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Robust Indoor Localization on a Commercial Smart Phone

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Abstract

Low-cost localization solutions for indoor environments have a variety of real-world applications ranging from emergency evacuation to mobility aids for people with disabilities. In this paper, we introduce a methodology for indoor localization using a commercial smart-phone combining dead reckoning and Wifi signal strength fingerprinting. Additionally, we outline an automated procedure for collecting Wifi calibration data that uses a robot equipped with a laser rangefinder and fiber optic gyroscope. These measurements along with a generated robot map of the environment are combined using a particle filter towards robust pose estimation. The uniqueness of our approach lies in the implementation of the complementary nature of the solution as well as in the efficient adaptation to the smart-phone platform. The system was tested using multiple participants in two different indoor environments, and achieved localization accuracies on the order of 5 meters; sufficient for a variety of navigation and context-aware applications.

Keywords: RSSI fingerprinting, inertial navigation solution, laser-baed map-representation, robot navigation

1. INTRODUCTION

In recent years, smart phones have re-defined the notion of mobile computing platforms. Some of the merits of mobile phones as tools include affordability, ubiquity, social acceptance, portability, increasing sensory and computational power, and low power consumption fueled by readily available batteries. Location-aware devices are able to reliably track their own locations. Most current location-aware applications use GPS tracking technology. In the absence of GPS, achieving sufficient localization accuracy on a consumer device is extremely challenging. We present a methodology that combines dead reckoning (DR) and Wifi signal strength strategies towards robust indoor GPS-free localization using

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commercial mobile phones. The complementary and redundant characteristics of the two approaches allow the system to operate robustly even when one or more individual sensors are disrupted. The suitability of a localization method depends on a number of factors, including the size and cost of the hardware, the time and money needed to deploy the system in a new environment, and the required accuracy. Our system operates on a consumer smart phone and takes advantage of existing Wifi access point infrastructure minimizing installation time and cost. The system utilizes the measurements of wireless-based Received Signal Strength Indication (RSSI) for position estimation. A fingerprinting technique is used to identify RSSI position dependency. Fast signal strength calibration is performed using an autonomous mobile robot.

2. RELATED WORK

A modern smart phone such as the Google/Samsung Nexus series has an array of available sensors, including Wifi radios, accelerometers, magnetometers, and gyroscopes all suitable for localization. While the short range properties of Bluetooth and Near Field Communication (NFC) have been used to constrain the estimate of the user's location [2] they have the drawback of requiring installation of markers in each environment where the solution is used. While there are obvious advantages to using the onboard camera for localization [3], drawbacks to its use include the need for the user to actively take pictures of the environment to localize and sensitivity to the camera calibration, positioning, and environment lighting. RSSI fingerprinting measures [1], [2], [6], [7] for pose estimation is an accepted and popular technique for indoor pose estimation with an accuracy range of 3-10 meters. Alternately, a DR system comprising of accelerometer, magnetometer, and gyroscope sensors can provide fast and accurate estimation of local pose [4], [6], [7]. While effective over short distances, DR solutions have the drawback of being local estimation techniques and have to be seeded with an accurate initial position for valid estimation. Furthermore, over time and distance the sensory error accumulation is unbounded. Particle Filters (PFs) are commonly used techniques for integrating disparate information sources from multiple sensors towards robust localization [5]. PF methods can readily incorporate nonlinearities introduced by Wifi signal strength filtering as well as handling restrictions imposed by the robot map and can track multiple hypotheses by dividing particles proportional to their likelihood.

A major drawback of existing RSSI-based solutions is that they are geared towards devices with significant computation capabilities and high-fidelity sensors. Further, current methods for building a RSSI calibration database is tedious, labor-intensive, and requires a large number of samples[9]. We build on the general ideas of DR and RSSI fingerprinting, from which we derive a baseline implementation using a PF and a k-nearest neighbor approach. The uniqueness of our approach lies in the implementation of the complementary nature of the solution as well as in the efficient adaptation to the smart-phone platform. The adaptations allow for a fast and high-quality solution at a relatively low computation cost.

