Towards collective perception hybrid testing in a roundabout scenario with AVs

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Abstract

Collective Perception (CP) allows connected autonomous vehicles to share and fuse processed sensor data via V2X communication. It can potentially allow for an increased object update rate, extended field-of-view awareness, and redundancy but it first requires a thorough evaluation and validation. Due to the CP's field testing practical challenges most of the previous work on CP has considered large scale-simulations with a focus on connectivity/network aspects. More recently, large-scale collaborative perception synthetic datasets and open source benchmarks have appeared, allowing the perception engineers to study CP from a perception point of view, which is missing so far. In this paper, the first building blocks (work in progress) towards CP scenario-based testing for a roundabout navigation use case are been set by proposing a Bayesian CP algorithm and its testing plan. The CP algorithm is described and metrics for CP assessment are discussed focusing on the fused information content produced by the algorithm. The next steps towards a hybrid evaluation plan combining real-world agents and simulation are outlined.

Keywords: Autonomous Vehicles, Collective perception, V2X communication

1 Introduction

Collective Perception (CP), currently standardized by ETSI as a second generation V2X communication service (but not limited to it), is especially promising for Autonomous Vehicles (AVs), as it allows connected AV agents "see through the eyes of others" who may share processed sensor data via V2X communication. Its benefit is typically assessed in terms of the increased object update rate, extended field-of-view awareness, and redundancy. In this work, part of which is described in this paper, a safety validation proof-of-concept (PoC) for CP scenario-based testing for a roundabout navigation scenario is designed. The PoC includes both connected AVs and non-connected vehicles, assuming connected virtual agents that can exchange ETSI-alike Collective Perception Message (CPM) information. Its primary goal is to develop and validate a vision-based CP module able to globally synthesise scene information based on local perception viewpoints produced by the available connected vehicles in the AV's neighbourhood. The secondary objective is the integration of CP information in a V2I-assisted urban platoon setting with reliability guarantees. The work is part of the European project EVENTS' advanced perception, decision making and self-assessment framework, which develops algorithms and methods to analyse the effects of V2X information fusion on AV perception and decision making.

Collective perception information generation serves a double research objective: a) develop algorithms for fusion of object information coming from multiple observers based on probabilistic scene state estimation via occupancy grid maps b) develop data reliability metrics enabling false data detection and object associations' conflict resolution. In this paper, the first point is described in detail, which sets the scene for the following point. Studying CP from a perception point of view implies that the focus is on the task of object data association from multiple observers and hence networking aspects can be omitted for reasons of simplicity (no network co-simulation is employed and ETSI-alike CP messages are assumed available with frequency/delay that can vary).

2 CP Module Functional Architecture

In this section, we provide an overview of the architecture of the CP module as this is conceived in EVENTS project experiment no.2 (EVENTS Deliverable, 2023a,b). As shown in Figure 1, CP essentially replaces the subject AV perception by providing enhanced scene understanding. CPMs received from connected agents sharing the same spatial area (in our case a roundabout area) with the subject CAV under test are fused with CAV's local perception. The probabilistic certainty of collective object detection plus further consistency/plausibility checks between CP output and the (claimed) Field of View (FoV)/perceived object list of each connected (CCAV) agent will be utilized for assessing the reliability of the CP.

In more detail, the collective perception module expects the following input from each CCAV present in the area of interest:
Ego FoV angle. A single front camera implies a FoV angle equal to the FoV of the camera. More cameras and and radar/Lidar sensors may imply a larger FoV angle. In the figures below, a 360o FoV angle is implied.
Ego state information. This information consists of the i. Position coordinates in x,y (valid also for CAM originators), ii. Speed vector v_x, v_y (valid also for CAM originators), iii. Acceleration vector a_x, a_y and iv. Heading (yaw angle).
Observed object information. This information concerns each one of the distinct objects observed by the CCAV consists of the i. Position coordinates in x,y, ii. Speed vector v_x, v_y, iii. Acceleration vector a_x, a_y and iv. Heading (yaw angle).

