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RUPS: Fixing Relative Distances among Urban Vehicles with Context-Aware Trajectories

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***Abstract*—Access to accurate relative *front-rear* distance information between vehicles can be of great interest to drivers as such information can be utilised to improve driving safety. Acquiring such information in urban settings is very challenging due to the high complexity of urban environments. In this paper, we propose a novel scheme, called RUPS, to tackle the relative distance fixing problem. We first investigate pervasive GSM signals and find that the received signal strength indicator (RSSI) of multiple GSM channels measured over a distance has ideal temporal-spatial characteristics for *temporary* fingerprinting. With this observation, an RUPS-enabled vehicle first perceives the information of its GSM-aware trajectory while moving. Then by exchanging and comparing its own trajectory with that of a neighbouring vehicle, the vehicle can identify common locations overlapped on both trajectories. Finally, the relative distance between this pair of vehicles can be obtained by further comparing their geographical trajectories since that common location. As a result, RUPS is a fully distributed and lightweight scheme, requiring only a minimum hardware deployment, and does not need synchronization between vehicles or any pre-constructed signal maps. Extensive trace-driven simulation results show that RUPS can work stably under complex urban environments and overwhelm the performance of GPS by 2.7 times on average.**

***Keywords*-GSM-aware trajectory, front-rear distance, fingerprinting, vehicle-to-vehicle communication**

I. Introduction

Recent reports show that rear-end accidents are one of the most common types of accidents that happen. For instance, there are over 6 million car accidents that occur in the U.S. every year and around 31% of these are rear-end collisions [1]. Therefore, how to acquire the instant information of the relative front-rear distance between two vehicles moving in the same lane, referred to as the *relative distance fixing* (RDF) problem, is essential to a wide range of driving safety related applications. For example, drivers can be alerted when a front vehicle is taking hard brakes to avoid sudden obstacles or potholes, or when there is a vehicle approaching rapidly from behind. Successful solutions to this problem can not only reduce accidents but also enhance the driving experience.

To solve the RDF problem under complex urban environments, however, is very challenging because of several rigorous requirements. First, queries for front-read distance information from nearby vehicles should be answered in *real time*. It is essential for many safety-related applications to get such information within a bounded period of time. Second, such a solution should achieve *good accuracy* as huge estimation errors could also lead to severe car accidents. Third, the solution should also be *robust* to the high complexity of urban environments such as time-varying traffic condition, various weather and light conditions, tall buildings, and complex road infrastructure. Last but not least, the solution should be *cost efficient* so that it is scalable to the vast number of urban vehicles as well as frequent queries posed by tracking applications.

In the literature, there are plenty of outdoor localization schemes, which can be used to solve the RDF problem. Given the current location information of two objects, such as their Global Positioning System (GPS) coordinates, their relative distance can be easily calculated. In urban settings, however, it is often the case that satellite signals get blocked due to the "concrete forest" effect, which can lead to huge localization errors or even no GPS reports. For example, we conduct intensive field driving experiments in Shanghai and examine the relative distance between two adjacent high-precision GPS receivers. Complying with the conclusion that nominal GPS accuracy is 15 meters [2], we have similar observation that relative location errors of GPS are above ten meters even for open roads. Differential GPS (DGPS) [2] is an enhancement to GPS that provides improved location accuracy to about 10 centimeters in the case of the best implementations. However, DGPS relies on additional infrastructure of a network of fixed ground-based reference stations. Localization schemes base on pattern-matching can localize an object with a high accuracy but they all rely on a fine fingerprint map. However, it is not easy to acquire such fingerprint maps at a scale of a city. Other vision-processing based solutions have strong requirements on the light condition. Besides localization schemes, many ranging techniques such as ToA [3][4] and AoA [5][6] can be used to measure the distance between a transmitter and a receiver. These schemes are vulnerable to ambient noise and limited to line-of-sight conditions. As a result, there is no existing successful solution, to the best of our knowledge, to the RDF problem in urban scenarios.

In this paper, we propose a novel scheme, called *Relative*

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Urban Positioning System (RUPS), which meets all requirements for fixing front-rear distances between urban vehicles. In essence, RUPS leverages the inherent locality of the RDF problem in space and time, which makes RUPS need no global information of any kind. The core idea of RUPS is to first let a vehicle to perceive and store the information of its geographical trajectory as well as the ambient broadband wireless signals measured along its way as its *context-aware* trajectory. After exchanging recent trajectory with its neighbours via vehicle-to-vehicle (V2V) communication (e.g., DSRC [7]), the vehicle can locally identify common overlapped trajectory segments among itself and its neighbours through cross-correlation calculation. Based on one such common trajectory segment, the vehicle can eventually obtain the relative front-rear distances between itself and its neighbours by further comparing their geographical trajectories. The main advantage of RUPS is that it is fully distributed and requires only widely-available cheap sensors and V2V communication. The minimum hardware deployment makes it easy to install on new as well as existing vehicles. Moreover, RUPS needs neither synchronization between vehicles nor new localization infrastructure and any global information including digital maps. In addition, RUPS leverages the pervasiveness of GSM signals and does not require line-of-sight conditions between vehicles, which makes RUPS resilient to complex urban environments. We implement a prototype system validating the feasibility of the RUPS design and conduct extensive trace-driven simulations. The results demonstrate that RUPS can work stably under complex urban environments and outperform GPS by 2.7 times on average.

We highlight our main contributions made in this work as follows:

- We intensively investigate the ambient signals of GSM, the most popular mobile networks ever built in the world, and have the observation that the GSM-aware trajectory has good characteristics of temporary stability, geographical uniqueness and fine resolution, making it ideal for characterizing the environmental context of moving vehicles.
- We have developed the RUPS scheme, which can fix relative front-rear distances between vehicles in urban scenarios. RUPS is a fully distributed scheme with a minimum hardware requirement for a vehicle, requiring no centralised unit or any global map as a priori. It can answer arbitrary relative distance queries in about 0.5s and scales well in the presence of heavy traffic and frequent queries.
- We have conducted extensive trace-driven simulations to evaluate the performance of RUPS. The results shows that RUPS is robust to complex urban environments and can achieve an average location accuracy of 4.5 meters over all road settings, outperforming GPS by 2.7 times.

