SmartLoc: Push the Limit of the Inertial Sensor Based Metropolitan Localization Using Smartphone

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ABSTRACT

We present *SmartLoc*, a localization system to estimate the location and the traveling distance by leveraging the lower-power inertial sensors embedded in smartphones as a supplementary to GPS. To minimize the negative impact of sensor noises, *SmartLoc* exploits the intermittent strong GPS signals and uses the linear regression to build a prediction model which is based on the trace estimated from inertial sensors and the one computed from the GPS. Furthermore, we utilize landmarks (*e.g.*, bridge, traffic lights) detected automatically and special driving patterns (*e.g.*, turning, uphill, and downhill) from inertial sensory data to improve the localization accuracy when the GPS signal is weak. Our evaluations of *SmartLoc* in the city demonstrates its technique viability and significant localization accuracy improvement compared with GPS and other approaches: the error is approximately 20m for 90% of time while the known mean error of GPS is 42.22m.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

Keywords

SmartLoc, Inertial Sensor, Localization

1. INTRODUCTION

Localization have attracted significant attentions in the past few decades, and numerous techniques [2, 11, 13] have been proposed to achieve high accuracy localization. In outdoor scenarios, GPS (Global Positioning System) or its variants are the most common technologies to provide accurate position [4] for various applications, such as trace and tracking [9, 12] in the wild, and environmental monitoring [7]. However, problems regarding low accuracy of GPS in critical regions such as metropolises have proposed the idea of war-driving and created the state of art large scale WiFi/GSM fingerprint database for positioning, like Skyhook [1]. These methods often sample and establish fingerprint databases, which are computationally intensive.

To study the severity of the GPS localization [6] errors in metropolises, we conducted comprehensive experiments in downtown Chicago to evaluate the performance of GPS positioning. Based on the experiment results, we observe that the GPS signals are very weak and unstable in some roads due to highrises, or even blocked completely in some complicated road structures, such as tunnels and underground. In addition, the largest location error we collected is over 100m on the ground, and nearly 400m in the underground segments. Thus, improving the location accuracy is imperative when the GPS signal is weak in metropolises.

In this work, we propose *SmartLoc*, a localization method which improves the localization accuracy in metropolises by leveraging embedded inertial sensors in smartphones to help improve the driving patterns according to various of road conditions. Although exploiting the data collected from inertial sensors has been used to measure the walking speed and distance of pedestrian in outdoor environment [3, 5, 8, 10], realtime localization of driving cars in metropolises is still far more challenging as such activity does not have a cyclic pattern in sensor data.

To address these challenges, during the dead reckoning process for calculating the current position of a car, we propose a dynamic trajectory model to estimate the driving speed and velocity based on current road condition, so that the impact of inherent noise and accumulated error could be reduced to a large extent. We also design a calibration strategy based on road infrastructures (*e.g.*, bridge, traffic lights, uphill, and downhill) and driving status (*e.g.*, turns, stops), which are inferred from the sensory data.

SmartLoc also exploits the current coarse-grained estimation of location to confine the search space, so that a much more accurate localization could be achieved through matching the road infrastructures and driving status.

2. APPROACH

The purpose of **SmartLoc** is to use inertial sensors in the smartphone to estimate the movement of the vehicle, and lively provide locations based on the traveling distance and orientation with high accuracy but low energy consumption. Remarkably, we not only address the inaccuracy caused by the complex infrastructures in downtown area, but also exploit them as landmarks in the map to improve the localization accuracy of localization.

2.1 Self-learning Predictive Model

According to the Newton's Law, we can obtain the distance after applying a double integration on the acceleration. However, the noises from the accelerometer will be accumulated also so that

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the estimation error gets enormously huge in just several minutes. However, we observe from our preliminary experiments that the majority of the road segments with bad GPS signals (error $\geq$ 30m) are usually shorter than 400m, which takes only 20-30 seconds to drive through in a normal condition. On the one hand, such distance is long enough to navigate drivers to wrong places, on the other hand it is short enough to endure the errors to some extent. Therefore, we propose the following predictive dynamic trajectory estimating model which adaptively calibrates itself using GPS signals and dead reckoning.

Velocity Estimator: Because of the inherent noises and measurement errors, the traditional velocity estimation model is no longer reliable. In this case, we denote the velocity V_i at the end of a timeslot i as

$$V_i = V_{i-1} + \beta \cdot a_i \cdot \Delta t + \mu$$

where β is the parameter to be learned and adjusted in real time, a_i is the average measured acceleration during the timeslot i, and μ is the noise. When GPS signals are strong, both V_i and V_{i-1} could be achieved from the GPS directly, and the mean linear acceleration a_i is extracted from the accelerometer. Then we regress the model to find the best β, and calculate the noise μ hiding behind. When the localization through GPS is unreliable, we use the trained model proposed to predict the velocity V_i.

