On Communication Aspects of Particle-Based Cooperative Positioning in GPS-aided VANETs

G.M. Hoang[†‡], B. Denis[†], J. Härri[‡], D. T.M. Slock[‡]

[†]CEA-Leti, MINATEC Campus, 17 avenue des Martyrs, F38054 Grenoble, Cedex 9, France

[‡]EURECOM, 450 route des Chappes, 06904 Sophia Antipolis, France

E-mails:{giaminh.hoang, benoit.denis}@cea.fr, {jerome.haerri, dirk.slock}@eurecom.fr

Abstract—**Precise location services are seen as key enablers to future Intelligent Transport Systems (ITSs). Relying on Vehicle-to-Vehicle (V2V) communication links, one promising solution consists in performing distributed Cooperative Positioning (CP). More specifically, Cooperative Awareness Message (CAM) broadcasts from neighboring vehicles (seen as "virtual anchors") are used to exchange positional information and to measure V2V radiolocation metrics such as the Received Signal Strength Indicator (RSSI). For the sake of fusing these non-linear hybrid data, Particle Filters (PFs) represent the required positional information by a set of particles with associated weights. However, in a jointly cooperative and distributed context, the transmission of explicit particle clouds (required by receiving neighbors to update their own location estimates) is hardly affordable under limited V2V channel capacity with typical numbers of particles. In this paper we thus combine and compare several solutions in terms of message representation and adaptive transmission policy so as to reduce simultaneously CAM overhead, channel congestion and computational complexity. Proposals are made at both signal processing level (parametric density approximation) and protocol level (jointly adaptive transmission payload, power and rate), showing no impact on channel load in congested scenarios and negligible CP accuracy degradation in comparison with standard CAM transmission at critical rates.**

I. INTRODUCTION

The availability of high-accuracy and seamless position awareness is indispensable to future road safety and traffic efficiency. However, the capability of the widely used Global Positioning System (GPS), which is dedicated to route navigation, is far below the requirements and expectations of these Intelligent Transport System (ITS) applications in terms of both accuracy and service continuity (especially in challenging -but still common- environments such as urban canyons and tunnels) [1]–[3]. To tackle this problem in Vehicular Ad hoc NETworks (VANETs), one solution is to benefit from the ubiquitous position awareness of surrounding vehicles, which is periodically received in the form of Cooperative Awareness Messages (CAMs) over ITS-G5 channels[1] [4]. Out of these incoming CAMs, Vehicle-to-Vehicle (V2V) range-dependent power measurements (i.e., Received Signal Strength Indicator (RSSI)) can be performed and time-stamped estimated locations (i.e., directly encapsulated in the payloads by source neighbors) are retrieved, thus making it possible to trigger ad hoc multilateration procedures with respect to fellow mobile

[1]CAM is similar to Basic Safety Message (BSM) in the U.S. and European ITS-G5 is the preferred technology for Dedicated Short Range Communications (DSRC).

neighbors, seen as "virtual anchors" (in the sense that they are mobile and cannot deliver their exact locations but only estimated values). This so-called Cooperative Positioning (CP) solution aims at providing spatial diversity and information redundancy so as to improve the "ego" vehicle's localization in a variety of cases (e.g., GNSS-denied environments, sparse road infrastructure...), but also to broadcast enhanced estimates back to other vehicles to assist them [2], [3] (See Fig. 1).

In this cooperative data fusion context, since real-world observations (typically, the V2V RSSI readings considered herein) are highly nonlinear with respect to the state variables of interest (e.g., position, velocity, heading...), the Particle Filter (PF) is a natural choice for sequential state estimation when Kalman Filter (KF)-based methods may diverge. Nevertheless, distributed particle-based CP induces not only high computational complexity but also extra communication cost (e.g., while exchanging particle clouds through message passing [5]) to achieve optimal performance levels. This limitation can be alleviated by adopting parametric message representations (e.g., well-known Gaussian Mixture Models (GMMs)) instead of propagating explicit particle clouds. In the literature, this has been considered mostly in iterative message-passing localization algorithms for generic, static and densely connected wireless networks so far [6]–[8]. Alternatively, other specific distributed positioning techniques can propagate and multiply densities to produce estimated locations [9] instead of redrawing samples out of the received densities. However, the latter solutions also rely on intermediary message approximation steps. All in all, in the VANET context, no in-depth investigation has been yet carried out in the literature to compare the various parameterization approaches and their performance trade-offs in terms of localization accuracy, communication traffic, channel load, computational complexity, latency..., whereas these metrics are expected to strongly impact the practicability and the implementability of particle-based CP. On the other hand, in case of channel congestion, Decentralized Congestion Control (DCC) mechanisms specified by the European Telecommunications Standard Institute (ETSI) recommend to scale the CAM transmission rate from 10 Hz down to 2 Hz (in order not to exceed 60–70% channel load), what is expected to degrade CP accuracy accordingly.

