Quality-Aware Broadcasting Strategies for Position Estimation in VANETs

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Abstract—The dissemination of vehicle position data all over the network is a fundamental task in Vehicular Ad Hoc Network (VANET) operations, as applications often need to know the position of other vehicles over a large area. In such cases, inter-vehicular communications should be exploited to satisfy application requirements, although congestion control mechanisms are required to minimize the packet collision probability. In this work, we face the issue of achieving accurate vehicle position estimation and prediction in a VANET scenario. State of the art solutions to the problem try to broadcast the positioning information periodically, so that vehicles can ensure that the information their neighbors have about them is never older than the inter-transmission period. However, the rate of decay of the information is not deterministic in complex urban scenarios: the movements and maneuvers of vehicles can often be erratic and unpredictable, making old positioning information inaccurate or downright misleading. To address this problem, we propose to use the Quality of Information (QoI) as the decision factor for broadcasting. We implement a threshold-based strategy to distribute position information whenever the positioning error passes a reference value, thereby shifting the objective of the network to limiting the actual positioning error and guaranteeing quality across the VANET. The threshold-based strategy can reduce the network load by avoiding the transmission of redundant messages, as well as improving the overall positioning accuracy by more than 20% in realistic urban scenarios.

Index Terms—VANETs; broadcasting strategies; position estimation; quality of information (QoI).

I. INTRODUCTION

In recent years, there has been a growing interest in Vehicular Ad Hoc Networks (VANETs) which have rapidly emerged as a means to enable safer traveling and improved traffic management, and to support infotainment applications [1]. As vehicular technologies evolve towards the support of more safety-critical applications, research efforts have been made towards the design of novel VANET architectures and implementations which guarantee timely and accurate positioning of vehicles [2], a fundamental prerequisite for safety systems as well as for Internet access and multimedia services.

The unique characteristics of VANETs might cause rapid dynamics and unpredictable changes in the network topology, thereby requiring regular position updates to be disseminated as timely as possible, i.e., ideally at the very same instant they are generated. However, next-generation Connected and Intelligent Transportation Systems (C-ITSs) and the heterogeneity of their requirements constrain the amount of information that can be successfully broadcast over bandwidth-constrained communication channels. High connectivity pressure on the VANET would likely lead to packet collisions and potentially degrade the accuracy and timeliness of VANET services [3].

In this scenario, the traditional strategy is to have each vehicle broadcast periodic updates [4] with its positioning information. Other vehicles in its communication range will then have the guarantee that the time from the last update never passes the inter-transmission period. However, the unpredictable variability of the VANET topology might make a periodic broadcasting strategy inefficient in terms of the absolute positioning error, thereby calling for innovative and more sophisticated information distribution solutions that explicitly consider the Quality of Information (QoI) [5] instead of using the time between subsequent updates as a proxy for it. Generally, congestion-avoidance mechanisms have also been proposed in the literature to regulate information distribution as a function of the network load. However, these techniques dynamically adapt the VANET transmission parameters, e.g., by controlling the number of neighboring vehicles [6] or by assigning different priorities to vehicles with different operating conditions [7], regardless of the level of positioning accuracy that is achieved from the information that is successfully delivered. The concept of value-anticipating vehicular networking has also been investigated as a means to efficiently disseminate data in resource-constrained vehicular networks, i.e., by discriminating the importance of the different positioning information sources, in order to use the limited transmission resources in a way that maximizes the utility for the target applications [8]. The value assessment process should be computationally efficient, so that it can be completed in low latency even with the limited on-board computational resources of mid-range and budget car models.

Following this rationale, in this paper we face the challenge of ensuring accurate vehicle position estimation and prediction while minimizing the network load in a cost-effective way. In this regard, among the original contributions of this paper, we design a threshold-based broadcasting algorithm which (i) estimates the positioning error of the vehicle and of its neighbors within communication range, based on purely predictive Unscented Kalman Filter (UKF) tracking operations, and (ii) forces vehicles to distribute state information messages in case the estimated error of the previously broadcast positioning information is above a predefined threshold. The performance of the proposed strategy is compared with that of an elementary constant inter-transmission period policy, with which vehicles broadcast state information updates at regular intervals.