3. THE INDOOR LOCALIZATION SYSTEM

We selected the Wifi radio combined with DR using accelerometer, magnetometer, and gyroscope sensors for use in our system. This sensor mix is attractive because it can provide a bounded-error solution that does not require any additional infrastructure investment, assuming that the environment already has an adequate number of Wifi access points. A gait-based motion model combined with a heading estimator provides a pre-filtered DR sensor estimate to the PF. Simultaneously, pose is estimated based on fingerprinting between observed Wifi signal strength readings and robot-based calibration database of RSSI estimates. The combined sensor data is fused and filtered using a PF which results in a smooth and continuous pose estimation state. Figure 1 shows the system architecture in more detail.

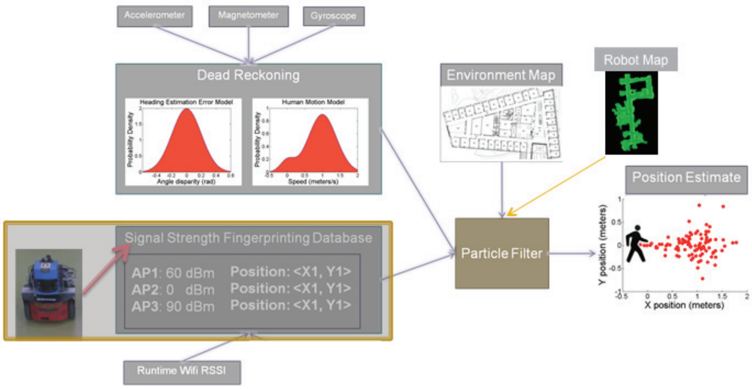

Figure 1: Localization System Architecture

3.1 Dead Reckoning (DR)

To minimize the computational requirements of the solution, it is desirable to keep the dimensionality of the PF as low as possible. Consequently, the DR is performed in a pre-processing step, and all the particles in the filter are periodically updated based on a model of the variance of the DR estimate. We track the orientation using two complementary methods. The first method is to employ an accelerometer and magnetometer to give a reference direction for gravity. The benefit of this method is that each measurement is externally referenced, so orientation errors do not accumulate over time. The drawback is that magnetic anomalies which interfere with the operation of the compass are common in indoor environments. Additional error will be imparted from imperfect separation of the gravity signal from the linear accelerations imposed on the phone. The second orientation tracking method is to use a gyroscopic sensor that is much less noisy and is not susceptible to external interference. However, as they measure angular velocity rather than angular position, only the relative movement of the phone can be derived from the gyroscope readings. Furthermore, the error in the orientation tracking accumulates over time without a bound, since the gyroscope readings are open-loop. To robustly determine heading, these two methods are merged. The combined orientation filter continuously accounts for drift in the gyroscope and error conditions in the magnetometer by using one sensor to compensate for the failings of the other. The inputs to the filter are raw accelerometer, magnetometer, and gyroscope readings as they are received. The output is an estimate of the azimuth, pitch, and roll of the phone in a global frame.

A preliminary analysis is done to assess the validity of the gravity and compass estimates. If the magnetic field strength deviates significantly from the strength expected for the user's approximate global location (~55uT in the Northeastern United States), the datum is marked as unreliable and is not used. Further, the gyroscope data is integrated using the trapezoidal method to capture the change in angular position in the local coordinate system. Once calculated, the change in angular position is converted into the global orientation frame. Occasionally, θ_{global} must be re-initialized from the accelerometer and magnetometer data to limit the accumulation of error from gyroscope integration.

$$\Delta\theta_{local} = \frac{1}{2}(gyro_{clean}(t) + gyro_{clean}(t-1)) * \Delta t; \qquad \Delta\theta_{global} = R\,\Delta\theta_{local} \tag{1}$$

If the transformation is *not* available, it must be derived from the filtered accelerometer and magnetometer readings. If one of those inputs is deemed unreliable, then there is insufficient information to initialize the orientation estimate and the system falls back on the PF until reliable orientation data is available. At this point, an additional check verifies the quality of the magnetic data. The angular displacement of the component of the magnetic field pointing in the down direction (magnetic inclination) provides important information about the magnetic field. If the inclination angle varies significantly from the expected value for the user's coarse global location, it is an indication of magnetic anomaly.

