An Assessment on the Use of Stationary Vehicles as a Support to Cooperative Positioning

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Abstract—In this paper, we consider the use of stationary vehicles as tools to enhance the localisation capabilities of moving vehicles in a VANET. We examine the idea in terms of its potential benefits, technical requirements, algorithmic design and experimental evaluation. Simulation results are given to illustrate the efficacy of the technique.

Index Terms—Cooperative Positioning, V2V Communications, Stationary vehicles, Parked vehicles, queue.

I. INTRODUCTION

Cooperative positioning (CP) for vehicular networks is a very topical problem. Exact road positioning is viewed as a key enabler of services such as road pricing (lane pricing), lane prioritisation for special vehicles (electric vehicles), and is also recognised as a key technology to enable autonomous driving. In this context, CP is being viewed as a means of overcoming the shortcomings of traditional Global Navigation Satellite systems (GNSS) for vehicular applications.

There already exist a range of CP techniques for realising on-road localisation. Many of these techniques rely heavily on support from dedicated infrastructure. Examples include Differential Global Positioning Systems (DGPS), Real Time Kinematic (RTK) positioning, and Assisted Global Positioning Systems (A-GPS). There are many excellent papers on CP, and ideas for realising this technology have appeared in various areas. The interested reader is referred to any one of the excellent papers on this topic; in particular, see the recent survey paper [1].

The main contribution of this paper is to assess the potential of stationary vehicles to support the current CP systems in a Vehicular Ad-hoc Network (VANET). This idea follows recent works that have recognised the ability of suitably equipped stationary vehicles, in the absence of any time constraints, to pinpoint their own locations in a precise manner, and have recommended their usage as general service delivery platforms [2]. We shall show that such a novel idea has the potential of greatly improving current CP systems, without requiring any dedicated infrastructure, and at the same time opening a new market for vehicle owners and car manufacturers to monetise vehicles in a non-traditional manner. Our vision imagines that vehicle owners make their vehicles available for such applications in exchange for monetary compensation, or for access to privileged services and facilities (e.g., parking spots).

Our paper is organised as follows. In Section II of the paper, we examine the state-of-the art concerning the use of stationary vehicles in providing VANET-related services. In Section III, we provide a discussion to assess the potential of stationary powered-on and powered-off vehicles in Intelligent Transportation Systems (ITS) applications. Section IV formally describes how stationary vehicles can be integrated in CP applications in practice, and some experimental evaluations are presented in Section V. Finally, Section VI concludes the paper.

II. STATE OF THE ART

Cooperative positioning is a topic that is of interest in many communities. As we have mentioned, the interested reader is referred to the excellent survey covering CP technologies in ITS applications [1], and to the EU Funded Project TEAM [3] which also covers related technologies and areas. We shall not repeat this discussion here. Rather, we shall focus on the use of stationary vehicles to provision services, as work on this topic is less well-known but relevant for the research reported in this paper [2].

Information collected from stationary vehicles (i.e., vehicles with time-invariant position) has been used to study the performance of VANETs. For example, information from stationary vehicles has been used to accurately determine the stop-delay or idling times at road junctions. This information is then used to enhance road safety by detecting stop-line violations at signalised/controlled intersections or stopped vehicles inside tunnels, or to determine the availability of free parking spaces [4]. In the past, stationary vehicles have been mostly considered as passive nodes, and the relevant information was collected by using passive techniques such as proximity detectors and cameras. However, thanks to the advent of modern ITS technologies allowing vehicle-to-vehicle/infrastructure (V2X) communication and cooperative awareness, the use of stationary vehicles as active nodes to enhance services for VANETs is becoming a topic of great relevance. Some of the aforementioned services include: the improvement of multi-channel operations [5], [6], the use as relays in content downloading and distribution [7], [8], and mitigation of signal attenuation in ITS applications [9].

Two main approaches can be distinguished when using stationary vehicles: the use of (i) powered-on vehicles, such as vehicles stopped in a queue; and (ii) the use of powered-off

vehicles, such as parked vehicles. While the usage of powered-on stationary vehicles does not pose any particular technical requirement in the provision of new services, an obvious concern associated with parked vehicles is battery discharge; we shall have more to say about this shortly. An application highlighting the use of powered-on stationary vehicles is presented in [5] and [6]. In [9], parked cars are postulated as relays in a multi-hop beaconing approach: they do not transmit their own information, but only retransmit information from moving vehicles. Battery consumption concerns are investigated in [10], where the authors present a study on the impact of the communication system and processing unit on energy consumption. The main conclusion is that the power demanded from the communication system and the processing unit is not particularly critical. Specifically, given a fully charged battery, services can be provided for a significant time before a critical point of the charge level is reached (we shall have more to say on this in the next section).

III. STATISTICS OF STATIONARY VEHICLES TO SUPPORT CP APPLICATIONS

A stationary vehicle without any hard time constraint for localisation, with a V2X communication system, and with access to Augmented GNSS (A-GNSS) based position estimation such as DGPS/AGPS [11], can easily fix its location precisely (with up to 10 cm of accuracy for Post-process DGPS). Thus it can become an anchor (anchor node) and, by broadcasting its location, it can help vehicles whose position is not known precisely (blind nodes) to localise themselves. Vehicles without hard time constraints include vehicles that are stationary for a long enough time, for possibly different reasons (e.g., traffic-light queues, bottlenecks, traffic jams and parked vehicles). We now give some basic statistics and facts to support the potential of stationary vehicles for CP applications.