In this paper, we extend a generic fusion-based CP framework relying on PF to cope with the stringent computation, latency and communication constraints without deteriorating
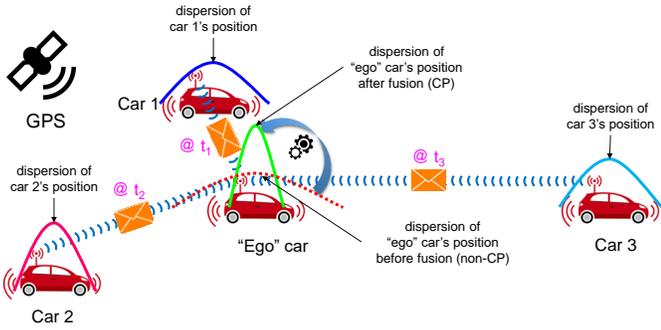
Fig. 1. "Ego" car receiving asynchronous CAMs from single-hop "virtual anchors" to perform distributed CP. The dispersion of CP location estimates (i.e. through GPS+ITS-G5) is expected to be lower than that of non-CP estimates (i.e., standalone GPS).

significantly the localization accuracy. The main contributions can be summarized as follows: (i) we perform an in-depth comparison of various GMMs in CP in order to select the best scheme; (ii) we point out the fact that using multimodal distributions for message approximation is not always helpful in practical deployment scenarios but adversely leads to high computational complexity (for modes identification and parameterization); (iii) besides message approximations, we also propose a transmission policy enabling adaptive transmit payload, power, and rate to maintain high-accuracy location awareness in any case including triggered ETSI DCC.

The paper is organized as follows. Section II presents the problem formulation. In Section III we describe the new proposed techniques. Next, simulation results illustrate the achievable performance in Section IV. Finally, Section V concludes the paper and provides an outlook of future works.

II. PROBLEM FORMULATION

A. Generic Cooperative Positioning in VANETs

We consider a network of cooperative GPS-equipped vehicles exchanging CAMs over ITS-G5 channels. The goal of an "ego" vehicle is to get high-accuracy awareness of its position (as part of its state) based on its own flawed GPS estimate, on V2V RSSIs with respect to single-hop neighbors (measured out of incoming CAMs), and on imperfect state information from the latter neighbors. Fig. 1 illustrates this CP concept. Without loss of generality, we do not consider here Vehicle-to-Infrastructure (V2I) communications to assist positioning bur more generic V2V configurations, since the availability of Road Side Units (RSU) may be not always guaranteed depending on the operating conditions.

CP is prone to several specific challenges. First, the intrinsic mobile nature of "virtual anchors" and vehicular wireless channels make that the indicated neighbors' positions as well as the received power over V2V links may be subject to errors and strong fading conditions respectively. The transmission intervals between CAMs are also constrained by channel load conditions, leading to non periodic transmissions and as such, non synchronous data reception from "virtual anchors" (See Figure 1). Moreover, to boost the CP accuracy, cooperative vehicles tend to broadcast their positional information (i.e., state

estimates or distributions) at maximum rates and/or ranges, thus leading to higher computational complexity (in terms of data processing and fusion) and more importantly, to increased network traffic, packet loss, triggered ETSI DCC, etc. that would be eventually counterproductive to localization. These limitations must be carefully considered when implementing CP in VANETs.

B. System Models and Particle-based CP in VANETs

Consider the state vector $\boldsymbol{\theta}_{i,k} = (\mathbf{x}_{i,k}^\dagger, \mathbf{v}_{i,k}^\dagger)^\dagger$ of vehicle i including, for a 2-D system, its position $\mathbf{x}_{i,k} = (x_{i,k}, y_{i,k})^\dagger$ and its velocity $\mathbf{v}_{i,k} = (v_{i,k}^x, v_{i,k}^y)^\dagger$ at its local discrete time index k_i, which both evolve according to a mobility model. At time k_i, a measurement vector $\mathbf{z}_{i,k}$ is observed, which is related to $\boldsymbol{\theta}_{i,k}$ via a measurement model.

1) Mobility Model: We consider a stochastic mobility model suitable to vehicular contexts, referred to as modified Gauss-Markov mobility model [2], as follow:

$$\boldsymbol{\theta}_{i,k+1} = \begin{pmatrix} \mathbf{I}_2 & \alpha \Delta T \cdot \mathbf{I}_2 \\ \mathbf{0}_2 & \alpha \cdot \mathbf{I}_2 \end{pmatrix} \boldsymbol{\theta}_{i,k} + (1-\alpha) \begin{pmatrix} \Delta T \cdot \mathbf{I}_2 \\ \mathbf{I}_2 \end{pmatrix} \bar{\mathbf{v}}_i \\ + \sqrt{1-\alpha^2} \begin{pmatrix} \Delta T^2 \cdot \mathbf{I}_2 \\ \Delta T \cdot \mathbf{I}_2 \end{pmatrix} \mathbf{w}_{i,k},$$ (1)

where α is the memory level, ΔT the time step, $\bar{\mathbf{v}}_i = (v_i^x, v_i^y)^\dagger$ the asymptotic 2-D velocity, $\mathbf{w}_{i,k} = (w_{i,k}^x, w_{i,k}^y)^\dagger$ the 2-D process noise vector, $\mathbf{I}_2$ the identity matrix of size 2×2. Note that we use this mobility model to perform the prediction of both "ego" and neighbors' estimated locations and resynchronize related data before fusion, like in [2], [3].