• investigate the impact of the channel conditions on
the overall position estimation accuracy. Inter-vehicular
broadcasting operations are modeled based on a realistic
implementation of the IEEE 802.11p frame structure.
- investigate the performance of the proposed broadcasting
scheme as a function of the VANET dynamics. In order to
have realistic movement of the vehicles, we generate
Mobility (SUMO) [9], an open road traffic simulator designed to
handle and model the traffic of large road networks.
- evaluate the performance of the Constant Turn Rate
and Acceleration (CTRA) motion model, which was
traditionally proven to be one of the most appropriate
models to track vehicular mobility, considering realistic
urban VANET scenarios.

Our results show that the proposed threshold-based broad-
casting algorithm, in spite of its simplicity, can improve the
position estimation accuracy by more than 20% compared to
state of the art approaches. We also demonstrate the impact
of the VANET topology dynamics on the overall network
performance, and prove that information can decay at different
rates depending on how well movements fit the broadcast model,
making the time since the last update an imperfect measure of the
real QoI. Moreover, we illustrate how the CTRA model
might not represent a suitable solution to characterize long-term
vehicular mobility, especially in dynamic urban environments,
in spite of its demonstrated success at short-term tracking. The
success of the threshold-based strategy is due to its ability to
compensate for these limitations, and our theoretical analysis
supports this explanation.

II. RELATED WORK

Estimating the position of VANET nodes can be considered
an extension of the target tracking problem [10]. In a VANET,
each vehicle makes use of on-board sensors and wireless
communication to collect data regarding the surrounding
environment. The gathered data can be used as the input of a
tracking system that has, as a target state, the set of positions
of all the VANET nodes. Since inter-vehicle communication
allows vehicles to share information, the performance of the
described tracking system becomes highly dependent on the
cooperation between VANET nodes. An example of a
tracking strategy in VANETs is given in [11], and most
research works dedicated to vehicle position estimation and
prediction are based on similar paradigms. The specificity of
each implementation mainly depends on the motion model
chosen to represent the behavior of the vehicles and on the
Bayesian Filtering (BF) algorithm used to process the input
data. An analysis of the main motion model used in vehicle
tracking is given in [12]. The best-known BF algorithms used for the same purpose are the Kalman Filter (KF) [13] and the
Particle Filter (PF) [14]. A vehicle tracking framework based on the UKF algorithm [15] and the CTRA motion model is
presented in [16]. Route information and digital map data are processed by a PF algorithm in [17]. In [18], vehicle position
forecasting is achieved by exploiting a system based on a
Hidden Markov Model (HMM) [19] and the Viterbi algorithm
[20]. We highlight that the performance of all the BF-based
systems strongly depends on the filter settings, which must be
defined a priori. A comprehensive analysis of the possible KF
configurations for vehicle tracking is given in [21].

Conventional tracking approaches mainly focus on the real-
time estimation of the target state. However, most advanced
C-ITS applications also require the prediction of the future
time of the target vehicle. Long-term forecasting can be
achieved by simply applying the predictive step of a BF filter
to the last available state estimation, although this solution does
not provide good performance when the behavior of the vehicle
is not properly represented by the chosen motion model. To
overcome this issue, more sophisticated approaches have been
proposed in the literature. In [22], the output of a KF system is
used to achieve the parametric interpolation of target vehicles’
future paths. In [23], the Dead Reckoning (DR) technique
is implemented in order to improve packet forwarding in a
highway scenario. Another possibility consists in describing
vehicle position prediction as a time series forecasting problem
[2]. Machine Learning (ML) techniques, such as Support Vector
Machines (SVMs) [24] and Neural Networks (NNs) [25],
can then be designed to improve state estimation. In [26],
SVMs are used to forecast vehicle trajectories during the time
period in which the GPS signal is not available. In [27] a NN
system trained with historical traffic data is used to predict
vehicles’ future speeds. Although ML approaches generally
guarantee accurate tracking, they require a large amount of
sensory observations for the training and suffer from significant
computational complexity.

