Another possibility is to consider the different fields of perception of the sources (e.g. an agent giving information about detected objects in an area outside the field-of-view of the ego-vehicle). Finally, the sources and pieces of information can be filtered, labeled as inlier or outlier, depending on how distant they are from the majority, or from a priori reliable data, ensuring that bad sources of information will not disturb the projected map of detected objects.

Concerning the relevance of a given information to a given vehicle, we consider that each detected object is a piece of information that can be communicated. Two evidences can be used to rank the set of possible messages in terms of relevance in three preference categories: (1) if the vehicle directly asks for the information related to a given portion of the space where the object was detected, (2) if the neighbor vehicle judges that the information is important to the ego-vehicle (because it anticipates a possible collision), and (3) the other objects. When an agent expresses a need of information, it is suggesting a first criterion to assess usefulness. The degree of usefulness of a piece of information is, however, a multi-faceted notion which takes into account the fact that it represents potential interest and trustability (Saurel et al., 2019). Another straightforward metric to determine relevance of a detected object is given by its probability of intercepting the ego-vehicle's trajectory, and the distance from the current position to the intercept position. For example, a vehicle that is near, but which is moving away, is less important to pay attention than a vehicle that is farther, but which is approaching.

5 CONCLUSION

In this article, we investigated how cooperative perception can impact decision making and planning of autonomous vehicles. Particularly, we proposed the sketch of a model for fusing the list of detected objects detected by neighbor vehicles into the list of detected objects of the ego-vehicle. We also suggested how a validation strategy can include humans in the loop in order to contemplate an ergonomic metric for evaluating the comfort produced by a solution, in addition to other metrics focused in reducing overall travel time and accidents.

Beyond safety and comfort, cooperation can be used to optimize trajectories, save energy, and improve traffic flows. Another important opportunity made possible by vehicle communication is the sharing of intentions, which allows the agents to find arrangements and negotiated solutions to their eventual conflicts, leading to an increased collective performance. The next steps of this research include precising and refining the aggregation method in order to consider source reputation and local trust, information reliability given by the source, and the confidence on it estimated by the ego-vehicle depending on the context.

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