2) Observation Model: In this paper, we consider as observations two kinds of measurements, issued respectively by the GPS receiver and the V2V communication module.

a) Absolute GPS Position: The 2-D position $\mathbf{x}_{i,k} = (x_{i,k}, y_{i,k})^\dagger$ estimated by a GPS receiver, $\mathbf{x}_{i,k}^{\text{GPS}} = (z_{i,k}^x, z_{i,k}^y)^\dagger$, is affected by additive noise $\mathbf{n}_{i,k}^{\text{GPS}} = (n_{i,k}^x, n_{i,k}^y)^\dagger$ (assumed i.i.d. centered Gaussian [2], [3], [10]), as follows:

$$z_{i,k}^x = x_{i,k} + n_{i,k}^x, \quad z_{i,k}^y = y_{i,k} + n_{i,k}^y.$$ (2)

b) V2V Received Power: Out of a received CAM, the RSSI denoted by $z_{j \to i,k}$ (on a dB scale) at vehicle i and local time k_i with respect to vehicle j while occupying position $\mathbf{x}_{j,k_i}$ is assumed to be measured in Line-Of-Sight (LOS) and to follow the widely used log-distance path loss model [11]:

$$z_{j \to i,k} = P(d_0) - 10 n_p \log_{10}(\|\mathbf{x}_{i,k} - \mathbf{x}_{j,k_i}\|) + X_{j \to i,k},$$ (3)

where $P(d_0)$ [dBm] is the average received power at a reference distance $d_0 = 1$ m, n_p the path loss exponent, and finally $X_{j \to i,k}$ a centered Gaussian shadowing term with standard deviation σ_{Sh}.

In the following filtering scheme, input observations can be composed of GPS and/or V2V RSSI measurements, depending on the cooperation level. Generally, given the set $\mathcal{S}_{\to i,k}$ of vehicle i's "virtual anchors" at time k_i, the full measurement vector is $\mathbf{z}_{i,k} = [z_{i,k}^x, z_{i,k}^y, \dots, z_{j \to i,k}, \dots]^\dagger$, $j \in \mathcal{S}_{\to i,k}$.
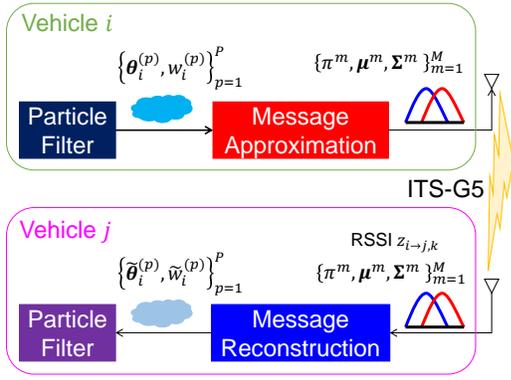
Fig. 2. Example of awareness data flow in PF-based CP framework for two vehicles i and j. Vehicle i firstly approximates its particle-based state $\{\boldsymbol{\theta}_i^{(p)}, w_i^{(p)}\}_{p=1}^P$ by a Gaussian (mixture) distribution, then encapsulates the parameters $\{\pi^m, \boldsymbol{\mu}^m, \boldsymbol{\Sigma}^m\}_{m=1}^M$ in a CAM to broadcast. Receiving vehicle j extracts these parameters to identify the distribution and draw samples from it to reconstruct the approximated $\{\tilde{\boldsymbol{\theta}}_i^{(p)}, \tilde{w}_i^{(p)}\}_{p=1}^P$.

3) Particle Filter: The key idea of PF is to approximately represent the *a posteriori* density $p(\boldsymbol{\theta}_{i,k}|\mathbf{z}_{1:k})$ by a particle cloud $\{\boldsymbol{\theta}_{i,k}^{(p)}, w_{i,k}^{(p)}\}_{p=1}^P$ of random samples $\boldsymbol{\theta}_{i,k}^{(p)}$ with associated weights $w_{i,k}^{(p)}$ and to compute various estimates (e.g., Minimum Mean Square Error (MMSE) estimator) based on these samples and weights. At time k_i, the PF recursively updates the previous particle cloud $\{\boldsymbol{\theta}_{i,k-1}^{(p)}, w_{i,k-1}^{(p)}\}_{p=1}^P$ using the observation $\mathbf{z}_{i,k}$ by doing prediction step (i.e., approximating the predicted *posterior* $p(\boldsymbol{\theta}_{i,k}|\mathbf{z}_{i,1:k-1})$) and correction step (i.e., computing these weights $w_{i,k}^{(p)}$ relying on the likelihood function given current observations, $p(\mathbf{z}_{i,k}|\boldsymbol{\theta}_{i,k}, \dots, \boldsymbol{\theta}_{j,k_i}, \dots)$, $j \in \mathcal{S}_{\rightarrow i,k})$. The details are presented in [2].