BF and ML approaches are often combined with the aim of
maximizing the performance of the vehicle position estimation
and prediction. A trajectory prediction system that makes use of
an HMM module to determine which maneuver a vehicle
is performing and an SVM module to achieve the position
prediction is presented in [28]. In [29], a Radial Basis Function
(RBF) classifier is used to compute the setting of a PF which
is then exploited to achieve a long-term motion prediction.
In [30], the results of a maneuver recognition system and a
tracking system based on the CTRA motion model are
combined together.

In general, the performance of tracking systems strongly
depends on the accuracy of the input data and on how often
new data are available. In this perspective, our work tries
minimize broadcasting operations while ensuring accurate
position estimation.

III. SYSTEM MODEL AND BROADCASTING STRATEGIES

In this section we present our system model. In particular,
Sec. III-A describes the VANET from an analytical point of
view, Sec. III-B presents the error function which is used as
the accuracy metric for the performance evaluation, Secs. III-C
and III-D describe the tracking system implemented by the
vehicles and the vehicular network channel model, respectively,
and Sec. III-E presents the broadcasting strategies we propose.

A. General model

We represent a VANET as a Euclidean graph \( G = (V, E, r) \),
i.e., an undirected graph whose vertices are points on a
Euclidean plane. \( V \) represents the set of nodes, \( E \) represents
the set of edges and \( r \) is the node’s communication range.
We say that two vehicles \( v_i \) and \( v_j \) are tracked by the ego vehicle, i.e., the target vehicles, are connected by connection \( < v_i, v_j > \) if the distance \( d_{i,j} \) between them is shorter than the communication range \( r \), i.e., \( E = \{ < v_i, v_j > : i \neq j \land d_{i,j} < r \} \). Since the composition of the edge set depends on the position of the vehicles, the topology of the VANET is time-variant, e.g., new edges can be activated or disabled according to vehicles movements.

By representing the network as a Euclidean graph, we assume that the vehicles are moving in a two-dimensional space; while not always realistic, this hypothesis does not compromise the accuracy of our analysis. Moreover, we assume that time can be divided into discrete timeslots. To highlight the time dependency of the VANET topology, we denote by \( G(t) = (V(t), E(t), r) \) the network graph at time \( t \). It becomes intuitive to define the neighbor set \( N_i(t) \) of vehicle \( v_i \) at time \( t \) as the set of vehicles connected to \( v_i \) by an edge in \( E(t) \): \( N_i(t) = \{ v_j \in V(t) : < v_i, v_j \rangle \in E(t) \} \).

The behavior of each vehicle \( v_i \) in the VANET at time \( t \) is represented by a 6-tuple \( s(t) = \{ x(t), y(t), h(t), u(t), a(t), \omega(t) \} \), which we call vehicle state. In particular, \( x \) and \( y \) are the Cartesian coordinates of the vehicle on the road topology, \( h \) is the vehicle’s heading direction, \( u \) and \( a \) are the vehicle’s tangent velocity and acceleration, respectively, and \( \omega \) is the vehicle’s angular velocity. A graphical representation of the vehicle state is given in Fig. 1. Since our work focuses on position estimation and prediction, we define the distance between two states \( s_i(t) \) and \( s_j(t) \) as the physical distance between the positions of vehicles \( v_i \) and \( v_j \), at time \( t \), i.e.,
\[
d(s_i(t), s_j(t)) = \sqrt{(x_i(t) - x_j(t))^2 + (y_i(t) - y_j(t))^2}.
\]

### B. Error function

Consider a reference vehicle \( v_i \in V(t) \), called the ego vehicle, which is connected to each vehicle \( v_j \in N_i(t) \), at time \( t \). We call \( N_i(t) \) the subset of \( N_i(t) \) containing the vehicles which are tracked by the ego vehicle, i.e., the target vehicles, and \( \hat{s}_{i,j}(t) \) the state estimate of \( v_j \) carried out by \( v_i \) at time \( t \). Under these hypotheses, the performance, in terms of position estimation accuracy, of the ego vehicle can be assessed by an error function \( \mathcal{F}(v_i, t) \), i.e.,
\[
\mathcal{F}(v_i, t) = \frac{1}{|N_i(t)| + 1} \left( \lambda_{i,i}(t) d(\hat{s}_{i,i}(t), s_i(t)) + \sum_{v_j \in N_i(t)} \lambda_{i,j}(t) d(\hat{s}_{i,j}(t), s_j(t)) \right).
\] (1)

