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# A localization algorithm based on V2I communications and AOA estimation

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***Abstract*—Motivated by safety applications in urban vehicular scenarios, where GPS does not typically provide the required positioning accuracy, a GPS-free localization technique that exploits vehicle-to-infrastructure communications is proposed. In particular, it provides for a vehicle to opportunistically use the beacon packets received from a roadside unit (RSU) in order to obtain estimates of their angle of arrival. Such estimates, together with the RSU's position information within beacon packets, are fed to a weighted least squares algorithm that aims at localizing the vehicle. The algorithm tries to take advantage of reliable measurements typically collected close to the RSU — where a very high signal-to-noise ratio and favorable geometrical conditions yield an accurate angular resolution — while keeping robustness against multipath phenomena. Simulation results show the effectiveness of the proposed technique.**

***Index Terms*—positioning, angle of arrival (AOA), vehicular ad-hoc network (VANET), vehicle-to-infrastructure (V2I).**

## I. INTRODUCTION

ROAD safety applications are emerging as an important feature of intelligent transportation systems (ITS). Such applications require that the vehicle position is accurately determined [1]. The global positioning system (GPS) is widely used for localization; however, as recent studies [2] show, the accuracy and availability of the GPS signal cannot always meet the requirements of crucial position-based applications, particularly, in dense urban environments, because of satellite visibility interruption, vehicle dynamics, and local errors (e.g., receiver noise and multipath) [3]. Preliminary research efforts, e.g., [4], [5], [6], have tackled this problem by focusing on standalone positioning systems that combine GPS data with additional measurements gathered from kinematic sensors available on board (Dead Reckoning, INS, etc.).

In recent years, vehicular ad-hoc networks (VANETs) [7] have been proposed by the automotive research community as a mean to realize a connected road environment where vehicles and infrastructure components can communicate to improve their location awareness [8], [9], [10], [11].

In this paper, we propose a GPS-free positioning technique for vehicle localization in urban environments. By exploiting vehicle-to-infrastructure (V2I) communications — in particular, the beacon packets transmitted from a roadside unit (RSU) in a VANET — the vehicle implements a weighted least squares (WLS) localization algorithm. In contrast to most positioning algorithms, where radio-ranging techniques such as received signal strength (RSS), time of arrival (TOA), and time difference of arrival (TDOA) are considered, we exploit estimates of the angle of arrival (AOA) obtained from an $M$-element uniform linear array (ULA). The use of ULAs is not completely new in the vehicular context. In [12], for instance, authors suggest the adoption of smart antennas to improve VANET communication performance via beamforming. However, to the best of our knowledge, the application of AOA for GPS-free localization in the V2I VANET framework is novel. The key idea is that AOA estimates can bring valuable information for positioning, especially close to the RSU, where a very high signal-to-noise ratio (SNR) and favorable geometrical conditions yield an accurate angular resolution. Exploiting such information requires to suitably weight the measurements collected along the trajectory, coping at the same time with multipath phenomena which inject a significant amount of variability in the received signal. The WLS algorithm we designed is effective to this aim and can outperform GPS-based localization in urban environments. Results are demonstrated through a realistic modeling that takes into account all relevant channel effects.

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## II. PROBLEM FORMULATION

We assume as reference scenario a VANET deployed along a given road segment with a single-lane width equal to $L$ meters, belonging to an urban canyon environment. In particular, two nodes are present: an RSU $R$ placed on the roadside and a vehicle $V$ which is traveling along an arbitrary trajectory. As mentioned, we are concerned with the problem of vehicle localization by exploiting V2I cooperation. Without loss of generality, we restrict our attention to planar localization. Fig. 1 depicts the reference scenario.

Let $\boldsymbol{p}_V(t_0) = [x_V(t_0)\ y_V(t_0)]^T$ (where $^T$ is the transpose operator) be the vehicle position at time instant $t_0$ which triggers the processing of the broadcast beacon packets (for the sake of simplicity, in the following $t_0$ corresponds to a given position of the vehicle). Moreover, let $\boldsymbol{p}_V(t_k) = [x_V(t_k)\ y_V(t_k)]^T$ the vehicle position at a certain time instant $t_k$ (relative to the $k$-th received beacon packet $k \geq 1$), $\theta_k$ the corresponding AOA, and $\boldsymbol{p}_R = [x_R\ y_R]^T$ the known fixed position of the RSU[1]. For a sufficiently high beacon packet rate (e.g., $f_{RSU} = 10$ Hz, which is typical for safety applications) it is reasonable to assume that the velocity of the vehicle

[1]To simplify the exposition, we neglect possible packet losses.

