Online Vehicle Front–Rear Distance Estimation With Urban Context-Aware Trajectories

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***Abstract*—Access to accurate relative *front–rear* distance information between vehicles is of great interest to drivers as such information can be utilized to improve driving safety. Acquiring such information based on systems such as the global positioning system (GPS) in urban settings is very challenging due to the high complexity of urban environments. In this paper, we propose a scheme, called relative urban positioning system (RUPS), to tackle the relative distance fixing problem. We first investigate the pervasive global system for mobile communication (GSM) signals and find that the received signal strength indicator measures of multiple GSM channels collected over a distance has ideal temporal–spatial characteristics for *temporary* fingerprinting. With this key insight, 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 neighboring vehicle, the vehicle can identify common locations overlapped between trajectories of itself and this neighbor. Finally, the relative distance between this pair of vehicles can be perceived by further comparing their geographical trajectories based on an identified 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 preconstructed signal maps. We implement a prototype system to validate the feasibility of the RUPS design. 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.**

***Index Terms*—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, referred to as the *front-rear distance fixing* (FRDF) 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 FRDF problem under complex urban environments, however, is very challenging because of several rigorous requirements. First, queries for front-rear 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 schemes proposed for localizing mobile objects in outdoor environments. Given the current location information of two objects, it is easy to derive the relative distance between them. Satellite-based localization schemes such as the Global Positioning System (GPS) have been broadly used for decades. In urban settings, however, it is often the case that satellite signals get blocked due to the "concrete forest" effect, which can lead to large localization errors. Comparing with the nominal GPS which has the accuracy of around 20 to 30 meters [2], 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

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to measure the distance between a transmitter and a receiver via laser, radio frequency or sound. These schemes are vulnerable to ambient noise and constrained in Line-of-Sight (LoS) conditions. As a result, there is no existing successful solution, to the best of our knowledge, to the FRDF problem in urban scenarios.

In this paper, we further improve our previous work, called *Relative Urban Positioning System* (RUPS) [7], which meets all requirements for fixing front-rear distances between urban vehicles. RUPS leverages the inherent locality of the FRDF problem in space and time, needing 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 received signal strength indicator (RSSI) measures of ambient broadband wireless signals, i.e., GSM (Global System for Mobile Communication) signals used in this paper, as its *context-aware* trajectory. After exchanging such trajectory information with its neighbors via vehicle-to-vehicle (V2V) communication (e.g., DSRC [8]), the vehicle can locally identify overlapped trajectory segments through cross-correlation calculation. With an overlapped trajectory segment, the vehicle can eventually obtain the relative front-rear distances between itself and its neighbors by further comparing their geographical trajectories. 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:

1) We intensively investigate the ambient signals of GSM 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.
2) We have developed the RUPS scheme, which can obtain 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 centralized unit or any global map as a priori. It can complete arbitrary relative distance queries in real time and scales well with surrounding heavy traffic and high-frequency queries.
3) We have built a prototype system, validating the feasibility of RUPS in practice. Furthermore, we have conducted extensive experiments to evaluate the performance of RUPS. The results shows that RUPS is robust to urban environments and can achieve an average location accuracy of 4.5 meters over all road settings, outperforming GPS by 2.7 times.

The remainder of this paper is organized as follows. Section II introduces the related work. We investigate on using GSM-aware trajectories for fingerprinting in Section III. Section IV elaborates the design of RUPS. Section V describes our prototype implementation. Several design issues encountered in practice are discussed in Section VI. In Section VII, we introduce the methodology that we use to evaluate the performance of RUPS and present experiment results. Finally, we present concluding remarks and outline the directions for future work in Section VIII.

II. Related Work

Outdoor localization or distance ranging techniques are most related to the FRDF problem.

A. Outdoor Localization Methods

GPS-based: Mikkel *et al.* [9] 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 al.* [10] 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 al.* [11] 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 [12], [13], FM [14], [15], sound [16], [17], and cell tower ID [18] has been extensively studied for indoor localization. Varshavsky *et al.* [19] 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 al.* [20] use a dynamic time warping method to derive the speed of vehicles by warping the GSM signal strengths collected with smart phones. Place Lab [21] and Skyhook [22] 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 [23]–[28]. 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 [29], [30]. 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

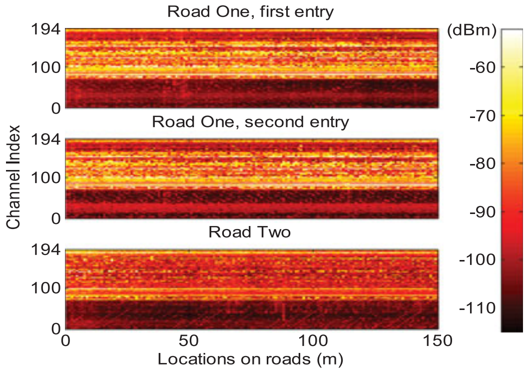

Fig. 1. R-GSM-900 power vectors measured on two different roads with the first road entered twice.