1) Battery issues: In the case of parked vehicles, the main technical challenge is keeping the on-board communication systems switched on when the vehicle is powered off. However, recent studies have shown that this is not a critical issue. In particular, by accessing a maximum of 10% of the charge of a 480 Wh car's battery, it has been recently demonstrated that a 1W on-board unit can be constantly powered for up to 2 days [9].

2) Availability of stationary powered-on vehicles: The average time spent in stop/idle mode between two consecutive intersections in urban scenarios can reach up to 50% of the whole time spent along the arterial road [12]. Idle times become even larger at pm rush hours as people drive in a more relaxed way since they feel that they do not have strong time constraints in returning home, which causes longer queues at signalised/controlled intersections [13]. Accordingly, these vehicles can be used with more priority for positioning applications.

3) Estimation of area occupancy of stationary powered-on vehicles: In order to evaluate the potential impact of sta-

tionary powered-on vehicles on CP applications, it is important to evaluate the mobility area that is actually occupied by such vehicles with respect to the overall mobility network. As a support to our analysis, we use the statistics of the vehicular flows that are stuck or very slowly moving in the traffic (i.e., stationary powered-on vehicles), collected from the area of Dublin centre, Ireland, from AA Roadwatch (a service offered by AA Ireland[1]) as shown in Fig. 1.
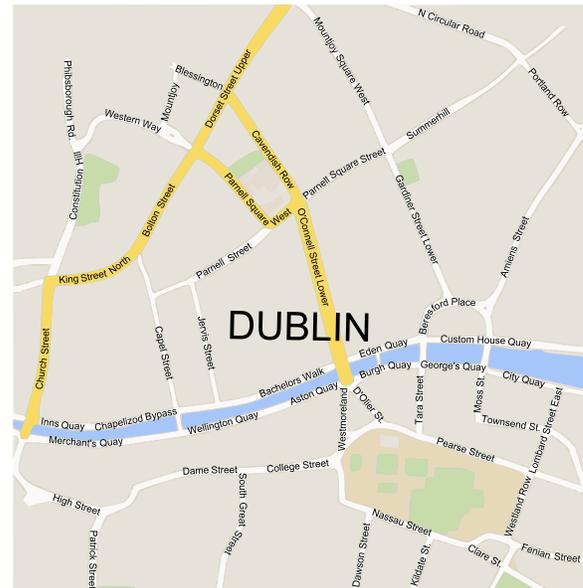
Fig. 1. Roads in Dublin city center monitored between 16th-23rd June, 2014 using AA Roadwatch
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Data were collected two times per day between 16th-23rd June, 2014: one measure at the lunchtime rush hour (at 1 pm), and one at the evening rush hour (at 7:30 pm); the results are reported in Table I. From Table I it is possible to conclude that, in the context of this small survey, an average of 22.64% and 15.71% of the main streets in Dublin's city centre are occupied by stationary powered-on vehicles at the rush hours of working days. Even though numbers decrease in the weekends to 14.36% (at lunchtime), and to 13.03% (in the evening), such numbers suggest the benefit of providing support for the localisation of blind vehicles during rush hours. In addition, note that the covered area is concentrated around intersections, as shown with black curves in Fig. 2, where most of the cars (and thus, of the blind nodes as well) are also concentrated.

4) Availability of stationary powered-off vehicles: A car is typically parked on average up to 23 hours a day [14], [15], and usually outdoor [7], [9]. For example, in a recent study of 61,000 daily parking events in Montreal City [16], 69.2% of all parked cars were parked on-street and 27.1% were parked in outside parking lots, while only 3.7% were parked in interior parking facilities, and the average duration of on-street parking was 6.64 hours. Further, current predictions concerning regulated parking spaces claim

[1]http://www.theaa.ie/AA/AA-Roadwatch.aspx

Day	Rush hour	
	Lunchtime	Evening
Monday	18.39%	13.07%
Tuesday	17.68%	16.17%
Wednesday	25.03%	14.58%
Thursday	23.49%	20.67%
Friday	28.63%	14.07%
Saturday	14.95%	9.72%
Sunday	13.77%	16.33%
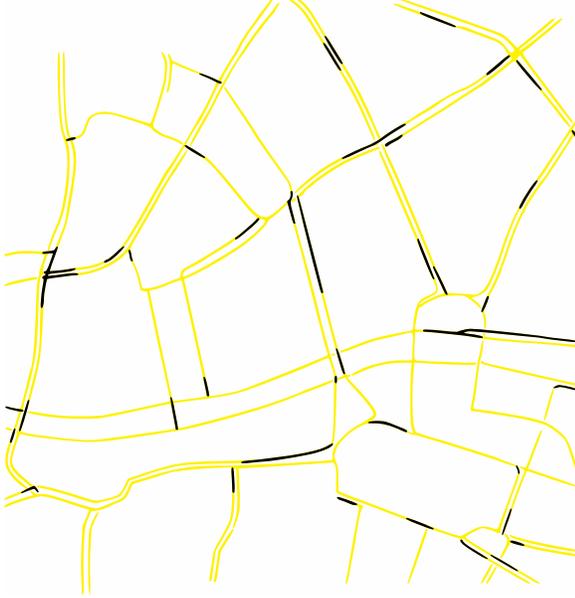
Fig. 2. Measured data on June 17th, 2014, at the evening rush hour. Black sections: occupied by stationary powered-one vehicles; yellow sections: free traffic.

that the average portion of on-street parking spaces, as a percentage of the overall total number of parking spaces, will be 30.17% (with up to 56.22% for Italy and 43.30% in Spain) [17]. Thus "parked cars" can be thought of as a (so far) unused and dense sensor network with no power or collection constraints, and whose position can be known very precisely. Consequently, such a network of static nodes can be used to help in solving the CP problem for ITS systems.