We use two different approaches to detect movement, both of which exploit the periodic nature of the walk cycle. The first uses a peak detection filter with alternating high and low thresholds to detect individual steps. In order to detect steps accurately, we compensate for momentary accelerations and noise which create spurious peaks and the effect of gravity. Depending on the orientation of the phone, accelerations from walking may alternately cancel or add to the gravitational signal, leading to incorrect estimation. These effects are handled by first smoothing the accelerations using a running average filter, and then removing offset errors and drifts by taking the first difference of the smoothed result. The second method, which has the advantage of detecting movement continuously in time rather than at the step level, looks at the variability of the acceleration readings, with the assumption that higher variability corresponds to movement. If the state of 'movement' was detected instead of individual steps, the user's estimated position could be updated much more frequently. A simple methodology to detect movement is to calculate the standard deviation of the acceleration values over a fixed time span. The size of the time span and the threshold that must be met to report movement both contribute to a tradeoff between the delays that are incurred before the filter is able to detect movement, and the potential for false positives.

3.2 Signal Strength Fingerprinting

To compensate for the drawbacks of the DR system, we use a Wifi-based signal strength fingerprinting approach. The signal strengths to several Wifi access points (APs) measured by the phone at run time are compared with a signal strength map generated earlier. The difference between the expected reading for that position in the map and the actual signal strength reading is used to adjust the weight of the particle. We use a Euclidean distance metric in signal space between the APs common to both readings. Effective distance is calculated as a weighted average of the nearby calibration points to reduce noise. In addition, a penalty is imposed for APs that were disjoint between the two readings in proportion to the signal strengths of those APs. The intuition is that a faint signal would be expected to drop in and out with changing conditions, but a strong signal should always be visible in a fixed location. Additionally at runtime, Wifi signal strength fingerprinting is used to initialize the system and provide a rough global location estimate. To perform the RSSI fingerprinting, it is necessary to create a database of signal strength information from the environment correlated to a free space map of the environment. This pose-RSSI database forms the basis for comparison and subsequent estimation. Collecting this information by hand is laborious and prone to error, so we developed an automated solution that uses a pioneer robot equipped with a SICK LMS200 laser rangefinder, a fiber optic gyroscope, and a mounted smartphone, to collect the signal measurements. The phone collects signal strength information continuously over the course of the automated run. At discrete intervals (~1m), the signal strength readings from the phone are correlated with the current position of the robot. The robot's on-board sensing allows for a continuous and accurate estimation of its pose. At the same time, the robot also builds a 2-D map of the environment using the laser rangefinder. The result is an accurate, high density sample of signal strength information in a short amount of time. Further, the shape and structure of the laser map allows us to speed up our pose estimation and reduce computation by discarding PF particles that lie outside the bounds of the map.