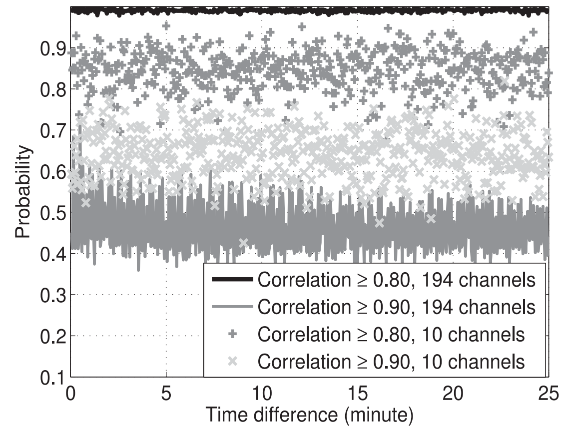

Fig. 2. Temporary stability of GSM power vectors.

schemes [4], [31] 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 [32] 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 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 very coarse relative location information. In contrast, RUPS focuses on front-rear distances between vehicles and does not have such requirements as multiple antennas and LoS condition.

III. Empirical Study on GSM-Aware Trajectories

We investigate what kind of information obtained by a moving vehicle can be leveraged as the context for the presence of this vehicle. As mobile networks, especially the GSM networks, have achieved the prevalent coverage in urban environments, it of great interest to know the characteristics of GSM signals for this purpose. In this section, we study the RSSI values of a wide GSM band, not only on one single location but over a trajectory (i.e., a series of adjacent locations) as the vehicle moves, forming a so-called *GSM-aware trajectory*.

A. Collecting GSM-Aware Trajectories

With the OsmocomBB project [33], all 194 channels in the R-GSM-900 band can be scanned within 2.85 seconds with a Motorola C118 cellphones. We refer to such a vector of RSSI values over 194 GSM channels at one location as a *GSM power vector*.

To collect a trace of GSM-aware trajectories, we randomly selected two hundred surface roads in three different environments, i.e., downtown, urban and suburban, in Shanghai city. For each road, we build a GSM-aware trajectory on every half an hour for three times (or entries) a day for two days, i.e., one workday and one weekend, respectively. All trajectories are 150-meter long with GSM power vectors measured at an distance interval of one meter. Fig. 1 demonstrates three such *GSM-aware trajectories*, i.e., the first and second entries of a road and the first entry of another road, respectively. It is clear to see that trajectories collected on the same road with different time are very similar and trajectories collected on different roads are quite distinct. We intensively investigate GSM-aware trajectories with respect to three 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: *the FRDF problem has an inherent property of locality both in time and in space because only vehicles in vicinity are of interest.* For example, two vehicles moving along the same trajectory would experience a similar environment in a short time. Therefore, as long as GSM-aware trajectories are *temporarily* stable, i.e., GSM-aware trajectories measured on the same road in a short time should be similar, they can be used to solve the FRDF problem.

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. 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 randomly choose 30,000 pairs of GSM power vectors and calculate their correlation coefficient. Fig. 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.

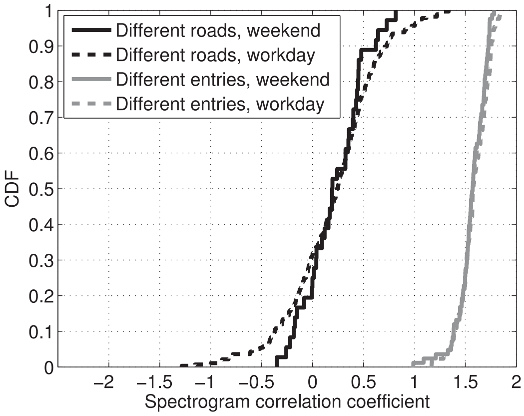

Fig. 3. CDF of correlation coefficient of GSM-aware trajectories.

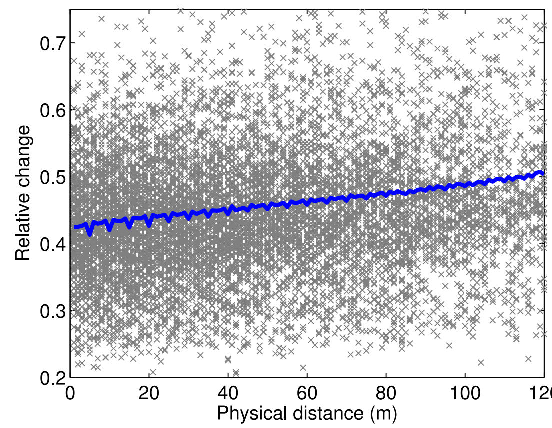

Fig. 4. Relative change of two power vectors over distance.