II. Related Work

Outdoor localization or distance ranging techniques can be used to solve the RDF problem.

A. Outdoor Localization Methods

GPS-based. Mikkel *et at.* [8] utilize the accelerometer and compass of a smart phone to track a car based on an initial start location provided by the GPS. Kaisen *et at.* [9] have proposed a scheme to periodically use the GPS to save energy and at the same time meet the requirement of location accuracy. Hedgecock *et at.* [10] enhance the performance of low-cost GPS receivers on relative distance tracking at an accuracy of several centimeters. Though it is quite accurate, it needs to know the precise start position. The usage of GPS-based schemes for fixing relative distance between vehicles in urban environments is limited due to signal availability problem.

Pattern-matching-based. Fingerprinting using WiFi [11], [12], FM [13], [14], sound [15], [16], and cell tower ID [17] has been extensively studied for indoor localization. Varshavsky *et at.* [18] have proposed an indoor localization scheme based on a pre-constructed map of GSM signals including the RSSI readings of additional cells along with the 6-strongest cells. They have achieved a median accuracy of 4m in large buildings. Chandrasekaran *et at.* [19] use a dynamic time warping method to derive the speed of vehicles by warping the GSM signal strengths collected with smart phones. Place Lab [20] and Skyhook [21] utilize existing radio beacon sources like WiFi APs and cell towers to construct a global digital map for localization. These pattern-matching based methods can perform well in indoor environment. However, they are not practical for outdoor localization due to the prohibitive man power cost for getting the global fingerprint database. Furthermore, the dynamic environment makes the fingerprint database inaccurate for localization.

Vision-processing-based. There are a large number of schemes that utilize image processing for lane detection and moving objects [22], [23], [24], [25]. Though they can be adapted to high speed scenarios and meet the real-time requirements of relative localization of vehicles, they have limitations on their instability when the weather or the light condition changes. Moreover, those schemes require the objects to be in line of sight which is often not the case in downtown areas.

B. Distance Ranging Methods

Model-based. Propagation-models of signal can be applied to obtain the distance between the transmitter and receiver [26], [27]. These approaches for localization is not so feasible when used in outdoor environments because the high dynamics of outdoor environments can bring a huge impact on theoretical models.

Measurement-based. ToA [3] can be used to measure distances but it requires synchronization between objects. TDoA schemes [4], [28] improve ToA which needs no synchronization between devices by increasing the number of wireless data transfers. Ranging based on distance measurement have a problem of obstructing effect caused by objects standing between the transmitter and receiver. MARVEL [29] is the most related work with RUPS in this direction, which determines the relative location of two vehicles at lane granularity with the help of four antennas installed on each vehicle. By comparing

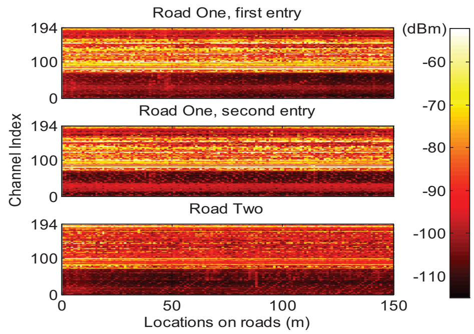

Fig. 1. R-GSM-900 power measurements on two different roads with the first road entered twice.

the pattern of signals received by the antennas respectively, it determines the relative location between vehicles. MARVEL needs four antennas carefully mounted on each vehicle and has the limitaion that vehicles should be in line of sight. In contrast, RUPS focuses on relative distances between vehicles in the same lane and does not have such requirements on antennas and the line-of-sight condition.

III. Empirical Study on GSM-aware Trajectories

Mobile networks especially the GSM networks have been well developed over decades and gained universal coverage in cities, which motivates us to examine whether GSM signals can be utilised for fixing relative distances. In this section, we first present the trace collection and then analyze the temporal and spatial characteristics of GSM signals.

A. Collecting GSM-aware Trajectories

With the OsmocomBB project [30] and Motorola C118 cellphones, we can capture the received signal strength indicator (RSSI) values over a wide band of GSM channels. The OsmocomBB project is an open-source GSM baseband software implementation, which provides drivers for GSM analog and digital baseband peripherals and the phone-side protocol stack from layer one up to layer three. With this platform, all 194 channels in the R-GSM-900 band can be scanned within 2.85 seconds. We refer to such a vector of RSSI measures over all GSM channels at one location as a *power vector*.

To collect a realistic trace of GSM power vectors over space and time, we randomly selected two hundred surface road segments in Shanghai, involving three different environments, i.e., downtown, urban and suburban. For each road segment, we measure GSM power vectors on every one meter over 150 meters for three times a day with an interval of half an hour and repeat the experiment for two days, i.e., one workday and one weekend, respectively. Figure 1 demonstrates three such *GSM-aware trajectories* (i.e., a series of power vectors consecutively measured in time and space) collected on two different roads with the first road measured twice. It is clear to see that trajectories are very similar when they are collected on the same road at different time but quite distinct when they are collected on different roads. We intensively investigate GSM-aware trajectories on three crucial temporal-spatial features, namely, *temporary stability*, *geographical uniqueness*, and *fine resolution*.

B. Temporary Stability

Challenges often arise when applying wireless signals for localization as they are susceptible to noise, interference, and other channel impediments. Furthermore, such impediments can change over time in unpredictable ways as a result of object movement and environmental dynamics. We have the following insight: *as vehicles in vicinity are of interest, the RDF problem has an inherent property of locality both in time and in space.* For example, two vehicles moving along the same trajectory would experience a similar (if not exactly the same) environment. Moreover, the time interval for the first vehicle and the second one traversing the same location is also short. Therefore, if GSM-aware trajectories have *temporary stability*, two GSM-aware trajectories measured on the same road should be similar if the time difference when they are measured is short.