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remains approximately constant during each time interval (e.g., 100 ms for $f_{RSU} = 10$ Hz); thus, $[v_x(t_k)\ v_y(t_k)]^T$ represents the velocity vector for $t \in [t_k, t_{k+1})$, read from an onboard odometer at time $t_k$, $k \geq 0$. As a consequence, the following kinematic model can be adopted for $k \geq 1$:

$$\boldsymbol{p}_V(t_k) = \begin{bmatrix} x_V(t_k) = x_V(t_0) + \sum_{j=1}^{k} v_x(t_{j-1})(t_j - t_{j-1}) \\ y_V(t_k) = y_V(t_0) + \sum_{j=1}^{k} v_y(t_{j-1})(t_j - t_{j-1}) \end{bmatrix}. \tag{1}$$

Two stages are involved in the localization process: AOA estimation and position estimation. In the first stage, AOA measurements are computed by vehicle $V$ for each received beacon packet. In the second stage, the AOA measurements and the RSU known position (included in each beacon packet) serve as input for the estimation of the vehicle position.

Looking at Fig. 1, the AOA can be expressed as:

$$\theta_k = \arccos\left(\frac{\|\boldsymbol{p}_V(t_k) - \boldsymbol{p}_c(t_k)\|}{\|\boldsymbol{p}_V(t_k) - \boldsymbol{p}_R\|}\right) \tag{2}$$

where $\boldsymbol{p}_c(t_k)$ is the intersection point between the vehicle trajectory in $[t_k, t_{k+1})$, assuming approximately constant velocity in the small time interval, and the normal line passing through the RSU position. It is not difficult to show that

$$\boldsymbol{p}_c(t_k) = \begin{bmatrix} x_c(t_k) = \frac{u(t_k)m(t_k)}{1+m^2(t_k)} \\ y_c(t_k) = y_V(t_k) + \frac{u(t_k)m^2(t_k)}{1+m^2(t_k)} - m(t_k)x_V(t_k) \end{bmatrix} \tag{3}$$

where $u(t_k) = y_R - y_V(t_k) + m(t_k)x_V(t_k) + x_R/m(t_k)$ and $m(t_k) = \frac{v_y(t_k)}{v_x(t_k)}$ corresponds to the vehicle heading.

As mentioned, the proposed solution is based on an $M$-element ULA, orthogonal to the vehicle heading, used for the signal acquisition. In particular, the incident signal, which takes into account the channel effects (path loss, fading, and shadowing), is represented in amplitude and phase by the complex quantity $s(t_k) \in \mathbb{C}$ at time $t_k$, so that the received signal $\boldsymbol{r}$ at time instant $t_k$, $\boldsymbol{r}(t_k) \in \mathbb{C}^{M\times 1}$, can be written as:

$$\boldsymbol{r}(t_k) = \boldsymbol{a}(\theta_k)s(t_k) + \boldsymbol{n}(t_k)$$

where $\boldsymbol{a}(\theta_k) = [1\ \mathrm{e}^{j\beta D \sin\theta_k}\ \cdots\ \mathrm{e}^{j(M-1)\beta D \sin\theta_k}]^T$ is the related steering vector, $\boldsymbol{n}(t_k) \in \mathbb{C}^{M\times 1}$ is the additive white Gaussian noise, $\beta = 2\pi/\lambda$ is the incident wave number, $\lambda = c/f_c$, $f_c$ is the carrier frequency, and $D = \lambda/2$ is the ULA inter-element spacing. This received signal serves as input for the AOA estimation. Several algorithms are available in the literature for this task, namely the multiple signal classification (MUSIC) [13], the ESPRIT [14], and numerous variants. The performance of such algorithms depend on some basic parameters such as SNR of the received signal, number $M$ of antennas in the uniform linear array, and number $K$ of snapshots (i.e., samples of the received signal at different antennas). In this paper we will refer to the MUSIC algorithm.