Note that the previous likelihood function requires the knowledge of particle-based neighboring states which raises challenges for message passing, now constrained by ITS-G5 impairments (e.g., 6-Mbps channel capacity with 60–70% load available for CAM exchange, 300–800-byte CAM, event-driven 2–10-Hz CAM rate, etc.).

III. PROPOSED APPROACHES

A. Parametric Message Approximation

In this section, the goal is to approximate the heavy particle cloud $\{\boldsymbol{\theta}^{(p)}, w^{(p)}\}_{p=1}^P$ to facilitate its broadcast to neighboring vehicles using Gaussian or Gaussian mixture distributions. The main motivation for using Gaussian representations lies in their tractable analytical properties whereas mixtures of Gaussians are convenient to approximate very complex densities by using a sufficient number of Gaussian components, while tuning their means, covariance matrices and weights. Mathematically, a Gaussian mixture distribution is indeed expressed by a linear combination [12] of the form $p(\boldsymbol{\theta}) = \sum_{m=1}^M \pi^m \mathcal{N}(\boldsymbol{\theta}|\boldsymbol{\mu}^m, \boldsymbol{\Sigma}^m)$, where $M \in \mathbb{Z}^+$ denotes the number of Gaussian components, $\{\boldsymbol{\mu}^m, \boldsymbol{\Sigma}^m, \pi^m\}$ are the mean, the covariance matrix and the normalized mixture weight of each multivariate normal density component $m = 1, \dots, M$, respectively.
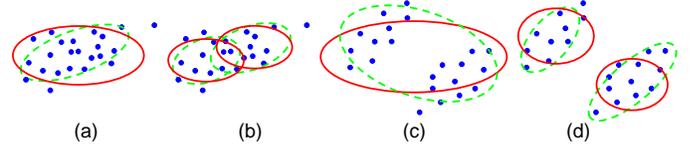
Fig. 3. Simplified 2-D position representations including nonparametric (i.e., particles as dots) and parametric (i.e., diagonal Gaussian modes as solid ellipses and full Gaussian modes as dashed ellipses) approaches. Unimodal data can be approximated by either unimodal Gaussian in (a) or bimodal Gaussian in (b) and bimodal data can be approximated by either unimodal Gaussian in (c) or bimodal Gaussian in (d). Each explicit particle representation costs two scalars, each diagonal Gaussian mode occupies 4 scalars, and each full Gaussian mode requires 5 scalars. One more scalar is needed for the weight in case of bimodal distribution.

Given uniformly weighted particles $\boldsymbol{\Theta} = \{\boldsymbol{\theta}^{(p)}, 1/P\}_{p=1}^P$ (thanks to resampling) as input data, one wishes to model these data using a mixture of Gaussians. The Gaussian mixture distribution is fully determined by the parameters $\boldsymbol{\pi} = \{\pi^m\}_{m=1}^M$, $\boldsymbol{\mu} = \{\boldsymbol{\mu}^m\}_{m=1}^M$, and $\boldsymbol{\Sigma} = \{\boldsymbol{\Sigma}^m\}_{m=1}^M$. To determine the latter, we employ a Maximum Likelihood (ML) estimator, assuming that the particles are drawn independently from the true distribution. The log-likelihood function is then determined as $\log p(\boldsymbol{\Theta}|\boldsymbol{\pi}, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \sum_{p=1}^P \log \left\{ \sum_{m=1}^M \pi^m \mathcal{N}(\boldsymbol{\theta}^{(p)}|\boldsymbol{\mu}^m, \boldsymbol{\Sigma}^m) \right\}$. Denoting the set of unknown parameters as $\boldsymbol{\alpha} = \{\boldsymbol{\mu}, \boldsymbol{\Sigma}, \boldsymbol{\pi}\}$, the ML estimate is defined by $\hat{\boldsymbol{\alpha}}_{\text{ML}} = \arg\max_{\boldsymbol{\alpha}} p(\boldsymbol{\Theta}|\boldsymbol{\alpha})$. This solution cannot be analytically determined in closed form. However, numerical iterative techniques such as the gradient descent or the Expectation Maximization (EM) [12] algorithms, can be used to optimize the previous likelihood function.

