Robust Cooperative and Communication-Friendly Localization in Vehicular Networks

Gia-Minh HOANG
CEA-Leti, MINATEC Campus, Grenoble, France
EURECOM, Sophia Antipolis, France

June 7, 2016

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 Localization (CLoc). 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). Then this information is fused with local onboard Global Navigation Satellite System (GNSS) data to enhance both estimated "ego" vehicle's position and that of neighboring vehicles, thus contributing to enrich Local Dynamic Maps (LDM). Conventional CLoc solutions may be unsuitable, or even non compliant, within the highly specific and challenging context of Vehicular Ad hoc NETworks (VANETs) (e.g., in terms of mobility patterns, protocol constraints, V2V channel load, network topology and connectivity...). This report thus describes and evaluates a new communication-friendly CLoc data fusion framework, along with adapted algorithms enabling robust location estimation, low-complexity cooperative link selection, low-overhead message approximation, and transmission/fusion rates adaptation.

1 Introduction

Geo-localization is a critical requirement of Cooperative - Intelligent Transport System (C-ITS) safety and traffic efficiency applications, as well as many other services. The currently proposed C-ITS Basic Set of Applications (BSA) [1] relies on the availability of Global Navigation Satellite System (GNSS), which provides a positioning precision on the order of 3–10 meters in favorable conditions [2]. This is obviously far from being sufficient for advanced applications, such as for Road Hazard Warning (RHW), safety of Vulnerable Road Users (VRU), or highly autonomous driving/platooning (HAD), which would require a sub-meter precision (typically less than 0.5 m) *in any operating condition*. Such a level of precision is not yet available with mass market GNSS technologies (including Galileo) [1, 3], but mostly with costly pieces of equipment (e.g., RTK, PPP or even special differential GNSS).

Dedicated Short Range Communication (DSRC) standards (a.k.a. IEEE 802.11p or ITS-G5), which can be viewed as vehicular-specific WiFi extensions, have been rapidly developing for the last past years to enable wireless communications between vehicles

(V2V), infrastructure (V2I), and devices belonging to the Internet of Things (V2IoT). Accordingly, each vehicle periodically broadcasts through Cooperative Awareness Messages (CAMs) in Europe [4] or Basic Safety Messages (BSMs) in the U.S. [5][1] its GNSS-aided estimated position, allowing neighboring vehicles to generate a cooperative situation awareness of their nearby traffic and potential danger. Such cooperative vehicular communications provide a unique opportunity to enhance geo-localization through Cooperative Localization (CLoc) [1, 3, 6–9] while the cooperative neighbors can be considered as "virtual anchors". However, the intrinsic mobile nature of CLoc "virtual anchors" and vehicular wireless channels make that the indicated GNSS positions, as well as the power received over V2V links, are affected by possibly strong errors and large fading dispersion respectively. Moreover, even is CLoc yet remains a very promising approach to enhance geo-localization, in particular in GNSS (partially) denied environments, it is also subject to novel and specific challenges, such as the asynchronism of CAM transmissions and local estimations among the involved vehicles (thus requiring advanced prediction mechanisms before fusing the received data), high computational complexity and high traffic under exhaustive/systematic cooperation with all the available neighbors (thus requiring low-complexity and context-aware links selection mechanisms), V2V channel congestion and limited CAM payloads (thus requiring V2V message simplifications and transmission rate/power adaptation), measurements space-time correlation under constrained vehicle mobility and refreshment rates (thus requiring correlation mitigation at both signal and protocol levels)...

The report is organized as follows. In Section 2, we state the generic CLoc problem and related challenges, before introducing state-of-the-art contributions in Section 3. Then, Section 4 presents the proposed CLoc data fusion framework and algorithms. Finally, Section 5 summarizes the main contributions and provides an outlook on future works.

2 Problematic and Challenges

In the field of wireless localization, cooperation is generally intended in a specific sense. Whereas so-called non-cooperative schemes consists in geo-localizing mobile nodes uniquely with respect to a set of fixed anchors at known locations, CLoc solutions make use of neighboring nodes (moving or static) as additional "virtual anchors" [10], typically through distributed message-passing approaches [11]. Such CLoc schemes have been mostly applied to static Wireless Sensor Networks (WSNs) or even Mobile Ad Hoc Networks (MANET) so far. Similarly, in Vehicular Ad hoc NETworks (VANETs), as illustrated on Figure 1, instead of considering only static anchors, namely geo-referenced Road Side Units (RSU) in our vehicular context, CLoc refers to strategies that consider neighboring vehicles as additional "virtual anchors". More specifically, their periodically broadcast CAM can be used primarily to receive and fuse the encapsulated GNSS data (or any location estimate) but also to opportunistically measure range-dependent metrics, such as the Received Signal Strength Indicator (RSSI). A major benefit of CLoc in comparison with non-cooperative approaches is that it does not need any prior map containing predefined anchor nodes' locations. It shall also benefit from other vehicles' data and communications, and more generally, from information redundancy and diversity. However, due to the particular mobility

[1] Due to equivalent roles played by CAMs and BSMs in our work, we will only refer to CAMs for simplicity, without loss of generality.