TABLE II
THE UNITED STATES FEDERAL COMMUNICATION COMMISSION (FCC)
CLASSIFICATION FOR DSRC DEVICES [18].

Device class	Max. Output Power (dBm)	Communication zone (meters)
A	0	15
B	10	100
C	20	400
D	28.8	1000

5) Estimation of the area covered by stationary powered-off vehicles: The expected size of the area that can be covered by parked vehicles does clearly depend on the specific

technology used to broadcast the required information, and on the amount of cars parked in the area. Table II summarizes the characteristics of the most popular Dedicated Short-Range Communication (DSRC) technologies. For instance, we are going to estimate the area coverage as follows:

1) Identify area of vehicular transit (blue area in Fig. 3.b), referred as $A_{Transit}$;
2) Identify stationary vehicles (black crosses in Fig. 3.b) and their total circular coverage (coloured circles in Fig. 3.b), referred as $A_{Coverage}$;
3) Calculate the intersection between the $A_{Coverage}$ and $A_{Transit}$, referred to as $A_{C \cap T}$.
4) Calculate the ratio between $A_{C \cap T}$ and $A_{Transit}$ as a function of the levels given in Table III.
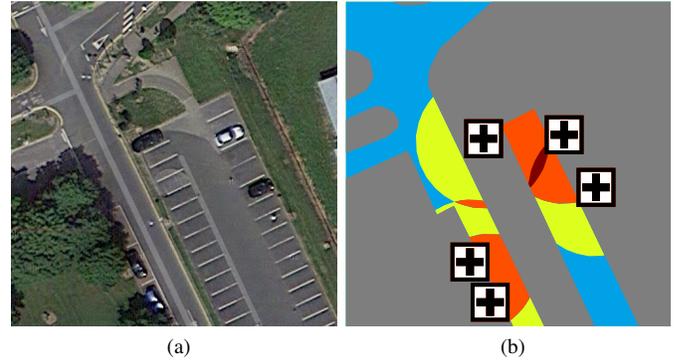
Fig. 3. Illustrative scenario for area coverage estimation: a) selected region, and b) identified areas: vehicular transit (blue), parked vehicles (black crosses), and covered area for a radius equal to 15 m. Color convention for levels of coverage (see Table III): yellow for Level 1, orange for Level 2, and red for Level 3.

TABLE III
PROPOSED LEVELS OF COVERAGE.

Level of coverage	Description
Level 1	Coverage with only 1 stationary car
Level 2	Coverage with only 2 stationary cars
Level 3	Coverage with 3 or more stationary cars

For illustration of this approach, we used top-view images from Google Maps of Maynooth Town (co. Kildare, Ireland) with an image from October 31st 2013. The parked vehicles and the area coverage using the above procedure are shown in Fig. 4 and Fig. 5 respectively, and the coverage percentage is summarised in Table IV.

TABLE IV
POTENTIAL COVERED AREAS FOR THE CASE STUDY. THE 100%
CORRESPONDS TO THE AREAS ALLOWED FOR VEHICULAR TRANSIT.

	Com. zone (meters)	
	15	100
Covered area of Level 3	27.78%	97.02%
Covered area of Level 2	11.98%	0.22%
Covered area of Level 1	14.81%	0.31%
No covered area	45.43%	2.45%

In this simple example, according to Table IV, 27.78% of the allowed area for vehicular transit can be covered using
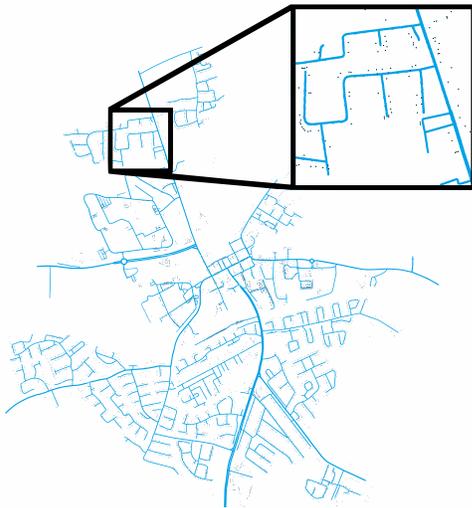
Fig. 4. Allowed area for vehicular transit (blue) and parked vehicles (black) in Maynooth, Co. Kildare, Dublin, using satellite imagery from Google Maps. A total of 4541 vehicles were identified as parked vehicles.

Class-A DSRC devices, and 97.02% using Class-B DSRC devices. Thus, parked vehicles can potentially cover most of the travelling area.

Comment 1: Note that in this study we are not explicitly considering multipath effects and possible shadowing consequences. Rather, we assume a direct line-of-sight between moving and stationary vehicles. In such circumstances, such effects are mitigated [19], [20]. From a practical perspective, this means in the remainder of the paper, we assume mainly short-range communications between vehicles with a communication range of 15 m - the underlying assumption being direct line-of-sight. As we see from Table IV, even with this assumption, the total covered area in our experiments is still significant (more than 54%).

Finally, note that the total coverage is actually greater, once one considers the stationary powered-on vehicles as well. Since, as already remarked, stationary powered-on vehicles can mainly contribute to cover the intersection areas, while stationary powered-off vehicles are usually densely distributed along the roads, in principle a full coverage of the whole urban mobility network can be potentially achieved.