We have two key observations. First, individual channels do change over time as the probability for all channels to be stable (e.g., setting a high correlation threshold of 0.9) is lower than that when only a subset of channels (e.g., ten randomly-selected channels demonstrated in Fig. 2) are used . Second, the majority of GSM channels are rather stable. For instance, 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. As a result, increasing the number of effective GSM channels would increase the stability probability of GSM power vectors when an appropriate stability threshold is chosen.

C. Geographical Uniqueness

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). In (2), we consider not only the correlation of each channel but also the correlation of averages of each channel between two trajectories. Fig. 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 FRDF 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 away in the same trajectory and change k from one to 120. Fig. 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 FRDF problem, a vehicle only cares about other vehicles in its vicinity (for example, within the range of a safe distance). In light of the inherent spatiotemporal locality of the problem, RUPS integrates two key components: *perceiving GSM-aware trajectory* and *fixing relative distance*, as depicted

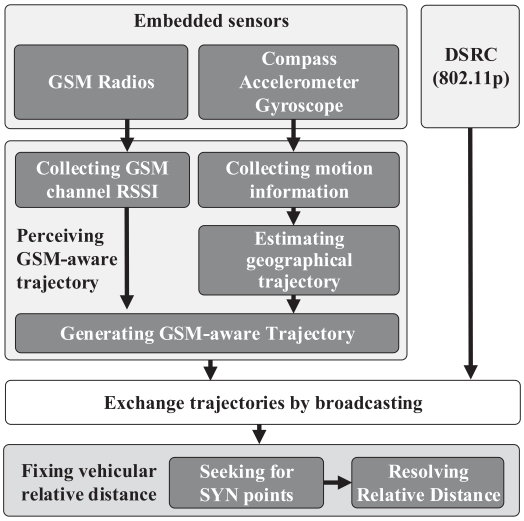

Fig. 5. System architecture of RUPS.

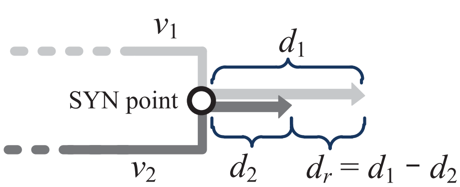

Fig. 6. Vehicular relative distance fixing example.

in Fig. 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 fine geographical trajectory information. At the same time, the vehicle also measures RSSI values of a wide band of GSM channels via GSM radios and binds the retrieved power measurements to its geographical trajectory, forming a GSM-aware trajectory. Then, the vehicle exchanges its own trajectory with its neighboring vehicles through V2V communications. Finally, with trajectories of neighbors, this vehicle conducts cross-correlation calculation, seeking for two highly-similar segments on each pair of trajectories. If succeed, the vehicle believes that it shares an overlapped trajectory segment (referred to as a SYN point) with the corresponding neighbor. Based on a found SYN point, the vehicle can obtain the relative distance between itself and this neighbor by further comparing the remainder of their geographical trajectories.

For example in Fig. 6, solid lines represent the most recent trajectories of vehicle v_1 and v_2 which are known to both vehicles after V2V communication. By comparing their trajectories, 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.

B. Estimating Geographical Trajectory

In RUPS, each vehicle needs to perceive its geographical trajectory information, i.e., the continuous location information of this vehicle as it moves, which is the basic of generating GSM-aware trajectory.

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.* [34], 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 instant speeds 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 [34].

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 of the trajectory.

C. Generating GSM-Aware Trajectory

Each vehicle continuously measures RSSI values of GSM channels as they move. The retrieved power measurements are time-domain signals and need to be bound with the associate geographical trajectory. More specifically, 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 $[t_{i-1}, t_i]$ is associated to the ith element (θ_i, t_i), $i \in [0, m]$ of a geographical trajectory $\mathcal{T}^m$ of a vehicle, forming the corresponding GSM-aware trajectory, denoted as $\mathcal{S}^{\mathcal{T}^m}$.

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 Fig. 7, 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

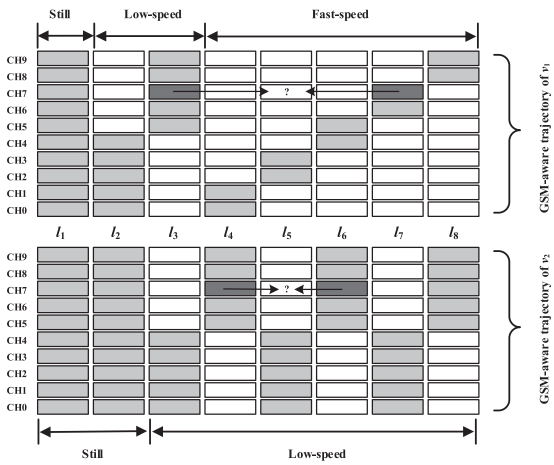

Fig. 7. Example of binding GSM power measurements to geographical trajectory.