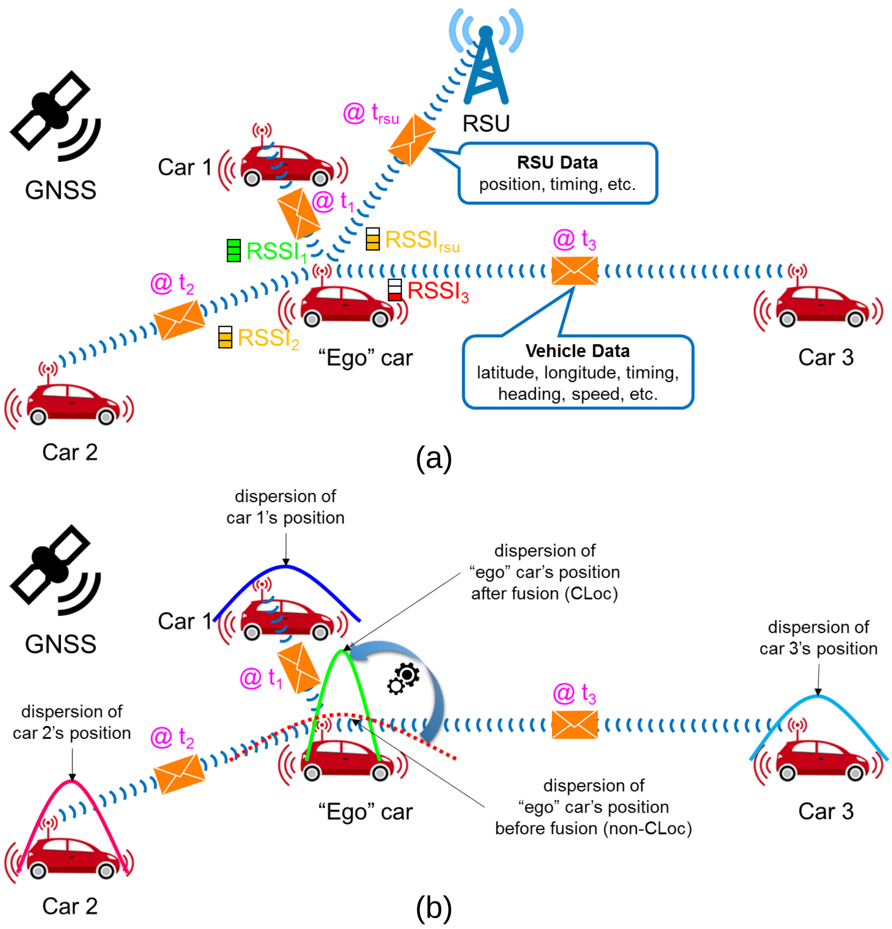

Figure 1: (a) Cooperative cars periodically exchange CAMs to maintain awareness of each other and to support distributed CLoc. Both the transmission time $@t_i$ and the received power level $RSSI_i$ depend on the transmission car i (and thus, on the V2V link). (b) "Ego" car receiving asynchronous CAMs from one-hop "virtual anchors" to perform distributed CLoc. The dispersion of CLoc location estimates (through both GNSS and DSRC) is expected to be lower than that of non-CLoc estimates (i.e., standalone GNSS).

patterns and route constraints, frequent fragmentation and rapid evolution of the network topology, short link life time (e.g., less than 1 second for vehicles traveling in opposite directions), applying CLoc to VANETs remains particularly challenging.

First of all, the transmission intervals between CAMs are constrained by channel load conditions, leading to non periodic transmissions and as such, non synchronous data reception from "virtual anchors" (See Figure 1). If not appropriately addressed by advanced filter designs (e.g., [1,6]), this can lead to severe geo-localization errors.

Another challenge is related to restrictions in the application of the core fusion filters, assuming that the GNSS/RSSI readings integrated as observations are affected by white error processes, whereas in practice they are strongly correlated over both space and time [1, 12–16], as a result from the combination of continuous physical propagation phenomena, highly specific vehicular mobility patterns and constrained refreshment rates. Such spatial correlations are viewed as a drastic limitation of current state-of-the-art CLoc approaches.

In addition, there exists a trade-off between localization accuracy and complexity (under limited embedded capabilities, latency, power consumption, etc.), as well as communication impairments (e.g., increased network traffic, channel congestion, packet loss, etc.). As an example, exhaustive cooperation, which aims at integrating all the V2V links with respect to available neighbors (i.e., regardless of the link quality) can generate high computational complexity (in the fusion step) and heavy communication loads (due to uncensored transmissions). On the other hand, popular Bayesian filtering techniques used for hybrid data fusion, such as the (cooperative) Particle Filter (PF) herein, can also induce high computational and communication costs (e.g., while accounting for the particle cloud through message passing) to guarantee optimal performance levels. Finally, transmitting CAMs at the critical rate (i.e., 10 Hz according to ETSI[2]) and maximum power would theoretically boost CLoc accuracy uniquely if and only if all the exchanged packets are well received, what cannot be ensured obviously.

3 Related works

Considering non-CLoc in the vehicular context, static elements of the road infrastructure (Road Side Units (RSUs) or LTE eNBs) are viewed as anchors and the vehicles independently estimate their locations through classical multilateration (i.e., measuring the relative distances between the anchors), range-free cell connectivity information (possibly combined with dead-reckoning [17]), or even fingerprinting (e.g., assisted by particle filtering [18]). However these solutions are dependent onto the density, availability and relative geometry of the road infrastructure. For instance, as illustrated on Figure 1, one single V2I link with respect to a RSU would be insufficient to get the "ego" vehicle positioned through standard multilateration with no geometrical ambiguity.

On the contrary, as already mentioned before, CLoc allows to complement these static anchors with neighboring vehicles to integrate additional position awareness and opportunistic V2V radio link measurements [3,7,11,19], as shown on Figure 1. For instance, the authors in [9] propose a distributed tracking algorithm relying on a standard Kalman Filter (KF), which fuses GNSS position estimates with nearby anchor node positions and V2V range measurements (assumed to be perfect) after detecting harsh GNSS conditions. As another example, the cooperative solution in [8] is based on a dissimilarity matrix composed of V2V RSSI measurements. The latter are injected as observations into an Extended KF (EKF), while using GNSS estimates for initialization purposes only. In [7], the V2V measurement matrix and the GNSS position are jointly incorporated as observations in the filter.