3.3 Particle Filter (PF)

The use of a PF is critical for minimizing the accumulation of localization error over time. PfS use sampling methods to track many possible hypotheses, updating them every time new information becomes available. They can easily be adapted to handle obstacles like walls, non-linearities and non-Gaussian noise models, multiple hypotheses, etc. Crucially, the performance of the filter can be scaled with available computation power by varying the number of particles that are tracked. A PF has 3 major components: a *motion model* that updates the positions of particles, an *observation model* that sets particle weights, and a *re-sampling algorithm* for modifying distribution to reduce variance. For our system, the motion model is derived from the DR information given by the accelerometer, magnetometer, and gyroscope. They are treated similar to the way wheel odometry is used in PFs for localizing robots. The heading and movement speed given by the DR methods described above are extended into a spatially directed Gaussian distribution. The variance in the forward component of the distribution is related to the walking speed of the user, and the variance of the angular component is related primarily to the measurement error introduced by the gyroscope during turns. During the movement model update, each particle is moved by an amount that is sampled from that distribution. The external measurements used by the filter to update particle likelihoods come from two different sources. The first is the robot map of the environment. Whenever a particle enters a space that is indicated to be impassable in the map, its likelihood is reduced to zero, so it is thrown away during the re-sampling step. Alternately, if the particle falls outside of the map by leaving it through an open area, it is not removed. The second source of external measurements is the aforementioned Wifi signal strength measurement. We use the importance sampling algorithm to resample particles [7]. This method reduces the variance of the particle distribution by throwing away unlikely particles and duplicating particles that are more likely. The pre-built environment map structure is used for weighing the sampling algorithms. Particles that lie outside the constraints of the environment are weighed lower than others. Specifically, the new particle distribution is formed from the old one by selecting particles (with replacement) with probability proportional to their weight. This focuses the particle distribution on the area of maximal interest.

4. EXPERIMENTS AND RESULTS

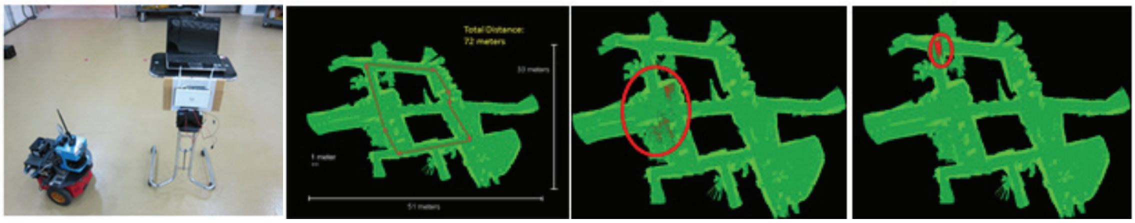

Figure 2: (left) RSSI database creation and map generation using a pioneer robot, and (right) PF change over time for a sample environment. The standard deviation of the PF bubble is ~1m over the duration of the run

We developed our localization solution for the Android platform using a Nexus S smart-phone. Towards analyzing the feasibility of the implemented solution, we tested the system in two different indoor environments. The user held the smart-phone pointing forward and walked at a normal pace. A closed loop test was performed in which the participants walked a path through hallways delineated with cones. Four individuals participated in the test for environment 1 and three for environment 2. Each set of experiment was repeated multiple times for consistency. The total length of the traversed path in environment 1 was approximately 120m, and the path in environment 2 was approximately 72m. There were approximately 30 Wifi access points in both environments. The DR information was obtained at a faster rate (30Hz) than the Wifi signal measurement (1 HZ). An RSSI database was constructed prior to experimentation using a Pioneer 3DX robot (see Figure 2), along with a laser map of the environment.

To better understand the quality of developed solution, we compared it against an offline standard PF solution (see Table I for details) as well as against the performance results outlined by Wang et. al. in [11]. In order to focus on analyzing the architecture, data from runs suffering from significant magnetic distortion was disregarded. In our offline system, sensor data collected from the above runs were passed through the PF and post-processed offline on a laptop. In contrast, the online version of the filter was run on the device and the resulting output tabulated. The limited processing capabilities of the Android handset required major modification to the PF algorithm used in the off-line version. Specifically, the updater (DR) portion of the PF has been separated so that the orientation accuracy can still be maintained while the PF processes the Wifi data. Further, the online version runs on a much more sparse data so as to not overwhelm the system, whereas the offline implementation has the advantage of running on the full set. Figure 3 illustrates the mean error is position over varying path distances collected over two indoor environments.