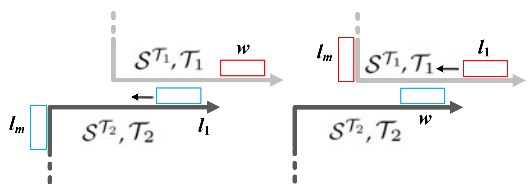

Fig. 8. Example of the double-sliding check for context consistence test.

wireless signals, in RUPS, missing channels are estimated by linearly interpolating between neighboring power vectors over distance. For example in Fig. 7, 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.

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 Fig. 8, 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 Fig. 8.

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. Note that random errors may arise during the procedures of estimating geographical trajectory and seeking for SYN points. To further reduce the impact, we select multiple most-recent context segments to locate SYN points and calculate the relative distance with each of these SYN points. With multiple relative distance estimates, different aggregation schemes can be adopted to improve the final result. In RUPS, we can take the selective average where the maximum and the minimum estimates are discarded before the rest estimates are averaged.

Fig. 9. The prototype implementation on an experimental car.

V. System Prototype

A. Implementation

To validate the RUPS design and prove its feasibility, we have built a prototype system consisting of two experimental cars (i.e., a Volkswagen Passat B5 and a Volkswagen Golf 6). As highlighted in Fig. 9, for each car, seven cheap GSM radios (i.e., Motorola C118 cellphones) are divided into three groups consisting of one, two and four phones, respectively. Each group divides the selected 45 channels into different parts according to the number of phones in that group and scans the spectrum in parallel. We use different groups of GSM radios to study the impact of missing channels to the system performance. Besides GSM radios, we use two Google Nexus 4 smartphones perceive the geographical trajectory of the vehicle, leveraging the motion sensors embedded in the smartphones. 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. Moreover, an Arada LocoMate OBU [35] is mounted on the roof of the vehicle for V2V communication via an IEEE 802.11p radio. This OBU also provides a high-performance GPS module, which is used for performance comparison. We synchronize all devices in one vehicle but we do not require both vehicles to be synchronized.

With our prototype system, we measure the accuracy of speed estimation via OBD and motion sensors. As the travel distance derived from the readings of the Hall sensor is quite accurate, we use the estimated speed derived from the Hall sensor as truth ground. We drive both cars along our experiment route (see next Section for details) and have the CDFs of speed estimation errors shown in Fig. 10. It can be seen that the average errors of speed estimated using OBD and using vibration data are

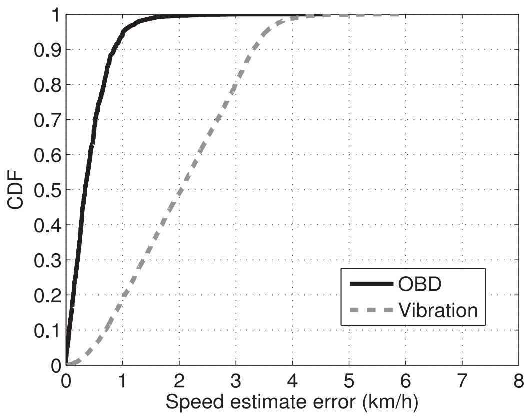

Fig. 10. CDFs of instant speed estimation errors using OBD and vibration data.

TABLE I
AVERAGE PACKET LOSS RATIO OVER RANGE

Range(Km)	1.5	1.6	1.7	1.8	1.9	2.0
PLR(%)	2.6	15.4	19.1	82.8	84.0	85.3

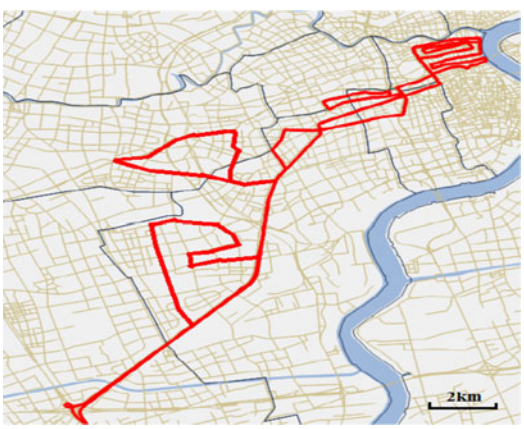

Fig. 11. Experiment route involving open, semi-open, and close roads.