Distance Estimator: For general cases, the trajectory distance gathered from GPS indicates the distance with some error. Therefore, letting $G(\Delta t_i)$ be the distance during a timeslot i read from GPS, which could be presented as:

$$G(\Delta t_i) = \lambda_1 \cdot V_{i-1} \cdot \Delta t + \frac{1}{2} \cdot \widehat{a_i} \cdot \Delta t^2 + \eta$$

where $\widehat{a_i}$ is the actual acceleration in the time slot i. Here λ_1 is multiplied to reflect the error in the estimated speed V_{i-1} for the time slot $i-1$. Since the known measured acceleration a_i contains both inherent noise and measurement errors, by assuming that these error follows normal distribution, we define the measured acceleration as: $a_i = (1+\varepsilon)\widehat{a_i} + \delta$, where $\widehat{a_i}$ is considered as the true acceleration which cannot be obtained. Then, we use the following formula to estimate the distance $G(\Delta t_i)$:

$$G(\Delta t_i) = \lambda_1 \cdot V_{i-1} \cdot \Delta t + \lambda_2 \frac{1}{2} \cdot a_i \cdot \Delta t^2 + \lambda_3 \cdot \Delta t^2 + \lambda_4 \cdot \Delta t + \eta \quad (1)$$

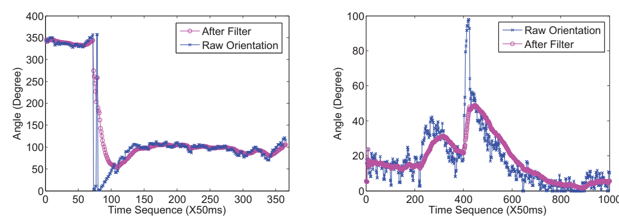
where $\lambda_1, \cdots, \lambda_4$ are parameters to be learned by our regression model. When GPS signals are strong (GPS error is $\leq$ 20m), based on the V_{i-1}, a_i is computed using the sensory data and the distance from GPS, we train our model using Eq. (1), which is in turn used to predict the distance $G(\Delta t_i)$ in the time slot i when GPS signals are bad. From the predicted trajectory distance $G(\Delta t_i)$, the location at the timeslot i could be estimated based on the obtained location, distance and orientation.

2.2 Calibration By Landmarks

The road infrastructures, including tunnels, bridges, crossroads and traffic lights, cause large noises in the GPS data, which results in large drift in the distance estimation if it is not treated rigorously. In this work, we exploit the precise location of these infrastructures that are available in Google Map to calibrate the localization without any extra cost.

Traffic Light: When the vehicle stops due to the traffic lights and drives through crossroads, unique patterns appear in the readings of sensors (Figure 1(a)). Actually, when vehicles encounters traffic lights, the whole process can be divided into two phases, braking and speeding up respectively. However, in rush hours with terrible traffic, the location where cars stop may not be near the crossroad, but with a certain distance from the crossroad. In this case, *SmartLoc* adjusts the moving distance based on the estimated stopping location from the empirical data, *i.e.*, subtracting the distance from the car to the crossroad. However, the distance between the car and the crossroad is determined by the traffic condition, it is difficult to measure the exact distance from the car to the crossroad. The main approach adopted by *SmartLoc* is to subtract the $\frac{n \cdot L}{2}$, where *L* indicates the average length of a vehicle, and *n* represents the current possible number of vehicles waiting for the green light. We calculate the number of vehicle based on the observed data, and *n* is also related to different time periods.

Turning: Sometimes, vehicles may turn at intersections, which could be detected by sensors. Figure 1(b) indicates the centripetal force sensed by the accelerometer, and the scale of the acceleration depends on the speed at which the vehicle is turning. Simultaneously, the angular velocity sensed by the gyroscope also reaches up to 0.5 rad/s in our test case (Figure 1(c)), and the data from the magnetometer changes as well with a large fluctuation. Finally, the orientation of the smartphone also changes approximately 90 degrees when turning left or right. Although the angle may not be accurate enough due to the large noise in the magnetometer (the maximum error we experienced was approximately 30^o), we are still able to correctly determine the road segment to which the car is turning by calibration. Figure 2(a) shows a case when vehicle turns from the north, the angle is from about 350^o to 100^o, which is east. We also compare the measured angle difference for turning and lane changing (Figure 2(b)) since lane changing can be wrongly detected as a turning. The angle difference when a car changes its lane is much smaller than the one when a car make a turn.