We calculate the Pearson's correlation coefficient to measure the similarity between two power vectors as follows

$$r_{X^{t_1}X^{t_2}} = \frac{\sum_{i=1}^{n}(x_i^{t_1} - \overline{X^{t_1}})(x_i^{t_2} - \overline{X^{t_2}})}{\sqrt{\sum_{i=1}^{n}(x_i^{t_1} - \overline{X^{t_1}})^2}\sqrt{\sum_{i=1}^{n}(x_i^{t_2} - \overline{X^{t_2}})^2}}, \quad (1)$$

where $X^{t_1} = (x_1^{t_1}, x_2^{t_1}, \cdots, x_n^{t_1})$ and $X^{t_2} = (x_1^{t_2}, x_2^{t_2}, \cdots, x_n^{t_2})$ are power vectors measured at the same location over n GSM channels at time t_1 and t_2, respectively, and $\overline{X}$ denotes the average of all elements of a vector X.

In order to check the temporary stability of GSM power vectors, we randomly chose twenty distinct locations in the downtown area of Shanghai and measured GSM power vectors for half an hour at each location. For each location, we vary the time interval between a pair of power vectors from 5 seconds to 25 minutes and for each time interval we randomly select one hundred pairs of power vectors to calculate the correlation coefficient. Figure 2 plots the probability that a pair of power vectors is *stable* (i.e., the corresponding correlation coefficient value is higher than a threshold) as a function of the time difference between this pair, calculated over all pairs at a location and over all locations.

We have three key observations. First, individual channels do vary over time as the probability for all channels to stay un-changed (e.g., setting a high correlation threshold of 0.9) is lower than that when only a subset of channels are used (e.g., ten randomly-selected channels as shown in Figure 2). Second, if we loose the stability condition (e.g., reducing the correlation threshold to 0.8), with high probability (i.e., $\geq$0.95), the GSM power vectors are stable over a sufficient long period of time. The reason is also clear that the chance for a large portion of channels to change at the same time is slim. Third, increasing the number of channels will also increase the stability probability of GSM power vectors when an appropriate stability threshold is chosen.

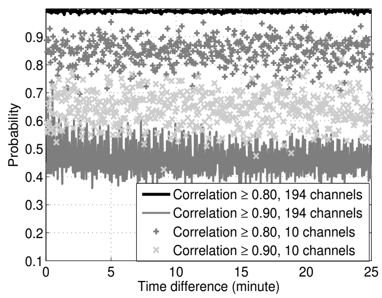

Fig. 2. Temporary stability of GSM power vectors.

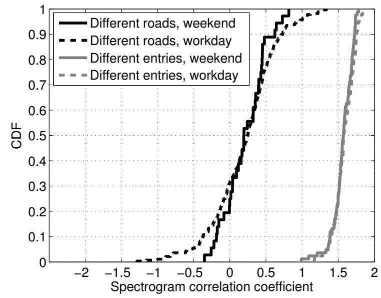

Fig. 3. CDF of correlation coefficient of GSM-aware trajectories.

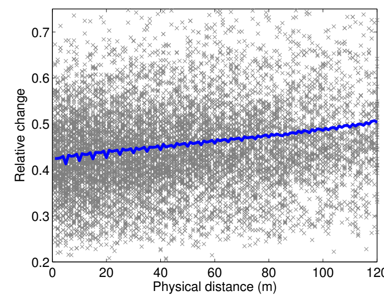

Fig. 4. Relative change of two power vectors over distance.

C. Geographical Uniqueness

Besides temporary stability, in order to distinguish different locations, the corresponding GSM-aware trajectories collected from those locations should be unique. Let matrix $\mathcal{S}^{R_1} = [\mathcal{C}_1^{R_1}; \mathcal{C}_2^{R_1}; \cdots; \mathcal{C}_n^{R_1}]$ denote the GSM-aware trajectory collected on road R_1, where $\mathcal{C}_i^{R_1} = [x_i^{R_1,1}, x_i^{R_1,2}, \cdots, x_i^{R_1,m}], i = 1, 2, \cdots, n$, denotes the vector of RSSI values measured on channel i from location one to location m along road R_1. We say trajectory S^{R_1} has a width of n channels and a length of m meters. We check the geographical uniqueness of GSM-aware trajectories by calculate the *trajectory correlation coefficient* defined as follows,

$$r_{\mathcal{S}^{R_1}\mathcal{S}^{R_2}} = \frac{1}{n}\sum_{i=1}^{n} r_{\mathcal{C}_i^{R_1}\mathcal{C}_i^{R_2}} + r_{\overline{\mathcal{S}^{R_1}}\,\overline{\mathcal{S}^{R_2}}}, \tag{2}$$

where $\overline{\mathcal{S}^{R_1}}$ and $\overline{\mathcal{S}^{R_2}}$ are two vectors of $(\overline{\mathcal{C}_1^{R_1}}, \overline{\mathcal{C}_1^{R_1}}, \cdots, \overline{\mathcal{C}_n^{R_1}})$ and $(\overline{\mathcal{C}_1^{R_2}}, \overline{\mathcal{C}_1^{R_2}}, \cdots, \overline{\mathcal{C}_n^{R_2}})$, respectively, and the calculation of $r_{\mathcal{C}_i^{R_1}\mathcal{C}_i^{R_2}}$ and $r_{\overline{\mathcal{S}^{R_1}}\,\overline{\mathcal{S}^{R_2}}}$ is similar with (1). The reason that we use this definition is because it is essential to consider not only the correlation of each channel but also the correlation of averages of each channel between two trajectories. Figure 3 plots the cumulative distribution function (CDF) of trajectory correlation coefficients using all GSM-aware trajectories collected over different entries on same roads and over different roads, respectively.

