Enhancements to the LOCOSmotion Person Tracking System

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Abstract. Indoor localization is a key component in context-aware applications and assisted-living technologies. In prior work, we presented the design and implementation of the LOCOSmotion indoor person tracking system that uses Wireless LAN fingerprinting and accelerometer-based dead-reckoning [5]. In this paper, we analyze the optimization potentials of the previous implementation LOCOSmotion and propose modifications and enhancements which address them. In particular, we focus on reducing the time and cost of deployment, as well as on a number of refinements to improve the localization precision. Aside from optimization of the calibration tools and underlying localization algorithms, the refinements also encompass the use of feedback provided by the domestic robotics (domotics) in the Living Lab to improve the overall system performance.

Keywords: Localization, Tracking, Pervasive Computing, LOCOSmotion

1 Introduction

Pervasive computing envisions seamless and distraction-free support for tasks by means of context-aware applications. In many of these applications, knowledge about the user's location is a key requirement. However the use of the Global Positioning System for location determination is limited by the unavailability of its signals in indoor environments. Hence, in recent years, much attention has been focused on developing alternative solutions for indoor localization. Rapid advances in wireless communication technologies and the miniaturization of consumer electronics have led to an increase in the deployment and accessibility of wireless local area networks (WLAN) and WLAN-capable mobile devices. This presents an opportunity to leverage and reuse the existing infrastructure for the development of localization systems without incurring extra costs for setup and maintenance. Also, most of the mobile devices today come packed with a plethora of other sensors such as accelerometers and gyroscopes which make them ideal for use as location sensing platforms.

In previous work [5], we described the design and implementation of LOCOSmotion, a WLAN-based indoor localization system. The basic operational principle of LOCOSmotion is similar to RADAR [2] in that it uses WLAN-based fingerprinting for location estimation. However, in contrast to RADAR, LOCOSmotion additionally performs accelerometer-based dead-reckoning in order to improve the localization precision while guaranteeing a minimum location update rate of 2Hz.

In this paper, we describe the implementation of several optimizations to the LOCOSmotion system based on our experiences during the EvAAL 2012 competition. To evaluate the optimizations, we present the results of a number of experiments that we performed in our laboratory at the University of Duisburg-Essen. The optimizations focus on a significant reduction of the calibration effort by providing better tools for the initial training, as well as improvements to the robustness of the dead-reckoning algorithm. Furthermore, we enhance the LOCOSmotion system to intelligently take advantage of any domotic event notifications which may be provided in order to increase the accuracy of the system.

The rest of this paper is broken down as follows; in the next section, we discuss related work in the field of indoor localization and then briefly outline the basic architecture of LOCOSmotion system in the Section 3. In Section 4, we outline the potential optimizations and propose enhancements which address them. Section 5 presents an evaluation of the impact of the optimizations on the performance of the system. Finally, we conclude the paper with a short summary.

2 Related Work

Many different systems have been developed for indoor localization and they employ different technologies to perform location estimation. Vision-based systems make use of cameras and computer vision for location estimation [6]. Other indoor localization systems have been developed on the basis of infrared light [19], ultrasound [20], or magnetic signals [9]. However, since LOCOSmotion is using RF technology as basis for localization, we are focusing on RF-based systems in the following.

One of the earliest systems that uses WLAN fingerprinting for indoor localization is RADAR [2]. In RADAR, a fingerpint is a tuple of location coordinates and signal strengths of visible WLAN networks. In a training phase, WLAN fingerprints are collected at all locations in the target area to form a radio map. During localization, WLAN scans are matched against this radio map to estimate the location of the user. As described in [5], LOCOSmotion can be thought of as an extension of RADAR with accelerometer-based enhancements for tracking.

Building a radio map by means of fingerprinting can be labor-intensive, hence there have been several approaches which seek to reduce the mapping effort by performing simultaneous localization and mapping [14] or using signal propagation models[12][22]. ARIADNE [12] proposes to collect only a single measurement and together with a two-dimensional construction floor plan, generates a radio map for localization. Xiang et al [22] use a signal distribution training scheme and achieve an accuracy of 5m with 90% probability for moving devices. The main limitations of indoor localization using propagation models are that due to the complexity of signal propagation in indoor environments, they either result in a high modeling effort or they only consider some of the variables affecting the signal distribution which reduces their precision.

