

PRECISE VEHICLE POSITIONING BY COOPERATIVE FEATURE ASSOCIATION AND TRACKING IN VEHICULAR NETWORKS

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ABSTRACT

In cooperative intelligent transportation systems, precise vehicle positioning is a critical requirement that cannot be met by stand-alone Global Positioning Systems (GPSs). This paper proposes a distributed Bayesian data association and localization method, called Implicit Cooperative Positioning with Data Association (ICP-DA), where connected vehicles detect a set of passive features in the driving environment, solve the association task by pairing them with on-board sensor measurements and cooperatively localize the features to enhance the GPS accuracy. Results show that ICP-DA significantly outperforms GPS, with negligible performance loss compared to ICP with perfect data association knowledge.

Index Terms— Cooperative positioning, data association, distributed Bayesian tracking, vehicular networks.

1. INTRODUCTION

Vehicle positioning plays a key role in Cooperative Intelligent Transportation Systems (C-ITS) [1, 2] where vehicles engage in cooperative assisted/automated driving by sharing information through Vehicle-to-Vehicle (V2V) communications for improving safety and traffic efficiency [3–5]. In most critical C-ITS use-cases, Global Positioning Systems (GPSs) are not able to meet the strict requirements of location accuracy and availability, especially in areas with challenging propagation conditions, such as urban canyons [6]. To tackle the problem, a number of cooperative positioning (CP) techniques [7–12] have been investigated augmenting GPS with information on vehicle kinematics, high-resolution maps and inter-vehicle measurements exchanged through V2V links.

Bayesian CP frameworks have been recently proposed in [13] and [14] for distributed localization in, respectively, wireless sensor and vehicular networks, including non-cooperative objects. Focusing on vehicular scenarios, the Implicit Cooperative Positioning (ICP) in [14] considers a network of vehicles that exploit on-board sensors to cooperatively detect and localize a set of non-cooperative features (e.g., traffic lights, parked cars, people) and use them as noisy reference points to implicitly improve the GPS accuracy. The method assumes perfect association between the local sensor measurements and the joint set of detected features. In

real scenarios, on the other hand, data association (DA) is a mandatory step that has to be performed before positioning to enable a consistent fusion of data collected by different vehicles. A DA belief propagation (BP) algorithm has been developed in [15] for centralized tracking of passive targets by Particle Filtering (PF) in sensor networks, based on an efficient DA procedure [16]. Low-complexity distributed techniques, however, are needed in C-ITS scenarios where the network is highly dynamic, with both vehicles and passive targets having unknown time-varying locations.

In this paper, we propose an extended ICP method which integrates the DA task into the cooperative Bayesian positioning approach, in a fully distributed way. The proposed ICP method with data association (ICP-DA) relies on two BP algorithms for data association and localization. Differently from [15, 16], where the position of the sensing agents is known and processing is centralized, here both vehicles and features have to be tracked in a distributed manner, and PF would require an unfeasible computational load. We thus propose a low-complexity ICP-DA implementation based on Maximum-A-Posteriori (MAP) detection for feature-measurement pairing and Gaussian message passing for cooperative localization. Numerical analysis in a simulated urban scenario shows that the ICP-DA method provides meaningful performance gains compared to GPS with negligible loss with respect to ICP with known DA.

2. VEHICULAR NETWORK SCENARIO

We denote with $\mathcal{V} = \{1, \dots, N_v\}$ and $\mathcal{F} = \{1, \dots, N_f\}$, respectively, the sets of N_v interconnected vehicles and of N_f non-cooperative features moving in a two-dimensional space. At time instant t , with sampling interval T_s , vehicle $i \in \mathcal{V}$ has position $\mathbf{p}_{i,t}^{(V)} \in \mathbb{R}^{2 \times 1}$ and velocity $\mathbf{v}_{i,t}^{(V)} \in \mathbb{R}^{2 \times 1}$. The vehicle state is $\mathbf{x}_{i,t}^{(V)} = [\mathbf{p}_{i,t}^{(V)T}, \mathbf{v}_{i,t}^{(V)T}]^T \in \mathbb{R}^{4 \times 1}$ and evolves over time according to the inertial sensor model [17]:

$$\mathbf{x}_{i,t}^{(V)} = \mathbf{A}\mathbf{x}_{i,t-1}^{(V)} + \mathbf{B}\mathbf{a}_{i,t-1}^{(V)} + \mathbf{w}_{i,t-1}^{(V)}, \quad (1)$$

where \mathbf{A} denotes the transition matrix, \mathbf{B} is the matrix relating the vehicle state to the acceleration information $\mathbf{a}_{i,t-1}^{(V)} \in \mathbb{R}^{2 \times 1}$ given by an inertial sensor and $\mathbf{w}_{i,t-1}^{(V)} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_{i,t-1}^{(V)})$ the zero-mean Gaussian driving process with covariance $\mathbf{Q}_{i,t-1}^{(V)}$ (see [17] for details). Similarly, the state of feature k

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is $\mathbf{x}_{k,t}^{(F)} = [\mathbf{p}_{k,t}^{(F)\top}, \mathbf{v}_{k,t}^{(F)\top}]^\top \in \mathbb{R}^{4 \times 1}$ and evolves as:

$$\mathbf{x}_{k,t}^{(F)} = \mathbf{A}\mathbf{x}_{k,t-1}^{(F)} + \mathbf{w}_{k,t-1}^{(F)}, \quad (2)$$

where $\mathbf{w}_{k,t-1}^{(F)} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_{k,t-1}^{(F)})$.

Each vehicle $i \in \mathcal{V}$ is assumed to be equipped with a V2V transceiver for exchanging data with the vehicles within the communication range R_c , i.e. with the neighbours in the set $\mathcal{N}_{i,t} = \{(i, j) \in \mathcal{V} \times \mathcal{V} : \|\mathbf{p}_{j,t}^{(V)} - \mathbf{p}_{i,t}^{(V)}\| \leq R_c\}$, a GPS positioning system and devices (radar, lidar or camera) to sense features within the sensing range R_s . The absolute location/velocity measurement provided by the GPS receiver is modelled as:

$$\boldsymbol{\rho}_{i,t}^{(\text{GPS})} = \mathbf{x}_{i,t}^{(V)} + \mathbf{n}_{i,t}^{(\text{GPS})}, \quad (3)$$

where $\mathbf{n}_{i,t}^{(\text{GPS})} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{i,t}^{(\text{GPS})})$ is the GPS uncertainty. Moreover, the on-board sensors provide a measurement of the relative position/velocity of the $O_{i,t} = |\mathcal{F}_{i,t}| \leq N_f$ features belonging to the subset $\mathcal{F}_{i,t} = \{k \in \mathcal{F} : \|\mathbf{p}_{k,t}^{(F)} - \mathbf{p}_{i,t}^{(V)}\| \leq R_s\}$. These Vehicle-to-Feature (V2F) observations are indexed in the set $\mathcal{O}_{i,t} = \{1, \dots, O_{i,t}\}$. Assuming that each feature can generate at most one V2F measurement at each vehicle, the V2F measurement $\ell \in \mathcal{O}_{i,t}$ at vehicle i is defined as:

$$\boldsymbol{\rho}_{i,\ell,t}^{(\text{V2F})} = \mathbf{x}_{k,t}^{(F)} - \mathbf{x}_{i,t}^{(V)} + \mathbf{n}_{i,\ell,t}^{(\text{V2F})} \quad (4)$$

where $k \in \mathcal{F}_{i,t}$ is the (unknown) feature associated to the measurement ℓ and $\mathbf{n}_{i,\ell,t}^{(\text{V2F})} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{i,\ell,t}^{(\text{V2F})})$ is the V2F uncertainty. Since the V2F measurements are not tagged, the association of the measurements to the features is unknown at the vehicle. Feature detection is considered as ideal at V2F sensors, i.e. false alarms and missing detections do not occur.

Focus of this paper is on the estimation of the state $\mathbf{x}_{i,t}^{(V)}$ at each vehicle i , based on all measurements (3)-(4) collected by the connected vehicles. The proposed method is described in Sec. 3, while the distributed implementation is in Sec. 4.