It can be seen that, in general, trajectories collected on the same road have much higher correlation coefficients than those collected on different roads. This implies that GSM-aware trajectories exhibit excellent geographical uniqueness when the length of trajectories for comparison is sufficient.

D. Fine Resolution

With temporary stability and geographical uniqueness, GSM-aware trajectories seems an ideal fingerprint for relative localization. Nevertheless, in the scenario of RDF problem, it is of great importance to examine the resolution of GSM-aware trajectories as it is closely related to the resolved distance accuracy. We refer to the *resolution* of GSM-aware trajectories as the smallest displacement in distance over which two trajectories are distinctive. We further examine the *relative change* of a pair of power vectors, defined as follows,

$$d = \frac{\|X - X'\|}{\|X\|}, \tag{3}$$

where X and X' are two power vectors separated at a distance on the same road, and $\|.\|$ is the Euclidean norm of a vector.

We randomly select one thousand power vectors from the trace. For each power vector X, we find the power vector X' which is k-meter in behind in the same trajectory and change k from one to 120. Figure 4 shows the scatter plot of the relative change between X and X' and their corresponding distances. The solid line in the figure shows the average relative change. We have two main observations. First, it can be seen that the relative change slightly rises as the distance between power vectors increases. This is reasonable as power vectors in vicinity tend to share more similar environment than those separated at a far distance. Second, the GSM-aware trajectories have fine resolution as the relative change reaches above 0.4 (i.e., 40% difference from the original vector) on average even when two power vectors are one meter away.

IV. System Design

A. Overview

As in the RDF problem, a vehicle only cares about other vehicles in its vicinity (for example, within the range of a safe distance). Furthermore, as vehicles move fast, the surrounding environment is transient. Recognising the strong inherent spatiotemporal locality of the problem, RUPS elegantly integrates two key components: *perceiving GSM-aware trajectory* and *fixing relative distance*, as depicted in Figure 5. The core idea of RUPS is to first let a vehicle utilize on-board motion sensors such as accelerometer, gyroscope, and compass to estimate its geographical trajectory information. At the same time, the vehicle also measure GSM channel RSSI values via GSM radios as it moves and binds the retrieved power measurements to its geographical trajectory, forming a GSM-aware trajectory. Then, the vehicle exchanges its own trajectory with its neighbouring vehicles through V2V communications. Finally, with trajectories of neighbours, this vehicle conducts cross-correlation calculation, seeking for two highly-similar segments on each pair of trajectories. If succeed,

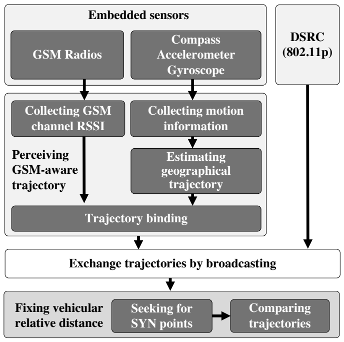

Fig. 5. System architecture of RUPS.

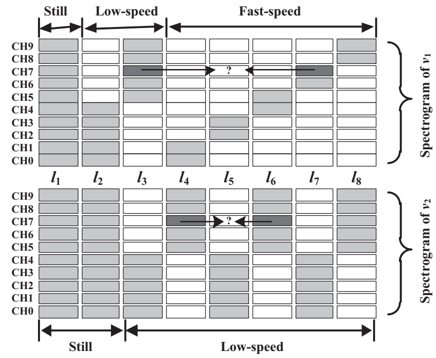

Fig. 6. Example of binding GSM power measurements to geographical trajectory.

the vehicle believes that it shares an overlapped trajectory segment (referred to as a *SYN point*) with the corresponding neighbour. Based on a found SYN point, the vehicle can fix the relative distance between itself and this neighbour by further comparing the remainder of their geographical trajectories.

B. Estimating Geographical Trajectory

In RUPS, the geographical trajectory information is of great importance as it is required in generating GSM-aware trajectory and in determining the ultimate relative distance based on found SYN points.

Coordinate reorientation. As RUPS estimates the trajectory of a vehicle using on-board motion sensors, it is possible that the coordinate system of those sensors are not aligned with that of the vehicle. Therefore, RUPS needs first to re-orient the coordinate system of motion sensors. We adopt the scheme proposed by Han *et al.* [31], where a rotation matrix $\mathcal{R} = [\vec{x}; \vec{y}; \vec{z}]$, where $\vec{x}$, $\vec{y}$ and $\vec{z}$ are three-dimensional coordinate vectors representing the x-, y- and z-axis direction of the vehicle coordinate system in the perspective of sensors, is used to align the readings of sensors to the coordinate of the vehicle. The three vectors can be derived from the accelerometer and gyroscope readings. In addition, the $\vec{z}$ vector can be recalibrated by $\vec{z} = \vec{x} \times \vec{y}$ to further eliminate the effect when the vehicle is running on a slope.

Inferring heading direction and moving speed. To estimate the moving trajectory, it is necessary to know the heading direction and the distance traversed along that direction. After the coordinate reorientation, it is easy to get both the strength and the direction of the magnetism of the earth on three axis in the coordinate system of the vehicle. The heading direction can be derived by the angle between the y-axis of the vehicle and the sum of magnetization vectors along x- and y-axis.

To get the distance traversed along one direction, one simple solution is to calculate the integral of the instant speed of a vehicle over time. In RUPS, one option to obtain the instant speed information is to gain access to the onboard Electronic Control Unit (ECU) in the vehicle through CAN bus using an OBD-II interface. The other option is to utilize motion sensor readings to estimate the instant speed as proposed in [31].

With the heading and distance information, the vehicle can estimate its m-meter geographical trajectory $\mathcal{T}^m$ as a vector of $m+1$ elements. Each element is a tuple (θ_i, t_i) for $i \in [0, m]$, where θ_i and t_i represent the heading angle and the timestamp at the ith meter on the trajectory.