This message approximation procedure must be computationally efficient from the latency point of view so as to cope with high CAM rates up to 10 Hz. Accordingly, unimodal and bimodal Gaussians are assumed sufficient to capture the salient properties of the true message, whereas multimodal Gaussians (i.e., involving more than 2 modes) can be discarded to avoid solving out too complex optimization problems. Actually, when one cannot rely on enough neighbors (e.g., in sparsely connected networks), the RSSI likelihood function may be multimodal and so is the *posterior* location distribution. However, this information shall be discarded by simply censoring the CAM transmission. Indeed, a too poorly localized vehicle shall not provide unreliable information to its neighbors for CP purposes. In contrast, as we expect to benefit from numerous cooperative neighbors in reasonably dense VANETs, the RSSI likelihood function is more prone to be unimodal, as suggested by previous studies like in [13]. Besides, GPS observation can also help to resolve geometrical ambiguities occurring in such multimodal circumstances.

Note that since the absolute position and the velocity are weakly correlated (e.g., x-to-v^x and x-to-v^y cross-correlations) in comparison with the internal correlations between their components (i.e., x-to-y and v^x-to-v^y cross-correlations) they can be separated and approximated independently in order to ease the optimization problem (e.g., specifying a 4-D Gaussian distribution requires determining 14 parameters). Furthermore, the velocity is naturally unimodal
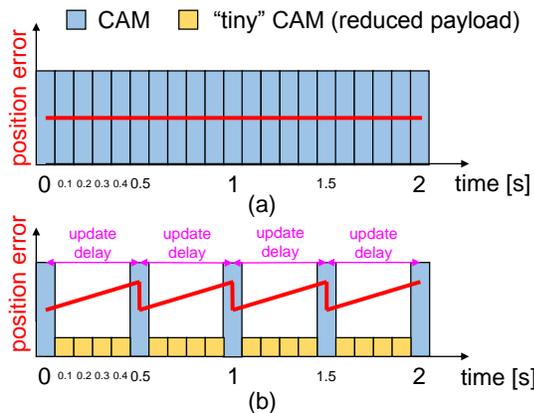
Fig. 4. Standard CAM transmission policy (10 Hz) in (a) vs. adjusted mixed CAM traffic (including tiny/frequent CAMs at 10 Hz and nominal/infrequent CAMs at 2 Hz) in (b).

so a Gaussian is sufficient. Fig. 2 summarizes the message approximation needs in CP based on a simplified example, where vehicle i broadcasts its particle-based state over ITS-G5 channel to support vehicle j's CP. Fig. 3 illustrates for 2-D particle-based positions the aforementioned possible message representations in both non-ambiguous and ambiguous cases (See Fig. 3(a)-(b) and 3(c)-(d), respectively).

B. Transmission Control Strategy

Basically, ITS-G5 standard supports critical 10-Hz CAM to provide and maintain superior quality of position awareness (See Fig 4(a)). Accordingly, our opportunistic CP exploits this network information to boost location accuracy. However, the ITS-G5 channels are vulnerable to such critical broadcast, especially in dense traffic conditions. In this case, the ETSI DCC scales the CAM rate to 2 Hz to avoid congestion, thus loosing four fifth of the cooperative information amount for CP (i.e., neighbors' positions and RSSIs). The idea is to design a transmission protocol coping with the ETSI DCC without compensating for such information loss.

Again, CP performance strongly relies on neighboring position awareness, as well as on associated range-dependent measurements. Using a single kind of messages for both purposes does not appear fully efficient because the former position can be predicted quite reliably in the short term (e.g., within the sub-second horizon). Hence, we can contextually select what we need to transmit at any instant. More particularly, we propose to mix "tiny" CAMs with reduced payload (i.e., containing only vehicle's ID without estimated state and associated attributes) at the critical rate of 10 Hz to provide range-dependent information (i.e., RSSI) and normal CAMs at the lower rate of 2 Hz (in compliance with ETSI DCC). Fig. 4(b) represents this joint transmission payload and rate adaptation. Accordingly, we let the "ego" vehicle predict the neighbors' states and we reduce the burden of broadcasting critical CAMs. Although additional "tiny" CAMs are required, Table IV shows that they do not increase traffic.

The objective of "tiny" CAMs is to provide RSSI measurements for CP, which is deliberately restricted to the closest
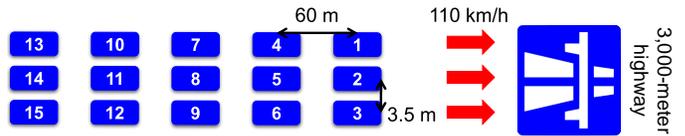
Fig. 5. Evaluated VANETs and related attributes in highway scenario.

ring of neighboring vehicles (in compliance with the link selection strategies described in [2]) due to several reasons (e.g., significantly larger relative RSSI dispersion at large distances, high probability of non-visibility configurations, etc.) Accordingly, it is wasteful to broadcast the "tiny" CAMs at critical transmission power (i.e., 33 dBm to reach the maximum range). In addition to CAM payload and transmission rate control, we thus also propose power control to adaptively manage different ranges (say, 50–100-m for "tiny" CAMs, 800–1,000-m for normal CAMs) to save even more communication traffic. Once a desired transmission range is set *a priori* for each type of CAM, one can determine the corresponding transmission power, assuming the knowledge of the log-distance path loss model in Equation (3) and receiver sensitivity (e.g., known by calibration).