IV. EMBEDDING STATIONARY VEHICLES INTO A CP TECHNIQUE

The objective of this section is to illustrate how any available technique to realise cooperative positioning (e.g., triangulation, trilateration, cooperative estimation) can be improved by further using stationary vehicles.

A. Using a stationary vehicle as an anchor node

A stationary vehicle can act as an anchor node to support the localisation of other vehicles, only after its own position is precisely known. Note that powered-off stationary vehicles (e.g., parked vehicles) do not have hard time constraints for

(a)
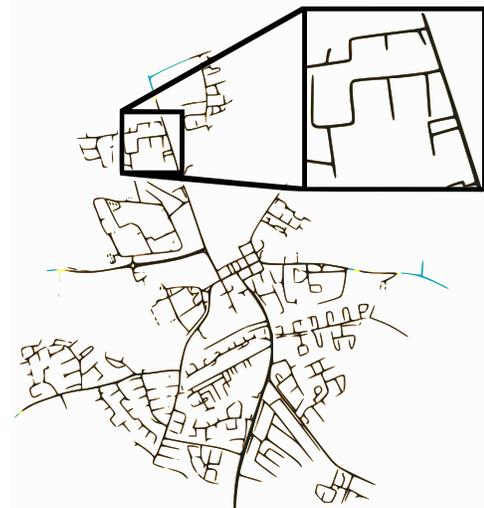
(b)

Fig. 5. Covered areas for the case study using different communication zones: a) 15 m (Class-A DSRC devices), and b) 100 m (Class-B DSRC devices). Color convention for levels of coverage (see Table III): yellow for Level 1, orange for Level 2, and red for Level 3.

localisation, and they can localise themselves in an accurate manner using any (possibly slow) localisation technique. For instance, they can localise themselves using A-GNSS-based position estimation and V2I communication systems, or if they have access to enough information from some nearby anchor nodes via V2V communication, then multilateration can be used for localisation. Once a stationary vehicle has a precise fix on its location, then it can be used as an anchor node to support the CP of other vehicles. Assuming that some stationary vehicles exist, we shall now provide algorithms to localise other vehicles using the stationary vehicles as anchor nodes.

B. Localising blind stationary vehicles

A blind stationary vehicle is a stationary vehicle whose localisation is not yet precise. To localise blind stationary vehicles, the following strategy is adopted:

- If 3 or more anchor neighbours are available:
  - (default option): localise using a CP technique supported by V2V communication to anchor nodes;
  - (back-up option): localise over longer time horizon using blue A-GNSS-based position estimation.
- If 2 anchor neighbours are available:
  - (default option): localise using a CP technique supported by V2V communication to anchor nodes and additional information from other surrounding vehicles (e.g., previous positions/speeds/ranges) to solve ambiguities;
  - (back-up option): localise over longer time horizon using A-GNSS-based position estimation.
- Otherwise:
  - (default option): localise only using A-GNSS-based position estimation.

In addition, a blind powered-off stationary vehicle remains as an inactive node in the VANET always before becoming an anchor. Also recall that a blind stationary vehicle can only become an anchor after having reached a high accuracy in the localisation procedure (e.g., when having access to enough anchors, or via A-GNSS-based position estimation).

Comment 2: The interested reader will notice that some blind nodes will eventually know their position in a more accurate fashion than others, mainly depending on both the quality of the inter-vehicle distance measurements and the specific localisation procedure. However, in the sequel, we shall ignore this transient effect for powered-off stationary cars, and assume that all remaining stationary cars localise themselves accurately and quickly. Only precisely located cars are used as anchors; the effects of different levels of accuracy of anchor nodes is beyond the scope of this present paper.

C. Localising blind moving vehicles

The procedure is similar to that given before. However, in this case, at the end of the localisation process, moving vehicles are not considered as anchor nodes. A blind moving vehicle with access to accurate information from anchor nodes, will become a *pseudo-anchor* node, and will be used with certain priority in the localisation of other vehicles, if needed.

D. Node selection strategy for localisation

A smart selection of the neighbouring nodes for CP can speed up the localisation procedure and mitigate energy requirements, and thus, battery consumption. In practical cases, a large number of anchor nodes can be used for localisation, and strategies to select the "best" subset of nodes have been already investigated in the literature. See for example [21] where an optimal subset of anchor nodes is identified according to a geometric dilution of precision (GDOP) process. Here, we adopt a simple deterministic selection strategy that assigns priorities to anchor nodes, pseudo-anchor nodes and blind nodes respectively. Although in principle any other method for node selection can be used, we use the following procedure.

- Any surrounding car c_i has a priority level p given by

$$p(c_i) = \begin{cases} 1, & \text{if } c_i \text{ is an anchor node,} \\ 2, & \text{if } c_i \text{ is a pseudo-anchor node,} \\ 3, & \text{otherwise (i.e., blind nodes).} \end{cases} \quad (1)$$

where 1 is the highest priority.

Three surrounding vehicles inside the communication zone of the target vehicle are sufficient for the localisation process. Accordingly, the selection strategy has to choose the three "best" neighbours, for which we recommend those with higher priority should be selected first. Given the availability of vehicles with the same priority, then we choose those that are closest to the vehicle to be localised. If fewer than three are available, we choose the highest number of available cars.