C. Trajectory Binding

In RUPS, vehicles continuously measure the RSSI of GSM channels as they move. The retrieved power measurements, however, are time-domain signals, which are inconvenient for comparison as vehicles may move in different speeds. As a result, we need to bind the power measurements with the associate geographical trajectory. More specifically, for each element (θ_i, t_i), $i \in [0, m]$, of a geographical trajectory $\mathcal{T}^m$ of the vehicle, the power vector $X^{t_i} = (x_1^{t_i}, x_2^{t_i}, \cdots, x_n^{t_i})$ measured over n channels during time interval of $[t_{i-1}, t_i]$ can be associated, forming the corresponding GSM-aware trajectory $\mathcal{S}^{\mathcal{T}^m}$.

It should be noted that, as it takes time to scan GSM channels, when the vehicle moves fast, it is possible that some channels (referred to as *missing channels*) within a power vector at a particular location are not measured. In this case, missing channels cause blanks with no valid RSSI values in the resolved GSM-aware trajectory. For example in Figure 6, When vehicle v_1 stands still at location l_1, it can get a complete power vector from channel 0 to channel 9. When it moves at a low speed, the retrieved power vector spans over location l_2 and l_3. The situation gets more severe when the vehicle moves at a high speed. As a result, at one specific location, there might be missing channels in the corresponding power vector.

As it is very hard to estimate the exact RSSI measures for missing channels due to the unpredictable impediments of wireless signals, in RUPS, missing channels are estimated by linearly interpolating between neighbouring power vectors over distance. For example in Figure 6, the RSSI value of channel 7 at location l_5 is estimated by averaging the RSSI measures taken at location l_3 and l_7.

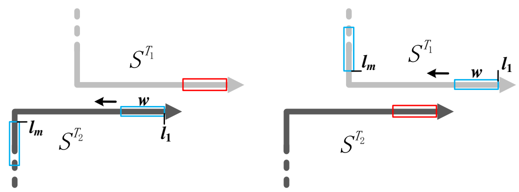

Fig. 7. Example of the double-sliding check for context consistence test.

D. Seeking for SYN Points

Given GSM-aware trajectories of two vehicles, a *cross-correlation check* is conducted in order to find overlapped segments on both trajectories.

In specific, as shown in the left subplot of Figure 7, for two trajectories $\mathcal{S}^{\mathcal{T}_1}$ and $\mathcal{S}^{\mathcal{T}_2}$, a most-recent segment of $\mathcal{S}^{\mathcal{T}_1}$ is selected to compare with a window of the same length sliding from the most-recent position l_1 to the oldest position l_m on $\mathcal{S}^{\mathcal{T}_2}$. For each position of the window, we examine whether the trajectory correlation coefficient defined in (2) of both segments is higher than a given threshold, referred to as the *coherency threshold*. After sliding on $\mathcal{S}^{\mathcal{T}_2}$, the most-recent context segment on $\mathcal{S}^{\mathcal{T}_2}$ is then checked by a window sliding on $\mathcal{S}^{\mathcal{T}_1}$ as illustrated in the right subplot of Figure 7.

After the cross correlation check, if there is no such location found that can satisfy the coherency threshold, the two compared trajectories are considered to be unrelated. Otherwise, the window location where the trajectory correlation coefficient reaches the maximum during the double-sliding check process is treated as the optimal estimation of a SYN point.

E. Resolving Relative Distance

After a SYN point has been found, a pair of vehicles can resolve the relative distance between each other by further comparing the distances from the SYN point to their individual current locations using their geographical trajectories. For example in Figure 8, solid lines represent the most recent journey contexts of vehicle v_1 and v_2 which are available to both vehicles after V2V communication. By comparing their journey contexts, a SYN point (illustrated by the dot) where v_1 and v_2 both traversed can be identified. Based on this SYN point, the relative distance d_r between v_1 and v_2 can be solved by subtracting the distance d_2 between the current location of v_2 and the SYN point from the distance d_1 between the current location of v_1 and the same SYN point.

V. Discussion

In this section, we discuss design issues that RUPS might encounter in practice.

A. Computational Complexity

In the RDF problem, vehicles only care about other vehicles in vicinity and therefore exchange only local journey contexts. With a limited sample rate of sensors needed (e.g., 0.3Hz for OBD and around 200Hz for motion sensors), the computational overhead for the perception of journey contexts is trivial and negligible. In our algorithm, the most expensive step is to identify SYN points over a pair of journey contexts. Therefore, our algorithm complexity is bounded by the length of journey contexts needed for analysis. Given a journey context of m-meter long and a checking window of k-channel wide and w-meter long, the computational cost for searching a SYN point is $O(mwk)$.

In our implementation, we consider journey contexts of 1,000 meters and set the window width and length as 45 channels and 100 meters, respectively. We implemented RUPS on a laptop with an Intel i7-2640M processor and measured the average processing time of our algorithm as about 1.2 milliseconds.

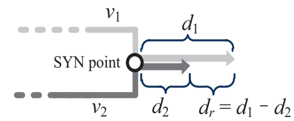

Fig. 8. Vehicular relative distance fixing example.

B. Responding Time and System Scalability

As analyzed in above subsection, the delay overhead caused by computation in RUPS is light and negligible comparing to that caused by communications. In our implementation, with IEEE 802.11p radios, the maximum payload of a WAVE Short Message (WSM) [32] packet is 1400 bytes and the average round trip time of such packets is 4ms. In order to exchange journey context information of one kilometre, containing GSM-aware trajectory information, two vehicles need to transfer about 182KB data, which requires 130 WSM packets and takes about 0.52 second.