IV. PERFORMANCE EVALUATION

A. Simulation Settings and Scenarios

We model a common 3-lane highway where 15 802.11p-connected vehicles are driving steadily (in the same direction) at the average speed of 110 km/h (i.e., $\approx$ 30 m/s) for 3,000 meters, as shown in Fig. 5. We use MATLAB Monte Carlo simulations in our evaluation framework. The main simulation parameters are summarized in Table I.

TABLE I
MAIN SIMULATION PARAMETERS.

Parameter	Value
Memory level α	0.95
Tangential acc. uncertainty	1 [m/s^2]
Perpendicular acc. uncertainty	0.1 [m/s^2] (to satisfy road constraints)
Sampling period ΔT	0.1 [s]
Std. of GPS errors in x and y	5–10 [m] (highway) [10]
GPS rate	10 [Hz]
CAM rate	10 [Hz] (critical), 2 [Hz] (congestion)
CAM size	300 [bytes]
"Tiny" CAM size	30 [bytes] (hypothesis)
Transmit power	33 [dBm] (critical, 1,000-m range) -5 [dBm] (adaptive, 50–100-m range)
Receiver sensitivity	-87 [dBm] [14]
Path loss exponent n_p	1.9 (V2V in highways) [11]
Std. of shadowing σ_{Sh}	2.5 [dB] (V2V in highways) [11]
Number of particles	1,000

While evaluating the performance of the proposed approaches, we aim at assessing practical operating trade-offs between localization accuracy, communication impairments, and complexity, by undertaking "factor-by-factor" investigations. More particularly, we firstly analyze the effects of parametric message approximation on localization accuracy while assuming a default critical 10-Hz CAM rate. Then we evaluate the effects of ETSI DCC and the proposed

transmission control strategy on CP performance without any message approximation. Finally, we consider combining both signal-level (i.e., message approximation) and protocol-level (i.e., transmission control) techniques into a single solution.

B. Simulation Results

1) Signal-Level Message Approximation: Table II shows the achieved positioning accuracy over 100 Monte Carlo runs in terms of both median and so-called "worst-case" (WC) localization errors (arbitrarily defined for a Cumulative Density Function (CDF) of 90%). Table II also summarizes the CAM overhead associated with each message approximation strategy. While identifying the density modes, the bimodal Gaussians with full covariance matrices does not converge within a few Monte Carlo runs due to the higher-dimensional optimization problem, we thus deliberately ignore them in the performance evaluation. One can remark the modest accuracy degradation caused by parametric message approximations in comparison with the nonparametric approach. This means in our localization problem, the *posterior* distribution is rather simple under practical deployment/connectivity conditions. It can thus be approximated with either unimodal or bimodal Gaussian. More importantly, Table II shows the minimum awareness payload that needs to be carried by the 300–800-byte CAMs and then transmitted over 6-Mbps ITS-G5 channels with 2312-byte MTU. Thus, without message approximations, it is almost impossible to perform particle-based CP in VANETS using explicit cloud disclosure and passing.

Since message approximation is solved by iterative methods such as EM, computational complexity and latency are also important factors besides the accuracy performance indicator. Table III shows the number of variables in each optimization problem the average number of iterations required to achieve convergence over 1 trial run. As expected, we observe that this number increases dramatically within high-dimensional optimization problems. Based on the previous results, considering a Gaussian mixture distribution provides too marginal accuracy gain but leads to high computation/latency. Thus, unimodal Gaussian with full covariance matrix is advantageous.