Under drastic mobility constraints, most of the above cooperative schemes rely on too simplistic or even too optimistic assumptions in terms of propagation (e.g., constant V2V RSSI shadowing parameter, no space-time correlation of GNSS errors and/or V2V RSSI readings...), network connectivity (e.g., constant transmission range, large and constant instantaneous number of available neighbors...) and/or protocol constraints (e.g., synchronous and periodic transmissions, no control of transmission power

[2]European Telecommunications Standards Institute.

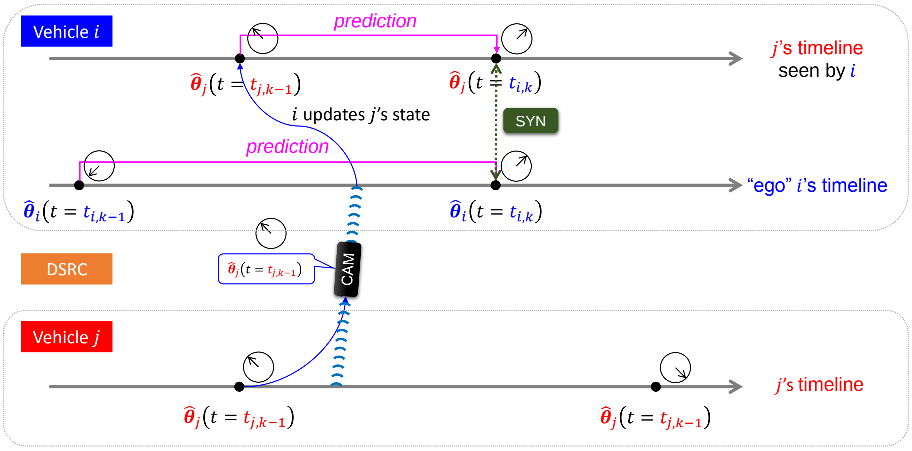

Figure 2: Example of CLoc space-time data management at the "ego" vehicle i with respect to its neighboring vehicle j. Due to asynchronous estimated states $\hat{\boldsymbol{\theta}}_i(\cdot)$ and $\hat{\boldsymbol{\theta}}_j(\cdot)$, vehicle i needs to perform a prediction of the received information at any fusion time of interest $t_{i,k}$.

or rate…). Moreover the achieved level of localization accuracy, which is equivalent to that of nominal GNSS in the most favorable operating conditions, is still largely insufficient for the safety-oriented applications mentioned above.

4 Contributions

4.1 CLoc Data Fusion Architecture in GNSS-aided VANETs

In Section 2, we have acknowledged that the combination of V2V and GNSS information in such distributed CLoc contexts raises unprecedented challenges that necessitate in-depth understanding and careful assessment. Therefore, a judicious CLoc data fusion architecture in GNSS-aided VANETs should include the following functions, as described in Algorithm 4.1: i) prediction-based data resynchronization mechanisms to properly incorporate cooperative information incoming from asynchronous neighboring cars relying on an *a priori* mobility model, as described in [6] and illustrated in Figure 2; ii) signal processing techniques including link selection mechanisms based on theoretical performance bounds so as to reduce complexity and traffic without significantly affecting accuracy/latency and several decorrelation mechanisms, capable of transforming the correlated input data into independent data; iii) revised transmission strategies adapting power and/or rate so as to control communication impairments (as well as space-time measurement correlations); and finally iv) message approximation to broadcast the estimated state distribution in case of nonparametric estimation and cooperative PF-based data fusion, in compliance with affordable CAM formats.

4.2 Low-Complexity Link Selection

In our second contribution [20], we propose new link selection algorithms that aim at more efficient CLoc procedures under various GNSS conditions, by enabling lower

Algorithm 1 Overall CLoc Data Fusion Framework for GNSS-aided VANETs

1: **Collection of CAMs:** Receive asynchronous CAMs from the neighbors, perfom RSSI measurements, and extract the neighboring awareness encapsulated in the payload (i.e., estimated state and optionally, any related uncertainty information).
2: **Data Resynchronization:** Perform prediction of both "ego" and neighboring states at the same desired instant by using mobility model and build the Local Dynamic Map (LDM) of all the neighbors as first output.
3: **Link selection and signal space-time decorrelation:** Among the sensed neighbors in the LDM, perform link selection to combine the best subset of "virtual anchors" in the fusion process, then process the retained measurements to eliminate possible space-time correlation.
4: **Observation Update:** Use the processed measurements to correct the predicted state to produce the enhanced "ego" position estimate as second output.
5: **Transmission Control Strategies:** Adapt power and/or rate and/or CAM payload to control communication impairments (e.g., channel congestion, packet collision, space-time correlation, etc.)
6: **Broadcast:** If the CAM is triggered and must carry a distribution (i.e., accounting for the uncertainty of location estimates), perform parametric message representation then encapsulate the resulted parameters (along with other vehicles' attributes) in the CAM and broadcast to the neighbors.