In the case when the traffic is heavy or the high-level applications need to track the relative distances, it is of great importance to consider the system scalability. For example, one application may need to track a neighboring vehicle on every 0.1 second. Transferring all journey context for tracking is then infeasible. One possible solution is to only transfer trajectory information after a SYN point has been identified and transfer the complete journey context when the estimated accumulative error is beyond a threshold. To deal with heavy traffic, one reasonable solution is to reduce the context scope needed to transfer as the distances between nearby vehicles also shrink when the traffic is heavy. This matches the nature of the RDF problem.

C. Short Contexts and Missing Channels.

It is often the case that a vehicle makes a turn, entering another road segment. If a fixed checking window is required for the context consistence test, it is possible that the vehicle has insufficient context about newly-entered road segment. This may make RUPS have to wait until the vehicle gets enough context information. To solve this problem, in RUPS, we can use a flexible checking window and consistency threshold, which are adaptive to the mount of context available. Combined with a smaller threshold, even when the window length is as short as ten meters, RUPS can still guarantee to identify related vehicles with acceptable false positive ratio. With this improvement, it allows a vehicle to make a fast judgment about nearby vehicles even when it just moves to a new road segment and to further improve accuracy as it moves on.

The motion of vehicles leads to missing channels in their journey contexts, which could affect the accuracy of found SYN points and therefore the ultimate relative distances. One practical solution to missing channel problems is to use multiple GSM radios to sense the GSM spectrum in parallel as GSM radios are very cheap. For example, it takes about 15ms to sense a channel. Therefore, scanning a band of 90 GSM channels with ten parallel radios would take 135ms. For a vehicle moving at a speed of 80km/h, a power vector can only span a distance of 3 meter. We will examine the effect of using multiple GSM radios to the system performance in Section VI.

VI. Performance Evaluation

A. Methodology

In order to extensively investigate the impact of the complexity of urban environment, we select an experiment route of 97km which involves roads of three general types, i.e., *open* (e.g., 8-lane urban major roads and elevated roads, 2-lane suburban roads), *semi-open* (e.g., 4-lane urban surface roads with surrounding buildings and trees) and *close* (e.g., under elevated roads). We drove two experiment cars along the selected route once on every two days for nearly three months from March 21^{st} and June 18^{th}. We also selected different time in a day to drive, varying from 14pm to 12pm. We encountered both heavy and light traffic when the trace was collected. Both vehicles collected the information of their trajectories and the associate GSM-aware trajectories for trace-driven simulations.

To get the ground truth of front-rear distance between our experiment cars, we mounted a laser rangefinder with an effective range of 50 meters [33] on the rear car and recorded on each drive for verification. In addition, for each car, seven Motorola C118 cellphones are divided into three groups of one, two and four phones, respectively. Each group divides the selected 115 channels as described in Subsection 4.5 into different parts according to the number of phones and scans the spectrum in parallel. Besides normal GSM cellphones, we leverage one HTC S720t and one Samsung Galaxy S4 smartphones for the usage of motion sensors including 3D accelerometer, compass, and gyroscope to perceive the geographical trajectory of the vehicle. In addition, we also gain the instant speed of the vehicle via an OBD-II interface. To acquire accurate travel distance information over time, we mount a magnet on the rear-left wheel and a Hall sensor on the car body to detect the revolution of the wheel. In addition, we mount an Arada LocoMate OBU [34] on the roof for the usage of the 802.11p radio running WAVE protocols (i.e., IEEE 802.11p and 1609) [35] and the high-performance GPS module.

We compare RUPS with GPS since both schemes do not need line-of-sight communications and special hardware or new infrastructure. We consider the following metric to evaluate the performance of RUPS and GPS:

Relative distance error (RDE): refers to the absolute distance difference between the estimated relative distances and the ground truth. We calculate the ground-truth relative distance between the pair of cars as the difference of their travelling distances since last stop.

B. Impact of the Number and Position of Scanning Radios

In order to study the impact of missing channels, we use three groups of GSM radios, i.e., one radio, two radios and four radios on the top of the instrument panel of each vehicle (we denote those cases as "1 front radio, 1front radio", "2 front radios, 2 front radios" and "4 front radios, 4 front radios"), respectively. In addition, we also put an addition group of four radios at the center of the Passat (denoted as "4 central radios, 4 front radios") to examine whether radio placement would affect the performance of RUPS. We set the consistency threshold as 1.2 and use a checking window of top 45 channels wide and 85 meters long. We randomly select 1,000 points from the trajectory of the first car, estimate the relative distance between the pair of cars according to RUPS.

Figure 9 depicts the CDFs of RDE of all SYN points found in all cases. It can be seen that adding more scanning radios can reduce the RDE of found SYN points. The reason is that more radios will leave less missing channels as vehicles move at a high speed, which facilitates the comparison of GSM-aware trajectories. In addition, it can also be seen that the placement of those scanning radios counts a great deal. For instance, only about 75% SYN points found with the central group of radios have an error less than ten meters. In summary, as GSM radios are cheap and widely-available, deploying multiple GSM radios is feasible and can achieve obvious accuracy gain. Furthermore, radios should be deployed at places where the availability of GSM signals is good.

C. Impact of Dynamic Environments

In this experiment, we first examine the impact of passing vehicles. Specifically, we select 8-lane urban roads and drive both vehicles in the same lane with four radios placed on the front instrument panel of each vehicle. We randomly select 500 points on the trajectory of the first car and estimate the relative distance between vehicles.

Figure 10 depicts the CDFs of distance errors of the resolved relative distances. It can be seen that, with the original RUPS where only one SYN points are used to estimate the relative distance, about one quarter of errors are larger than ten meters as illustrated by the elliptical mark. After checking with the video we taped, most large errors occur when there is a big vehicle passing by. To remedy the side effect, we can select multiple most-recent journey context segments to do the context coherence test and therefore locate multiple SYN

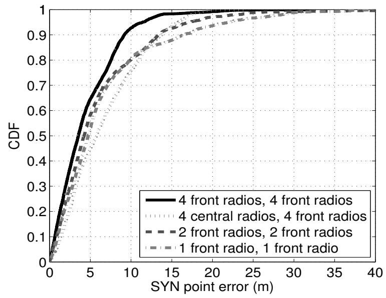

Fig. 9. SYN point distance errors with varying numbers and positions of GSM radios.