3. ICP-DA LOCALIZATION APPROACH

The ICP approach is based on a cooperative localization of the features \mathcal{F} by the vehicles \mathcal{V} by V2V interactions. The joint observation of a same feature by multiple vehicles enables to enhance the localization accuracy of the feature and, in turn, of all vehicles sensing that feature. As features are passive objects, the association between the V2F observations at each vehicle and the features \mathcal{F} is clearly a mandatory issue to be solved before the cooperation with other vehicles can take place. The DA problem, not covered in [14], is shown in Fig. 1-(top), where vehicles $\mathbf{x}_{1,t}^{(V)}$ and $\mathbf{x}_{2,t}^{(V)}$ jointly sense two features, $\mathbf{x}_{1,t}^{(F)}$ and $\mathbf{x}_{2,t}^{(F)}$. Each vehicle $i \in \{1, 2\}$ gathers two V2F observations and has to associate each observation $\boldsymbol{\rho}_{i,\ell,t}^{(\text{V2F})}$, $\ell \in \{1, 2\}$, to the feature $k \in \{1, 2\}$ that generated that measurement. Once DA is locally solved, vehicles can cooperatively combine the V2F measurements associated with

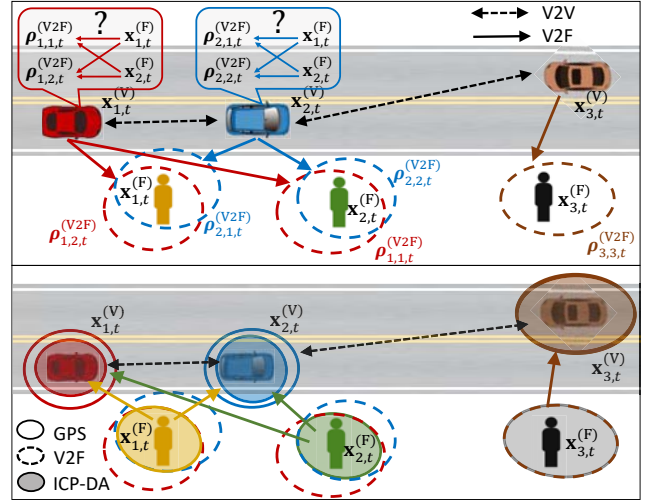


Fig. 1: Joint sensing of features $\mathbf{x}_{1,t}^{(F)}$ and $\mathbf{x}_{2,t}^{(F)}$ by vehicles $\mathbf{x}_{1,t}^{(V)}$ and $\mathbf{x}_{2,t}^{(V)}$ with unknown association (top). Measurement-feature association and cooperative estimation of the feature location (filled ellipses) to improve the GPS accuracy (contours) (bottom).

each feature as in Fig. 1-(bottom), to get a more accurate feature location (yellow and green ellipses) and, as a result, an improved vehicle location information (red and blue ellipses) compared to GPS (red and blue contours). Note that a feature has to be jointly sensed by at least two vehicles to provide any benefit, as shown in Fig. 1-(bottom) for vehicle $\mathbf{x}_{3,t}^{(V)}$ that individually detects feature $\mathbf{x}_{3,t}^{(F)}$ and cannot gain any improvement.

We propose to solve the association problem jointly with localization using a Bayesian approach. Let $\boldsymbol{\theta}_t = [\mathbf{x}_t^{(V)\top}, \mathbf{x}_t^{(F)\top}]^\top$ collect all vehicle/feature states $\mathbf{x}_t^{(V)} = [\mathbf{x}_{i,t}^{(V)}]_{i \in \mathcal{V}}$ and $\mathbf{x}_t^{(F)} = [\mathbf{x}_{k,t}^{(F)}]_{k \in \mathcal{F}}$, $\boldsymbol{\rho}_t = [\boldsymbol{\rho}_t^{(\text{GPS})\top}, \boldsymbol{\rho}_t^{(\text{V2F})\top}]^\top$ aggregate all the measurements $\boldsymbol{\rho}_t^{(\text{GPS})} = [\boldsymbol{\rho}_{i,t}^{(\text{GPS})}]_{i \in \mathcal{V}}$ and $\boldsymbol{\rho}_t^{(\text{V2F})} = [\boldsymbol{\rho}_{i,\ell,t}^{(\text{V2F})}]_{i \in \mathcal{V}}$, with $\boldsymbol{\rho}_{i,\ell,t}^{(\text{V2F})} = [\boldsymbol{\rho}_{i,\ell,t}^{(\text{V2F})}]_{\ell \in \mathcal{O}_{i,t}}$, the Bayesian estimate of the overall dynamic state based on the measurements up to time t , $\boldsymbol{\rho}_{1:t} = [\boldsymbol{\rho}_\tau]_{\tau \leq t}$, can be obtained according to the minimum mean square error (MMSE) criterion as $\hat{\boldsymbol{\theta}}_{t|t} = \int \boldsymbol{\theta}_t p(\boldsymbol{\theta}_t | \boldsymbol{\rho}_{1:t}) d\boldsymbol{\theta}_t$. As the evaluation of the posterior probability density function (pdf), $p(\boldsymbol{\theta}_t | \boldsymbol{\rho}_{1:t})$, requires the V2F observations in $\boldsymbol{\rho}_t$ to be paired with the feature states in $\boldsymbol{\theta}_t$, we model the association by the *feature-oriented* (F \rightarrow O) association variable $\alpha_{i,k,t}$, $i \in \mathcal{V}$, $k \in \mathcal{F}$, defined as [16]:

