Indoor Pedestrian Localization for Mobile Devices
The Model

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Abstract: Indoor localization using mobile devices is one of the emerging areas of today's interest. This paper presents a model for indoor localization based on 802.11 Wi-Fi fingerprinting in combination of inertial navigation running in parallel. We introduce a novel model scheme, where we use a state-of-the-art Compass system. The system is enhanced by clustering and the position calculation is influenced by the distance travelled between each fingerprinting, allowing us to eliminate improbable location estimations. Proposed system is supposed to be resilient to received signal strength blocking caused by a human body, and also to be more accurate than other up-to-date solutions.

1 INTRODUCTION

Navigation has become inherent part of human lives. The ability to successfully navigate oneself in an unknown environment has lead into constructing various means of navigation. These techniques and technologies were gradually enhanced resulting into more precise and reliable navigating systems. In 1994 United States Department of Defense finished fully operational Global Positioning System (GPS) providing the Standard Positioning Service for everyone. With the decrease of prices of consumer electronics in which was GPS frequently integrated, it became widely spread technology used in navigation systems. Location has proven to be an important source of contextual information. If a device can determine its own location then it can infer its surroundings and adapt accordingly (Woodman, 2010). One of the features of navigation systems is to track position of pedestrians. But despite the usage of GPS in open spaces, it is almost impossible to use it indoors. Tracking GPS signals indoors typically requires a receiver capable of tracking signals with power levels ranging from 160dBW to 200dBW, however a typical receiver has a noise floor of around 131dBW (Dedes, 2005). Furthermore, to be fully functional, GPS relies on direct visibility of at least 4 satellites (Kumar, 2008), which is hardly attainable in closed spaces. Multipath effects (signal multiplication caused by reflections) are likely to cause degradation in accuracy even if a receiver is able to track signals from a sufficient number of satellites. Unlike in outdoor environments, reflected signals are often stronger than those received via direct line-of-sight when indoors. Hence it is difficult for a receiver to identify and track the correct (i.e. direct) signals (Woodman, 2010).

It came into realization that for indoor use, GPS has to be substituted by a different system. Emerged solutions were based on a range of technologies including lasers (Gutmann, 1996), ultrasound, wireless networks, even a magnetic field (Woodman, 2010; Storms, 2009). Unfortunately, those solutions are depending on preinstalled infrastructure, thus making them unusable in ordinary environments.

2 RELATED WORK

Radiolocation based on 802.11 localization has been an active area of research for the past two decades. Originally, the research was focused on robot navigation. Over the years, area of interest became focused on pedestrians. Wi-Fi APs are now densely deployed in many urban environments. A device can estimate its position by searching a database containing the locations of such APs for ones that are visible from its current location. The accuracy of

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such approach is highly dependent on the density of APs. However, positioning errors are at worst equal to the range of an AP (typically 50 – 100 m) (Woodman, 2010). Recent development has brought focus on cheap Bluetooth LE sensors, which can substitute more expensive Wi-Fi APs. Possible disadvantages of radiolocation are that a database of Wi-Fi APs/Bluetooth sensors must be constructed beforehand and it must be frequently updated, since there may be changes in the infrastructure.

2.1 Techniques Using AP Location

This approach is based on constructing a radio map, in which Wi-Fi signals are recorded at locations of interest along with a vector of received signal strength (RSS). This technique is known as fingerprinting. Location estimation than can be reproduced by matching measured RSS readings against previously established database. One of the first techniques using deterministic fingerprinting (computes a single best guess of a position of a device) was RADAR (Gutmann, 1996; Bahl, 2000). This technique shows error less than 9 m 95% of the time. RADAR was enhanced over the years. One of the successors is Horus (Youssef, 2005), which uses a stochastic description of the RSS map with the combination of maximum likelihood – probabilistic based approach. The Horus system reports accuracy of 1.4 m 95% of the time. Also, Horus was enhanced in the technique Compass by using digital compasses and measuring RSS in 8 directions in one location. There is also other technique, such as (Varshavsky, 2007), which presents possibilities of using GSM signal, or (Azizyan, 2009), presenting map building, based on notable environment features such as sound, light, colors etc.