In (1), \( d(\hat{s}_{i,i}(t), s_i(t)) \) represents the error made by \( v_i \) in estimating its own state \( s_i(t) \), \( d(\hat{s}_{i,j}(t), s_j(t)) \) represents the error made by \( v_i \) in estimating the neighbor state \( s_j(t) \), \( |N_i(t)| + 1 \) represents the total number of estimations carried out by \( v_i \) and \( \lambda_{i,j}(t) \) is the logistic function defined as
\[
\lambda_{i,j}(t) = A + \frac{K - A}{(C + Qe^{-B(d(s_i(t), s_j(t)) - d_{i,j})})^{1/e}}.
\] (2)

Parameters in (2) characterize the logistic function’s shape and guarantee that errors referred to spatially close vehicles, the most safety-constrained neighbors, are weighted more than others. Their values will be detailed in Sec. IV. To evaluate the performance of the whole VANET, we define \( \mathcal{F}(V, t) \) as the average of \( \mathcal{F}(v_i, t) \) among all vehicles \( v_i \in V(t) \):
\[
\mathcal{F}(V, t) = \frac{1}{|V(t)|} \sum_{v_i \in V(t)} \mathcal{F}(v_i, t).
\] (3)

### C. Tracking system

To minimize the positioning error defined in (1), at every timeslot the ego vehicle must estimate its state and the state of every other vehicle in the set \( N_i(t) \). To reach this goal, the ego vehicle exploits both the information gathered by its on-board sensors and the information received from its neighbors through inter-vehicle communications. To allow the estimation of \( s_i(t) \), we assume that, at every timeslot, the ego vehicle’s on-board sensors provide a new observation \( o(t) \) of \( s_i(t) \). Hence, the ego vehicle can model the evolution of its own state through a Bayesian approach, obtaining the system
\[
\begin{align*}
\lambda_{i,j}(t) &= A + \frac{K - A}{(C + Qe^{-B(d(s_i(t), s_j(t)) - d_{i,j})})^{1/e}}. \\
\mathcal{F}(V, t) &= \frac{1}{|V(t)|} \sum_{v_i \in V(t)} \mathcal{F}(v_i, t). \\
C &= \text{Tracking system}.
\end{align*}
\]

In (3), the first equation describes the evolution of the vehicle state \( s(t) \) over time, while the second equation describes the relation between \( s(t) \) and the state observation \( o(t) \). In particular, \( f \) is a function describing the CTRA motion model given in [31], while \( m \) is a function representing the vehicle’s measurement system operation. Moreover, \( \mu(t) \) and \( \nu(t) \) represent the process and measurement noises, respectively, and are modeled as Gaussian processes with zero mean and covariance matrices \( Q \) and \( R \). We highlight that \( Q \) is an identity matrix multiplied by a constant, i.e., \( Q = q \cdot I \), while \( R \) is a diagonal matrix whose values correspond to the accuracy of the vehicle’s measurement system. Once all the parameters in (3) are defined, the ego vehicle can estimate its own state by using a BF algorithm. In our model, each vehicle implements a UKF algorithm exploiting the sigma points parameterization given in [32]. The UKF is a widely used BF method that allows to estimate the state of a system that evolves according to a nonlinear model. By exploiting the UKF and the system equations given in (3), the ego vehicle can obtain the state estimate \( \hat{s}_{i}(t) \) of its own state \( s(t) \) at each timeslot \( t \). The UKF framework alternates two working steps. During the predictive step the state estimate is propagated through the CTRA equations; during the updating step the state estimate is updated with the new information provided by the observation \( o(t) \).
To allow $v_i$ to estimate the states of the other VANET nodes, each vehicle $v_j \in V(t)$ broadcasts its last estimated state $\hat{s}_{j,i}(t)$ and the related covariance matrix. The time frame by which new transmissions are initiated depends on the selected broadcasting strategy, as described in Sec. III-E. Each message transmitted by $v_j$ is received by all the vehicles in $N_j(t)$ after a certain communication delay. If, by this process, a new neighbor is detected, the ego vehicle initializes a new UKF having as initial state and uncertainty the received state and covariance matrix, respectively. The new filter propagates the initial state over time by exploiting only its predictive step. In case the ego vehicle receives a packet from a vehicle $v_j$ who was already detected, the UKF assigned to $v_j$ is updated with the new data contained in the packet.

