Poster Abstract: eNav – a Smartphone-based Energy Efficient Vehicular Navigation System

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***Abstract*—We present eNav, a smartphone-based vehicular GPS navigation system that has an *energy-saving* location sensing mode capable of drastically reducing navigation energy needs. Traditional implementations sample the phone GPS at the highest possible rate (usually 1Hz) to ensure constant highest possible localization accuracy. This practice results in excessive phone battery consumption and reduces the attainable length of a navigation session. The seemingly most common solution would be to always use a car-charger and keep the phone plugged-in during navigation at all times. However, according to a comprehensive survey we conducted, only a small percent of people would actually always carry around their phones' car-chargers and cables, as doing so is inconvenient and defeats the true "wireless" nature of mobile phones. In addressing this problem, eNav exploits the phone's lower-energy on-board motion sensors for approximate location sensing when the vehicle is sufficiently far from the next navigation waypoint, using actual GPS sampling only when close. Our user study shows that, while remaining virtually transparent to users, eNav can reduce navigation energy consumption by over 80% without compromising navigation quality or user experience.**

I. Introduction

We present eNav, a smartphone-based vehicular navigation system with an important power-conserving mode. Attracted by the streamlined user experience, more and more people are using their smartphones for navigation, as reflected by the continuous increase in smartphone sales and the contrasting downfalls in traditional dedicated GPS navigation devices [2]. It has been commonly recognized that the GPS module is one of the most power-hungry components on phones [5]. By running GPS-heavy applications, some phones' batteries may be depleted within a few hours.

Ironically, vehicular GPS navigation is quite a "mission critical" activity on phones. A seemingly obvious solution to the potential navigation-time energy depletion problem would be to simply bring the phone's car-charger on all trips and keep the phone plugged in during navigation at all times. We argue that doing so, however, is quite inconvenient and defeats the true "wireless" nature of mobile phones, and that a much more elegant solution would be to design an energy-efficient vehicular navigation system from the ground up. To make sure this is NOT just our own isolated opinion, and also to have a better understanding of people's in-vehicle phone usage patterns, we conducted a comprehensive anonymous online survey using CrowdFlower.com [1] to ask people about various aspects of their experiences and preferences regarding phone-based vehicular navigation, for which 416 participants from 329 cities in 46 US states responded.[1] Our key findings include, i) About 70% of people use phone-based GPS navigation systems while driving and only about 15% would always use car-chargers to plug in their phones during navigation; and ii) 92% of people would like to have an energy-efficient phone navigation app, of whom, 3/4 would use it when their phones are running low on battery, and 1/4 want to use it for all navigations regardless of phone battery levels.

Our eNav system employs an adaptive design that intelligently carries out estimations (using motion sensors and dead-reckoning [3], low-power but noisy) and localizations (using GPS, high-power but accurate) depending on distance to the next navigation waypoints (the locations along the planned route where the user needs to perform certain actions). Without missing the obvious, eNav also strategically turns on and off the phone screen depending on the distance to the next waypoint, as keeping the screen on at all times seems unnecessary and wastes energy—according to our survey, 83% of all people are willing to even rely solely on turn-by-turn voice guidance during navigation to preserve energy. Key challenges lie in the mobility nature of phones and the generally low quality of the onboard sensors. It is therefore *not* immediately obvious how to map the phone's local sensor readings to reason about the car's motion and how to handle the noise in the sensor to guarantee navigation quality. To the best of our knowledge, eNav is the first smartphone-based system that exploits the phone's on-board motion sensors to achieve energy-efficient vehicular navigation.

II. System Overview

The eNav system employs an adaptive design that relies on a simple intuition, namely, the path from a source to a destination usually includes only a limited number of pre-computed critical waypoints where the user needs to perform certain actions (e.g., making turns) that require the navigation application to deliver the corresponding notifications to the user beforehand. When a vehicle is far away from the next waypoint, there is no need for positioning to be accurate. Instead, one can sample GPS at a much lower rate or replace it altogether with less power-hungry sensors, such as an accelerometer or gyroscope with dead-reckoning, which, however, can provide only an approximate location. Once the

[1] With IRB Approval Number #14266. All questions were of multiple-choice type. Each survey was served containing 5 repeated questions with reordered choices to filter out less reliable responses that were possibly due to responders not paying enough attention or simply providing random responses.

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estimated distance to the next waypoint gets close to the uncertainty margin in the current position estimate, a GPS reading is taken. In realizing this idea, our system consists of two main components: the basic location-sensing core and the enhancement modules, as discussed below.

A. Basic Location-Sensing

We use low-power less-accurate dead-reckoning to get rough location estimations while being far away from navigation waypoints. Only when getting close do we turn on GPS for spot-on location information and navigate the user with necessary notifications delivered at appropriate timing.

