COMMANDO TRACKING UNDER CLOSED AREA USING WI-FI ROUTERS

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ABSTRACT

In last two decades, smart phones are becoming more and more powerful. Applications in smart phones providing location based services. Many smart phones are equipped with a powerful sensor set (GPS, Wi-Fi, the acceleration sensor, the orientation sensor, etc.), which makes them capable of accomplishing complicated tasks. Nowadays most of the smart phones use GPS or Google positioning system for location tracking. As the GPS takes too much energy to connect to the satellite that causes drain in battery of phone. Google location tracking require the network connection and more data transfer. To avoid this drawback of traditional positioning system we introduce the Wi-Fi tracking. Wi-Fi tracking resolves the battery consumption problem. Well, It has more accuracy than the GPS and here we don't require any data connection. This can be used in closed area.

***Terms*—Location tracking, smart phone, sensor.**

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I. INTRODUCTION

Locating human mobility in daily life is a fundamental resource for the applications that provide location based services.In past few years most of the smart phone users are tends to use location tracking applications. Consumer and advertiser expenditure on location based services is expected to approach $ 10 billionby 2016 [1]. This application are more favorite. Global Positioning System (GPS) is main technology to be used, other technologies also available like Wi-Fi and GSM, each of which can vary widely in energy consumption and localization accuracy. As it is known to be more accurate, GPS is often preferred on mobile platforms over its alternatives such as GSM/Wi-Fi based positioning systems.

In this paper, we present the design of Wi-Fi tracking. It is location tracking service that provides user's moving trajectory while reducing its impact on the devices's battery life. Wi-Fi tracking have small area of tracking but consume less battery. Wi-Fi and GPS are two most important sensors on smart phones. We have implemented android application prototype on the Smartphone, which continuously collects data from the acceleration sensor and the orientation sensor, and records the location samples from GPS and Wi-Fi[25]. Experiments have been conducted on a real world path while the phone was carried by a mobile user in a region of our university campus. To predict the user's original trajectory, a track reconstruction algorithm based on a machine learning technique is also implemented on the server side[25]. Performance evaluation on the real data sets shows that Wi-Fi tracking only needs 7% GPS samples of the naive approach and saves nearly 90% GPS activated time[25]. Wi-Fi tracking reconstructs the user's trajectory with high accuracy and better coverage.

The main contributions of this paper are listed as follows:

We present the detailed design of an energy-efficient location tracking service. Wi-Fi tracking. A track reconstruction algorithm based on Gaussian Process Regression is proposed. Other mechanisms for making smart adaptive sampling decisions are also discussed.

II. DETAIL ABOUT GPS AND WI-FI

To track the users' locations, many energy-efficient sensing approaches with adaptive sensing policies have been proposed to minimize the energy consumption [3], [7]–[9]. With the objective of minimizing the location error for a given energy budget, EnLoc [3], an energy-efficient localization framework, includes a heuristic with a local mobility tree to predict the next sensing time by utilizing the dynamic programming technique. Here we uses the information obtained from the acceleration sensor to continuously monitor activities. According to the user's mobility patterns, a discrete-time Markov Decision Process is employed to learn the optimal GPS duty cycle schedule

with a given energy budget. An adaptive location service for mobile devices, a-Loc [7] uses a
Bayesian estimation framework to determine the dynamic accuracy requirement, and tunes the energy expenditure accordingly. It is founded that the GPS position refresh rate is less than the Wi-Fi refresh rate. It is The rate-adaptive positioning system for smart phone applications was then proposed to minimize energy consumption with given accuracy threshold by using the information of moving distance, space-time history, and cell tower-based blacklisting.

III. PROBLEMS IN GPS

In this section, we are describing the defects of typical location-based applications that utilize GPS.

Traditional GPS cannot work properly under the indoor environment. Figure 1(a) shows one track that we took using GPS on a mobile device. Although we did not stop recording, the track ends once it entered the building (the Academic Quadrangle in our campus), which indicates the performance of GPS largely depends on the working condition[25]. The signals from GPS satellites can be blocked by buildings, by canyon walls, trees, and even thick clouds. When the user walks through buildings.GPS units may consume more energy than the normal situation when there is no satellite signals [14]. Android OS provides a network based localization mechanism, which exploits GSM footprints from cell towers and Wi-Fi signals to obtain an approximate location[25].

IV. WI-FI TRACKING: DESIGN DETAILS

A. Overview

The main start of step of Wi-Fi tracking is to upload the coordinates of sampled locations to an online server that uses a machine learning algorithm to reconstruct a smooth and accurate trajectory.