In addition to WLAN, there are several indoor localization systems based on RFID technologies. RFID has been developed for automated identification of objects and people [13]. An RFID system usually comprises a tag and a reader. There are both active - where the tag has a battery - and passive - where the tag is induced by the reader - RFID based localization systems. LANDMARC [17] is an RFID-based localization system which uses multiple reference tags instead of multiple readers to mitigate cost. SpotON [10] is another RFID based localization system which uses custom RFID readers to detect the tag and triangulate its position using signal strength measurements. RFID systems can produce submeter precision levels, but have the downside of requiring extra hardware and infrastructure to be acquired and installed.

Aside from WLAN and RFID, many other RF technologies have been used for indoor localization. For example, there are IEEE 802.15.4-based [4] systems, Bluetooth-based indoor localization systems [1], Ultrawideband [11], and hybrid systems which use a combination of multiple RF technologies for indoor positioning. One such system is proposed by Baniukevic et al in [3]. It uses a combination of Bluetooth and WLAN signals for positioning. A good overview of possible approaches and technologies can be found in [15] and [7]. Most of these systems differ from LOCOSmotion in that they require extra infrastructure to be purchased which can be sometimes expensive.

3 LOCOSmotion

LOCOSmotion relies on a dense deployment of off-the-shelf wireless access points that continuously broadcast WLAN signals and provide good coverage of the target area. As with every other system that is based on RF fingerprinting, there are two phases involved in deployment; the training phase and localization phase. In the first phase – the training phase – we calibrate the system by performing WLAN scans with an Android-based mobile phone to capture and store WLAN fingerprints for several known locations. In the second phase – the localization phase – we run a background service on the mobile phone that continuously performs WLAN scans and matches the resulting fingerprint against the stored ones. The location of the closest matching fingerprint is returned as the estimated location. In between consecutive WLAN scans, accelerometer-based dead-reckoning is used to extrapolate intermediate locations using the phone's previous movement vector.

As described in [5], the LOCOSmotion system was specifically built to address the five goals set out by the EvAAL competition which are to provide a high accuracy, a low installation complexity, a high user acceptance, a high availablilty as well as enabling interoperability. In the following, we briefly explain how LOCOSmotion addresses these goals.

- *High Accuracy* – To ensure a high accuracy, LOCOSmotion relies on WLAN fingerprinting as this approach is known to exhibit better performance than systems which use simple forms of signal propagation modeling [7].
- *Low Installation Complexity* – To ensure a low installation complexity, LOCOSmotion relies on off-the-shelf hardware with customized software. To enable a speedy deployment in different environments, LOCOSmotion provides an Android application with a graphical user interface that allows the on-site collection of fingerprints for different locations.
- *High User Acceptance* – To ensure a high user acceptance, LOCOSmotion only requires the user to carry a mobile phone which performs all measurements and computations. Consequently, it is easy to integrate in the daily activities of users since many users will be already carrying a phone anyway.
- *High Availability* – Due to measurement imprecision, WLAN fingerprinting usually requires several measurements to accurately determine the location of the user. Thus, in order to achieve the location update rate goal of 2 Hz, LOCOSmotion combines fingerprinting with acceleration-based dead-reckoning.
- *Interoperability* – To enable and ease interoperability, LOCOSmotion relies solely on unmodified off-the-shelf hardware. To facilitate extensibility and to ease software integration, LOCOSmotion is using the NARF component system [8] developed by members of our research group. The NARF component system is a generic framework for personal context recognition which facilitates modularity and software reuse.

More technical details and a more thorough description of LOCOSmotion including a detailed analysis of the results of deploying and using the system during the EvAAL 2012 competition can be found in [5]. In the following sections, we focus primarily on several enhancements that we implemented and tested to improve overall performance of the system.

4 Enhancements

The LOCOSmotion system was designed to achieve a high accuracy, a low installation complexity, a high user acceptance, a high availability and interoperability. As demonstrated by the results of the EvAAL 2012 competition, the system largely fulfills the last four design goals. Yet, the results also indicate that there is considerable optimization potential with respect to installation complexity and accuracy. In the following, we discuss three enhancements to the original system that address this potential.

