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RESEARCH ARTICLE

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ACCURATE TRAJECTORY TRACKING WITH LOW POWER CONSUMPTION

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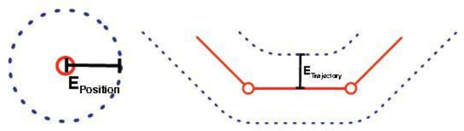
ABSTRACT

An important feature of a modern mobile device is its ability to determine its current position.Many mobilelocation-aware applications require the sampling of trajectory data accurately over an extended period of time. However, continuous trajectory tracking poses new challenges to the overall battery life of the device, and thus novel energy-efficient sensor management strategies are necessary for improving the lifetime of such applications.we proposed the concept of Enabling the GPS will automatically plot the points on map and record the paths as a video. Recorded paths can be reused when they are needed. By using this we can save power.

Key Words—Energy-efficiency, positioning, trajectory, trajectory simplification, GPS

I. INTRODUCTION

An important feature of a modern mobile device is its ability to determine its current position. In increasinglymany applications, however, knowledge about the location of the device is not sufficient, but informationabout the movement history or trajectory of the device isessential. Examples of applications that depend on trajectories rather than just on the current position includesports trackers that log running paths [16], shared ride recommenders [1], health care applications that visualize daily patterns or habits of patients [25], and collaborative sensing applications for generating maps [23], monitoring environmental impact [24] or mapping cycling experiences [8].Continuous sensing of the user's position rapidly depletes the battery of a mobile device. To mitigate this issue, previous research has proposed to improve the energy-efficiency of position sensing using intelligent sensor management strategies [20], [22], [25], [26].The intuition behind these approaches is illustrated in Fig.1(a). In the figure, the most recently sensed positions depicted at the center of the circle. Energy-efficient position sensing schemes obtain a new estimate of the user's position and report it to applications only when the position of the target cannot anymore be ensured tube within a certain error threshold (or distance) EPosition from the previous estimate, i.e., within the larger circle. Trajectory tracking, on the other hand, does not focus on individual position estimates, but instead attempts to ensure that the error between the sensed and actual motion history of the user remains within a specified threshold. The threshold corresponds to an error corridor around the true movement trajectory, and the sensed trajectory is required to remain within this corridor; see Fig. 1(b). Intuitively, this requirement can be ensured as long as points where the motion Curve 'bends' are accurately sensed, i.e., when the user's motion changes significantly in terms of direction or speed.



(a) Position tracking. (b) Trajectory tracking.

In proposed system, contributes by describing and evaluating a system for robust and energy efficient position and trajectory tracking. EnTrackedRT builds on our previous EnTrackedT system, extending it to support robust trajectory tracking and providing applications with a mechanism to specify the desired levels of tracking accuracy as well as of robustness. The system is then responsible for automatically determining the optimal sensing and uploading strategies so that the desired robustness is achieved while keeping the overall power consumption as low as possible. We also introduce situational bounding as a general mechanism for improving tracking robustness without decreasing energy-efficiency. The intuition in situational bounding is to adjust the sensor management strategies to the user's current situation by taking into consideration recently recorded sensing data. We focus specifically on a simpleutilization of instantaneous speed estimates to obtain acoarse-grained estimate of the user's expected motion behavior and transportation modality. We then use this information to adapt our sensor management strategies to cope with dynamic changes in the user's speed. While the main focus in this paper is on exploiting speed information, the concept of situational bounding is generic and other sources of situational information, such as calendar appointments, daily movement routines, proximity of other devices, and type of the environment(urban vs. rural) could be exploited as well.

The present project contributes by describing and evaluating the concept of enabling the GPS will automatically plot the points on map and record the paths as a video. Recorded paths can be reused when they are needed. By using this we can save power. The application we developed converts the path in map to video format so it is easy show the path for other who is going to the same place. We can also share it with other for other purpose .By using this we can save energy as much as possible.