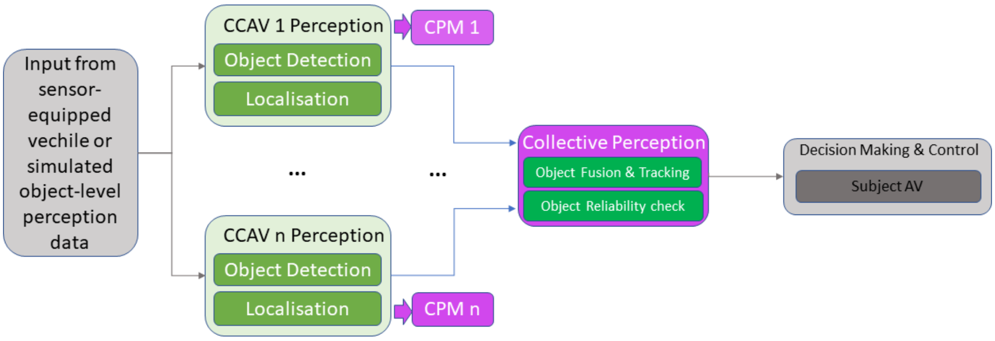

Fig. 1 The architecture of the EVENTS experiment.

Estimated free space. This field is optional, since it can be partially deduced from the observed objects information.
Uncertainty of the measured values. A quantification of the uncertainty of each measurement via e.g. respective standard deviations.

3 CP Module Algorithmic Approach

In this section, the formalization of the output of the collective perception module as a probabilistic occupancy grid is presented. The chosen representation exploits the straightforward and intuitive Bayesian method for fusing observations derived from multiple observers and has been very popular for solving multi-object tracking problems due to its inherent explainability properties leading to well-defined reliability metrics for the output (Godoy et al, 2021; Nuss et al, 2018).

3.1 Formalizations and problem statement

Consider a 2-dimensional bird's eye view image of the area of interest. We discretize it using a rectangular grid of size NxN, whose cells are indexed by $i = 1, \ldots, N^2$. To each cell i we associate the binary random variable $A_i \in \{0, 1\}$ where $A_i = 1$ means "cell i is occupied" and $A_i = 0$ means "cell i is not occupied". A Probabilistic Occupancy Grid is essentially a collection of N^2 probabilities $P(A_i = 1), i = 1, \ldots, N^2$, each one indicating the probability with which the corresponding cell i is occupied.

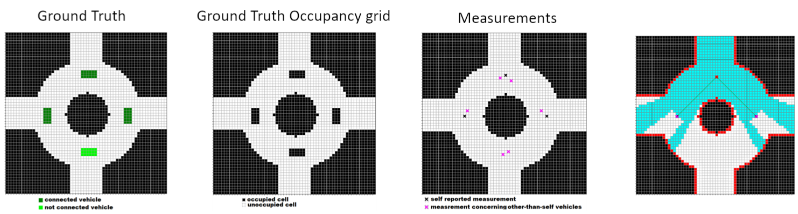

Fig. 2 Ground truth, measurements and FoV estimation bird-eye view representation

Let the area of interest be an urban roundabout, like the one depicted in Figure 2. We assume the presence of both connected and not connected vehicles. Connected vehicles have the capability to share information concerning i. their current individual heading, position, speed and acceleration, ii. the presence or absence of objects within their respective individual FoVs, and iii. heading, position, speed and acceleration for each of the perceived objects, in line with the description of inputs in Section 2. The ground truth of the scene is a non-random occupancy grid, where we know exactly which cells are occupied or not (middle illustration in Figure 2). We are now ready to properly state the problem of interest as follows: Given the observations and measurements of each individual CCAV and their statistical uncertainties/errors, how can we estimate the Ground Truth in terms of a Probabilistic Occupancy Grid?

3.2 Algorithm overview

The proposed algorithm consists of the following four equally important steps.

Step 1: The first step aims at the localization of reporting agents (in our case, CCAVs). For each distinct CCAV we apply a Kalman Filter taking into account only its self-reporting measurements. The rational for excluding other measurements is that self-reporting measurements are based on differential GPS for location and on-board sensors for velocity, acceleration and heading, which can be considered more trustworthy. Apart from that, initial experiments show that clustering measurements around centroids corresponding to unknown guessed vehicle positions can be extremely error prone due to the unknown number of present vehicles and noisy measurements, leading to unstable estimations.

Step 2: The second step aims at estimating the FoV of each CCAV. Each CCAV is placed in its estimated (by step 1) grid position. Each other-than-self measurement (other objects detected around) obtained by CCAV is translated according to the CCAV estimated position and placed in the grid. Subsequently, a custom, GPU-implemented algorithm calculates the FoV of the CCAV, i.e., the grid cells for which the CCAV can provide information on their occupancy status (first 3 figures below). Estimated FoVs may be eroded to account for measurement uncertainties (4^{th} illustration in Figure 2).