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Figure 4 demonstrates the Wi-Fi tracking's system architecture. The service consists of two stages: the first is to collect the location samples; and the second is to reconstruct the original trajectory. Given the working conditions, Wi-Fi tracking switches between the GPS-based and the network-based localization methods using the GPS or Wi-Fi sensors, respectively[25]. By utilizing the sensor hints from the acceleration sensor and the orientation sensor, Wi-Fi tracking is able to make smart adaptive sampling decisions in the GPS mode[25]. For example, when the smart phone detects a turning point or if it estimates a unreasonable speed or a unexpected large traveling distance, it uses GPS to record the current location. After the server side receives all the collected location samples, a Gaussian Process Regression algorithm is then employed to predict the trajectory that the user has taken.

Track Reconstruction: Gaussian Process Regression

Once the collection of location samples is finished, it is not ideal to simply connect all the recorded locations, since the distances between any two successive locations may not be the same. For some parts of a trajectory, the recorded locations can be very sparse, while for other parts, the location samples may be relatively intensive. If we simply connect the location samples, the resultant trajectory can be very abstract. Therefore, uploading the collected data to the online server either by a wireless or wired connection to reconstruct the trajectory is our last stage. We adopt the Gaussian Process Regression (GPR), a machine learning technique to perform the interpolation. The training set of the algorithm is the recorded critical locations decided by the sensor hints which capture most of key features of a trajectory. And the testing set is the predicted locations between the successive but far-away location samples. Combing both input and output gives us the final trajectory. We next detailed describe GPR and how the user's trajectory can be reconstructed by using GPR. A Gaussian process is a collection of random variables, any finite number of which have a joint Gaussian distri-bution, and is fully specified by a mean function and a covariance function [21]. The inference of continuous values with a Gaussian process prior is known as Gaussian Process Regression. Consider x as a general random variable.

We define the mean function $m(x)$ and the covariance function

$k(x, x\_{343})$ of a real process $f(x)$ as

$m(x) = E[f(x)]$,

$k(x, x\_) = E[(f(x) - m(x))(f(x\_) - m(x\_))]$,

and can write the Gaussian process as

$f(x) \sim gp(m(x), k(x, x\_{347}))$.

For notational simplicity the mean function is usually set to be zero. In our method the covariance function will be the squared exponential covariance function, although other covariance functions may also be useful. Assuming that observations are noise-free, the covariance function specifies the covariance between pairs of random variables

$cov(f(x_p), f(x_q)) = k(x_p, x_q) = exp(-12|x_p - x_q|_2)$. (1)

For a estimate data set X_*, we can generate a random Gaussian vector f_* for target values with the covariance matrix calculated from Equation 1

$f_* \sim N(0, K(X_*, X_*))$.

Therefore, the joint distribution of the training outputs f and the test outputs f_* according to the prior is

$$\begin{bmatrix} f \\ f_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X, X) & K(X, X_*) \\ K(K_*, X) & K(X_*, X_*) \end{bmatrix}\right)$$

. (2)

If X contains n training points and X_* contains n_* test points, then $K(X, X_*)$ is the $n \times n_*$ matrix of the covariances evaluated at all pairs of training and test points. And the other entries $K(X, X)$, $K(X_*, X)$, and $K(X_*, X_*)$ are similar.

V. ACTUAL IMLPIMENTATION PART

Fig. 3 shows the process view implementation of the application. Fig 5 shows triangulation method for tracking.

Trilateration/Tringulation.

In trigonometry and geometry, triangulation is the process of determining the location of a point by measuring angles to it from known points at either end of a fixed baseline, rather than measuring distances to the point directly (trilateration). The point can then be fixed as the third point of a triangle with one known side and two known angles.

Triangulation can also refer to the accurate surveying of systems of very large triangles, called triangulation networks.

FSPL

FSPL is shown in the fig. 7.

In telecommunication, free-space path loss (FSPL) is the loss in signal strength of an electromagnetic wave that would result from a line-of-sight path through free space (usually air), with no obstacles nearby to cause reflection or diffraction.

Free-space path loss is proportional to the square of the distance between the transmitter and receiver, and also proportional to the square of the frequency of the radio signal.

The equation for FSPL is

$$\mathrm{FSPL} = \left(\frac{4\pi d}{\lambda}\right)^2 = \left(\frac{4\pi d f}{c}\right)^2$$

where:

a. λ is the signal wavelength (in metres),
b. f is the signal frequency (in hertz),
c. d is the distance from the transmitter (in metres),
d. c is the speed of light in a vacuum, 2.99792458×10^8 metres per second.