$$\alpha_{i,k,t} = \begin{cases} \ell \in \mathcal{O}_{i,t} & \text{if at time } t \text{ feature } k \in \mathcal{F}_{i,t} \text{ generates} \\ & \text{measurement } \ell \text{ at vehicle } i \\ 0 & \text{if at time } t \text{ feature } k \text{ does not generate any} \\ & \text{measurement at vehicle } i \text{ (i.e., } k \notin \mathcal{F}_{i,t} \text{)} \end{cases} \quad (5)$$

Defining the $N_f \times 1$ association vector for all the features sensed by vehicle i as $\boldsymbol{\alpha}_{i,t} = [\alpha_{i,k,t}]_{k \in \mathcal{F}_{i,t}}$ and the $N_v N_f \times 1$ vector for all vehicles as $\boldsymbol{\alpha}_t = [\boldsymbol{\alpha}_{i,t}]_{i \in \mathcal{V}}$, we then evaluate the posterior pdf of the vehicle-feature dynamics as:

$$p(\boldsymbol{\theta}_t | \boldsymbol{\rho}_{1:t}) = \sum_{\alpha_t \in \mathcal{A}} p(\boldsymbol{\theta}_t | \alpha_t, \boldsymbol{\rho}_{1:t}) p(\alpha_t | \boldsymbol{\rho}_{1:t}), \quad (6)$$

where summation is over the set \mathcal{A} of all the admissible association values (i.e., excluding values where, for any vehicle, a same measurement is associated to more than one feature).

The above approach requires all data to be collected and processed by a fusion centre. A decentralized approach, however, is to be preferred in C-ITS scenarios where data processing for positioning is performed locally by the vehicles. For this reason, in the following section we propose a distributed method that allows the evaluation of the marginal pdf $p(\boldsymbol{\theta}_t | \boldsymbol{\rho}_{1:t})$ at vehicle i , by extending the former ICP method for known association [14] with an algorithm that solves locally the association by the computation of $p(\alpha_{i,t} | \boldsymbol{\rho}_{1:t})$.

4. DISTRIBUTED ICP-DA METHOD

Following [16], in addition to the variable (5), we introduce the *observation-oriented* (O→F) association variable $\beta_{i,\ell,t}$, $i \in \mathcal{V}$, $\ell \in \mathcal{O}_{i,t}$, with the following definition: $\beta_{i,\ell,t} = k$, if at time t measurement ℓ at vehicle i is generated by feature $k \in \mathcal{F}_{i,t}$, $\beta_{i,\ell,t} = 0$, if the measurement ℓ is not related to any feature¹. This allows to efficiently impose the constraint that, at any vehicle, each feature can generate at most one measurement and each measurement can be generated by at most one feature, by the exclusion-enforcing function [16]:

$$\Psi(\alpha_{i,k,t}, \beta_{i,\ell,t}) = \begin{cases} 0 & \text{if } (\alpha_{i,k,t} = \ell \wedge \beta_{i,\ell,t} \neq k) \vee \\ & (\alpha_{i,k,t} \neq \ell \wedge \beta_{i,\ell,t} = k) \\ 1 & \text{otherwise,} \end{cases} \quad (7)$$