All these presented approaches are depending on detailed environment measurements. Some sources (Haeberlen, 2004) state that 28 man-hours were required to construct a radio map covering a 12,000 m^2 building. Moreover, this process must be repeated whenever an AP is moved/added/removed, to ensure reliable results. To avoid such time consuming operations, there have been made several efforts. For example DAIR (Bahl, 2005) does not involve mapping at all, but it assumes, that used environment is densely equipped with APs. We have to realize, that all presented accuracy results were made in areas housing multiple APs (typically not family houses or apartments). In order to achieve usable results it is required to have installed at least 3 APs (Woodman, 2010).

2.2 Inertial Positioning and Dead Reckoning

Inertial positioning uses MEMS, particularly magnetometers, accelerometers and gyroscopes, to calculate change in mobile device’s location in time. These systems (Cho, 2006) are based on dead reckoning. We can use course heading from magnetometer and readings from accelerometer can serve as a step detector. With known course and traveled distance, it is possible to calculate position of the measuring device. When tracking a pedestrian, we can use information from sensors along with an estimate of a stride length to track his approximate position relative to his starting point. Over time, the calculated position will become less accurate. This is caused by adding fixed stride lengths (which differ from the actual ones), so that the overall error accumulates. The longer path the pedestrian walks the bigger error it accumulates. This accumulation of error is commonly referred to as drift (Ojeda, 2007). Drift is acceptable if the target is tracked only for a short period of time. It is apparent that if we want to build a system, which is capable of tracking for a long period of time, to avoid drift, position must be regularly calibrated by absolute positioning system.

Pedestrian dead reckoning can be divided into 2 groups. One group is based on step detection, the other on inertial navigation. Step based pedestrian dead reckoning is based on detecting steps and estimating stride length. As mentioned above, when the step is detected, heading and step length is used to update position of the tracked pedestrian. Main advantage of this approach is that the tracking device can be mounted almost anywhere on the pedestrian’s body. Usual locations are foot, waist or head. Since, 1 axis accelerometers are used for this method; step is detected by peaks in the received signals (Steinhoff, 2010). This also have a disadvantage, because having only 1 axis accelerometer means that this system works with the assumption, that pedestrian is moving only forwards. Step length estimation is also problematical, since step length varies from step to step. Several algorithms have been developed for estimating step length. As presented in (Alvarez, 2006) step length can be estimated using user-specific constants or neural networks. Problem is that neural networks must be trained for each individual user, which can be time consuming. The last drawback is that such systems cannot differentiate vertical displacement, thus it is impossible to recognize for example movement up on the stairs.

The second group of pedestrian dead reckoning is based on inertial navigation. It is a navigation technique in which measurements provided by accelerometers and gyroscopes are used to track the position and orientation of an object relative to a known starting point, orientation and velocity. Thus it must use full 3 dimensional inertial navigation unit (Foxlin, 2005). Actions must be taken to prevent accumulation of drift – namely by placing measuring device exclusively on the foot of the pedestrian and then correcting the inertial navigation system when the foot is grounded. At the time, sensors report near-zero velocity. As shown in (Godha, 2006) Bayesian filters prove to offer an ideal framework to track such correlations that exist between accumulating errors in different components and to apply zero velocity updates in a way that allows correlated errors in all components of the state of the inertial navigation system to be corrected. Particularly, Kalman filters are widely used (Woodman, 2010). The main advantage of this group of pedestrian dead reckoning is that the system does not assume only forward movement. Hence, it can correctly handle moving backwards or strafing.

