ProbIN: Probabilistic Infrastructureless Navigation

Le T. Nguyen and Ying Zhang

Carnegie Mellon University,
NASA Research Park Building 23,
Moffett Field, CA 95035, USA
{le.nguyen,joy.zhang}@sv.cmu.edu

1 Introduction

With the increasing popularity of smart phones, knowing the accurate position of a user has become critical to many context-aware applications. In outdoor environments, standardized Global Positioning System (GPS) is often used. However, for indoor environments such as airports, hospitals or shopping malls GPS signals are usually unavailable or unreliable. Most of the existing indoor positioning solutions try to address this problem by utilizing existing infrastructures such as Wi-Fi access points or Bluetooth beacons.

In cases when the infrastructure is not available, self-contained systems provide a more flexible solution. These systems use sensors such as accelerometers, gyroscopes and magnetometers. In order to derive a user's current location, the movement of the user is tracked by the continuous logging of sensor readings. Since this technique does not rely on an external infrastructure, theoretically it can be used in any environment. The main drawback of self-contained positioning approaches is error accumulation. Since the sensors utilized are noisy by nature, the error of position estimation grows with time and distance traveled. Moreover, the noise portion in sensor measurements is significantly higher when the phone is held in the hand versus mounting it on certain parts of the body. Positioning in the hand accelerates the accumulation of error and causes a substantial decrease of estimation accuracy.

The purpose of our work is to deliver a system providing positioning and navigation functionality for consumer mobile devices in GPS-challenging environments. In the demo we will focus on a novel probabilistic approach of self-contained positioning providing a user's current location. In order to overcome the problem with noisy sensor readings of consumer mobile devices, a statistical model well-known in the field of the statistical machine translation (SMT) is utilized for positioning purposes.

In our work, the positioning problem is framed as a noisy-channel problem, where we try to recover the actual user's position from the distorted sensor inputs. To recover the user's position, we use a statistical model to map the sensor readings directly to the displacement. This is fundamentally different from state-of-the-art dead reckoning approaches. In these approaches the sensor readings are interpreted by their actual physical meanings, i.e., the accelerometer

J.Y. Zhang et al. (Eds.): MobiCASE 2011, LNICST 95, pp. 115–117, 2012.

readings are considered as being the actual acceleration of the device. Thus, theoretically based on the laws of physics the travelled displacement can be obtained by double integrating the acceleration.

In ProbIN the sensor readings are interpreted as observed "signals" which are directly mapped to the corresponding displacement based on a statistical model. The statistical model is trained by using SMT techniques adjusted for positioning purposes. During the training phase, ProbIN builds statistical models from the user's data. These models capture the user's walking patterns and adapts to the sensor errors of the mobile device. Thus, although the sensors on the mobile devices are noisy, ProbIN can still estimate the user's current position at a much higher accuracy rate than the state-of-the-art dead reckoning approaches.

2 ProbIN

Probabilistic Infrastructureless Navigation (ProbIN) is a system providing the positioning and navigation functionality for GPS-challenging environment. In the demo, we will focus on the positioning part of ProbIN, which allows tracking of a person.

The ProbIN is intended for daily applications such as assisting the user in the shopping malls or at the airports. Therefore, it needs to fulfill the three essential requirements:

1. *Scalability*: ProbIN delivers positioning functionality even without an existing external infrastructure.
2. *Affordability*: ProbIN can be run on consumer mobile devices with relatively low-quality sensors.
3. *Usability*: The user should be able to hold the devices in the hand or in a pocket without degrading delivered functionality.

In order to fulfill the first requirement ProbIN essentially utilizes the inertial sensors. As such, a self-contained positioning system can be delivered, which does not rely on any external infrastructure. ProbIN can be also improved by utilizing a magnetometer and/or digital maps in order to achieve higher positioning accuracy. The advantage for this case is that the system will remain self-contained. A viable extension would be the integration of modules utilizing external infrastructures such as GPS or a Wi-Fi network. These modules would be activated only when an infrastructure is available.

Due to the second and the third requirements, a novel approach of positioning needs to developed in order to address high error rates of the sensors. It is known that when utilizing low-cost sensors measurements are typically very inaccurate, especially when the sensors are not mounted to the user's body. In this case, the traditional physics-based positioning performs badly, since an error in the sensor reading causes an error in the estimated displacement. ProbIN addresses this issue by learning a mapping between the sensor readings and the actual true displacements based on training data. Thus, when the ProbIN is deployed, even a noisy sensor reading can be mapped to the correct displacement. The problem of minimizing the error rate is thereby transformed into a machine learning problem. In the demo, we will present a solution to this problem by utilizing machine learning techniques well-known to the field of the statistical machine translation (SMT).

As mentioned above, ProbIN utilizes a machine learning technique that is divided into training and testing phases. First, the sensor readings with corresponding true displacements are collected in the training phase. The relationship between the measurements and the displacements are used for creating a statistical model. Then in the testing phase, the statistical model is employed for mapping the sensor readings of the tracked person into a trajectory. The result of the testing phase is typically used for evaluating the approach.

3 Demo

For the demo we will be using an iPhone 4 for collecting sensor readings and a laptop for displaying user's trajectory. Since sensor readings are periodically sent to the server, we need a reliable Wifi connection. We will let attendees try out our positioning system. Therefore, we would prefer having our booth in a bigger room so that the users can walk around in order to test the positioning functionality. Our demonstration will not interference with other demonstrations. Other people being in the room can be seen as obstacles, which will help us to demonstrate the robustness of the system.