which is null for any inconsistent F-O pairing. Let the vectors $\boldsymbol{\beta}_{i,t} = [\beta_{i,\ell,t}]_{\ell \in \mathcal{O}_{i,t}}$ and $\boldsymbol{\beta}_t = [\beta_{i,t}]_{i \in \mathcal{V}}$ collect all the O→F associations for, respectively, vehicle i and all vehicles, the ICP-DA method evaluates the posterior pdf $p(\boldsymbol{\alpha}_t | \boldsymbol{\rho}_{1:t})$ and $p(\boldsymbol{\theta}_t | \boldsymbol{\rho}_{1:t})$ in (6) by marginalizing the joint posterior pdf $p(\boldsymbol{\theta}_{1:t}, \boldsymbol{\alpha}_{1:t}, \boldsymbol{\beta}_{1:t} | \boldsymbol{\rho}_{1:t})$, being $\boldsymbol{\theta}_{1:t} = [\boldsymbol{\theta}_\tau]_{\tau \leq t}$ all the vehicle-feature states up to time t . Since measurements are conditionally independent, the association variables are independent over time and from the vehicle-feature states, and the vehicle/feature states evolve independently according to the models (1)-(2), the joint posterior pdf can be factorized as:

$$p(\boldsymbol{\theta}_{1:t}, \boldsymbol{\alpha}_{1:t}, \boldsymbol{\beta}_{1:t} | \boldsymbol{\rho}_{1:t}) \propto \left(\prod_{i=1}^{N_v} p(\mathbf{x}_{i,0}^{(V)}) \prod_{\tau=1}^t p(\mathbf{x}_{i,\tau}^{(V)} | \mathbf{x}_{i,\tau-1}^{(V)}) \times \right. \\ \left. p(\boldsymbol{\rho}_{i,\tau}^{(\text{GPS})} | \mathbf{x}_{i,\tau}^{(V)}) \prod_{k=1}^{N_f} p(\boldsymbol{\rho}_{i,\tau}^{(\text{V2F})} | \mathbf{x}_{i,\tau}^{(V)}, \mathbf{x}_{k,\tau}^{(F)}, \alpha_{i,k,\tau}) \times \right. \\ \left. \prod_{\ell=1}^{O_{i,\tau}} \Psi(\alpha_{i,k,\tau}, \beta_{i,\ell,\tau}) \times \left(\prod_{k=1}^{N_f} p(\mathbf{x}_{k,0}^{(F)}) \prod_{\tau'=1}^t p(\mathbf{x}_{k,\tau'}^{(F)} | \mathbf{x}_{k,\tau'-1}^{(F)}) \right) \right) \quad (8)$$

Here $p(\mathbf{x}_{i,0}^{(V)})$ and $p(\mathbf{x}_{k,0}^{(F)})$ denote the prior pdfs at time $t = 0$. The GPS likelihood $p(\boldsymbol{\rho}_{i,\tau}^{(\text{GPS})} | \mathbf{x}_{i,\tau}^{(V)})$ is Gaussian with mean $\mathbf{x}_{i,t}^{(V)}$ and covariance $\mathbf{R}_{i,t}^{(\text{GPS})}$. The V2F likelihood is:

¹Though clutter measurements are not considered in this paper, the case $\beta_{i,\ell,t} = 0$ is introduced to exclude ambiguous measurements and reduce errors during the detection process.

$$p(\boldsymbol{\rho}_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(V)}, \mathbf{x}_{k,t}^{(F)}, \alpha_{i,k,t}) \propto \begin{cases} p(\boldsymbol{\rho}_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(V)}, \mathbf{x}_{k,t}^{(F)}) & \text{if } \alpha_{i,k,t} = \ell \\ 1 & \text{if } \alpha_{i,k,t} = 0 \end{cases} \quad (9)$$

where $p(\boldsymbol{\rho}_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(V)}, \mathbf{x}_{k,t}^{(F)})$ is Gaussian with mean $\mathbf{x}_{k,t}^{(F)} - \mathbf{x}_{i,t}^{(V)}$ and covariance $\mathbf{R}_{i,t}^{(\text{V2F})}$, while the case $\alpha_{i,k,t} = 0$ refers to a feature that is not sensed by vehicle i .