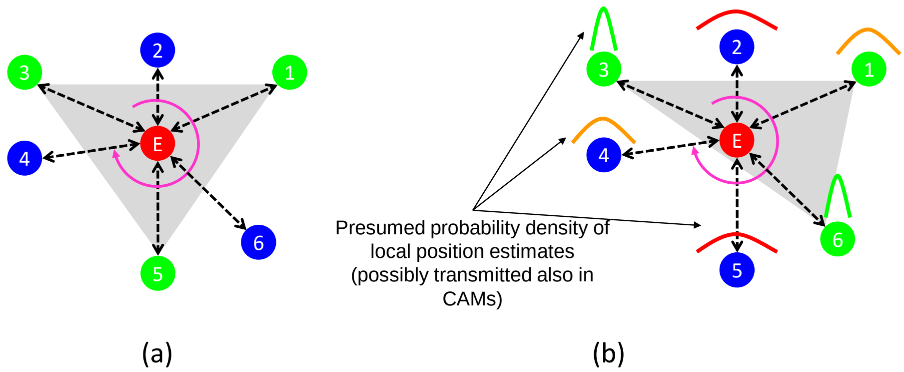

Figure 3: Sets of selected cooperative neighbors (green) with respect to the "ego" vehicle (red), following (a) non-Bayesian and (b) Bayesian CRLB criteria. In this example, the wrongly positioned vehicle 5 could trick the non-Bayesian selection scheme (and thus, be included in the selected fusion set), whereas the Bayesian version would account for its location uncertainty (and reject it as unreliable neighbor).

footprint with respect to communication means and lower computational complexity. More specifically, we propose a couple of low complexity link selection criteria based on non-Bayesian and Bayesian versions of the Cramér-Rao Lower Bound (CRLB) characterizing cooperative location estimates given a subset of the available neighbors, in conjunction with a fast sub-optimal closest search instead of a computationally greedy exhaustive search (i.e., restricting heuristically the CRLB-based comparison to a subset of the nearest neighbors). CLoc performance actually depends on the pair-wise radio link quality (e.g., via the average power attenuation and shadowing dispersion), the relative geometrical constellation (i.e., the relative positions of "virtual anchors" with respect to the "ego" vehicle) or Geometric Dilution Of Precision (GDOP), and the uncertainties of both "ego" vehicle's and neighbors' estimated positions. The non-Bayesian CRLB criterion initially proposed in [6] can account for the first two factors but fails in capturing the last one. This may be sufficient in non-CLoc, when considering only the selection of known static anchors (i.e., RSU here). However, since CLoc incorporates additional neighboring vehicles as "virtual anchors" that are imperfectly localized, a Bayesian CRLB criterion is proposed to capture all three factors and select only the most informative neighbors and links for the final fusion step.

In [20], we thus present a comparative study of both non-Bayesian and Bayesian CRLB selection criteria in two complementary scenarios, which are both representative of usual operating conditions. In the first scenario, we consider GNSS signals degradation in a urban canyon, with large-scale error correlations (i.e., with a significant amount of cooperative vehicles experiencing simultaneously the same error statistics), whereas in the other scenario, we consider small-scale disparities in the GNSS quality (i.e., heterogeneous GNSS receiver capabilities among the cooperative vehicles). On this occasion, in comparison with exhaustive cooperation schemes, we show that selective CLoc experiences significantly reduces complexity in terms of both required traffic and computations in terms of integrated incoming packets/links (by more than 70%), while suffering only little precision degradation (about 10%) in normal operating conditions and reasonable degradation (about 14–18%) in very poor or lost GNSS signal in the long term. We also point out practical operating conditions (with locally heterogeneous GNSS conditions in a group of cooperative vehicles) when the Bayesian CRLB selection criterion would outperform the non-Bayesian one, thus opening the floor to context-aware selection and fusion.

In brief, we have first shown that it is worth employing selective fusion in vehicular CLoc owing to the heavy required communication traffic and computational complexity with no significant accuracy gain. Secondly, the dispersion of "virtual anchors" uncertainties should be monitored and shared to prevent from integrating irrelevant information from wrong cooperative neighbors, with no extra complexity.

4.3 Mitigation of Observation Noise Correlations

The next contribution concerns the observation noise correlations specifically found under vehicular mobility. Practically speaking, the spatial correlation of observed measurement processes (and thus, their time correlation under vehicles mobility) results from the conjunction of different factors triggered by constrained vehicular mobility. First of all, GNSS conditions (good or bad) may not change much over multiple samples and between neighboring vehicles. Similarly, the channel fading conditions (obstructed or not) may not change much between two consecutive CAM transmissions (e.g., every 100 ms) by neighboring vehicles. Jointly or independently, these effects lead to correlated GNSS/RSSI measurements. A major issue when integrating such correlated measures into fusion filters is that they are no longer affected by white Gaussian noise terms (but hence, by dependent contributions) and as such, they break a core assumption of most CLoc fusion approaches [19, 21–23] leading to inconsistent estimates with large fluctuations.

We intuitively illustrate these spatial correlations on Figure 4. Considering the V2V link between the "ego" car and "car 1", successive RSSIs for this single link are autocorrelated over time if the inter-transmit time between received packets is higher than the rate change of their mobility patterns and fading conditions. Similarly, considering now the two V2V links between the "ego" car and "car 1" on one hand and between the "ego" car and "car 2" on the other hand, successive RSSIs are cross-correlated if