2) Protocol-Level Transmission Control: In this section, we study the impact on both localization accuracy and local channel congestion of different transmission and fusion rate policies, possibly in conjunction with unimodal message approximations. The corresponding empirical CDFs of localization errors are first summarized in Fig. 6. As expected and in compliance with previous results from [2], [3], we observe that the fusion of several modalities (i.e., GPS and V2V RSSIs) outperforms the standalone filtered GPS solution. Interestingly, in case of either triggered ETSI DCC or reduced CAM rate, the fused GPS and 2-Hz RSSI scheme only yields modest gain in case of high errors (i.e., larger than 1.2 m). This can be explained by the fact that CP suffers from a loss of cooperative information (neighboring positions and associated RSSIs). This information loss can be either a temporal loss (from a specific neighbor) or a spatial loss (from the number of cooperative neighbors due to their asynchronous 2-Hz CAM
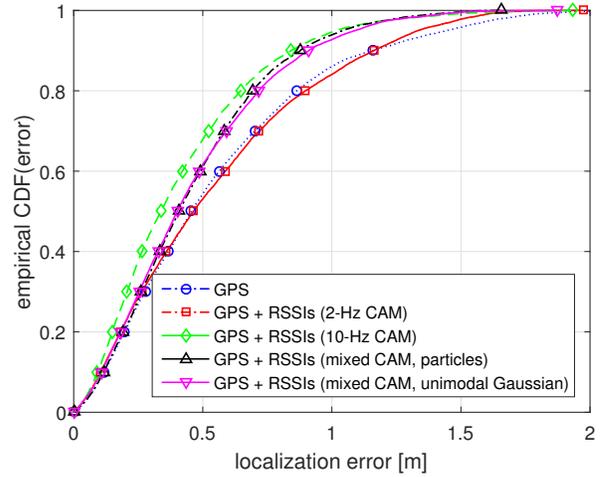
Fig. 6. Empirical CDF of localization errors for different schemes w.r.t. fused modalities, message approximation and transmission control.

transmissions[2]). Then we observe that the proposed method relying on "tiny" CAMs (still without message approximation) improves accuracy at a level equivalent to that of fused GPS with 10-Hz CAM. The observed slight accuracy degradation is due to accumulated prediction errors (See again Fig. 4(b)) and local cooperation with nearby neighbors only (in a 100-m radius coverage), as constrained by power control with "tiny" CAMs transmissions. In brief, our transmission control strategy intentionally avoids critical CAM exchange but ensures comparable localization accuracy.

3) Cross-Signal-Protocol-Level Transmission Control: We now combine both signal level and protocol level techniques to achieve simultaneously high precision and communication-efficient CP. Specifically, in addition to transmission control, we integrate message approximation with a unimodal Gaussian (shown to be sufficient from previous simulations) when broadcasting CAMs at 2 Hz. Note that the 10-Hz "tiny" CAMs do not include any state awareness. Thus, they do not require message approximation and contribute to save further computations. The result is also shown in Fig. 4. As expected, we observe marginal accuracy degradation caused by message approximation when considering also transmission control.

Finally, we assess the impact of our proposed transmission control on the channel load. Approximately, with our simulation settings and scenario (i.e., 3-lane highway, 30-m/s speed, 2-s safety rule, steady vehicle movement, etc.), the number of 1-hop neighbors in normal CAM's range (i.e., 1,000 m) and in "tiny" CAM's range can be up to 100 vehicles (worst case) and 10 vehicles respectively[3]. The channel load is roughly given in Table IV[4]. We remark that transmitting critical 10-Hz "tiny"

---

[2]With 10-Hz fusion and asynchronous 2-Hz CAM reception, the sufficient number of cooperative neighbors is not always guaranteed.

[3]It does not contradict the 15-vehicle scenario (i.e., 250-m road segment) because CP only uses nearby neighbors in the range of 200–300 m (where the path loss model is still reliable) though vehicles can receive CAMs from isolated neighbors (up to 800–1,000 m) for maximizing awareness.

[4]The channel load $L[\%]$ may be roughly computed as $L = N \times R \times P/C$, where N is the number of vehicles in range, R the Tx rate, P the packet size, and C the maximum channel capacity (i.e., 6 Mbps).

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT MESSAGE REPRESENTATIONS W.R.T. COMMUNICATION REQUIREMENT AND LOCALIZATION ACCURACY

Rep.	2-D Position	2-D Velocity	Med. [m]	WC [m]	No. Scalars per CAM[a]	Payload [bytes]	Broadcast
1	Particles	Particles	0.3222	0.7573	4,000	32,000	No
2	Uni. Gauss. (diag.)	Uni. Gauss. (diag.)	0.3268	0.7628	8	64	Yes
3	Uni. Gauss. (full)	Uni. Gauss. (full)	0.3253	0.7652	10	80	Yes
4	Bi. Gauss. (diag.)	Uni. Gauss. (diag.)	0.3255	0.7628	13	104	Yes

[a] Number of scalars that need to be encapsulated in a CAM. Each scalar costs 8 bytes (binary64).

TABLE III
x-DIMENSIONAL OPTIMIZATION VS. AVERAGE NUMBER OF ITERATIONS.

Representation	x-D Optimization	No. of Iterations
Uni. Gauss. (diag.)	4	3
Uni. Gauss. (full)	5	3
Bi. Gauss. (diag.)	9	45
Bi. Gauss. (full)	11	187

CAMs does not congest the channel (only cost 0.4% channel load) but improves the accuracy gain (relative drop of 13%, 22% respectively and in median and WC errors in comparison with the fused GPS and 2-Hz CAM). Last but not least, our proposed approach is not limited to the case of triggered ETSI DCC but also applicable to the case of no congestion in order to enable communication-efficient CP. In other words, it may be a waste to broadcast full CAMs at 10 Hz while prediction can contribute to save a significant amount of resources.