Starting from (8), the ICP-DA problem can be solved in a distributed manner by running a loopy belief propagation algorithm (BPA) [18] on the factor graph describing the factorization. This enables the association/location pdf of each vehicle to be computed locally, by iterated message exchange with other vehicles through the V2V links. The algorithm is the cascade of two separate BPAs. A first BPA procedure (BPA-DA) is carried out independently at each vehicle i for data association as in [16] to approximate the posterior pdf of the association variable by the belief $b_{i,k,t}^{(p)}(\alpha_{i,k,t}) \approx p(\alpha_{i,k,t} | \boldsymbol{\rho}_{i,t})$ through the iterations $p = 1, \dots, P$. These beliefs are then used to perform a second BPA for cooperative localization (BPA-L), which computes over the iterations $n = 1, \dots, N$ the location-velocity beliefs $b_{i,t}^{(n)}(\mathbf{x}_{i,t}^{(V)}) \approx p(\mathbf{x}_{i,t}^{(V)} | \boldsymbol{\rho}_{1:t})$ and $b_{k,t}^{(n)}(\mathbf{x}_{k,t}^{(F)}) \approx p(\mathbf{x}_{k,t}^{(F)} | \boldsymbol{\rho}_{1:t})$ for all the vehicles and features.

Considering the non-Gaussian statistics (due to the association variables), PF should be employed for BPA implementation as in [15]. However, in C-ITS scenarios where both vehicles and features have to be tracked, a huge number of particles would be required to sample the vehicle/feature pdfs with enough accuracy and the computational burden would get unfeasible. To lower the complexity, we propose to perform a *hard* Bayesian detection of the association variables at the end of BPA-DA, based on the belief $b_{i,k,t}^{(p)}(\alpha_{i,k,t})$, and to reduce BPA-L to a Gaussian BPA where vehicle/feature beliefs can be simply computed by the first two statistical moments. Differently from [15], the proposed approach is fully distributed.

The ICP-DA method consists of the following steps:

1 - *Prediction*: at time t the beliefs are initialized as:

$$b_{i,t}^{(0)}(\mathbf{x}_{i,t}^{(V)}) = p(\boldsymbol{\rho}_{i,t}^{(\text{GPS})} | \mathbf{x}_{i,t}^{(V)}) \int p(\mathbf{x}_{i,t}^{(V)} | \mathbf{x}_{i,t-1}^{(V)}) b_{i,t-1}^{(N)}(\mathbf{x}_{i,t-1}^{(V)}) d\mathbf{x}_{i,t-1}^{(V)}, \quad (10)$$

$$b_{k,t}^{(0)}(\mathbf{x}_{k,t}^{(F)}) = \int p(\mathbf{x}_{k,t}^{(F)} | \mathbf{x}_{k,t-1}^{(F)}) b_{k,t-1}^{(N)}(\mathbf{x}_{k,t-1}^{(F)}) d\mathbf{x}_{k,t-1}^{(F)}, \quad (11)$$

using the beliefs $b_{i,t-1}^{(N)}(\mathbf{x}_{i,t-1}^{(V)})$ and $b_{k,t-1}^{(N)}(\mathbf{x}_{k,t-1}^{(F)})$ of previous time interval, along with the transition pdfs $p(\mathbf{x}_{i,t}^{(V)} | \mathbf{x}_{i,t-1}^{(V)})$ and $p(\mathbf{x}_{k,t}^{(F)} | \mathbf{x}_{k,t-1}^{(F)})$ computed from (1) and (2).

2 - *V2F measurement evaluation for association*: each vehicle i evaluates the likelihood of any O→F association by integrating the V2F measurement likelihood in (9) over the vehicle and feature locations using the prior beliefs (10)-(11):

$$p(\boldsymbol{\rho}_{i,t}^{(\text{V2F})} | \alpha_{i,k,t}) = \iint p(\boldsymbol{\rho}_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(V)}, \mathbf{x}_{k,t}^{(F)}, \alpha_{i,k,t}) \times b_{i,t}^{(0)}(\mathbf{x}_{i,t}^{(V)}) b_{k,t}^{(0)}(\mathbf{x}_{k,t}^{(F)}) d\mathbf{x}_{i,t}^{(V)} d\mathbf{x}_{k,t}^{(F)}. \quad (12)$$

3 - *BPA-DA for measurement-feature association*: each vehicle i runs the BPA procedure [15, 16] to evaluate the association belief $b_{i,k,t}^{(p)}(\alpha_{i,k,t}) \forall k \in \mathcal{F}$ by repeated exchanges of messages for $p = 1, 2, \dots$ from the $F \rightarrow O$ association variable $\alpha_{i,k,t}$ to the $O \rightarrow F$ association variable $\beta_{i,\ell,t}$ and vice-versa.