### D. Channel model

Inter-vehicle communications are modeled following the IEEE 802.11p standard, which supports the Physical (PHY) and Medium Access Control (MAC) layers of the Dedicated Short Range Communication (DSRC) transmission protocol [33]. DSRC defines seven different channels at the PHY layer, each constituted by $N_{sc,tot} = 52$ sub-carriers [34]. For simplicity of discussion, we assume that only a limited number of sub-carriers $N_{sc} < N_{sc,tot}$ can be used for broadcasting state information messages, while the rest of the sub-carriers is used by other VANET applications.

DSRC implements the Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA) scheme at the MAC layer, where nodes listen to the wireless channel before sending. CSMA/CA allows for reduced signaling overhead with respect to other IEEE 802.11 standards and enables uncoordinated channel access. We consider a 1-persistent system: when a vehicle senses that its chosen channel is occupied, it attempts to send the positioning update in the next timeslot. On the other hand, contentention-based access is prone to the hidden node problem, which may result in packet collision if an out-of-range vehicle is transmitting towards the same potential receiver. In our model, we assume that if, in any timeslot, a vehicle $v_i$ receives two packets sent by two other vehicles using the same sub-carrier during the same timeslot, both packets are discarded.

### E. Broadcasting strategies

In our model two different broadcasting strategies for the distribution of the vehicles’ state information are implemented.

a) **Constant inter-transmission period policy:** A constant inter-transmission period $T_p$ is chosen, so that vehicles initiate new transmissions at regular time frames. This approach is already implemented by most VANET positioning applications and represents the benchmark solution of our analysis.

b) **Threshold-based policy:** In this case, vehicles try to adjust the broadcasting operations according to the specific characteristics of the VANET in which they are deployed. On a practical level, new transmissions are initiated only when the expected position estimation error of the neighboring vehicles overcomes a predetermined threshold $E_{thr}$. To reach this goal, the ego vehicle defines a UKF algorithm, as described in Sec. III-C, which replicates the working behavior of all VANET nodes that are tracking the ego vehicle itself. In this case, the ego vehicle’s state is propagated by the UKF algorithm over time by using only its predictive step, and is updated every time the ego vehicle carries out a new transmission. Hence, in any timeslot the ego vehicle has available both the a posteriori state estimate $\hat{s}_{i,i}(t)$, which is the output of its main filter, and the a priori state estimate $\hat{s}_{i,i}^p(t)$, which is the output of its purely predictive filter. In each timeslot, the ego vehicle compares $\hat{s}_{i,i}(t)$ and $\hat{s}_{i,i}^p(t)$: if the state difference $d(\hat{s}_{i,i}(t), \hat{s}_{i,i}^p(t))$ is bigger than $E_{thr}$, a new transmission is immediately initiated. The threshold $E_{thr}$ is a function of the traffic density and is selected through an exhaustive approach. In particular, we consider $N_{E_{thr}}$ different values of the error threshold and select the one that minimizes the positioning error.

We highlight that the behavior of both policies can change according to some specific events. First, both strategies define a maximum inter-transmission period, i.e., a maximum number of consecutive timeslots during which no transmissions are initiated. Second, both strategies force the ego vehicle to broadcast immediately its position information every time it receives a message from an undetected vehicle. This aims at reducing the number of vehicles that are undetected, i.e., the vehicles $v_j$ which belong to $N_i(t)$ but not to $\hat{N}_i(t)$.