2.3 Hybrid Models

Hybrid models are based on combining various localization techniques to achieve better accuracy results. It is important to note that combining more localization techniques also results into higher inner complexity, thus overall position error may be influenced by more factors. For the purposes of our research we are going to focus only for those based on 802.11 and inertial localization.

The work (Evennou, 2006) introduces solution based on Wi-Fi, inertial navigation system, and particle filtering. This system is using 6-degrees-of-freedom zero velocity updating. Main supporting feature of this system is particle filtering. Possible disadvantage is relatedness to known precise building layout (needed for particle filtering) and placement of the measuring unit to the foot of the user.

Another most advanced hybrid system (Frank, 2009) presents Wi-Fi localization system supported by inertial navigation. Emphasis of this system is given to sparse Wi-Fi fingerprint sampling. Authors used fingerprinting points with a span of 5 m. As opposed to the previously mentioned system (Evennou, 2006), inertial navigation implements acquiring a heading data from the additional magnetometer. The inertial system is processed by its own Bayesian filter to estimate individual steps of the user; these estimates are then combined with the estimate of the location from fingerprinting. This approach allows precise data processing at sensors' local sampling rates, which reduces overall complexity without suffering from significant loss of final estimation accuracy (Frank, 2009). This system shows arithmetic mean error of 3.1777 m for pure Wi-Fi fingerprinting and 1.6468 m for the fusion of fingerprinting and shoe data.

The goal of presented hybrid systems is to use as few calibration locations as possible and to rely on the short-term accuracy of foot mounted inertial dead-reckoning (for instance zero velocity update based techniques) among these points. The role of the Wi-Fi positioning here is to provide long term accuracy in the area of interest (Frank, 2009).

3 PROPOSED MODEL

We have identified, that current known solutions are either not mobile-based (Frank, 2009; Ojeda, 2007 etc.), they are dependent on construction of support infrastructure (Lukianto, 2011) or the operating hardware is directly mounted to the foot or leg (Serra, 2010). Even in the cases when a mobile device is used, the solutions are entirely based on Wi-Fi or Bluetooth localization (Martin, 2010), or a combination of visual tracking and step detection based systems (Kothari, 2012; Lukianto, 2011; Serra, 2010 etc.). Author of (Woodman, 2010) claims that step detection based inertial navigation is suitable for usage with mobile devices, but we believe otherwise. From studies (Serra, 2010; Shala, 2011) it is visible, that approach based on step detection is not optimal. In combination with Wi-Fi tracking, it is possible to achieve accuracy improvement (comparing to pure Wi-Fi localization system), but results in (Ševčík, 2013) show gradual increase of drift over the travelled distance, which had grown in the worst case by 7 m. This actually made fused position estimate worse than using just plain Wi-Fi positioning. The study (Serra, 2010) reveals comparable results and claims that using a particle filter might improve drift accumulation, which was proved wrong in (Ševčík, 2013), where particle filter was already used. The same results were confirmed in (Shala, 2011). After taking into consideration all above mentioned systems and techniques, our objective is to create universally applicable hybrid system for mobile indoor localization. Proposed novel solution, as presented by Figure 1, will be composed of 2 localization techniques combined together for achieving better accuracy. We have decided to adopt parallel approach in order to process data locally and to reduce overall complexity. This separation also allows estimation filters to run at their local sampling rates, helping to process data without significant loss of final destination accuracy. Location estimation will be based on probabilistic Wi-Fi localization, using techniques proposed in Horus system (Youssef, 2005), but for dealing with problem of blocking effects caused by a human body, we will extend this system by introducing Compass system – orientation based Wi-Fi fingerprinting as proposed in (King, 2006). Sampling of the signal strength for selected orientations at each reference point during the fingerprint gathering phase and combining a subset of these values to histograms in the location estimation phase, allows orientation specific signal strength distribution to be computed and utilized to increase the accuracy of position estimates. The Compass system indicates average error distance of less than 1.6 m. Therefore, it will be used for initial position estimation and further position calibrations. Furthermore, Compass is optimal for addressing the influence of human body as an obstacle, which is blocking Wi-Fi signal.