4 - *V2F measurement evaluation for localization*: each vehicle i performs a threshold detection to decide if the feature $k \in \mathcal{F}$ has been sensed by its sensors, by comparing the belief of the association to any of its measurements with a threshold η_{TH} , here set to 0.5. If $b_{i,k,t}^{(p)}(\alpha_{i,k,t} = 0) < 1 - \eta_{\text{TH}}$ the feature k is detected and paired with the most probable measurement:

$$\hat{\alpha}_{i,k,t} = \underset{\ell \in \mathcal{O}_{i,t}}{\operatorname{argmax}} b_{i,k,t}^{(p)}(\alpha_{i,k,t} = \ell). \quad (13)$$

The related likelihood is evaluated as $p(\rho_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(\text{V})}, \mathbf{x}_{k,t}^{(\text{F})}) = p(\rho_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(\text{V})}, \mathbf{x}_{k,t}^{(\text{F})}, \hat{\alpha}_{i,k,t})$.

5 - *BPA-L for localization*: the beliefs of all vehicles' and features' states are computed by an iterative BPA as follows. At iteration $n = 1, 2, \dots$ the procedure starts at each vehicle $i \in \mathcal{V}$ by sending the message

$$m_{i \rightarrow k}^{(n)}(\mathbf{x}_{k,t}^{(\text{F})}) \propto \int \frac{b_{i,t}^{(n-1)}(\mathbf{x}_{i,t}^{(\text{V})})}{m_{k \rightarrow i}^{(n-1)}(\mathbf{x}_{i,t}^{(\text{V})})} p(\rho_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(\text{V})}, \mathbf{x}_{k,t}^{(\text{F})}) d\mathbf{x}_{i,t}^{(\text{V})} \quad (14)$$

to all the sensed features $k \in \mathcal{F}_{i,t}$. Then, each feature k combines all the incoming messages to refine its own belief as:

$$b_{k,t}^{(n)}(\mathbf{x}_{k,t}^{(\text{F})}) \propto b_{k,t}^{(0)}(\mathbf{x}_{k,t}^{(\text{F})}) \prod_{i \in \mathcal{V}_{k,t}} m_{i \rightarrow k}^{(n)}(\mathbf{x}_{k,t}^{(\text{F})}), \quad (15)$$

with $\mathcal{V}_{k,t}$ denoting the set of vehicles sensing feature k . Similarly to (14)-(15), each vehicle $i \in \mathcal{V}$ receives the following messages from the sensed features $k \in \mathcal{F}_{i,t}$

$$m_{k \rightarrow i}^{(n)}(\mathbf{x}_{i,t}^{(\text{V})}) \propto \int \frac{b_{k,t}^{(n)}(\mathbf{x}_{k,t}^{(\text{F})})}{m_{i \rightarrow k}^{(n)}(\mathbf{x}_{k,t}^{(\text{F})})} p(\rho_{i,t}^{(\text{V2F})} | \mathbf{x}_{i,t}^{(\text{V})}, \mathbf{x}_{k,t}^{(\text{F})}) d\mathbf{x}_{k,t}^{(\text{F})} \quad (16)$$

and uses them to refine its own belief as:

$$b_{i,t}^{(n)}(\mathbf{x}_{i,t}^{(\text{V})}) \propto b_{i,t}^{(0)}(\mathbf{x}_{i,t}^{(\text{V})}) \prod_{k \in \mathcal{F}_{i,t}} m_{k \rightarrow i}^{(n)}(\mathbf{x}_{i,t}^{(\text{V})}). \quad (17)$$

This iterative algorithm is performed till convergence. Since features are not actively involved in computations and communications with vehicles, messages and beliefs (14)-(15) have to be distributively computed by vehicles. A consensus method is employed as in [14] for the evaluation of the Gaussian features' beliefs (i.e., the first two statistical moments) through data exchanges over the V2V links.