### IV. Performance analysis

The simulation parameters have been chosen based on realistic system design considerations and are summarized in Table I.

| Parameter | Value | Description |
|-----------|-------|-------------|
| $T_{sim}$ | 300 s | Simulation duration |
| $T_i$ | 100 ms | Timeslot duration |
| $r$ | 140 m | Communication range |
| $T_d$ | 100 ms | Communication delay |
| $d_0$ | 42 m | Safety distance |
| $v_{max}$ | 13.89 km/h | Max. speed in VANET |
| $A_S$ | 0.5168 km² | VANET area size |
| $E_{thr}$ | {0, ..., 42} m | Error threshold |
| $T_p$ | {0, ..., 10} s | Inter-transmission period |

#### TABLE I: Simulation parameters.

| Parameter | Value | Description |
|-----------|-------|-------------|
| $R_{1,1}$ | 1.18535 m² | Position accuracy along x |
| $R_{2,2}$ | 1.18535 m² | Position accuracy along y |
| $R_{3,3}$ | 0.5 (m/s)² | Speed accuracy |
| $R_{4,4}$ | 0.39 (m/s)² | Acceleration accuracy |
| $R_{5,5}$ | 0.09211 rad² | Heading accuracy |
| $R_{6,6}$ | 0.01587 (rad/s)² | Turn rate accuracy |

#### TABLE II: Accuracy for vehicle state parameters.
by a non-negligible measurement noise which is modeled as a Gaussian process with zero mean and covariance matrix $R$. The elements of $R$ are reported in Table I and are derived from the models in [30]-[33]. Moreover, we assign to the logistic function parameters in (2) the following values: $A = 1$ and $K = 0$, $C = 1$, $Q = 1$, $B = 0.05$, $\nu = 0.2$, and $d_0 = 42$ m (in this way, $\lambda_{i,j}(t) \simeq 1$ as $d(s_i(t), s_j(t)) \to 0$ and $\lambda_{i,j}(t) \to 0$ as $d(s_i(t), s_j(t)) \to +\infty$). In particular, $d_0$ represents the safety distance that must be held in an urban scenario, and determines the threshold beyond which $\lambda_{i,j}(t)$ starts decreasing.

c) Broadcasting strategies parameters: For the constant inter-transmission period policy, we make $T_p$ vary from 0 to 10 s: the trade off involves position estimation accuracy and broadcasting overhead. For the threshold-based policy, we consider $N_{E_{thr}} = 30$ different values of the error threshold, ranging between 0 and 42 m, until minimum position error is achieved.

d) Scenario parameters: For our simulations, we use a real road map data imported from OpenStreetMap (OSM), an open-source software which combines wiki-like user generated data with publicly available information. We consider the OSM map of New York City, as represented in Fig. 2a, to characterize a very dynamic urban environment, and the total simulation area is set to $A_S = 0.5168$ km$^2$. Moreover, in order to consider realistic mobility routes that are representative of the behavior of vehicles in the VANET, we simulate the mobility of cars using SUMO, as represented in Fig. 2b. The vehicles move through the street network according to a randomTrip mobility model, which generates trips with random origins and destinations, and speeds which depend on the realistic interaction of the vehicle with the road and network elements. The maximum speed is set to $v_{max} = 13.89$ m/s, which is consistent with an urban scenario. A density of $d_v = 120$ vehicles/km$^2$ is considered, making $|V| = 62$ the number of vehicles deployed in the considered VANET scenario.

e) Evaluation metrics: The performance of the proposed broadcasting strategy is assessed in terms of

- **CTRA model accuracy**, i.e., how well the CTRA model tracks vehicle mobility;
- Average positioning error, i.e., the average error committed by the ego vehicle to estimate its own state, i.e., geographical position, and that of its neighbors;
- 95th percentile of the positioning error, i.e., the average positioning error relative to the worst 5% of the vehicles;
- Detection error, i.e., the sum of the undetection (i.e., unknown vehicles in the neighborhood) and misdetection (i.e., vehicles that are believed to be in the area but are outside the communication range) event probabilities.