## III. Resolution Approach

The innovative contribution of our work resides in the proposed position estimation algorithm. Assuming that the velocities of the vehicle are known — estimates from the onboard odometer will be used in practice, so we will include velocity errors in the simulations of Section IV — the only parameter to be estimated is the (initial) position $\boldsymbol{p}_V(t_0)$. Measurements $\hat{\theta}_1, \ldots, \hat{\theta}_k$, available up to time $t_k$, result from the application of the MUSIC algorithm each time a new beacon packet has been received, i.e.,

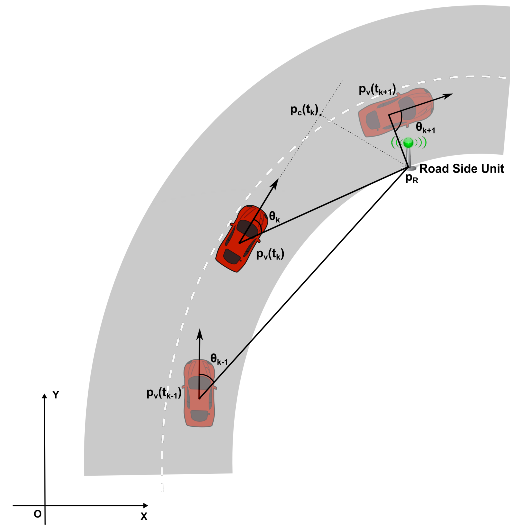


Fig. 1. Model of a vehicle moving along an arbitrary trajectory.

$$\hat{\theta}_i = \theta_i + e_i$$

with $e_i$ denoting the estimation error for $i = 1, \ldots, k$. If the distribution of $e_i$ were known, under independence assumption, the estimation problem could be addressed by a maximum likelihood (ML) approach, namely

$$\hat{\boldsymbol{p}}_V(t_0) = \underset{\tilde{\boldsymbol{p}}_V(t_0)}{\arg\max} \prod_{i=1}^{k} f(\hat{\theta}_i | \tilde{\boldsymbol{p}}_V(t_0)) \tag{4}$$

where $f(\hat{\theta}_i | \tilde{\boldsymbol{p}}_V(t_0))$ denotes the probability density function of $\hat{\theta}_i$ given an initial position $\tilde{\boldsymbol{p}}_V(t_0) = [\tilde{x}_V(t_0)\ \tilde{y}_V(t_0)]^T$.

In addition, for Gaussian-distributed errors, i.e., $e_i \sim \mathcal{N}(0, \sigma_i^2)$, maximization of the likelihood in (4) would result in the following minimization problem:

$$\hat{\boldsymbol{p}}_V(t_0) = \underset{\tilde{\boldsymbol{p}}_V(t_0)}{\arg\min} \sum_{i=1}^{k} \left\{ \log(2\pi\sigma_i^2) + \frac{1}{\sigma_i^2}(\hat{\theta}_i - \tilde{\theta}_i)^2 \right\} \tag{5}$$

where $\sigma_i^2$ is the variance of the $i$-th AOA estimate and $\tilde{\theta}_i$ is given by (2) (using (1) and (3)) with the true (unknown) initial position $\boldsymbol{p}_V(t_0)$ replaced by the optimization variable $\tilde{\boldsymbol{p}}_V(t_0)$. Based on the estimated initial position from (5), the whole trajectory would be retrieved through the kinematic model (1).

The algorithm above requires that the $\sigma_i^2$s are known; unfortunately, there is no simple and practical way to obtain such an information. Moreover, the ML estimator works under the assumption of Gaussian distributed measurement noise $e_i$, which is not guaranteed to be always in force. In order to tackle these drawbacks, we propose a WLS estimator, which is tantamount to neglecting the logarithmic term in eq. (5) while choosing suitable weights $w_i$ as surrogate of $1/\sigma_i^2$, i.e.,

$$\hat{\boldsymbol{p}}_V(t_0) = \underset{\tilde{\boldsymbol{p}}_V(t_0)}{\arg\min} \sum_{i=1}^{k} w_i \left(\hat{\theta}_i - \tilde{\theta}_i\right)^2. \tag{6}$$

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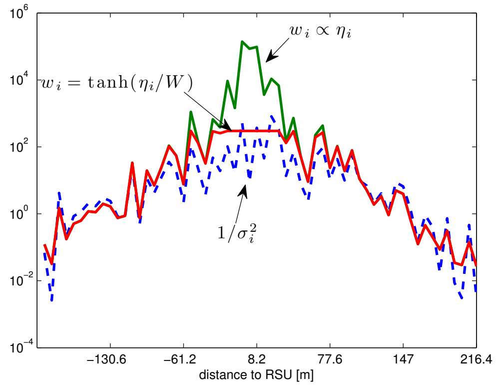


Fig. 2. Comparison between $1/\sigma_i^2$, weights (7), and proposed weights (9).