4.1 Training Effort

With the original implementation of LOCOSmotion, the training phase was performed by a person (the trainer) performing scans with one phone at discrete points in a grid defined on top of the target area. The scans were performed in multiple orientations to account for signal attenuation induced by the trainer. This improves accuracy, but is also time-consuming.

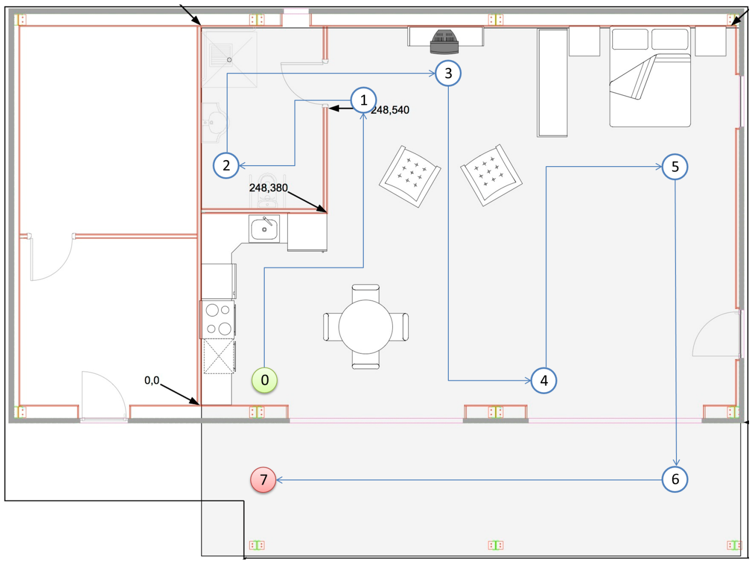

Fig. 1. Training Path and Markers

Instead of using discrete scans, we have enhanced the system to continuously perform scans while the trainer moves around. To do this, we first define a path through the area by specifying a sequence of points as shown in Figure 1. The path is chosen to maximize coverage of the areas in the building where people are likely to be found. During the training phase, the trainer then follows the path and marks his current position whenever he reaches one of the pre-defined points.

In addition, the trainer is equipped with multiple devices that are put into the left and right, front and back pockets. Multiple devices enable the coverage of different orientations to account for signal attenuation due to the human body. Taking different orientations into consideration has been shown to provide performance improvements of up to 67% [2]. In order to enable the correlation of measurements from different phones, we synchronize their clocks shortly before the training using Network Time Protocol (NTP).

Once the data collection is complete, the fingerprints from the different phones are aggregated and the (X, Y) coordinates are computed for each fingerprint by interpolating the intermediate locations based on timing information. The resulting output is a radio map with a dense distribution of the fingerprints collected from multiple devices facing different directions. Using this technique results in time savings of 75% to 83 % for training, while maintaining the accuracy of the original implementation.

4.2 Dead-reckoning

The LOCOSmotion system uses the accelerometer of the Android phone to determine its speed and extrapolate locations between WLAN scans using its previous movement vector. This enables the system to guarantee an update rate that exceeds the WLAN scanning rate. However, our original implementation used a simple algorithm that estimated the steps taken by a person by simply counting events during which the acceleration exceeded a given threshold. Despite our positive experimental laboratory evaluation, this turned out to be not very robust in the EvAAL 2012 setting as the person performing the test was following a pace-setter. This, in turn, resulted in an atypical acceleration pattern which caused imprecise intermediate estimates.

To address this issue, we completely redesigned the fundamental algorithm to determine the speed of the phone [16]. Instead of the simple threshold-based approach, the new implementation uses a tiered approach to determine the number of steps and the resulting distance covered. As a first step, we differentiate between 4 typical classes of movements, namely no movement, slow walk, normal walk and running. To do this, we determine the minimum and maximum acceleration as well as the variance over a 1 second frame using a simple tree classifier that we trained with data gathered from 5 persons. If a movement is detected, we apply a low pass filter over the signal which we parameterize with a cut-off frequency of 2, 3 or 4 Hz depending on the modality (i.e. 2 Hz for slow walking speed and 4 Hz for running). As a last step, we count the number of maximas in the frame and use this as our number of steps. Finally, in order to determine the distance covered we apply the formula described in [21]. We consistently use a k-value of 0.55 in order to avoid personalization effort.