The remainder of this section is organized as follows: we evaluate the performance of the CTRA motion model considering long- and short-term tracking in Sec. IV-A while in Sec. IV-B we compare the position estimation accuracy of the proposed threshold-based broadcasting strategy against a constant inter-transmission period scheme.

A. CTRA analysis

The quality of the tracking and the accuracy of the CTRA approach strongly depend on the scenario. A model such as CTRA is designed to deal with slow variations, and rapid changes in the acceleration are extremely difficult for it to track.

Intuitively, a regular and almost time-invariant scenario seems to fit this kind of model better. In such a scenario, a regular transmission strategy might not be too damaging, since the CTRA model is essentially correct; the errors are predictable within the model, as well as relatively slow. In a more dynamic scenario, such as the urban one we consider, several elements make the environment more unpredictable: traffic or pedestrians might cause the driver to brake sharply, and navigation is not simple, as turns, crossings and traffic lights make the vehicle brake, turn or accelerate suddenly. These discontinuities reduce the accuracy of the model, showing its limits in complex scenarios. Finding out their frequency and severity is then extremely important in the design of both improved tracking algorithms and more efficient information dissemination strategies: the final objective is to track vehicles in the VANET accurately with limited signaling overhead.

The accuracy of the CTRA model is a way to determine the relation between time and QoI if the model is accurate, the decay of information follows a known distribution, and periodic transmissions can optimize QoI reasonably well. Inaccuracies in the model reflect an increased randomness in the relation.

In order to compare the results of the CTRA tracking model with the empirical reality, we can use the inter-transmission interval as a proxy for the accuracy of the CTRA model: if we assume a threshold-based transmission policy, the theoretical inter-transmission interval distribution is determined by the parameters of the UKF. The error on the vehicle position tracking after $i$ UKF prediction steps is a multivariate Gaussian random variable with zero mean and a semidefinite positive covariance matrix $P_i$. The probability that the error $e_i$ after $i$ UKF prediction steps is higher than the threshold $E_{thr}$ is then given by the inverse Cumulative Distribution Functions (CDFs) of the position error over the circle with radius $E_{thr}$:

$$P(e_i > E_{thr}) = 1 - \int_{B(E_{thr})} \phi((x,y)) \, d(x,y),$$

where $B(E_{thr})$ represents the circle of radius $E_{thr}$, i.e., $B(E_{thr}) = \{(x, y) : \sqrt{x^2 + y^2} \leq E_{thr}\}$, and $\phi((x,y))$ is the bivariate normal probability density function (PDF). We now need to calculate the probability of going over the threshold for the first time after $i$ steps:

$$P_{tx}(i) = P(e_i > E_{thr}) \prod_{j=1}^{i-1} (1 - P(e_j > E_{thr})).$$  

Fig. 2: Representation of a portion of the urban map that is considered for the performance evaluation.
This is a slight approximation, since \( P(e_i > x) \) is actually different from \( P(e_i > x|e_{i-1} \leq x) \); in the former case the position error is multivariate Gaussian, while in the latter the real error on each axis is the sum of a multivariate Gaussian and a truncated multivariate Gaussian variable, which is considerably more complex to compute numerically. However, the error introduced by this approximation is minimal, since the first step is the one with the lowest variance. It is also biased in a conservative direction: the approximation slightly overestimates the error compared to the actual model.

The theoretical inter-transmission time distribution we defined above is compared with the empirical distribution obtained from our simulations in Fig. 3, which shows a Q-Q plot of the two with three different threshold \( E_{thr} \) parameters: 1.94 m, 4.59 m, and 8.29 m, sorted by increasing average inter-transmission time. The results are obtained in an ideal scenario without the effects of the channel conditions. The plot shows that the CTRA model evolves inaccurately with time, consistently overestimating the long-term error. There are two interesting effects in the plot: firstly, the time distribution calculated by CTRA does not model the actual behavior of the system (black diagonal) very well, and secondly, there is a significant number of transmissions (around 20% for the \( E_{thr} = 1.94 \) m and \( E_{thr} = 4.59 \) m cases) performed almost immediately. The former highlights the well-known issues of the CTRA model in long-term prediction [39], while the latter is probably caused by unpredictable maneuvers such as lane switches, turns or hard brakes. This explanation is supported by the absence of immediate transmissions for the system with the 8.29 m threshold, which is probably wide enough to avoid triggering a transmission after one of these maneuvers.