0.4 km/h and 2 km/h, respectively. We measure the average Round Trip Time (RTT) of WSM packets with the maximum payload of 1400 bytes and the average packet loss ratio over distance on a major road near our campus. The average RTT is 4ms and the average packet loss ratio is shown in Table I. In general, V2V communication is very reliable within range of one kilometer.

B. Optimal Parameter Configuration

Selecting effective GSM channels and minimizing the checking window size: As depicted in Fig. 1, some channels (e.g., channel index from 0 to 60) seem rather dull with RSSI values unchanged over distance. Dull channels can lead to extra cost of RSSI measurement and network transmission. To make things even worse, dull channels would degrade the performance of cross-correlation calculation for seeking SYN points. Therefore, dull channels should be excluded from GSM-aware trajectories. On the other hand, a checking window involving more valid GSM channels and more refined power vectors will certainly

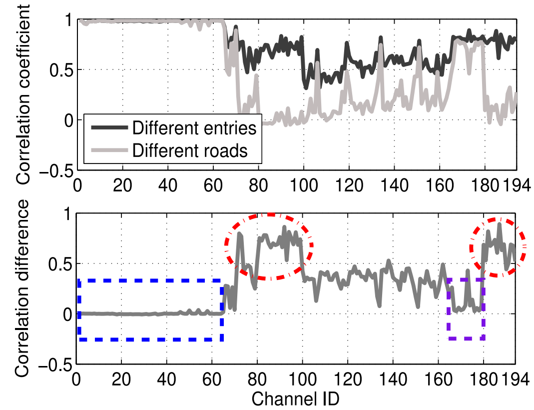

Fig. 12. GSM channel utility for fingerprinting.

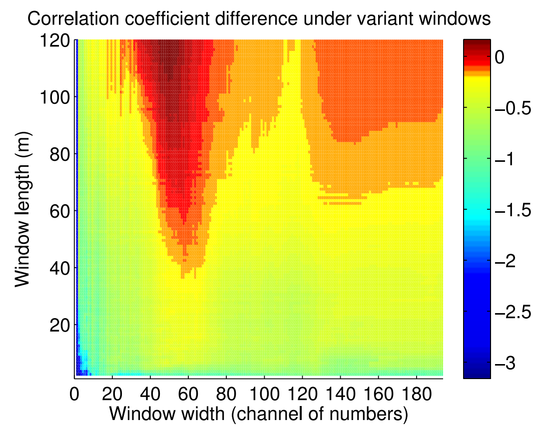

Fig. 13. Difference between the min coefficient obtained on same roads and the max obtained on different roads.

increase the accuracy of the resolved relative distance but it can also increase the network cost and the complexity of computation too.

We first study which channels are effective and how many of them are sufficient. With the trace described in Section III, we calculate the Pearson's correlation coefficient for each channel between different entries on the same roads and between different roads. The upper subplot in Fig. 12 depicts the average correlation coefficient over all pairs of different entries and all pairs of different roads, respectively, and the lower subplot depicts the difference between the coefficient calculated on the same roads and that calculated on different roads. It can be seen in Fig. 12 that the effectiveness of GSM channels in terms of the utility for fingerprinting varies significantly. We discard two spans of channels from channel 0 to channel 64 and from channel 165 to channel 178, as labeled by the dash rectangles, as they are not geographically sensitive. Moreover, we rank the GSM channels according to the coefficient difference in a descending order.

We further extensively cross study the effect of increasing both the number of sorted channels and the number of measured power vectors to the effect of using GSM-aware trajectories for fingerprinting. Fig. 13 depicts the correlation difference with varying window sizes by subtracting the maximum coefficient achieved among all pairs on different roads from the minimum

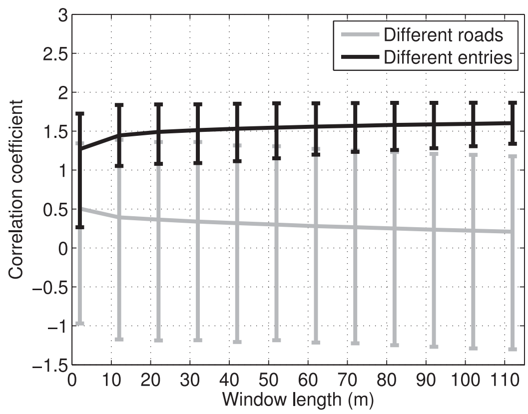

Fig. 14. Correlation coefficient vs. the length of checking window with top 45 channels involved.

coefficient achieved among all pairs of different entries on same roads. It can be seen that the correlation difference reaches the maximum when top 45 channels are involved. Furthermore, with those channels, add more power vectors can further increase the difference.