5. SIMULATION RESULTS

The ICP-DA method is validated by Monte Carlo simulations in the scenario of Fig. 2-(top), where a convoy of $N_v = 6$ vehicles, interconnected with V2V range $R_c = 250$ m and travelling in open sky with average velocity 60 km/h and average heading 20 m, enter a road section of length 200 m where the GPS accuracy suddenly degrades. The

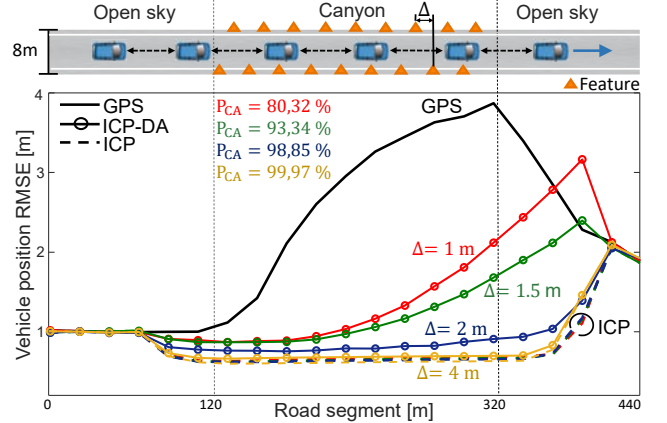


Fig. 2: Vehicular C-ITS scenario (top). Vehicle position accuracy along the road for varying spacing Δ between features (bottom).

GPS accuracy is $\mathbf{R}_{i,t}^{(\text{GPS})} = \text{diag}(\sigma_p^{(\text{GPS})^2} \mathbf{I}_2, \sigma_v^{(\text{GPS})^2} \mathbf{I}_2)$ with $\sigma_p^{(\text{GPS})} = 5$ m and $\sigma_v^{(\text{GPS})} = 0.1$ m/s outside the canyon, and $\sigma_p^{(\text{GPS})} = 17$ m and $\sigma_v^{(\text{GPS})} = 2.5$ m/s inside. A set of $N_f = 200/\Delta$ static features is uniformly distributed over the canyon area, with spacing $\Delta \in \{1, 1.5, 2, 4\}$ m. The vehicles sense these features with V2F range $R_s = 50$ m and accuracy $\mathbf{R}_{i,t}^{(\text{V2F})} = \text{diag}(\sigma_p^{(\text{V2F})^2} \mathbf{I}_2, \sigma_v^{(\text{V2F})^2} \mathbf{I}_2)$, with $\sigma_p^{(\text{V2F})} = 0.1$ m and $\sigma_v^{(\text{V2F})} = 0.1$ m/s. The vehicles' motion is generated as in (1) with $T_s = 1$ s, $\mathbf{Q}_{i,t-1}^{(\text{V})} = \mathbf{B} \text{diag}(\sigma_{w_x}^2, \sigma_{w_y}^2) \mathbf{B}^T$, where $\sigma_{w_x} = 0.5$ m/s² and $\sigma_{w_y} = 0.001$ m/s² are the driving noise powers over the two axes. In Fig. 2-(bottom) the Root Mean Square Error (RMSE) of the location estimate (averaged over vehicles) is plotted along the road for ICP-DA, ICP with known DA [14] and GPS-based Kalman filtering. As the feature density increases, it can be seen that the probability of correct association, P_{CA} , decreases and the ICP-DA performance degrades with respect to ICP, still maintaining a significant gain over GPS in the canyon. On the other hand, when the feature spacing is large enough compared to the location accuracy ($\Delta > 1.5$ m), the association becomes highly reliable and the ICP-DA closely approaches the ICP method with perfect association.

6. CONCLUSIONS

In this paper, a distributed Bayesian data association and positioning method was proposed for vehicular networks, where vehicles jointly detect a set of non-cooperative features, associate the local sensor measurements to the features and cooperatively localize the features for GPS augmentation. Performance results showed that the proposed method is able to significantly improve the GPS-based location accuracy, especially in harsh environments with highly degraded or denied GPS signal (e.g., urban canyons or tunnels). A negligible performance loss is observed with respect to the cooperative positioning solution with known DA for feature spacing above 1.5 m.

7. REFERENCES

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