E. Integrating stationary vehicles into any CP algorithm

Stationary vehicles have the potential to improve CP algorithms in several ways:

(i) Parked vehicles augment fixed roadside-like infrastructure, and so more accurate and reliable range information is available to moving vehicles. Thus, parked vehicles have the potential to greatly augment *range based-*, *fine-grained-* , *anchor-based-* , *absolute-* , *sequential-*, and *distributed CP algorithms.*

(ii) Incorporating parked vehicles into CP algorithms implies that even when other moving vehicles or dedicated infrastructure are not available for positioning, cooperative positioning may still be possible by using parked vehicles. This greatly helps a host of CP algorithms, including *range-free-*, *coarse-grained-*, *anchor-free-*, *relative-*, *multi-hop-*, *concurrent-*, and *centralised CP algorithms* (the latter in small-scale networks).

(iii) As parked vehicles are usually in close proximity to the road, there might be an advantage with respect to noise properties over dedicated infrastructure for: *single-hop-*, *line-of-sight-*, *Bayesian CP algorithms*, and *standard/modern estimation algorithms for CP.*

(iv) Finally, localised stationary vehicles can help to localise other stationary vehicles with no position information. Thus, they augment *CP algorithms for static networks.*

V. Performance evaluation

In order to evaluate the proposed approach, we used simulations in SUMO, a popular mobility simulator[2]. In the following, we consider both stationary powered-on and powered-off cars represented by not moving cars in traffic and parked cars, respectively. Moreover, DGPS/AGPS are assumed to be running in parallel on each vehicle (see Section IV-B), and we also assume that all parked vehicles are available to be used as anchor nodes from the beginning of all simulations.

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[2]www.dlr.de/ts/sumo/en/, commonly used in the ITS community

A. CP algorithms to be evaluated

The first CP algorithm to be evaluated is a decentralised estimation algorithm based on Guaranteed Convergence Particle Swarm Optimiser (GCPSO) [22], using inter-vehicle distance measurements to minimise the cost function

$$f\left(\hat{\mathbf{x}}_{i,t}\right) = \sum_{\forall j \in S} \|d_{ij,t} - \|\hat{\mathbf{x}}_{i,t} - \mathbf{x}_{j,t}\|\|^2 + \|\hat{\mathbf{x}}_{i,t} - T_s \mathbf{v}_{i,t-1}\|^2,$$

where $\hat{\mathbf{x}}_{i,t}$ is the estimate of the real (unavailable) 2D position $\mathbf{x}_i$ of car i at time step t, S is the set of all one-hop neighbour cars of car i inside its communication zone, $\mathbf{x}_j$ is the available 2D position for car j shared to car i, $\mathbf{v}_i$ is the 2D speed of car i, T_s is the sampling time for data collection, and d_{ij} is the measured distance between cars i and j, where j is the index of a car in S. Thus, this is a distributed, range-based CP algorithm based on a heuristic optimiser.

The second CP algorithm to be evaluated is the conventional Extended Kalman Filter (EKF) [23]. The implementation in [23] fuses inter-vehicle distance measurements and vehicle kinematics (speed information), to obtain a sequential Bayesian estimation of the cars' position. Thus, this is a distributed, range-based, Bayesian CP algorithm. For a detailed description of this algorithm please refer to [23].

In our simulations we use the following parameter settings and make the following assumptions:

- General assumptions [19], [23]:
  - sampling time $T_s = 1s$, ranging-error and GPS noise assumed as zero-mean Gaussian variable with standard deviations $\sigma_{\mathbf{R}} \in \{0.2, 4\}$ and $\sigma_{GPS} = 6$, respectively;
- GCPSO [22]:
  - number of particles = 4, number of iterations = 20, $s_c = 15$, $f_c = 5$, $\rho = 1$, $c_{1,2} = 2$, linearly decreasing inertia weight from 0.9 to 0.2, minimum fitness value for stopping criteria = 0, initial swarm: 2 particles at the position of the neighbour with the highest priority and 2 particles at $T_s \mathbf{v}_{i,t-1}$;
- EKF [23]:
  - $\mathbf{Q}_{k-1} = \sigma_{\mathbf{Q}}^2 \mathbf{I}$, $\mathbf{R}_k = \sigma_{\mathbf{R}}^2 \mathbf{I}$, $\mathbf{\Gamma}_{k-1} = \sigma_{\mathbf{\Gamma}}^2 \mathbf{I}$, with $\mathbf{I}$ the identity matrix with proper dimensions, and with $\sigma_{\mathbf{\Gamma}} = 0.5$, $\sigma_{\mathbf{Q}} = 2$ and $\sigma_{\mathbf{R}}$ as in general assumptions.

All the previous assumptions, and the choice of parameters, are consistent with those used in [19], [22], [23], where $\sigma_{\mathbf{R}} = 0.2$ corresponds to UBW-based ranging and $\sigma_{\mathbf{R}} = 4$ corresponds to radio-based ranging.

Finally, the position estimation for isolated cars (i.e., those with no surrounding neighbours) is updated using their past position estimates and new velocity measurements. Since this method leads to an increasing localisation error due to cumulative effects, we occasionally use the measured GPS position to avoid long term effects from this kind of error in isolated cars.

B. Small scale scenario

The first scenario to be tested is a street circuit inside the NUIM North Campus (Fig. 6). Here, the main idea is to evaluate the performance of the proposed approach in terms of the range of communication zones for V2V communication corresponding to Class-A/B DSRC devices (see Table II), i.e., 15 m and 100 m respectively. The results obtained for an ensemble of 40 experiments per CP approach are given in Table V.

In Table V we observe that an average improvement of up to 9.92 % in the localisation RMSE can be obtained when using stationary vehicles as prioritised nodes in the CP process and a communication zone of 15 m. This result allow us to conclude that a communication zone of even 15 m potentially offers a significant improvement for the proposed CP approach over the traditional approaches in particular, even when there are small numbers of parked vehicles.