Table 1: Experimental Results

	Mean Error of Most Probable Location		**Additional Features**	
	Environment 1	Environment 2	Auto Init. Pos.	Bounded Error
DR Only	5±3 meters	6±2 meters	No	No
Wifi Only	15±10 meters	10±4 meters	Yes(<5 seconds)	Yes
DR and Wifi (offline)	5±3 meters	7±2 meters	Yes(<5 seconds)	Yes
DR and Wifi (online)	3±3 meters	5±4meters	Yes(<5 seconds)	Yes

Over the relatively short duration of the experiments, the DR method was able to track the participants with relatively low error and outperformed the Wifi only estimation. Table I shows the offline DR had a mean path error of approximately 5m, whereas the Wifi approach error was on the order of 10-15m. This is somewhat misleading, because of two factors. First, in both instances, the PF was manually initialized to the correct position for the DR-only results, whereas it was given a uniformly random initialization in the trials that used Wifi. Having a confident estimation of the starting location is not a given for all situations. Ideally it would not be necessary to manually initialize the filter, as this places an additional burden on the user of the system. Second, DR is known to drift unbounded over time. Finally, a DR-based method that uses magnetometer is susceptible to magnetic anomalies prevalent in the environment. This is emphasized in Figure 3, where the increase in mean error over path length can be attributed to drift in the dead-reckoning solution.

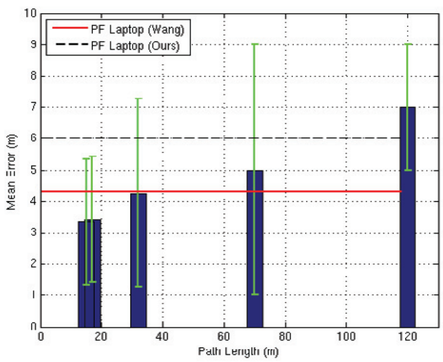

Figure 3: Quality of localization solution over path distance

Further analysis of the collected data revealed that the offline PF takes about 0.5s per processed reading whereas the online system can only output a reading about once every 1.5s. Interestingly, the online system shows at least as good a performance as the offline system, the laptop-based PF method implemented by Wang et. al. has a mean error of 4.3m, while our offline PF method has a mean error of 5 m. Additionally, both the online and offline systems had similar closed loop error measurements (~6 m) averaged over the different runs. Our reasoning is that while the higher computation of a laptop allows the offline system to process the data at a much faster rate, it introduces an increased sensitivity to sensor variation, especially from Wifi readings, leading to a reduced performance. On the other hand, the lower processing rate of the online system results in the error growing at a much slower rate leading to an improved estimation.

We can see that our adapted localization solution for a commercial smart-phone performs as well as the alternate solutions developed for higher-computational platforms with higher-resolution and dedicated sensors. Additionally, the online system further highlights the robustness of the developed system if one of the components is unavailable, by simply not feeding that measurement to the PF. If errors are intermittent, the filter will continue to function without any significant disruption. On the other hand, it is important to note that the tight constraints based on robot map and the reduced the number of particles in operation, make the filter sensitive to change. Consequently, once error accumulates in the system it takes longer to dissipate than for the traditional PF-based systems.

5. CONCLUSIONS AND FUTURE WORK

We describe a smart phone-based indoor localization system using DR and Wifi RSSI fingerprinting that is precise enough for providing way-finding directions (~5m) and for use in context-aware applications. We have shown that our system benefits from the precision of DR and the favourable initialization and error recovery properties of Wifi. We also describe a robot-based technique for reducing the time needed for data calibration and building the RSSI database. As a result, the time and effort needed to set the system up are minimized, maximizing its commercial relevance. There are several interesting directions to explore in future work. A drawback to the current system is that the performance of Wifi is restricted by the extent of the collected RSSI database. This shortcoming could be potentially mitigated using better signal strength interpolation methods. Further, the quality of localization can be refined by exploring the extent to which the system can improve through learning. The history of users' paths through an environment provides information that could be exploited to increase the system's performance.

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