In a first attempt, one may choose such weights as

$$w_i \propto \eta_i = \hat{\text{SNR}}_i \sin^2 \hat{\theta}_i \tag{7}$$

where $\hat{\text{SNR}}_i$ is the SNR measured at time instant $t_i$ from the received signal samples. The rationale for (7) stems from the fact that, in additive white Gaussian noise (AWGN), the Cramér-Rao lower bound (CRLB) for AOA estimation is [15]

$$\text{CRLB}(\theta) \propto \frac{1}{\text{SNR} \sin^2 \theta}. \tag{8}$$

In other words, $\eta_i$ can be interpreted as a reliability coefficient associated with the $i$-th AOA estimate, i.e., greater weights are given to more reliable data. However, in fading channels, $\eta_i$ exhibits a span several orders of magnitude greater than the actual variance, with large deviations as the vehicle approaches the RSU. To clarify this point, Fig. 2 shows (for a linear, constant speed trajectory) the reciprocal of AOA estimation variance ($1/\sigma_i^2$) computed via Monte Carlo simulation, together with (7) for a typical channel realization[2] — the latter renormalized so as to match the scale of the former. It is immediate to observe that $\eta_i$s are too optimistic about observations gathered near the RSU, i.e., they give them too much weight in the cost function, practically reducing the sample to those observations once they are collected. This weakens the robustness of the estimation because, as mentioned, $\eta_i$ is inversely proportional to the variance of AOA estimates only for AWGN channel; conversely, in presence of fading, there is a random fluctuation that cannot be exactly caught by $\eta_i$, making a few observations dominate the whole sample even when they are less reliable due to adverse multipath conditions.

To avoid such a drawback, we pass $\eta_i$ through a nonlinearity that saturates large weights, preventing a too peaked weight profile, as shown in Fig. 2 which reports the curve of

$$w_i = W \tanh(\eta_i/W) \tag{9}$$

where $W$ is a design parameter (here $W = 300$). It is worth remarking that the introduced saturation makes the weight profile more similar to the actual curve of inverse variance $1/\sigma_i^2$; however, this cannot be exploited to implement the ML algorithm since the unknown proportionality factor, unnecessary in the WLS function (6), is not irrelevant in the likelihood function (5).

[2]Details on the implemented channel are given in Section IV.

## IV. Simulation Model and Results

To validate the proposed approach we simulate several phenomena and non-idealities that are found in realistic urban scenarios. At each of 1000 trials of the Monte Carlo simulation, we consider a road segment of length 400 m with single-lane width $L = 5$ m, mildly bending to the right, where the vehicle $V$ proceeds at uniformly accelerated motion for one third of the path (from 25 km/h to 50 km/h in modulus), then proceeds at constant speed modulus 50 km/h (urban limit) for the second third, and finally decelerates until reaching the original 25 km/h. This pattern is aimed at simulating the possible variations typical of a dynamic urban scenario. $t_0$ corresponds to the vehicle position at the beginning of the considered road segment. The RSU $R$ is placed 300 m ahead (see Fig. 1). The $f_{RSU}$ send frequency is set to 10 Hz. Following the ETSI standard [16], a carrier frequency $f_c = 5.9$ GHz, a transmit power $P_{T,dB} = 18$ dBm, and a bandwidth $B = 10$ MHz have been assumed. The propagation on the wireless channel has been modeled according to the specifications provided in a ETSI technical report [17]. In particular, the path loss is described by the *dual slope model* which evaluates the signal attenuation at a certain distance $d$ from the transmitter according to the following formula:

$$L_{PL,dB}(d) = \begin{cases} L_{F,dB}(d_0) + 10\gamma_1 \log_{10}\left(\dfrac{d}{d_0}\right), d_0 < d \le d_c \\ L_{F,dB}(d_0) + 10\gamma_2 \log_{10}\left(\dfrac{d}{d_c}\right) \\ + 10\gamma_1 \log_{10}\left(\dfrac{d_c}{d_0}\right), \qquad d > d_c \end{cases}$$

where $d_0$ is the *reference distance*, $d_c$ is the *cutoff distance*, $L_{F,dB}(d_0)$ is the signal attenuation in free space (Friis propagation model [18]) at the distance $d_0$, and $\gamma_1$, $\gamma_2$ are two attenuation coefficients. According to [17], the values of the parameters are set to $d_0 = 10$ m, $d_c = 80$ m, $\gamma_1 = 1.9$, and $\gamma_2 = 3.8$. Shadowing effects are also taken into account through a lognormal factor with standard deviation 6 dB.

In addition, a Rayleigh or Rice fast fading is considered, to model the non-line-of-sight (NLOS) or LOS condition of the link, respectively. Links are randomly assigned to NLOS with probability 0.5. More precisely, the fading term is given by

$$Z(t_k) = X(t_k) + jY(t_k) \sim \mathcal{CN}(\rho\delta_{\ell 1}, 2\sigma_\ell^2)$$

and $\delta_{\ell 1}$ is the Kronecker symbol. As to $\ell$, $\ell = 0$ (resp., $\ell = 1$) implies a Rayleigh (resp., Rice) random variable; moreover, for the Ricean fading $\rho$ was set such that $10 \log_{10} \frac{\rho^2}{2\sigma_1^2} = 6$ dB. Therefore, the incident signal $s(t_k)$ can be equivalently rewritten as:

$$s(t_k) = \alpha_{\text{SNR}}(t_k) Z(t_k)$$

where $\text{E}[|Z(t_k)|^2] = 1$ and $\alpha_{\text{SNR}}(t_k)$ takes into account the lognormal shadowing; the SNR at time $t_k$ is given by

$$\text{SNR}_k = \frac{\text{E}\left[s^*(t_k)\, \boldsymbol{a}^H(\theta_k) s(t_k) \boldsymbol{a}(\theta_k)\right]}{N_0} = M \frac{\text{E}\left[\alpha^2_{\text{SNR}}(t_k)\right]}{N_0}$$

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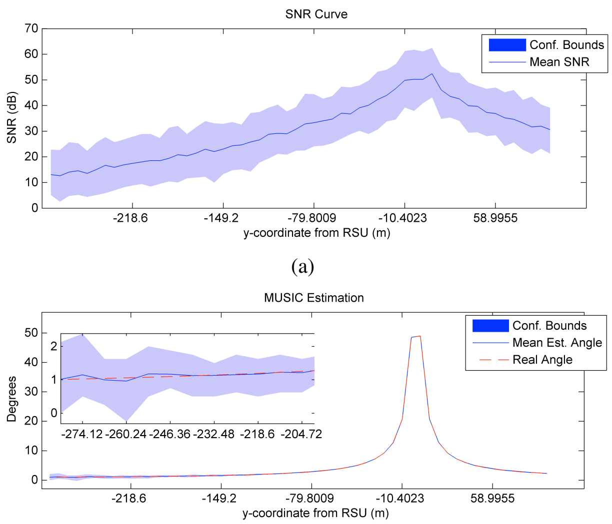


(a)

(b)

Fig. 3. Curves of (a) SNR and (b) true/estimated AOA versus distance from RSU (in $y$ coordinate).

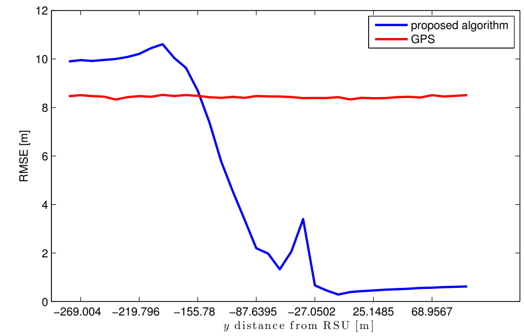


Fig. 4. Performance comparison (root mean square error) between the proposed WLS algorithm and the GPS system in the considered scenario.

with $\mathrm{E}\left[\alpha^2_{\mathrm{SNR}}(t_k)\right]$ computed according to the above path loss model and $N_0$ the receiver noise figure, i.e., $N_0 = k_B T_0 B$, $k_B$ being the Boltzmann constant and $T_0$ the standard noise temperature. For AOA estimation we adopt the MUSIC algorithm with $M = 4$ antennas and $K = 20$ snapshots.