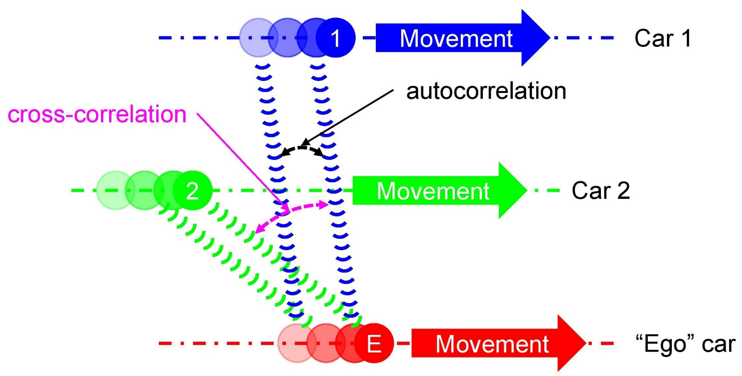

Figure 4: Possible autocorrelation/cross-correlation of received power shadowing on/between V2V link(s) under dual mobility in VANETs.

these two links have long common propagation path or the distance between "car 1" and "car 2" is shorter than the correlation distance. But cross-correlations and auto-correlations also impact the use of GNSS information at the "ego car". Successive CAMs transmission of GNSS estimate from "car 1" and from "car 2" will integrate spatially correlated GNSS information if their inter-transmit time is higher than the time to move over the GNSS decorrelation distance. Therefore, in [24], we propose correlation mitigation mechanisms at both signal and protocol levels, which can be combined, to eliminate almost completely the deleterious effects of correlated input GNSS/RSSI observation noises on the performance of the fusion filter.

The first signal-level technique applying to V2V RSSI relies on the intuition that the knowledge of cross-correlation between the different components of a measurements vector can provide relevant information [16]. More specifically, the latter information is helpful to filter out the observation noise in the observation update (i.e., correction step) in Algorithm 4.1, since the noise (i.e., RSSI shadowing) distribution is better accounted. In our V2V context, this cross-correlation information can be estimated by using the Peer-to-Peer (P2P) correlated shadowing model of Wang *et al.* [25].

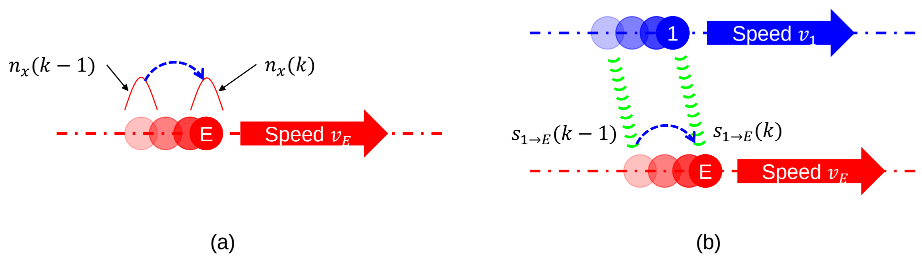

Figure 5: Illustration of the DM technique applied for (a) GNSS x-coordinate and (b) V2V RSSI measurement. The GNSS noise terms $n_x(k)$ and $n_x(k-1)$ are temporally correlated (due to mobility in spatially correlated GNSS environments) with known correlation properties. Thus, the correlated part in $n_x(k)$ can be predicted from $n_x(k-1)$ and then subtracted from $n_x(k)$. Eventually, the resulting differential noise is i.i.d with much smaller variance. The extension for correlated shadowing $s_{1\to E}(k)$ and $s_{1\to E}(k-1)$ affecting V2V RSSI measurements is straightforward.

The second signal-level technique, also called Differential Measurement (DM), can be used with both GNSS data and RSSI readings. As suggested by its name, the key idea is to whiten the noise terms by subtracting their common correlated part, while keeping untouched the uncorrelated/independent part. This problem is solved by building a noise prediction model based on its *a priori* known correlation properties. Considering the class of covariance functions (of a decreasing exponential form), both GNSS residual errors and RSSI shadowing can thus be predicted by first order Gauss-Markov models. Particularly, the DM technique subtracts a one-step predicted version from the new current observation instead of feeding the latter directly into the fusion engine, as illustrated in Figure 5.

Unlike the two signal-level mitigation approaches above, the last protocol-level adaptive sampling technique eliminates the correlation by artificially decreasing the cooperative fusion rate (in comparison with the available rate) without manipulating the observations. For each source of observation (i.e., GNSS positions or RSSI readings), as the observations are correlated in space with a limited correlation distance d_{cor}, a vehicle moving over a distance D along a straight line can temporally collect up to $1 + \lfloor D/(\gamma d_{\text{cor}}) \rfloor$ uncorrelated measurements where $\gamma \geq 1$ measures the quality of independent instantiations (e.g., $\gamma_1 = 1$ and $\gamma_2 = 2$ correspond to 50% and 75% reduction in the correlation respectively) , as shown in Figure 6. This simple technique may not be appropriate for GNSS collection because GNSS correlation distance can be up to hundreds of meters and GNSS-assisted dead-reckoning (DR) accumulates errors over time and distance [1]. However, it can be more beneficial for RSSIs due to the rather short shadowing correlation distance in urban environments (e.g. typically 10–20 m [14, 15, 25]).

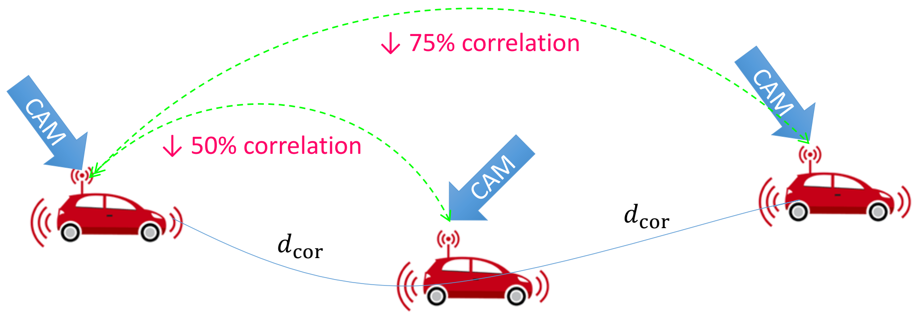

Figure 6: Illustration of the adaptive sampling techniques simply deceasing the cooperative fusion rate to collect uncorrelated RSSI measurements.