This equation is only accurate in the far field where spherical spreading can be assumed; it does not hold close to the transmitter.

VI. Further Discussion

A. Multiple Mobility Patterns

Although our work focuses on the pedestrians, it can be easily extended on multiple mobility patterns, such as running, biking, driving, etc, which are often with higher speeds. Intuitively these movements are more stable, and thus the trajectories are likely less complex, and thus the sensors on smart phones can easily capture the features of the path. Therefore, our approach at least paves the road of designing the efficient tracking service for multiple mobility patterns. However, given the characteristics of different movements, modifications should be carefully considered.

B. Energy Consumption of Accelerometer and Orientation Sensor

In this paper, to make our point clear, we assume a continuous sampling of the acceleration sensor and the orientation[8] sensor, which may cause unnecessary energy cost. It is not necessarily the case. Given that the energy-efficiency is a major goal of our design, users can further employ a low duty cycle on the usage of the acceleration sensor and the orientation sensor. Since the high speed movements are more stable, a low duty cycle can still allow the sensors to capture the features of the users' movements.

C. Other Indoor Localization Technologies

Our work chose the network-based method, which is mainly based on the Wi-Fi positioning system, as our indoor localization approach. The primary reason is that the implementation of this method is already provided as APIs in Android platforms (since API level 1). Other methods for the indoor localization can also be employed such as the specialized real time locating systems (RTLS) [23] or the inertial measurement unit (IMU)-based navigation systems [24]. However, many of these methods also require a costly infrastructure or additional[5] hardware, which hardly satisfy the need for a cost-effective solution. On the other hand, indoor localization is not our main concern in this paper, rather it is a supplementary of GPS to extended the coverage of Wi-Fi tracking.

VII. DIAGARM

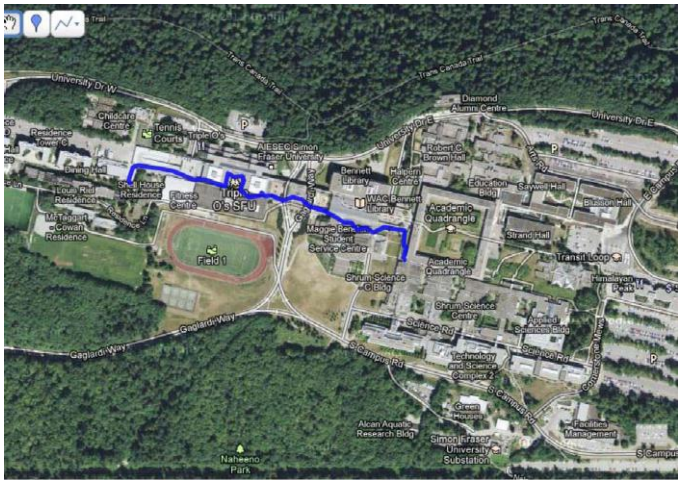

fig 1

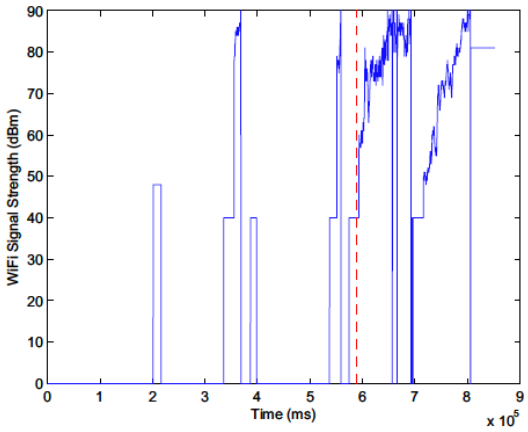

Fig. 2. WiFi signal strength along the track.