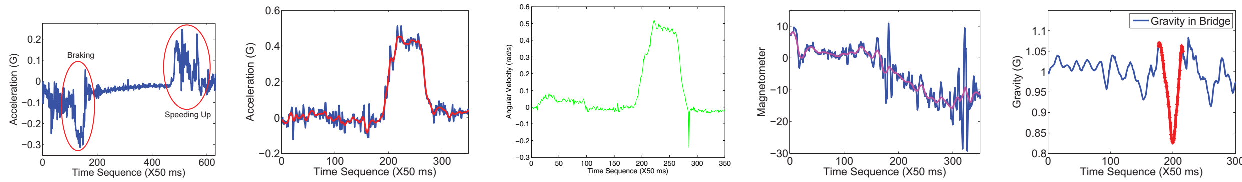
(a) Turning (b) Changing Lane

Figure 2: Turning or changing lanes, and Driving Trace

In fact, certain driving patterns, such as turing left or right and stopping for traffic lights or stop signs, can be more accurately detected and thus classified. To classify other road infrastructures, we collect the sensor readings of those patterns to store as the fingerprints, and then match the real-time sensor readings with the trained fingerprints. To improve the classification and the matching accuracy, we rely on the coarse-grained estimation of the location from dead-reckoning first, and then we further use our predictive regression model to confine the search space: only the road infrastructures (stored fingerprints) I within a certain distance δ from the estimated location x will considered as the matching candidate for the real-time pattern P achieved from the sensor data. We select the infrastructure that maximizes the *weighted matching score*:

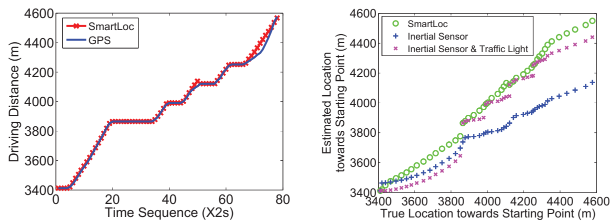
$$\alpha M(I,P) + (1-\alpha) e^{-D(x,L(I))}$$

where $M(I,P)$ is the matching score between the fingerprint of an infrastructure I and the observed pattern P, $\alpha \in (0,1)$ is a constant, and $D(x, L(I))$ is the geodesic distance between the location x and the location $L(I)$ of infrastructure I. Then, the estimated location x is updated as the location $L(I^*)$ of the infrastructure I^* which maximizes the weighted matching score.



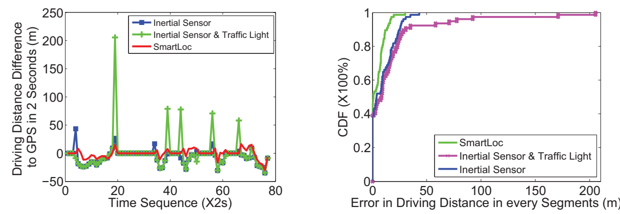
(a) Traffic lights (b) Centripetal force (c) Angular velocity (d) Magnetometer (e) Bridge

Figure 1: Pattern of the sensor data collected in different road infrastructures when driving: (a) car stopping and crossing a traffic light; (b), (c), and (d) car turning 90^o; and (e) car crossing a bridge.



(a) SmartLoc (b) Overall Comparison

Figure 3: Distance prediction comparison among three methods and ground truth.



(a) Error of driving distance in each time slot (b) Error of driving distance in each segment.

Figure 4: Comparison of three methods.

3. PRELIMINARY RESULTS

We conduct a preliminary evaluations of SmartLoc in downtown Chicago for over 100 different road segments ranging from 1km to 10km. Since the inertial sensors provide the driving orientation, combined with driving distance from the location in last timeslot, the real-time location could be obtained. Thus, the key problem becomes estimating the trajectory distance.

SmartLoc calibrates the location as soon as it detects specific patterns, especially traffic lights and turnings. We compare the performance of three different methods in detail: using inertial sensors only, using sensors and landmark calibration, and using *SmartLoc* with all learning model and calibration.

In this experiment, we assume the first 3400m is with reliable G-PS signals, and the precise locations are accessible. The estimation starts from 3400m, and the first three figures in Figure 3 indicate the driving distance from the starting point versus the elapsed time. Surprisingly, after combining our predictive regression model and the noise canceling technique, *SmartLoc*'s result almost coincides with the ground truth, as shown in Figure 3(a). For the first 900m, the curve of *SmartLoc* nearly overlaps with the curve of the ground truth. For the first 450m, the vehicle passes three crossroads with all green lights, and the error is less than 20m in most of the time. After the final traffic lights, the vehicle has to drive at a relatively low speed because of the road construction. The predicted distance consequently deviates from the ground truth a little, but at the end of the road, the errors remain small. We plot all the estimated distances by three methods in Figure 3(b), with the X axis being the ground truth distance and Y axis being the predicted distance, *i.e.*, the perfect prediction will have a diagonal line. *SmartLoc* results are distributed almost along the diagonal line, and pure sensor approach deviates greatly.

The deviation of the results from the ground truth comes from the accumulated errors from all time slots. Based on the previous experiments, we plot the error in every time slot in Figure 4(a). *SmartLoc* with landmarks calibration has the smallest mean error of the estimated locations for all time slots: 90% of them are lower than 20m from the CDF in Figure 4(b). The other two approaches have larger errors, and the last figure describes the CDF of the total driving distance error.

4. ACKNOWLEDGMENTS

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