We have evaluated and compared the proposed approaches in three representative scenarios and environments (i.e., highway, urban canyon, and tunnel) based on Monte Carlo simulations, showing that our proposed approach could provide up to 60% precision improvement in correlated environments, while matching by less than 15–20% deviation an optimal cooperative positioning considered under independent measurements. Based on the obtained results, we found that the characteristics of the environment, including correlation lengths, mobility patterns, GNSS availability. . . strongly influence how the CLoc data fusion processes the different input measurements to mitigate the noise correlation. A technique can be very favorable in one environment but may be less effective in the others. Thus, we suggest a so-called context-aware correlation mitigation strategy that assists the CLoc engine to achieve the best accuracy

Table 1: Recommended techniques for the context-aware mitigation of observation noise correlation.

Modality	Highway	Urban Canyon	Tunnel
V2V RSSI	adaptive sampling	optional	differential measurement
GNSS position	differential measurement	differential measurement	N/A

regardless of the operating conditions. Out of the obtained results, Table 1 summarizes the recommended techniques (or combination of techniques) regarding each modality and each environment. When the vehicle enters a specific environment (e.g., based on the *a priori* map knowledge), the system could thus determine the most suitable technique and the associated attributes/parameters to perform correlation mitigation before fusion. The goal is to match as close as possible the accuracy of the optimal schemes under optimistic i.i.d measurement assumptions and accordingly, to provide a constant quality of the navigation service (i.e., delivering the highest accuracy), while ensuring the minimum computational complexity.

4.4 Message Approximation and Transmit Power/Rate Control

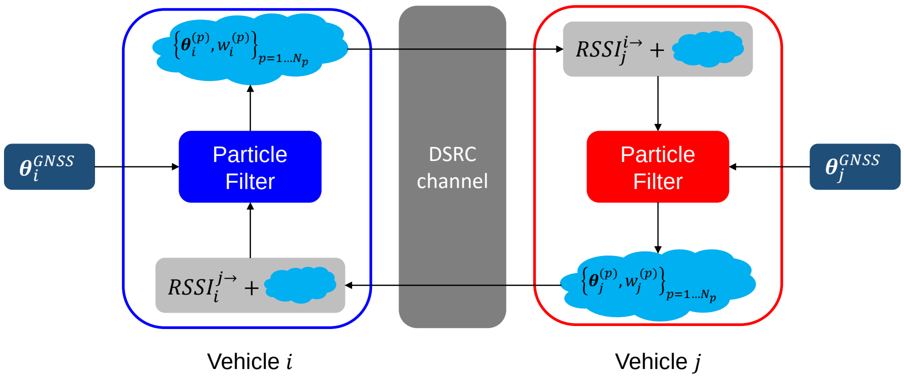

Figure 7: Data flow in PF-based CLoc framework for two vehicles for simplicity where at vehicle i, θ_i^{GNSS}, $RSSI_i^{j\rightarrow}$ and $\{\theta_i^{(p)}, w_i^{(p)}\}_{p=1\ldots N_p}$ stand for respectively the on-board GNSS estimate, the RSSI observation out of received vehicle j's CAM, and the cloud of N_p particles with associated states $\theta_i^{(p)}$ and weights $w_i^{(p)}$.

In our cooperative data fusion context, since real-world observations (typically, the V2V RSSIs considered herein) are highly nonlinear with respect to the state variables of interest, the PF becomes a natural choice for sequential state estimation (e.g., position, velocity, heading…). However, the latter notoriously induces rather high computational and communication cost (e.g., while accounting for the particle cloud through message passing) to achieve optimal performance levels. For example, thousands of particles (say on the order of 1000, as a rather conservative number) are commonly considered [26]. Thus a 2-D particle-based position would cost 16000 bytes[3],

[3] A 1-D particle is usually represented by the IEEE 754 double-precision binary floating-point format (binary64) that occupies 8 bytes (64 bits).

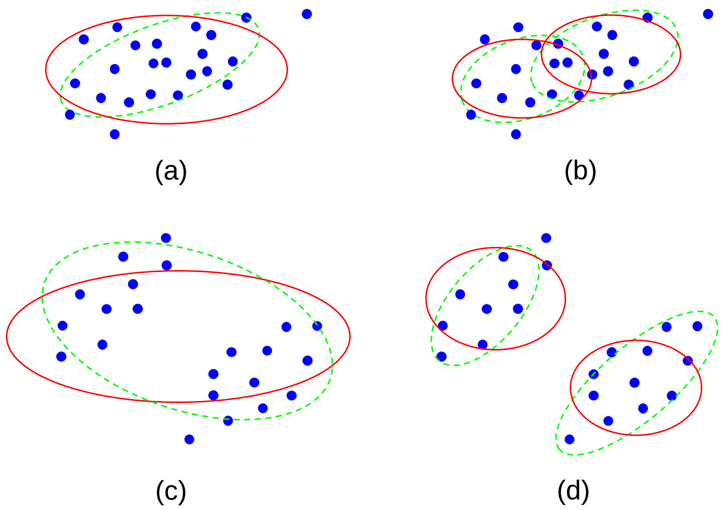

Figure 8: Simplified 2-D position representations including nonparametric (i.e., particles as blue dots) and parametric (i.e., diagonal Gaussian modes as red ellipses and full Gaussian modes as green dash ellipses) approaches. Each explicit particle representation costs two scalars, each diagonal Gaussian 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.