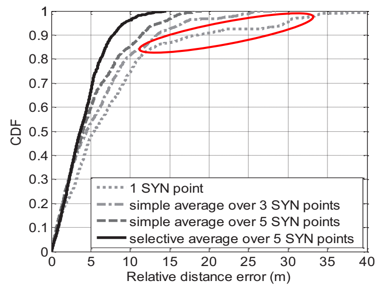

Fig. 10. CDFs of RDE derived with one and multiple SYN points.

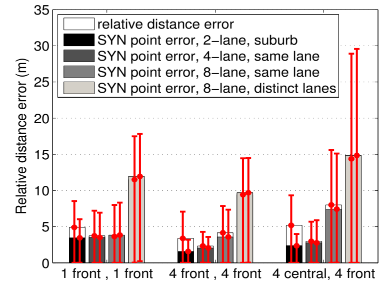

Fig. 11. Average RDE under dynamic environments and radio configurations.

points to calculate the relative distance with each SYN point. With multiple relative distance estimates, different aggregation schemes can be adopted. For example, we can take the simple average of all estimates or take the *selective average* where the maximum and the minimum estimates are discarded and then the rest estimates are averaged. It can also be seen that, when adopting aggregation schemes, especially with the selective average scheme, the resolved relative distance can be greatly reduced.

We then study the impact of dynamic environments to the performance of RUPS in different urban environments, i.e., on 2-lane suburb surface roads, on 4-lane urban surface roads and on 8-lane urban surface roads. In each environment, we also drive vehicles on distinct lanes when 8-lane urban roads are available. We also combine different numbers and placement of scanning radios in this experiment. For each environment and radio configuration, we randomly select 500 points on the trajectory of the first car and estimate the relative distance between vehicles using the selected average over five SYN points.

Figure 11 depicts the average error and the 95% confidence interval of found SYN points and the resolved relative distances. It can be seen that, with maximum number and front placement of radios, we can achieve best localization accuracy in all environments. Moreover, RUPS can achieve very stable performance over different urban environments and the best performance on 4-lane urban roads. For example, both SYN point and resolved relative distance errors are below 4.5m on average over all road conditions. The reason is two-fold. First, GSM signals are pervasive and stable in urban settings. Second, RUPS with selective average is robust to dynamic environments. Nevertheless, it can be seen that when driving on different lanes, the average SYN point error can reach to around ten meter, which also make the resolved relative distance errors stay at the same level. Note that, as we calculate the ground-truth relative distance between the pair of cars as the difference of their travelling distances since last stop, it is more likely that the trajectory of each vehicle is slightly different when moving in different lanes than in the same lane, which makes the ground truth not accurate. Despite the inaccuracy of ground truth, relative distance errors of ten meters in different lanes are not that critical as far as the RDF

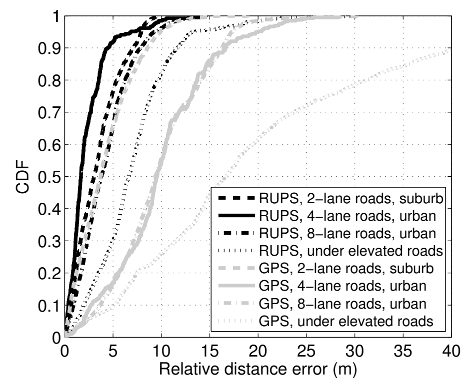

Fig. 12. Comparison with GPS under different urban environments.

problem is concerned.

D. Performance Comparison under Urban Environments

In this experiment, we compare RUPS with GPS in four different types of urban environments i.e., on 2-lane suburb surface roads, on 4-lane urban surface roads, on 8-lane urban surface roads and under elevated roads. For each environment, we randomly select 500 points on the trajectory of the first car and estimate the relative distance between vehicles through RUPS and GPS.

Figure 12 depicts the CDFs of the relative distance errors. It can be seen that RUPS is robust under all types of environments whereas the performance of GPS varies tremendously. The average relative distance errors for RUPS on 2-lane suburban, 4-lane urban, 8-lane urban roads, and under elevated roads are 3.4, 2.3, 4.2 and 6.9 meters, respectively. In comparison, the average relative distance errors of GPS in those environments are 4.2, 9.9, 9.8 and 21.1 meters, respectively. As a result, RUPS can outperform GPS by 2.7 times on average.

VII. Conclusion and Future Work

In this paper, we have investigated using GSM-aware trajectories for fixing relative front-rear distance between urban vehicles. Analysis results show that GSM-aware trajectories have not only wide availability but also good temporary stability, geographical uniqueness, and fine resolution. With this observation, we have developed a vehicular relative distance fixing scheme RUPS, which needs a minimum hardware deployment of widely available onboard sensors and a DSRC communication module. We have built a prototype system which verifies the feasibility of RUPS design. Moreover, we have conducted extensive trace-driven experiments. The results shows that RUPS can work stably under urban environments and overwhelm the performance of GPS by 2.7 times on average.

The future work can be directed in the following directions. First, we will further improve the accuracy of RUPS by involving other ambient wireless signals such as the 3G/4G, FM and TV bands. Another interesting direction is to extend RUPS to users of mobile devices such as pedestrians and bicyclists.

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REFERENCES

[1] "Rear-end collisions: Statistics, injuries and prevention." http://www.articlesbase.com/personal-injury-articles/rear-end-collisions-statistics-injuries-and-prevention-5306559.html.

[2] "Differential GPS." http://en.wikipedia.org/wiki/Differential_GPS.

[3] Y.-T. Chan, W.-Y. Tsui, H.-C. So, and P.-c. Ching, "Time-of-arrival based localization under NLOS conditions," *IEEE Transactions on Vehicular Technology*, vol. 55, no. 1, pp. 17–24, 2006.