We conclude that a periodic transmission policy based on the CTRA parameters would consistently overestimate the system error and consequently underperform, while a threshold-based approach that considers the tracking error directly would simply transmit whenever the error is above the threshold, increasing the average inter-transmission time to avoid congestion and compensating for the systematic error.

**B. Performance comparison**

The performance of a policy is not easy to compare: since the positioning error for any policy is a distribution, there is no single parameter that defines which one is better. However, a comparison of the plots in Fig. 4 shows that the threshold-based policy performs better than one considering constant inter-transmission periods: both the mean and the variance of the error are lower, resulting in a more accurate picture of the state of the VANET.

We highlight that the mean inter-transmission time shown on the x-axis of Fig. 4 and all subsequent ones takes medium access effects into consideration. As stated in Sec. III-E the two policies can indeed either transmit more often than set to react to the appearance of new vehicles in the communication range, or their broadcasts can be delayed by the medium access mechanism. Fig. 5 shows the actual average inter-transmission time as a function of the policy parameter. Even the periodic policy does not strictly respect its set period, shown as the purple diagonal in Fig. 5a, it generally transmits more often because of the unscheduled transmissions when new vehicles are detected, but reducing the policy’s inter-transmission period below a certain point leads to delayed transmissions due to the limits of CSMA/CA (e.g., vehicles that try to transmit every...
access to vehicular communications, reducing network load without compromising positioning accuracy would significantly improve the system performance. The same considerations are valid when we use a worst-case approach: Fig. 7 shows the 95th percentile of the position estimation error as a function of the average inter-transmission time, and the patterns we observed in the previous plot are even more evident. The above discussion motivates efforts towards the design of QoI-aware mechanisms that take quality of information, rather than age, as the decision factor for broadcasting.

Finally, the probability of having undetection (i.e., unknown vehicles in the neighborhood) or misdetection events (i.e., vehicles that are believed to be in the area but are outside the communication range) is another important system parameter. If a vehicle is wrong about its neighbors, its local dynamic map will become wrong in unpredictable ways. Fig. 8 shows the sum of these two probabilities, measured as the number of events over the number of neighbors. The policies have similar detection error probabilities, which are mostly due to undetection events: the probability increases with the inter-transmission time, since transmissions are sparser and vehicles can enter the neighborhood without being detected, but it also becomes very high when vehicles transmit very often: the packet losses and transmission delays due to MAC congestion can effectively hide vehicles, causing a significant undetection problem.

V. CONCLUSIONS AND FUTURE WORK

In this work, we have investigated the possibility of improving position estimation and prediction in VANETS by implementing a threshold-based broadcasting strategy. Nowadays, most VANET applications exploit tracking systems in which the target state coincides with the set of the vehicle positions. To avoid the decay of information, such systems need to be very frequently updated with the data collected through inter-vehicular communications. This conflicts with the specific characteristics of the VANET scenario, in which the channel access cannot be centrally managed and transmissions are affected by packet collisions.

To study this trade-off, we built a comprehensive VANET model, which uses SUMO to incorporate realistic vehicle mobility traces in an urban scenario. Our results show that tracking systems based on the CTRA motion model ensure good forecasting performance only for short-time predictions.
We also demonstrated through simulation that the proposed threshold-based strategy, which considers QoI as the decision factor for disseminating positioning information, outperforms a benchmark scheme which broadcasts positioning updates periodically, since it reduces the communication overhead while ensuring the same forecasting performance.

As part of our future work, we will analyze the relation between the optimal system performance and the broadcast strategy settings, so that vehicles can autonomously adapt their behavior according to the network dynamics. We will also improve our model framework by implementing congestion control mechanisms. Finally, we are interested in developing more advanced communication strategies, e.g., by exploiting ML targeting improved tracking accuracy.

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