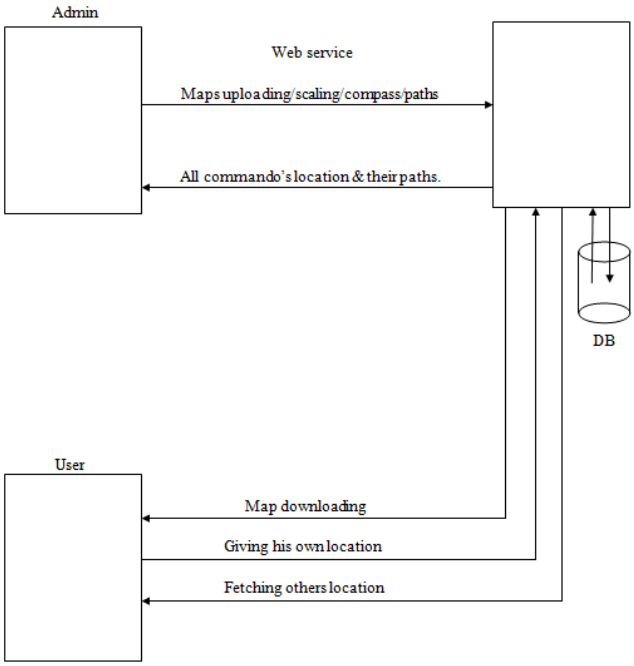

Fig. 3. System process overview

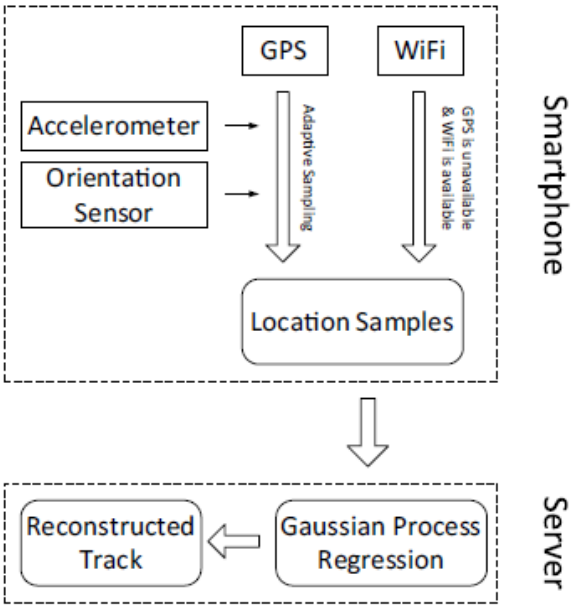

Fig 4.System Architecture

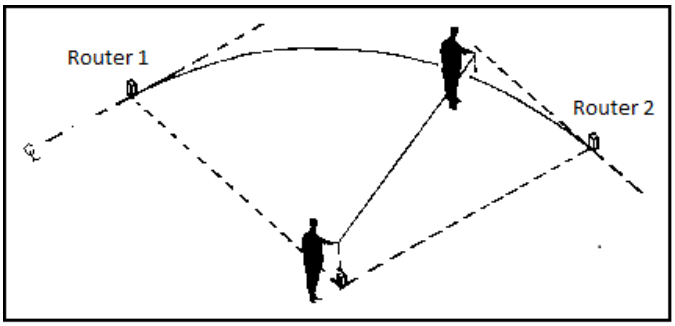

Fig 5. Triangulation Method

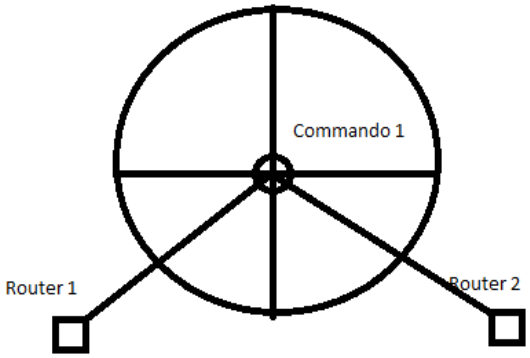

Fig 6. One commando and two router

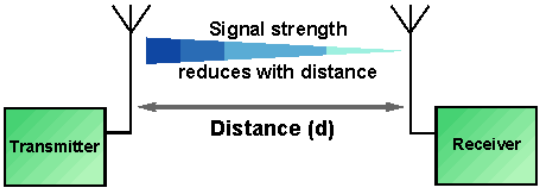

Fig 7. FSPL

VIII. Conclusion

In this paper, we have proposed a novel location tracking service, Wi-Fi tracking. We first discussed the limitations of the traditional GPS-based approach and opportunities of improvements. Next, the detailed design of Wi-Fi tracking was presented including: the trajectory reconstruction algorithm based on the Gaussian Process Regression, the rules of switching between two location sensing methods, and the principles for exploiting the sensor hints. We then used the real traces to evaluate the performance of Wi-Fi tracking, which shows that Wi-Fi tracking can significantly reduce the usage of GPS and generate accurate tracking results. The design of Wi-Fi tracking and evaluation presented above reveal several interesting challenges which remain for future work including resilient accelerometer data processing, tracking for multiple mobility patterns, and joint optimization of energy and accuracy.

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