Choosing coherency threshold: For illustration, Fig. 14 plots the correlation coefficient of GSM-aware trajectories as a function of window size for context coherence tests when the top 45 channels are used. It can be seen that if the window is sufficiently long, there would exist ideal thresholds (e.g., 1.3 with a 90-meter window) with which all correlated and unrelated contexts can be well differentiated. When the window length is short (e.g., due to the context availability reason), however, the policy to choose the coherency threshold is critical. On one hand, if an inappropriately-high threshold is adopted, the probability for two correlated contexts being treated as unrelated (i.e., false negative errors) would increase. On the other, a small threshold would cause unrelated ones being treated as correlated (i.e., false positive errors). In safety-related applications, zero false negative ratio should be achieved. We will further study the effect of the window size and the consistency threshold to the system performance through intensive field experiments in Section VII.

VI. Discussion

A. Network Overhead and Computational Complexity

In the FRDF problem, vehicles only care about vehicles in vicinity and therefore exchange only recent trajectory information. As suggested in IEEE 802.11p protocols, each vehicle should broadcast at least one WAVE Short Message (WSM) packet on every 100 ms [36]. RUPS can utilize WSM packets to exchange trajectories. For instance, with the maximum payload of a WSM packet, i.e.,1400 bytes, each vehicle can broadcast about 14 KB data per second, which can carry a 45-channel GSM-aware trajectory of about 280 meters. For a vehicle moving at the maximum high speed of 120 Km/h, its newly generated trajectory is only about 34 m per second. Thus, each vehicle can utilize the extra network capacity to send its history trajectory.

With a limited sample rate of sensors needed (e.g., 0.3 Hz for OBD and around 200 Hz for motion sensors), the computational overhead for generating trajectory is trivial and negligible. In our algorithm, the most expensive step is to identify SYN points over a pair of trajectories. Therefore, our algorithm complexity is bounded by the length of trajectory needed for analysis. Given a trajectory 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 $O(mwk)$. For instance, in our prototype implementation, we consider trajectories of 500 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 0.6 milliseconds.

B. Multipath Fading and Dynamic Environments

The multipath fading of GSM signals may bring uncertainty to the RUPS scheme. For example, multipath fading in urban canyons is known to decorrelate over half a wavelength or about 15 cm in the 900 MHz band. To study the multipath fading problem, we have conducted extensive field experiments in Shanghai city on a route of around 100 km over three months. We find that RUPS can achieve stable performance in finding SYN points. The influence of a small number of faded channels at limited number of spots contained in journey contexts is reduced when doing the correlation calculation.

In addition, in urban settings, the dynamic of urban environments (e.g., variant numbers of lanes, surrounding buildings, and different traffic conditions) may also affect the efficacy of RUPS. After carefully examine the experiment results, we find that, when the SYN points found using the context where there is a big vehicle such as a bus or a truck passing by one of the two experiment vehicles, large errors could occur. With the scheme of selective average over multiple SYN points proposed in Section IV-E, outlier results and random errors can be greatly reduced and we report the results in Section VII.

C. Short Trajectories and Missing Channels

When a vehicle enters a road segment, it is possible that it has insufficient context for the context consistence test. To solve this problem, in RUPS, we can adopt a flexible checking window and consistency threshold adaptive to the mount of context available. As shown in Fig. 13, 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 trajectories, 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 15 ms to sense a channel. Therefore, scanning a band of 45 GSM channels with ten parallel radios would take 68 ms. For a vehicle moving at a speed of 80 km/h, a power vector can only span a distance of 1.5 meters. We will examine the effect of using multiple GSM radios to the system performance in Section VII.

D. Limitations of RUPS

There are several limitations of RUPS when applying RUPS in different urban settings. First, RUPS requires vehicles to be capable of sensing wireless channels of mobile networks. Currently, it employs the GSM network but other mobile networks such as 3G/4G can be utilized. In addition, vehicles should also be able to communicate with each other via V2V communication. This condition can be gradually satisfied as DSRC will be deployed on all future vehicles. Second, RUPS requires dense deployment of GSM base stations so that the derived GSM-aware trajectories have fine RSSI measurements over a wide band GSM channels. This makes RUPS less accurate when used in rural environments where base stations are deployed more sparse. We explain that in such scenarios accurate location information can be reliably obtained using GPS and RUPS focuses on urban settings where GPS performs poorly.

VII. Performance Evaluation

A. Methodology

We select an experiment route of 97 km 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 our experiment cars along the selected route as shown in Fig. 11 once on every two days for nearly three months from March 21st and June 18th. We also select 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. The ground truth is obtained with a laser rangefinder [37]. In addition, although it is not needed by RUPS, we also taped on each drive for verification.

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 three metrics to evaluate the performance of RUPS and GPS:

False positive ratio (FPR): refers to the proportion of all unrelated trajectories that are falsely identified as correlated ones. With false positive errors, vehicles that are not within the same range of interest can be treated as neighbors.