II. RELATED WORK:

Existing systems for the energy-efficient tracking of a mobile device, such as EnTracked [20], typically focus on optimized GPS usage with duty cycling and selecting sensors with low power consumption whenever possible. As an example, H¨opfner and Schirmer [13] develop a position tracking system for pedestrian locomotion. The authors utilize accelerometer to detect stationaryperiods, and the number of steps taken by the user.The authors also employ adaptive duty cycling on the GPS based on estimated distance to the closest road intersection. Zhu et al. [25] combine a pedestrian dead reckoning approach with a map matching algorithm to determine a user's location accurately. The authors use GPS to reduce ambiguity in identifying the correct route, but do not evaluate energy consumption. The RAPS system [25] focuses on position tracking in urban areas, where GPS positioning tends to be less accurate and sometimes unavailable. To reduce power consumption, the system i) uses GSM information to predict whetherGPS information is likely to be inaccurate, in whichcase other, generally less accurate but more energyefficientpositioning methods are used instead, and ii)employs stationary detection and uses Bluetooth to sharepositions among neighboring peers. A-Loc [22] targets energy-efficient location tracking with dynamic accuracy requirements in mobile search applications where the required accuracy depends on the spatial density of search results. Zhuang et al. [26] study the problem of energy usage when several location-based applications are running at the same time and how to adapt behavior in low battery situations. They propose four techniques addressing the problems, termed substitution, suppression, piggybacking and adaptation. Kim et al. [14] propose SensLoc to use place sensing to start and stop trajectory collection by observingwhen a target leaves and enters places, e.g., in orderto replace the start and stop buttons of sport trackers.Chon et al. [6] propose the Smart DC system for learning and monitoring user's mobility patterns. The SmartDCsystem achieves energy-savings through an elaborate adaptive duty-cycling scheme which relies on a Markovdecision process. Neither SensLoc nor smart DCfocus on capturing the user's continuous trajectory accurately, but their ideas could be combined with those presented here to increase the energy-efficiency of trajectory tracking.

Ramos et al. [28] propose to offload GPS position computations to a server in order to lower the onphoneenergy consumption for GPS fix computations for locationtracking. System support for handling trajectories has been provided in the area of moving object databases [11],including, middleware and database abstractions for representing, querying and processing trajectory data; also simplification of trajectories has been studied [2],[4]. Wolfson et al. [23] presented protocols for efficient position updating, which reduced communication costs via exploiting the target's motion status. Lange et al. [21] presented a tracking system, which allowed simplifying the target's trajectory.

In previous paper emphasizes robustness, i.e., consistency in achieving the application specific error threshold, in tracking and proposes EnTrackedRT, a system for robust and energy-efficient position and trajectory tracking. The proposed system provides competitive trade-offs between energy-efficiency, tracking accuracy, and robustness. EnTrackedRTalso provides applications mechanisms for specifying the desiredtrade-offs.directly on the mobile device. However, their system ties position and trajectory tracking together, which limits the system's adaptability to application specific requirements. Furthermore, their system does not address how to reduce the overall power consumption resulting from sensing. Thiagarajanet al. [21] and Paek et al. [26] present solutionsfor trajectory tracking relying on cellular signals only instead of using GPS. These approaches offer higher power savings, however, cannot achieve high tracking accuracies. For example, Thiagarajan et al. use map information to snap observed GSM fingerprints to roads segments, achieving around 175 m tracking accuracy. Paek et al. improve accuracy in tracking to around 50 mby opportunistically learning a user's mobility patterns on mobile devices.

In contrast to previous work, we proposed that reducing the power consumption on mobile phones can be done by enabling the GPS When it is needed. We provide accuracy with power consumption using the video that has been recorded.

III. SYSTEM OVERVIEW

The application will be developed using the Android SDK.SDK is a software development kit that will enable us to create application for android plat form. The SDK will requires Eclipse (a software development Environment),JDK(Java Development Kit) and Android Development Tools(ADT)plug in.