which overload 100–800-byte CAMs [27] and strongly exceed the 2312-byte Maximum Transfer Unit (MTU) of the DSRC channels[4]. Figure 7 provides a simplified illustration of the information exchanges enabling CLoc between two vehicles i and j where, at vehicle i, θ_i^{GNSS}, $RSSI_i^{j\rightarrow}$ and $\{\theta_i^{(p)}, w_i^{(p)}\}_{p=1\ldots N_p}$ stand for respectively the onboard GNSS estimate, the RSSI observation out of received vehicle j's CAM, and the cloud of N_p particles with associated states $\theta_i^{(p)}$ and weights $w_i^{(p)}$. As already mentioned, it is absolutely impossible to broadcast explicitly heavy particle clouds through DSRC channels. Thus the cloud representation has to be simplified to a few scalars that can be practically carried by the CAMs. The neighboring vehicles receiving these CAMs must be able to simply reconstruct the initial particle cloud from these scalars. One solution consists in making parametric message approximations. Particularly, each particle cloud is approximated by a known distribution, which is commonly a Gaussian or a mixture of Gaussians. Figure 8 illustrates how 2-D particle-based positions can be approximated by the previous representations in both non-ambiguous and ambiguous cases (See Figure 8(a)-(b) and 8(a)(c)-(d) respectively).

In [29], we first perform an in-depth comparison of various Gaussian Mixture Models (GMMs) in the specific context of vehicular CLoc in order to select the best scheme. We then point out the fact that using multimodal distributions for message approximation is not always beneficial in practical deployment scenarios (even in the case of flip ambiguity) but it may adversely lead to high computational complexity for the modes identification and parameterization.

Besides, in case of channel congestion, the ETSI Decentralized Congestion Con-

[4]The well-known Wireless Local Area Network (WLAN) standard IEEE 802.11, whose MTU is 2312 bytes, is widely selected as basic DSRC technology [28].

trol (DCC) rules recommend to scale the CAM transmission rate from 10 Hz down to 2 Hz (corresponding to 60% channel load) leading to expected accuracy degradation accordingly. To compensate for the information loss, on top of the previous message approximations, we also consider revised transmission policies to support heterogeneous payloads and rates, by mixing "tiny" CAMs with no payload at the critical rate of 10 Hz and normal CAMs at the rate of 2 Hz (triggered by ETSI DCC). The "tiny" CAMs thus enable 10-Hz RSSI observations refreshment to enable 10-Hz fusion rate to boost the CLoc accuracy[5]. Moreover, thanks to power control mechanisms, these "tiny" CAMs are broadcast at shorter transmission ranges (i.e., shorter than that of normal nominal CAMs). In line with the link selection strategies described in section 4.2, CLoc is indeed deliberately restricted to the closest ring of neighboring vehicles, just like in [6, 20]. By the time this report has been written, this advanced transmission policy is still under evaluation. The obtained results should appear in the final version of the full paper [29].

5 Summary and Future Work

In this first part of these PhD investigations, we have proposed and evaluated elementary functions and building blocks of a global CLoc data fusion framework suitable to the very specific context of GNSS-aided "networks on wheels". On this occasion, we have also disclose promising opportunities in terms of "context-aware" CLoc, where the fusion engine would be capable of automatically combining the most efficient techniques depending on the operating conditions, while coping with drastic V2V communication/protocol and low complexity constraints.

For the next steps ahead, one first axis of investigation is to integrate and compare different radio and non-radio (e.g., Inertial units and wheel speed counter) modalities within our global fusion framework. Even more specifically, alternative radio technologies such as Impulse Radio - Ultra Wide Band (IR-UWB), should be considered to provide more accurate V2x ranging observations (instead of using RSSI measurements), most likely while still keeping IEEE802.11p as V2V communication means to support the cooperative exchange of positional information (i.e., still using CAMs to fuse neighbors' information through message-passing).

Besides, the effect of congestion control is also of interest to identify and reach practical trade-offs between high awareness/accuracy levels and reduced interference patterns. As a result, there seems to be still some room for studying the effects of both power and traffic control in IEEE 802.11p (for communication only and/or ranging, or for both) on the instantaneous radius of cooperation and the required a priori models. Critical non-visibility configurations, which can generate strongly biased measurements or cause harmful packets' losses, will be also carefully addressed and mitigated in a variety of novel scenarios (e.g., including urban intersections).

Finally, practical experiments shall be also carried out to validate some of the proposed theoretical solutions above, based on hardware demonstration platforms in the frame of the *HIGHTS* European project (636537-H2020) [30].

[5] We also need 10-Hz positions of the "virtual anchors" which cannot be supported by the constrained 2-Hz normal CAM rate. Fortunately, it can be solved by prediction based on mobility model.

List of Publications

- G.M Hoang, B. Denis, J. Härri, D.T.M. Slock, "On communication aspects of particle-based cooperative positioning in GPS-aided VANETs," *extended abstract submitted to Proc. CCP IV'15,* Jun. 2016.
- G.M Hoang, B. Denis, J. Härri, D.T.M. Slock, "Breaking the gridlock of spatial correlation in GPS-aided IEEE 802.11p-based cooperative positioning," *conditionally accepted by IEEE Trans. on Veh. Technol.,* Jun. 2016.
- G.M Hoang, B. Denis, J. Härri, D.T.M. Slock, "Select thy neighbors: Low complexity link selection for high precision cooperative vehicular localization," in *Proc. VNC'15,* Dec. 2015.
- G.M Hoang, B. Denis, J. Härri, 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.