Note also that with an increased communication range of 100 m, significant improvements can be obtained. For example, this increased communication range allows, for our example, an improvement[3] of up to 49.04% in the localisation RMSE, with an accuracy level up to 3.26 m (EKF with $\sigma_R = 0.2$). Clearly, in this case, multipath and shadowing effects cannot be neglected.
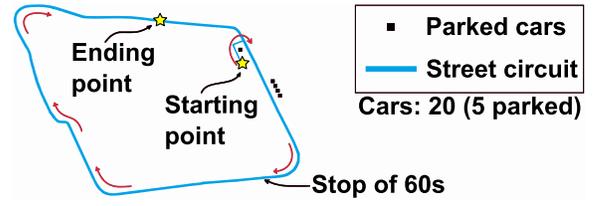
Fig. 6. Circuit for the small scale test (blue) and selected parked cars (black).

TABLE V
RESULTS FOR THE SMALL SCALE SCENARIO USING TWO DIFFERENT VALUES FOR THE COMMUNICATION ZONE (CZ): LOCALISATION RMSE AND IMPROVEMENTS FOR THE TARGET CAR.

| | | | RMSE (meters) | | | | |
| | | | Traditional CP | | Proposed CP | | |
		σ_R	Mean	σ	Mean	σ	Average improvement
CZ: 15 m	GCPSO	0.2	6.92	4.05	6.31	3.75	8.74%
		4	8.00	4.37	7.62	4.33	4.82%
	EKF	0.2	7.63	4.47	6.88	4.50	9.92%
		4	7.78	4.17	7.18	4.12	7.65%
CZ: 100 m	GCPSO	0.2	6.84	4.12	3.49	2.57	49.04%
		4	13.69	8.19	8.22	5.46	39.92%
	EKF	0.2	5.98	3.27	3.26	2.26	45.45%
		4	7.65	4.34	5.15	3.32	32.71%

CZ: Communication zone.
Mean: average of 40 different measurements.
σ: standard deviation.

C. Large scale scenario

The second scenario to be evaluated is a large scale network of vehicles deployed around Maynooth town, based on the information provided in Section III. Here, we take into account a large number of cars (both moving and stationary), and also a number of controlled intersections.

[3]Concerning the proposed approach with respect to the traditional approach.
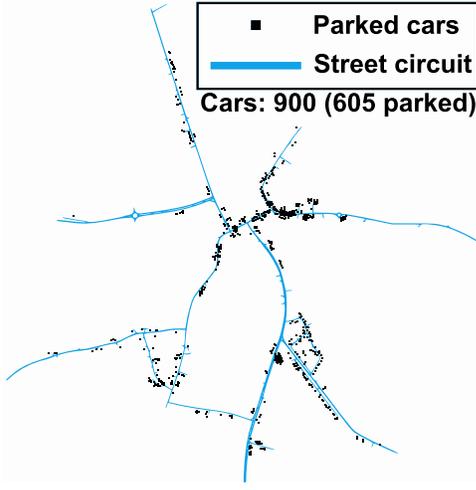
Fig. 7. Chosen street circuit for the large scale test (blue) and selected parked cars (black).

TABLE VII
RESULTS FOR THE LARGE SCALE SCENARIO USING EKF AND 15 M OF COMMUNICATION ZONE: LOCALISATION RMSE AND IMPROVEMENTS FOR THE FIVE CARS WITH THE LONGEST ROUTES.

		RMSE (meters)				
		Traditional CP approach		Proposed CP approach		
		Mean	σ	Mean	σ	Average improvement
$\sigma_R = 0.2$ m	Car 1	7.77	6.67	7.22	7.25	7.06%
	Car 2	7.44	4.20	6.69	5.62	10.19%
	Car 3	9.12	7.75	5.99	7.11	34.32%
	Car 4	9.17	6.88	5.74	6.17	37.37%
	Car 5	10.84	6.76	3.65	5.12	66.35%
$\sigma_R = 4$ m	Car 1	8.18	7.69	7.87	6.13	3.81%
	Car 2	8.76	6.43	8.13	7.34	7.12%
	Car 3	9.80	7.59	7.03	7.06	28.21%
	Car 4	9.76	6.93	7.10	5.42	27.23%
	Car 5	10.19	7.01	5.37	5.13	47.23%

Mean: average of 40 different measurements.
σ: standard deviation.

TABLE VI
RESULTS FOR THE LARGE SCALE SCENARIO USING GCPSO AND 15 M OF COMMUNICATION ZONE: LOCALISATION RMSE AND IMPROVEMENTS FOR THE FIVE CARS WITH THE LONGEST ROUTES.

		RMSE (meters)				
		Traditional CP approach		Proposed CP approach		
		Mean	σ	Mean	σ	Average improvement
$\sigma_R = 0.2$ m	Car 1	8.30	7.14	6.92	7.11	16.59%
	Car 2	8.63	5.23	6.71	5.71	22.20%
	Car 3	9.44	7.26	5.79	6.87	38.71%
	Car 4	9.80	7.16	5.48	5.57	44.05%
	Car 5	10.67	7.20	3.96	5.22	62.86%
$\sigma_R = 4$ m	Car 1	9.30	7.03	8.35	6.53	10.22%
	Car 2	8.92	5.23	7.91	5.82	11.30%
	Car 3	9.70	7.30	7.47	6.93	23.06%
	Car 4	9.83	7.10	6.92	5.02	29.57%
	Car 5	11.4	7.09	5.78	4.56	49.49%

Mean: average of 40 different measurements.
σ: standard deviation.