False negative ratio (FNR): refers to the proportion of all actually correlated trajectories that are incorrectly rejected in the context consistence test. With false negative errors, nearby vehicles are wrongly ignored, which are critical to safety-related applications.

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

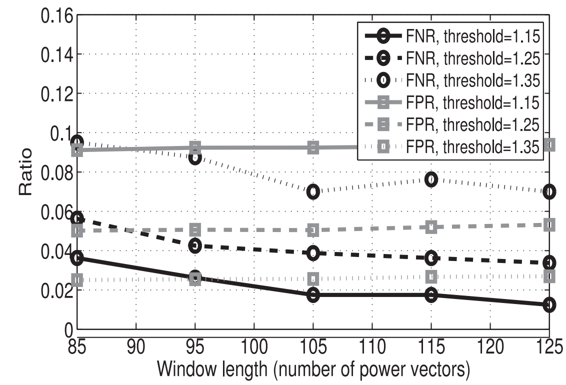

Fig. 15. FNR and FPR vs. checking window length.

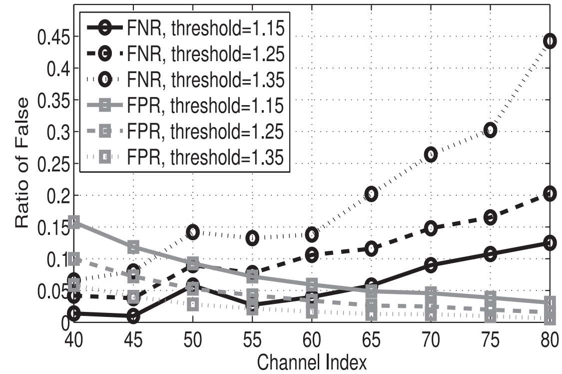

Fig. 16. FNR and FPR vs. checking window width.

between the pair of cars as the difference of their traveling distances since last stop.

In the following trace-driven simulations, we first investigate the effect of system parameter configuration to the system performance, and then use the optimal parameter configuration to compare the performance of RUPS with that of GPS.

B. Effect of Checking Window Size

We examine the effect of the checking window size, i.e., the window length in terms of the number of refined power vectors and the window width in terms of the number of channels. We first use the top 45 channels ranked according to channel utility for fingerprinting as described in Subsection V.B and vary the length of the checking window in the context coherence test from 85 to 125 meters. We randomly select 500 points from the trajectory of the first car, estimate the relative distance between the pair of cars according to RUPS, and take the average. Fig. 15 plots the FNR and FPR as a function of the window length, with the consistency threshold set to 1.15, 1.25 and 1.35, respectively. It can be seen that both FNR and FPR are not sensitive to the window length even though slight drops can be found with FNR. This indicates that 85 meters is a practical configuration for the window length in the experiment.

We then fix the window length to 85 meters and vary the number of channels involved in the test. Fig. 16 plots the results. Note that channels are pre-ordered according to their utility to be used as fingerprints. It can be seen that, with more channels involved, the FNR increases. The reason is that noisy channels can reduce the correlation. We adopt the top 45 channels as

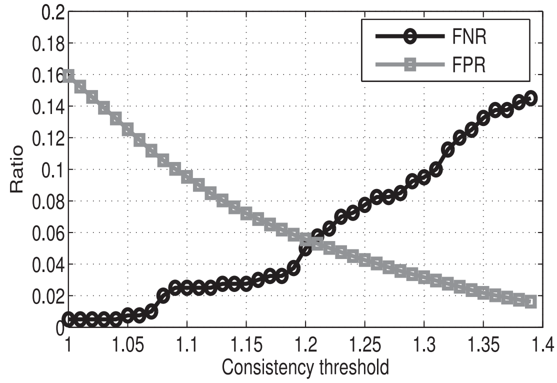

Fig. 17. FNR and FPR vs. consistency threshold.

a practical solution as the sum of FNR and FPR reaches the minimum with all thresholds.

C. Effect of Consistency Threshold

With the size of the checking window properly configured, we examine the effect of the consistency threshold. We use the same settings as in the above experiment and vary the consistency threshold from one to 1.4 with an interval of 0.01.

Fig. 17 depicts the average FNR and FPR as a function of the consistency threshold. It is clear to see that the FNR increases with the consistency threshold whereas FPR drops. The reason is that, as the consistence requirement increases, it is more likely for two similar contexts being rejected by the consistence test, resulting a high FNR. It is the same reason that FPR drops. It can also be seen that, in general, 1.2 is a good consistency threshold trading off between FNR and FPR. The policy for choosing an appropriate consistency threshold relies on the requirements of high-level applications.