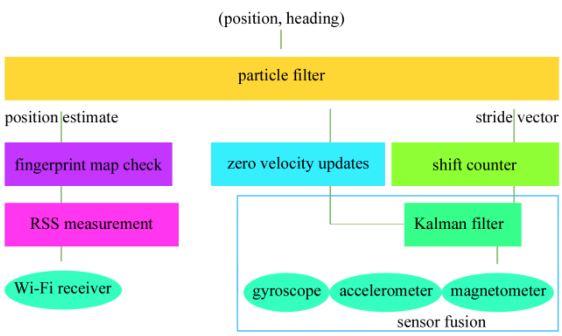

Figure 1: Localization system abstraction.

The second localization technique will feature inertial navigation. Inertial navigation will be used for improving accuracy of Wi-Fi localization. We propose a system based on gyroscope, accelerometer, and magnetometer fusion. The fusion will help to reduce sensor flaws. Data from accelerometer and gyroscope will be filtered, normalized and processed by step detection algorithm, to be consequently used for zero velocity updating (calibration technique reducing drift accumulation). Subsequently, normalized linear acceleration vector and course will be processed by extended Kalman filter (EKF). We have chosen EKF to estimate the instantaneous state of a linear dynamic system, with measurements linearly related to the state but influenced by white noise. The estimator uses incomplete and noise-corrupted measurements to estimate the tracking object's state, and the resulting estimation is statistically optimal with respect to any quadratic function of estimation error. Thus parallel EKF will be used to estimate position errors, velocity errors, and hand movement errors in terms of a Gaussian probability density function. Integration of inertial navigation system and Wi-Fi localization system will be performed via the main particle filter, which will keep track of position and course (heading). With a particle filter, more information than RSS location and inertial navigation data can be fused. In particular, a building map is another very useful information source, since a lot of location related data can be extracted from the building structure information. For the tracking problem, this information helps to reduce the uncertainty of the walking trajectory. Using a particle filter, the estimation can be improved by deleting impossible particles, i.e. the particles which would have crossed a wall.

The Compass as it is introduced in (King, 2006) does not integrate any clustering algorithm, therefore when calculating user's position, all database data need to be evaluated. This is not needed for small data sets, but for large data sets, it is necessary to select only a subset of fingerprint data, for the system to be capable of running in real time. We propose usage of Incremental Triangulation algorithm as it is presented in (Youssef, 2006). If during the location determination phase APs are used incrementally, one after the other, then starting with the first AP (with the highest value of RSS), the algorithm restrict our search space to the locations covered by this AP. The second AP chooses only the locations in the range of the first AP and covered by the second AP and so on, leading to a multi-level clustering process. Location clustering can be further enhanced using mobile sensors. We suggest additional AP filtering using heuristics. From the data obtained from inertial localization we can improve the AP selection. Knowing user's course and approximate travelled distance from the last known location, we can constrain the final location estimation only to those points, which are in the evaluated travel distance.

4 CONCLUSIONS AND FUTURE WORK

This paper presented hybrid pedestrian localization system for mobile devices. The key concept is parallel combination of inertial navigation and Wi-Fi localization, where both parts are mutually beneficial. Inertial navigation can be calibrated by data obtained by Wi-Fi localization. On the other hand, Wi-Fi localization accuracy can be enhanced by restraining a selection of improbable results, when taking sensor data into account – mainly the digital compass and the approximated travelled distance.

In our previous research, we have focused on developing inertial navigation based on step counting. We have implemented techniques for step detection, which proved to be nearly 100% positive in detecting steps while walking continuously. Now, we are implementing the Compass system enhanced by clustering. Current prototype is capable of localizing a pedestrian with an error close to 4 meters. We believe that combination with inertial navigation will reduce this error and provide better results. Scaling will also affect the overall speed of the system.

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