The street circuit for this test is mostly composed by secondary and tertiary roads, and the parked cars to be used are those in a proximity of 15 m to the selected roads (a total of 605 parked cars), as shown in Fig. 7. This assumption of 15 m for the communication range is consistent with a clear line-of-sight condition between parked cars and moving vehicles.

Our experiments are constructed as follows. We use 295 blind moving cars are divided into two groups: 200 cars are selected with a random route and with initial position randomly distributed along the entire street circuit, and 95 other cars enter the street circuit at a rate of one every 4 seconds with a route defined by a random starting/ending pair of edges. The obtained results for the five cars with the longest routes are presented in Tables VI, VII, Fig. 8 and Table VIII.

From Tables VI and VII it can be observed that the proposed approach to enhance CP gives an average improvement of 56.48% in the localisation RMSE for the best case (with maximum at 66.35% for EKF with $\sigma_R = 0.2$ m, and minimum at 47.23% for EKF with $\sigma_R = 4$ m), with respect to the traditional approach. In Table VIII it can be observed that

the density of parked vehicles experienced by a given moving car affects considerably the accuracy of the positioning. Note that despite the fact that radio ranging techniques cannot provide accurate inter-vehicle distance measurements for CP purposes, simulation results have shown that their utility for the localisation of moving vehicles can be potentially greatly improved using the suggested approach, even in the case of simplistic and imprecise CP algorithms.
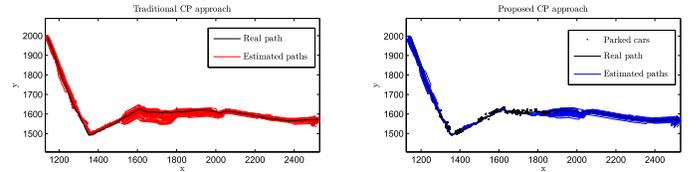
(a) Car 5, GCPSO with $\sigma_R = 0.2$ m.
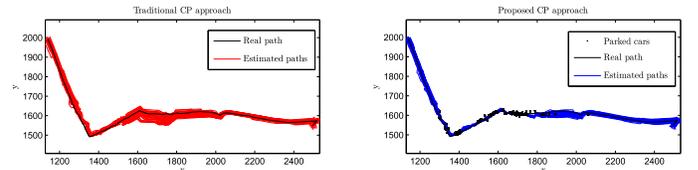
(b) Car 5, GCPSO with $\sigma_R = 4$ m.
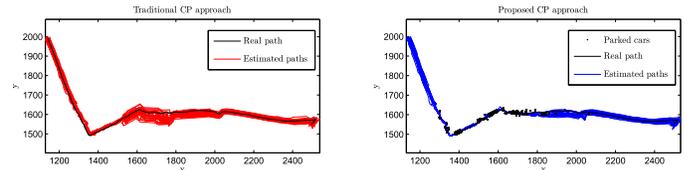
(c) Car 5, EKF with $\sigma_R = 0.2$ m.
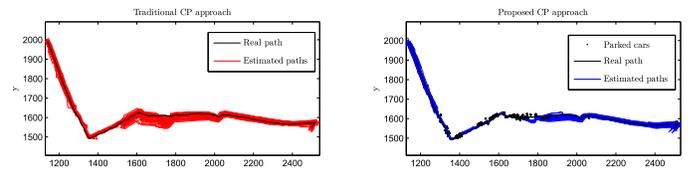
(d) Car 5, EKF with $\sigma_R = 4$ m.

Fig. 8. Simulations results for Car 5 (40 different estimations).

In our experiments we used a short-range communication distance of 15 m, mainly for mitigating the effects of shadowing and multipath (see references [19], [20]). Clearly, the results for the large scale scenario can be improved if an extended communication range is adopted (as preliminary concluded in Section V-B), but, as we have already mentioned, in such a case the effects of shadowing and multipath cannot be neglected.

TABLE VIII

OVERALL IMPROVEMENTS OF THE LOCALISATION RMSE FOR THE FIVE CARS WITH THE LONGEST ROUTES IN FUNCTION OF THE NUMBER OF PARKED CARS EXPERIENCED (*), TRAVELLED DISTANCE (**), AND THE RATIO (*)/(**).

	Parked cars experienced (*)	Travelled path [Km] (**)	Ratio (*) / (**)	Overall average improvement
Car 1	6	2.34	2.57	9.42%
Car 2	18	2.62	6.86	12.70%
Car 3	51	4.21	12.11	31.08%
Car 4	58	5.10	11.37	34.56%
Car 5	97	3.23	30.05	56.48%

VI. CONCLUSIONS AND FUTURE WORK

CP is a localisation approach that is based on cooperation among several agents (nodes). In the case of VANETs, such agents can either be vehicles or road-side units (RSUs). Vehicles are traditionally the mobile part of the VANETs, while the RSUs constitute the static part. RSUs are, in general, fixed roadside stations that act like beacons or anchors depending on the accuracy with which their position is known (obtained via a dedicated calibration process). Despite the benefits of having a large number of RSUs in the VANETs, their deployment usually requires a complex and expensive process.

The contribution of this paper was, among others, to evaluate the use of on-street parked cars as an alternative to RSUs. Such an alternative solution is generally cheaper, easier (no extra hardware is required), and more flexible than fixed infrastructure. Further, as the vehicle fleet refreshes itself after a number of years, technology updates are easier to realise using vehicles as a platform. In addition, such new anchor nodes are usually close to on-street blind cars, which is convenient to mitigate measurement noise due to shadowing and multipath effects of V2X measurements. Also, the proximity of on-street stationary cars reduces the requirements on communication ranges, which in turn shortens the time required for accurate localisation of blind cars. Finally, parked cars are dense, thus offering a potential platform for autonomous vehicles in urban situations. Our simulations demonstrate the power of this technique in several settings. On-going work involves testing these and related ideas in cooperation with a vehicle manufacturer.