D. Impact of the Number and Position of Scanning Radios

In order to study the impact of missing channels, we examine three groups of GSM radio configurations, i.e., one radio, two radios and four radios on the top of the instrument panel of each vehicle (denoted 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”). 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.

Fig. 18 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. 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, deploying multiple cheap 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.

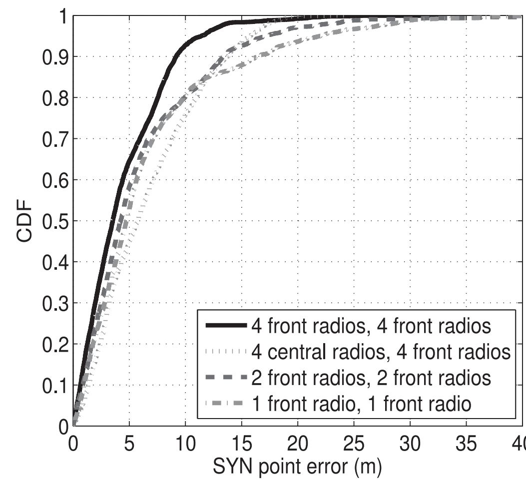

Fig. 18. SYN point distance errors with varying numbers and positions of GSM radios.

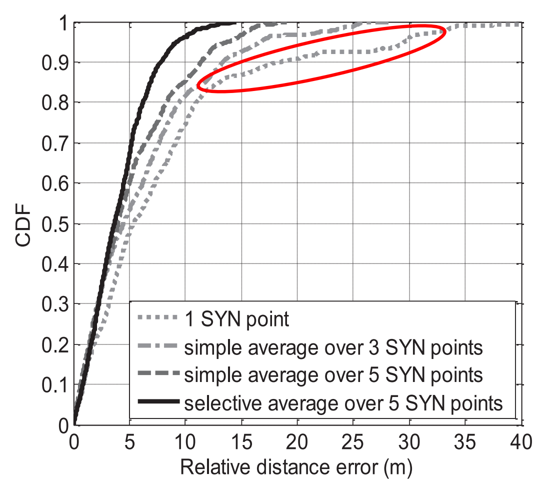

Fig. 19. CDFs of RDE derived with one and multiple SYN points.

E. Impact of Dynamic Environments and Different Lanes

We first examine the impact of surrounding traffic. 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. Fig. 19 depicts the CDFs of distance errors of the resolved relative distances. It can be seen that, with the original RUPS, 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 this, we can select multiple most-recent trajectory segments to get multiple relative distance estimates and aggregate such estimates to improve the accuracy. 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.

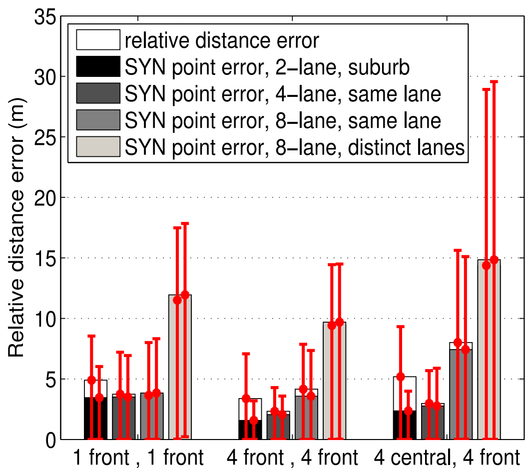

Fig. 20. Average RDE under dynamic environments and radio configurations.

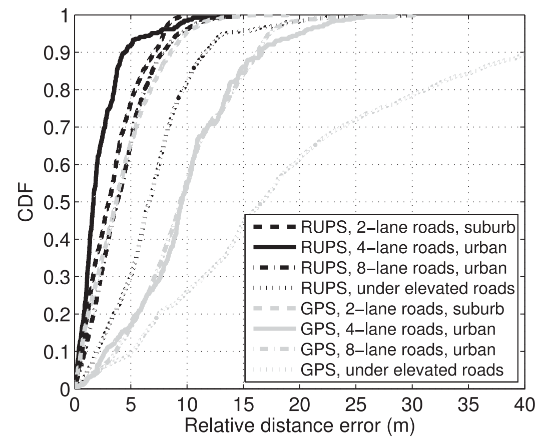

Fig. 21. Comparison with GPS under different urban environments.

We then study the impact of dynamic 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. We also combine different numbers and placement of scanning radios. 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. Fig. 20 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 4.5 m on average over all road conditions. Nevertheless, it can be seen that when driving on different lanes, the average SYN point error can reach to around ten meter. Note that, 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.

F. Performance Comparison under Urban Environments

In this experiment, we compare RUPS with GPS in the same lane under 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.

Fig. 21 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.

VIII. Conclusion

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.

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