Step 3: The third step aims at fusing the observations of each CCAV to form a probabilistic estimation for the occupancy grid of the entire area of interest. We assume a known individual perception model for each CCAV, provided in terms of the four probabilities $P(M_i = 0|A_i = 0)$, $P(M_i = 1|A_i = 0)$, $P(M_i = 0|A_i = 1)$, $P(M_i = 1|A_i = 1)$ of the standard forward sensor model (Nuss et al, 2018).

With these probabilities and the environment observations of each particular CCAV within the CCAV's FoV, we can take into account all observations regarding the occupancy state of any particular cell by applying Bayes rule recursively. Hence, when a cell belongs in the intersection of several CCAV FoVs, applying the Bayes rule recursively will allow us to enable the joint consideration of all respective individual observations regarding its occupancy state, ultimately providing a probabilistic estimate constituting the collective perception of the CCAVs.

Step 4: Step 4 aims at tracking the temporal evolution of the occupancy grid. There is a variety of proposed methods to approach this, each one with its merits and disadvantages (Nuss et al, 2018; Nègre et al, 2014). In all of these methods, the basic heuristic idea is common; in each time step, instead of setting the initial prior probabilities $P(A_i = 1)$, $P(A_i = 0)$ equal to 0.5 to reflect the unknown occupancy state of each cell, knowledge regarding the previous time step is taken into account. Specifically, the cells of the previous step occupied with high probability are moved according to corresponding velocity measurements to new cells, and the resulting predicted occupancy grid is used to derive the priors for the current time step (Coué et al, 2006).

3.2.1 Metrics for perception self-assessment

Off-line evaluation of the proposed method essentially entails the comparison of the output of the module with the known ground truth. There is a variety of ways to quantify the result of such comparisons;in our approach, we focus on the on-line self-assessment of the module output reliability based on the proababilistic occupancy grid properties. Since this is still an ongoing experimental study, in this section, we briefly mention some examples of such indicators. A straightforward and intuitive indicator of reliability of the output is the set of covariance matrices of the current Kalman filter recursions. For example, differential GPS systems provide measurements with errors in the order of 20-30 cm. Thus, position variance estimations above the order of 20-30 cm can be considered problematic. Both the percentage and the contiguity of grid cell regions with high confidence occupancy values (i.e., very high or very low occupancy probabilities) can also provide a reliability indicator for the output. Such indicators may be also be applied locally, i.e., to quantify uncertainties in current critical regions of interest, like regions to be occupied in the immediate future.

4 CP Module Evaluation Plan

To determine the safety improvement thanks to a camera-based CP module (typically hosted off-board, e.g. on a smart road side unit), the authors will a) perform a state-of-the art review (metrics for CP assessment based on sensor data late fusion methods are provided in V2XSim(Li et al, 2022) for instance) b) select a small set of round-about test scenarios also considering non-line of sight scenarios c) design a simulation pipeline built around CARLA able to model object's presence uncertainties through different added types of artificially generated noise, and d) introduce new metrics, which quantify the AVs' environmental awareness.

For points (a) and (b) generation of new collective perception scenarios using Mathworks RoadRunner, CARLA and ROS/Python external modules is foreseen. A mixed-reality simulation setup will also be utilized for a real vehicle in the loop simulation involving a single-seat Renault Twizy 80 equipped with automated driving software and hardware adapted and owned by TECNALIA (EVENTS partner). The ROS2 bridge will be used by the real AV modules to interact in real-time with the Carla simulator server, while the virtual vehicles will be controlled by CARLA applying autopilot mode through another client. ROS2 bridge will also be used for connecting the proposed collective perception module assumed to sit within a virtual sRSU, and CARLA. For emulating uncertainty in objects' presence, artificially generated noise will be applied on top of CARLA perception groundtruth (filtered objects within AV FoV). The proposed virtual/hybrid validation framework will be used to understand limits and benefits of CPM-enabled perception under assumptions of different object detection uncertainties generated in simulation.

5 Conclusion & Future Work

In this paper, a preview of the core algorithmic implementation behind a probabilistic collective perception module is presented. A Bayesian scheme is employed for CP information fusion generated by multiple connected traffic agents due it its inherent explainability which leads to easily defined output reliability metrics. The outlined hybrid validation framework of this CP module will be used to understand limits and benefits (on the perception level) of an ETSI-alike CPM-enabled CP under assumptions of different object detection uncertainties generated in simulation under different operational domain conditions. Proof-of-concept results will be published soon.

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