In realistic everyday driving scenarios, we need to extract the acceleration measures along the car's direction of motion by using the phone's local sensor readings without prior knowledge on the phone's orientation relative to the car. This is accomplished by our Principal Motion Extraction (PME) method. We accumulate a window (empirically 1min) of the phone's 3-axis accelerometer data, and apply PCA [4] to it. The first component then captures the largest variability of the car's acceleration, which corresponds to the car's motion along it's driving direction. Note that the principal component has ambiguous signs; to determine the correct sign, we also sample the GPS along with the accelerometer to get the car's ground-truth motion during the training phase.

Due to sensor noise, there is uncertainty in the car displacement estimation, which we handle as follows. Throughout the navigation, we maintain a confidence bound ahead of the car's estimated displacement, i.e., $\hat{s}_i^c = \hat{s}_i + 2\sigma$. As long as this confidence bound has not yet crossed over the next waypoint, we can say, with confidence, that the car has not miss the next waypoint. Therefore, if the confidence bound is getting sufficiently close to the next waypoint (e.g., distance below some threshold), we obtain the accurate location of the car by sampling the GPS, and see if the car is actually close to the waypoint or not, and act accordingly. Specifically, the bound $\hat{s}_i^c$ gives us a confidence measure of 97.72%. The standard deviation σ for the acceleration estimation errors can be obtained during an initial training phase of the navigation.

B. Enhancements to Location Estimation

We also incorporate two enhancements to improve the car's motion and location estimations from analyzing additional types of car dynamics besides the forward driving motion, namely car-idle and car-turning. Knowing the car being idle, though does not reveal actual location information, can help control the accumulation of dead-reckoning errors. We also keep track of a possible location range for the car during low-power location estimations. Thus, upon detecting a car-turning, map information can be used to snap the car to its true location if only one intersection is within the car's possible location range, all done without using the GPS at all.

Both detections are formulated as classification problems. We simply take the magnitude of the raw 3-axis data for each time slot and compute the min, max, $mean$, and $standard\ deviation$ to form the feature vector for the classification task. In the training phase (the initial portion of the navigation session), we label the time slots using the speed and bearing information in the corresponding GPS trace. Our experiments show that decision trees [6] classifier achieves near perfect accuracies (over 99%) for both detections.

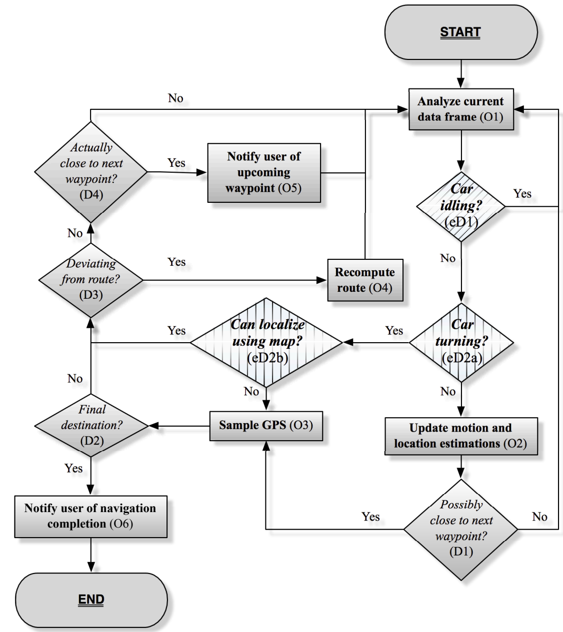

Fig. 1: System workflow chart of eNav's energy-efficient navigation

Fig. 1 consolidates the various components discussed and illustrates eNav's energy-efficient navigation flow.

III. Evaluation

The energy saving and navigation quality of eNav were evaluated via user studies. About 4000mi driving data were collected and analyzed, from which we observed an average saving of navigation energy by about 82%. When users were allowed to toggle the navigator between energy-saving and traditional modes (screen-on, GPS sampling at 1Hz) at will, we also observed excellent energy saving results, as illustrated by the CDF in Fig. 2. Note that eNav never missed a single waypoint during any of the navigation sessions in our user studies. Most users expressed through their exit-interview that it was hard to tell the difference between eNav and traditional navigation system regarding the user experience, which well aligned with our original design goal.

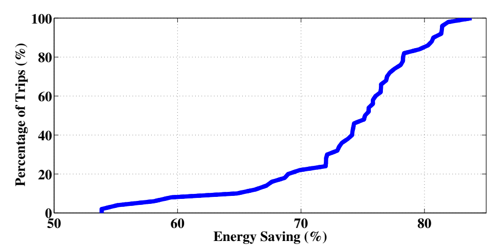

Fig. 2: The CDF of energy savings of eNav in real navigation uses

Acknowledgement

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