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REFERENCES

[1] N. Alam and A. Dempster, "Cooperative Positioning for Vehicular Networks: Facts and Future," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, pp. 1708–1717, Dec 2013.

[2] R. Cogill, O. Gallay, W. Griggs, C. Lee, Z. Nabi, R. Ordonez, M. Rufli, R. Shorten, T. Tchrakian, R. Verago, F. Wirth, and S. Zhuk, "Parked cars as a service delivery platform," in *The 2014 International Conference on Connected Vehicles and Expo (ICCVE 2014) (accepted)*, 2014.

[3] T. Project, "Tomorrow's elastic adaptive mobility." Available: https://www.collaborative-team.eu/. [Aug. 09, 2014].

[4] S. Mathur, T. Jin, N. Kasturirangan, J. Chandrasekaran, W. Xue, M. Gruteser, and W. Trappe, "Parknet: Drive-by sensing of road-side parking statistics," in *Proceedings of the 8th International Conference on Mobile Systems, Applications, and Services*, MobiSys '10, (New York, NY, USA), pp. 123–136, ACM, 2010.

[5] C. Campolo and A. Molinaro, "Dream: Ieee 802.11p/wave extended access mode in drive-thru vehicular scenarios," in *Communications (ICC), 2012 IEEE International Conference on*, pp. 5301–5305, June 2012.

[6] C. Campolo and A. Molinaro, "Improving multi-channel operations in VANETs by leveraging stopped vehicles," in *24th IEEE PIMRC'13*, pp. 2229–2233, Sept 2013.

[7] F. Malandrino, C. Casetti, C. F. Chiasserini, C. Sommer, and F. Dressler, "Content downloading in vehicular networks: Bringing parked cars into the picture," in *23rd IEEE PIMRC'12*, pp. 1534–1539, 2012.

[8] N. Liu, M. Liu, G. Chen, and J. Cao, "The sharing at roadside: Vehicular content distribution using parked vehicles," in *INFOCOM, 2012 Proceedings IEEE*, pp. 2641–2645, 2012.

[9] C. Sommer, D. Eckhoff, and F. Dressler, "IVC in cities: Signal attenuation by buildings and how parked cars can improve the situation," *IEEE Transactions on Mobile Computing*, vol. 13, no. 8, pp. 1733–1745, 2014.

[10] R. Crepaldi, R. Welsh, and R. Kravets, "Governing energy for parked cars," in *10th WONS '13*, pp. 87–94, 2013.

[11] E. C. L. Chan and G. Baciu, *Introduction to Wireless Localization: With iPhone SDK Examples*, ch. Chapter 9: Differential GPS and Assisted GPS, pp. 157–184. John Wiley & Sons, Ltd, 2012.

[12] W. Lin, Y. ru Su, F. Chang, K.-Y. Chen, and S.-H. Huang, "Evaluation approaches of fuel saving and carbon reduction benefits for arterial signal retiming," in *12th ITST '12*, pp. 370–374, Nov 2012.

[13] T. Sando and R. Moses, "Influence of intersection geometries on the operation of triple left-turn lanes," *Journal of transportation engineering*, vol. 135, no. 5, pp. 253–259, 2009.

[14] G. Pasaoglu, D. Fiorello, A. Martino, G. Scarcella, A. Alemanno, A. Zubaryeva, and C. Thiel, "Driving and parking patterns of european car drivers—a mobility survey.," EUR - Scientific and Technical Research Reports JRC77079, Joint Research Centre of the European Commission, 2012.

[15] T. Litman, *Parking management: strategies, evaluation and planning*. Victoria Transport Policy Institute, 2013.

[16] C. Morency and M. Trépanier, "Characterizing parking spaces using travel survey data," tech. rep., CIRRELT, May 2008.

[17] EPA and I.-U. team, "Scope of parking in europe," tech. rep., European Paking Association, http://www.europeanparking.eu/, 2013.

[18] J. Kenney, "Dedicated short-range communications (dsrc) standards in the united states," *Proceedings of the IEEE*, vol. 99, no. 7, pp. 1162–1182, 2011.

[19] G. Bellusci, G. J. M. Janssen, J. Yan, and C. C. J. M. Tiberius, "Modeling distance and bandwidth dependency of TOA-based UWB ranging error for positioning," *Research Letters in Communications*, vol. 2009, p. 4 p., 2009. Article ID 468597.

[20] J. Gozalvez, M. Sepulcre, and R. Bauza, "Impact of the radio channel modelling on the performance of âvanet communication protocols," *Telecommunication Systems*, vol. 50, no. 3, pp. 149–167, 2012.

[21] S. Zhang, J. Wang, X. Liu, and J. Cao, "Range-free selective multilateration for anisotropic wireless sensor networks," in *Sensor, Mesh and Ad Hoc Communications and Networks (SECON), 2012 9th Annual IEEE Communications Society Conference on*, pp. 299–307, 2012.

[22] F. Van den Bergh and A. P. Engelbrecht, "A convergence proof for the particle swarm optimiser," *Fundamenta Informaticae*, vol. 105, no. 4, pp. 341–374, 2010.

[23] R. Parker and S. Valaee, "Cooperative vehicle position estimation," in *IEEE ICC '07*, pp. 5837–5842, June 2007.

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