[4] K. Ho and W. Xu, "An accurate algebraic solution for moving source location using TDOA and FDOA measurements," *IEEE Transactions on Signal Processing*, vol. 52, no. 9, pp. 2453–2463, 2004.

[5] D. Niculescu and B. Nath, "Ad hoc positioning system (APS) using AoA," in *Proceedings of IEEE INFOCOM*, 2003.

[6] J. Vidal, D. Brooks, *et al.*, "Closed-form solution for positioning based on angle of arrival measurements," in *Proceedings of IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, 2002.

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

[8] M. B. Kjærgaard, S. Bhattacharya, H. Blunck, and P. Nurmi, "Energy-efficient trajectory tracking for mobile devices," in *Proceedings of ACM MobiSys*, 2011.

[9] K. Lin, A. Kansal, D. Lymberopoulos, and F. Zhao, "Energy-accuracy trade-off for continuous mobile device location," in *Proceedings of ACM MobiSys*, 2010.

[10] W. Hedgecock, M. Maroti, J. Sallai, P. Volgyesi, and A. Ledeczi, "High-accuracy differential tracking of low-cost GPS receivers," in *Proceeding of ACM MobiSys*, 2013.

[11] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building rf-based user location and tracking system," in *Proceedings of IEEE INFOCOM*, 2000.

[12] J.-g. Park, B. Charrow, D. Curtis, J. Battat, E. Minkov, J. Hicks, S. Teller, and J. Ledlie, "Growing an organic indoor location system," in *Proceedings of ACM MobiSys*, 2010.

[13] S. Yoon, K. Lee, and I. Rhee, "FM-based indoor localization via automatic fingerprint DB construction and matching," in *Proceeding of ACM MobiSys*, 2013.

[14] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha, "FM-based indoor localization," in *Proceedings of ACM MobiSys*, 2012.

[15] M. Azizyan, I. Constandache, and R. Roy Choudhury, "SurroundSense: mobile phone localization via ambience fingerprinting," in *Proceedings of ACM MobiCom*, 2009.

[16] H. Lu, W. Pan, N. D. Lane, T. Choudhury, and A. T. Campbell, "SoundSense: scalable sound sensing for people-centric applications on mobile phones," in *Proceedings of ACM MobiSys*, 2009.

[17] J. Paek, K.-H. Kim, J. P. Singh, and R. Govindan, "Energy-efficient positioning for smartphones using cell-ID sequence matching," in *Proceedings of ACM MobiSys*, 2011.

[18] A. Varshavsky, E. de Lara, J. Hightower, A. LaMarca, and V. Otsason, "GSM indoor localization," *Journal of Pervasive and Mobile Computing*, vol. 3, no. 6, pp. 698–720, 2007.

[19] G. Chandrasekaran, T. Vu, A. Varshavsky, M. Gruteser, R. P. Martin, J. Yang, and Y. Chen, "Tracking vehicular speed variations by warping mobile phone signal strengths," in *Proceedings of IEEE PerCom*, 2011.

[20] A. LaMarca, Y. Chawathe, S. Consolvo, J. Hightower, I. Smith, J. Scott, T. Sohn, J. Howard, J. Hughes, F. Potter, *et al.*, "Place Lab: Device positioning using radio beacons in the wild," *Pervasive Computing*, vol. 3468, pp. 116–133, 2005.

[21] "Skyhook." http://www.skyhookwireless.com/.

[22] J. G. Manweiler, P. Jain, and R. Roy Choudhury, "Satellites in our pockets: an object positioning system using smartphones," in *Proceedings of ACM MobiSys*, 2012.

[23] C.-C. Wang, C. Thorpe, and A. Suppe, "Ladar-based detection and tracking of moving objects from a ground vehicle at high speeds," in *Proceedings of IEEE Intelligent Vehicles Symposium*, 2003.

[24] S. J. Park, T. Y. Kim, S. M. Kang, and K. H. Koo, "A novel signal processing technique for vehicle detection radar," in *Proceedings of IEEE MTT-S International Microwave Symposium Digest*, 2003.

[25] C.-C. Wang, S.-S. Huang, and L.-C. Fu, "Driver assistance system for lane detection and vehicle recognition with night vision," in *Proceedings of IEEE/RSJ Intelligent Robots and Systems*, 2005.

[26] J. Fink and V. Kumar, "Online methods for radio signal mapping with mobile robots," in *Proceedings of IEEE International Conference onRobotics and Automation*, 2010.

[27] R. Nandakumar, K. K. Chintalapudi, and V. N. Padmanabhan, "Centaur: locating devices in an office environment," in *Proceedings of ACM MobiCom*, 2012.

[28] M. Youssef, A. Youssef, C. Rieger, U. Shankar, and A. Agrawala, "Pinpoint: An asynchronous time-based location determination system," in *Proceedings of ACM MobiSys*, 2006.

[29] D. Li, T. Bansal, Z. Lu, and P. Sinha, "MARVEL: multiple antenna based relative vehicle localizer," in *Proceedings of ACM MobiCom*, 2012.

[30] "The OsmocomBB Project." http://bb.osmocom.org/trac/.

[31] H. Han, J. Yu, H. Zhu, Y. Chen, J. Yang, Y. Zhu, G. Xue, and M. Li, "SenSpeed: Sensing driving conditions to estimate vehicle speed in urban environments," in *Proceedings of IEEE INFOCOM*, 2014.

[32] "P1609.3 - IEEE standard for wireless access in vehicular environments (WAVE) -networking services, 2010." http://standards.ieee.org/develop/project/1609.3.html.

[33] "Sf02 laser rangefinder 50 m." https://www.parallax.com/product/28043.

[34] "Arada LocoMate OBU." http://www.aradasystems.com/locomate-obu/.

[35] "802.11p." http://en.wikipedia.org/wiki/IEEE_802.11p.