Posters

- G.M Hoang, B. Denis, J. Härri, D.T.M. Slock, "Cooperative Data Fusion for GPS-aided Positioning in IEEE 802.11p VANETs," *presented at BMW Summer School,* Jul. 2015.

List of Courses

- BMW Summer School, "Connected vehicles driving on digital roads", Bavaria, Jul. 2015 (4 ECTS) (Best Ideation Award).

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] C. R. Drane and C. Rizos, *Positioning Systems in Intelligent Transportation Systems*. Norwood, MA, USA: Artech House, Inc., 1st ed., 1998.

[3] D. Caveney, "Cooperative vehicular safety applications," *IEEE Cont. Syst.*, vol. 30, pp. 38–53, Aug. 2010.

[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] "Vehicle Safety Communications-Applications (VSC-A), Final Report," Tech. Rep. DOT HS 811 492A, U.S. Dept. Transp., Nat. Highway Traffic Safety Admin., Sept. 2011.

[6] 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.

[7] J. Yao, A. Balaei, M. Hassan, N. Alam, and A. Dempster, "Improving cooperative positioning for vehicular networks," *IEEE Trans. on Veh. Technol.*, vol. 60, pp. 2810–2823, Jul. 2011.

[8] R. Parker and S. Valaee, "Vehicular node localization using received-signal-strength indicator," *IEEE Trans. on Veh. Technol.*, vol. 56, pp. 3371–3380, Nov. 2007.

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

[10] N. Patwari, A. Hero, M. Perkins, N. Correal, and R. O'Dea, "Relative location estimation in wireless sensor networks," *IEEE Trans. on Sig. Proc.*, vol. 51, pp. 2137–2148, Aug. 2003.

[11] H. Wymeersch, J. Lien, and M. Win, "Cooperative localization in wireless networks," *Proc. of the IEEE*, vol. 97, pp. 427–450, Feb. 2009.

[12] H. Noureddine Al Moussawi, *Some signal processing techniques for wireless cooperative localization and tracking*. Ph.D. dissertation, Télécom Bretagne, Université de Bretagne Occidentale, 2012.

[13] E. D. Kaplan and C. Hegarty, *Understanding GPS: Principles and Applications*. Boston, USA: Artech House, 2005.

[14] L. Mihaylova, D. Angelova, D. Bull, and N. Canagarajah, "Localization of mobile nodes in wireless networks with correlated in time measurement noise," *IEEE Trans. on Mob. Comp.*, vol. 10, pp. 44–53, Jan. 2011.

[15] M. Gudmundson, "Correlation model for shadow fading in mobile radio systems," *Elect. Lett.*, vol. 27, pp. 2145–2146, Nov. 1991.

[16] N. Patwari and P. Agrawal, "Effects of correlated shadowing: Connectivity, localization, and RF tomography," in *Proc. ACM/IEEE IPSN'08*, pp. 82–93, Apr. 2008.

[17] H. Lu, S. Zhang, X. Liu, and X. Lin, "Vehicle tracking using particle filter in Wi-Fi network," in *Proc. VTC'10-Fall*, Sept. 2010.

[18] L. Sun, Y. Wu, J. Xu, and Y. Xu, "An RSU-assisted localization method in non-GPS highway traffic with dead reckoning and V2R communications," in *Proc. CECNet'12*, pp. 149–152, Apr. 2012.

[19] H. Li and F. Nashashibi, "Cooperative multi-vehicle localization using split covariance intersection filter," *IEEE Intel. Transp. Syst. Mag.*, vol. 5, pp. 33–44, Apr. 2013.

[20] 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.

[21] D. Simon, *Optimal State Estimation: Kalman, H Infinity, and Nonlinear Approaches*. Newark, NJ, USA: Wiley, 2006.

[22] M. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, “A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking,” *IEEE Trans. on Sig. Proc.*, vol. 50, pp. 174–188, Feb. 2002.

[23] S. Särkkä, *Bayesian Filtering and Smoothing*. New York, NY, USA: Cambridge University Press, 2013.

[24] G. M. Hoang, B. Denis, J. Härri, and D. T. M. Slock, “Breaking the gridlock of spatial correlation in GPS-aided IEEE 802.11p-based cooperative positioning.” *conditionally accepted by IEEE Trans. on Veh. Technol.*, Jun. 2016.

[25] Z. Wang, E. Tameh, and A. Nix, “Joint shadowing process in urban peer-to-peer radio channels,” *IEEE Trans. on Veh. Technol.*, vol. 57, pp. 52–64, Jan. 2008.

[26] F. Gustafsson, F. Gunnarsson, N. Bergman, U. Forssell, J. Jansson, R. Karlsson, and P.-J. Nordlund, “Particle filters for positioning, navigation, and tracking,” *IEEE Trans. on Sig. Proc.*, vol. 50, pp. 425–437, Feb. 2002.

[27] K. S. Bilstrup, E. Uhlemann, and E. G. Strom, “Scalability issues of the mac methods stdma and csma of ieee 802.11p when used in vanets,” in *Proc. ICC’10*, pp. 1–5, May 2010.

[28] “Intelligent Transport Systems (ITS); Access layer specification for Intelligent Transport Systems operating in the 5 GHz frequency band,” *ETSI Std. EN 302 663 V1.2.0*, Nov. 2012.

[29] G. M. Hoang, B. Denis, J. Härri, and D. T. M. Slock, “On communication aspects of particle-based cooperative positioning in GPS-aided VANETs.” *extended abstract submitted to Proc. CCP IV’16*, Jun. 2016.

[30] “HIGHTS European project.” `http://www.hights.eu`.