TABLE IV
CHANNEL LOAD COMPARISON BETWEEN DIFFERENT STRATEGIES.

Scheme	Channel Load
10-Hz CAM	40%
2-Hz CAM	8%
Mixed 2-Hz CAM & 10-Hz "tiny" CAM	8.4%

V. CONCLUSION AND FUTURE WORK

This paper addressed the problem of V2V overhead and channel congestion inherent to particle-based CP in GPS-aided VANETs. On the one hand, results show that a significant amount of the CAM payloads could already be saved under standard protocol constraints (i.e., under normal transmission rates and packet sizes) through parametric messages approximation. This comes with almost no accuracy degradation in comparison with impractical solutions that would explicitly send each particles cloud to neighboring cars. Simulations also show that unimodal Gaussian approximations of the local estimates' probability densities are fairly sufficient to achieve the required localization accuracy with much lower computational complexity, while being still robust to occasional geometric ambiguities caused by sparse VANET connectivity. On the other hand, on top of message approximation, the jointly adaptive transmission payload, rate, and power control maintains the continuity of high-precision location service in channel congestion while reducing significantly communication traffic as well as computation load in congestion-free conditions without trading much accuracy. Future works shall further investigate the "context-aware" transmission control, by considering also vehicle dynamics, local vehicle density,

and neighbor-agnostic transmit censorship (in terms of blocking the broadcast of unreliable/ambiguous state information). The proposals should be also tested on more realistic mobility traces using dedicated traffic simulator and more sophisticated V2V propagation channels.

ACKNOWLEDGMENT

REFERENCES

[1] A. Boukerche, H. A. B. F. Oliveira, E. F. Nakamura, and A. A. Loureiro, "Vehicular ad hoc networks: A new challenge for localization-based systems," *Computer Communications*, vol. 31, no. 12, pp. 2838–2849, 2008.

[2] G. M. Hoang, B. Denis, J. Härri, and D. T. M. Slock, "Select thy neighbors: Low complexity link selection for high precision cooperative vehicular localization," in *Proc. VNC'15*, Dec. 2015.

[3] G. M. Hoang, B. Denis, J. Härri, and D. T. M. Slock, "Distributed link selection and data fusion for cooperative positioning in GPS-aided IEEE 802.11p VANETs," in *Proc. WPNC'15*, Mar. 2015.

[4] "Intelligent Transport Systems (ITS); Vehicular Communications; Basic Set of Applications; Part 2: Specification of Cooperative Awareness Basic Service," *ETSI Std. EN 302 637-2 V1.3.2*, Oct. 2014.

[5] F. Meyer, O. Hlinka, H. Wymeersch, E. Riegler, and F. Hlawatsch, "Distributed localization and tracking of mobile networks including noncooperative objects," *IEEE Trans. on Sig. and Info. Proc. over Net.*, vol. 2, pp. 57–71, Mar. 2016.

[6] K. Das and H. Wymeersch, "Censoring for Bayesian cooperative positioning in dense wireless networks," *IEEE JSAC*, vol. 30, pp. 1835–1842, Oct. 2012.

[7] J. Lien, U. J. Ferner, W. Srichavengsup, H. Wymeersch, and M. Z. Win, "A comparison of parametric and sample-based message representation in cooperative localization," *Int. J. of Nav. and Obs.*, vol. 2012, 2012.

[8] V. Savic and S. Zazo, "Cooperative localization in mobile networks using nonparametric variants of belief propagation," *Ad Hoc Networks*, vol. 11, no. 1, pp. 138–150, 2013.

[9] C. Pedersen, T. Pedersen, and B. H. Fleury, "A variational message passing algorithm for sensor self-localization in wireless networks," in *Proc. ISIT'11*, pp. 2158–2162, Jul. 2011.

[10] N. Drawil and O. Basir, "Intervehicle-communication-assisted localization," *IEEE Trans. on Intel. Transp. Syst.*, vol. 11, pp. 678–691, Sept. 2010.

[11] L. Cheng, B. E. Henty, F. Bai, and D. D. Stancil, "Highway and rural propagation channel modeling for vehicle-to-vehicle communications at 5.9 GHz," in *Proc. AP-S'08*, pp. 1–4, Jul. 2008.

[12] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Secaucus, NJ, USA: Springer-Verlag New York, Inc., 2006.

[13] O. Hlinka, F. Hlawatsch, and P. M. Djuric, "Distributed particle filtering in agent networks: A survey, classification, and comparison," *IEEE Sig. Proc. Mag.*, vol. 30, pp. 61–81, Jan. 2013.

[14] C. L. Huang, Y. P. Fallah, R. Sengupta, and H. Krishnan, "Adaptive intervehicle communication control for cooperative safety systems," *IEEE Network*, vol. 24, pp. 6–13, Jan. 2010.