The architecture shown in fig 2 consists of Linus Kernel which contains all the different drivers, such as the display driver, flash memory driver, the audio driver and the power management. There are also different libraries such as SQLite, Libc and OpenGL.The architecture also consists of the Android Runtime, which contains a set of core libraries. Next is the Application Framework, which consists of Activity Manager, Content Providers, Package Manager and Resource Manager of the operating System. At The top of the architecture is the application software

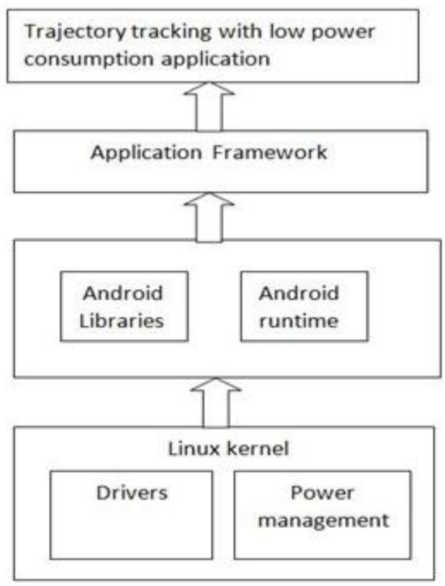


Fig2.Illustration of android architecture in stack form

IV. DESIGN DETAILS

A. Data collection:

The phone is equipped with integrated GPS, Wi-Fi sensor, accelerometer, and orientation sensor. During its runtime, the prototype continuously collects data from the acceleration sensor and the orientation sensor at default rate of the system service in Android OS.when the GPS signal is available ,a location listener in registered to request location update from GPS period and valid location samples to predically.The trajectory reconstruction algorithm based on GPR was also implemented on the server side, which uses the filtered and valid location samples to predicted the original trajectory.

B. Track Reconstruction:

In this, simply connect the location samples so the resultant trajectory can be very abstract. The Gaussian Process Regression (GPR) is a machine learning technique to perform the interpolation used for reconstructing the tracked position. Combined input and output gives the final trajectory.

A Gaussian process is collection of random variables, any finite number of which have a joint Gaussian distribution, and is fully specified by a mean function and a covariance function. The inference of continuous values with a Gaussian process prior is known as Gaussian process Regression.

C. Switching Location Sensing

Generally, cannot function properly indoors. To expand the coverage areas, switches the mobile devices between GPS and the network-based localization through the wireless connection. Basically, we want to use GPS outdoors and the network-based localization indoors, and thus it is important to decide when to switch. If GPS becomes available again, and the phone loses the Wi-Fi connection or the accuracy of location samples provided by the network decreases significantly, Sens- Track switches back into the GPS mode.

We note that are two conditions satisfied to switch the location sensing method: thecurrect method fails to obtain location samples, and the other method is guaranteed to work, which prevents from switching between the two modes too often. Frequently changing location sensing mechanism can be very energy consuming, because the high-power components associated with both location providers need to be active. In some cases, both of the two methods are available when the users passing by some buildings. accoring to our rules, we should not change SenTrack's working mode, since in these situations the wireless connection tends to be unstable and short.

D. Utilizing Sensor Hints:

Orientation: Orientation sensor as a detector of turning points when the user is moving. The idea is that there is no need to record the user's location if he/she is in a steady movement without changing direction.

Acceleration: The acceleration sensor in a mobiledevice has been widely used in many existing location sensing systems, in which it acts as a binary sensor to detect user movement or non-movement. We notice that distance is theoretically simple integral of speed, which in turn is an integral of acceleration.

V. SUMMARY:

In this paper, we proposed and evaluated techniques for providing robust and energy-efficient position and trajectory tracking to mobile applications. Our solution is useful for reducing the power while using GPS. It can also share the paths to others

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