To realistically reproduce the GPS error on localization data, an autoregressive model of type AR(1) has been used. This originates from the fact that, as shown in [19], the pseudoranges error components (i.e., ephemeris, ionosphere, troposphere, and multipath) are highly correlated; therefore, one can reasonably assume a significant correlation in the GPS position error, especially at moderate speed and high reading rate, which is typical in safety applications in urban scenario as considered here. Assuming, without loss of generality, that the transversal error and the longitudinal error statistics are the same, the GPS error at time $t_k$ can be modeled as:

$$\left[\begin{array}{c}\Delta X(t_k)\\ \Delta Y(t_k)\end{array}\right] = \phi\left[\begin{array}{c}\Delta X(t_{k-1})\\ \Delta Y(t_{k-1})\end{array}\right] + \left[\begin{array}{c}\epsilon_x(t_k)\\ \epsilon_y(t_k)\end{array}\right]$$

where $\Delta X(t_k)$ and $\Delta Y(t_k)$ are the GPS errors along the $x$ and $y$ axis respectively, $\phi = 0.9$ is the one-lag correlation coefficient, $\epsilon_x(t_k)$, $\epsilon_y(t_k) \sim \mathcal{N}(0, \sigma^2_\epsilon)$ are process noise, and $\sigma^2_\epsilon = \left(1 - \phi^2\right)\sigma^2$ where $\sigma = 4.5$ meters is the assumed GPS error standard deviation for the urban environment.

Additionally, a Gaussian variable with zero mean and standard deviation equal to $10\%$ of the velocity is introduced to model the odometer measurement error.

Fig. 3(b) reports the AOA estimates (mean and 5-95th percentiles confidence interval) obtained by means of the MUSIC algorithm. It is immediate to observe that the values of angle estimates increase as the vehicle approaches the RSU and reach the relative peak at the RSU crossing. The curve exhibits a little dispersion of values in correspondence of tails, as highlighted in the inset. This effect is due to the shadowing and multipath fading phenomena that determine SNR realizations as low as a few dB at large distance (see Fig. 3(a)), which have a detrimental impact on AOA estimation when the vehicle is far from the RSU.

Finally, Fig. 4 shows a comparison between the GPS and WLS estimator in terms of RMS error (RMSE). Remarkably, the proposed method achieves a high level of accuracy in the position estimation starting from more than a hundred meters before crossing the RSU. This behavior is a direct consequence of the increase in the size and quality of the available AOA measurements. The performance then stabilizes around smaller values of errors, significantly outperforming the GPS accuracy. It is worth noticing the increasing trend in the WLS curve after the crossing. This is due to the well known effect of error integration which characterizes the inertial sensors, such as the odometer, and suggests that the localization accuracy remains acceptable until the integrated inertial error grows too much; at that point, however, another RSU will be likely detected[3], allowing the vehicle to perform a new localization procedure. Furthermore, the algorithm — here presented in a single-RSU setting for the sake of simplicity — can be easily extended to process packets from multiple RSUs, which may further increase the performance.

## V. CONCLUSIONS

We have proposed and assessed a GPS-free localization technique. It is motivated by safety applications in urban vehicular scenarios, where GPS does not typically provide the required positioning accuracy. The main novelty of the paper is a weighted least squares localization algorithm that is fed by AOA measurements computed by the vehicle over its trajectory. To this end, the vehicle estimates the angle of arrival of impinging packets from an RSU in known position resorting to an ULA and implementing the MUSIC algorithm. The assessment in a simulated, though realistic scenario compliant with the ETSI standard for VANETs, shows that the algorithm can outperform GPS-based localization. Although the complexity of the proposed algorithm is compatible with the current DSP technology, our ongoing work is aimed at revisiting it within a recursive estimation framework, which should reduce its computational cost.

[3]In the VANET framework envisioned for Smart Cities, RSU nodes will be available with regularity, placed on traffic lights, at street corners, and possibly even on all street lights.

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