4.3 Domotic Events

Domestic robotic (domotic) systems in home automation typically comprise automated systems that control the heating, entertainment and energy consumption and more in a home. The Living Lab in Madrid is equipped with a domotic bus which provides notifications for events in the home such as a light switch being triggered (as well as the position of the switch) and other such events. The notification typically includes the location of the triggered sensor or event.

In order to leverage this potentially valuable information, we have enhanced LOCOSmotion to enable the integration with external event providers such as a domotic bus. The provider can increase the confidence level in the location estimate or it can correct the estimate. However, we realize that in cases where multiple persons are present in the target area, purely relying on external event notifications can reduce the accuracy of the system. Thus, we only allow location corrections in cases where the distance between the estimated and the corrected location is less than the average system error. If the distance is greater than that, the external event provider is ignored.

5 Evaluation

In this section, we evaluate the performance of the enhanced LOCOSmotion system. We first look at the performance of the improved algorithm for step detection and distance estimation which forms the basis of our dead-reckoning. Then we describe the results of an experimental evaluation of the improved system in our lab and compare it to the performance of the system without any of the optimizations made in this paper. Since our laboratory is not equipped with domotic systems, we do not evaluate the potential gains, however, it should be clear that they are heavily dependent on the accuracy of the available events.

5.1 Steps and Distance Estimation

To measure the effectiveness of our improved algorithm for step detection and distance estimation, we asked three persons to walk several rounds on the parking lot in front of the university building. Each person was walking three rounds in total, each one at different speeds - representing our three movement categories (i.e. slow and normal walking and running). Before the experiment we measured the distance of a single round and during the experiment we were manually counting the steps taken by the different persons. After the experiment, we contrasted the manually counted steps with the steps determined by our algorithms. Depending on the person, the precision of the step detection stage ranged between 85 and 95%. Furthermore, we contrasted the measured distance with the computed distance which resulted in slightly lower accuracies ranging between 80 and 85%.

5.2 LOCOSmotion Localization System

The evaluation of the system was carried out on the 5th floor of our university office building. The path was traced through the pathways of the building and the passable space in the office as shown in Figure 2. So basically, every place where people are likely to be found was covered by the trainer and fingerprints were collected. One lecture hall was not covered due to its unavailability at the time of the measurements, hence no paths can be seen in in this room.

In total, we collected 1783 fingerprints from the 4 Galaxy Nexus Android mobile devices which were used by the trainer. We also collected another set of fingerprints to use for the evaluation of the system. We principally evaluate the enhancements to the system, particularly the accuracy and precision of the enhanced LOCOSmotion localization system and the time for initial calibration. Due to lack of domestic home automation infrastructure at the office building, we do not include any evaluation of the impact of considering domotic events during localization.

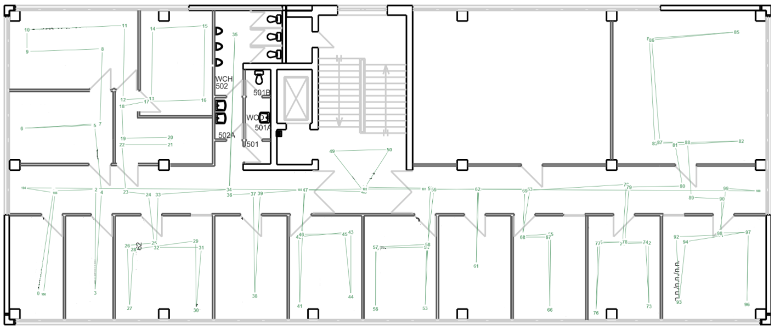

Fig. 2. Office Building Trace Path

Accuracy and Precision The accuracy measures the average error distance of the system. The fingerprints for the evaluation were collected in the same manner as the training fingerprints, with the user walking around the office building with the mobile device. The true location of the user was again interpolated from the markers in the path and then this was compared to the location estimated by the LOCOSmotion system. Figure 3 shows the results of the evaluation.

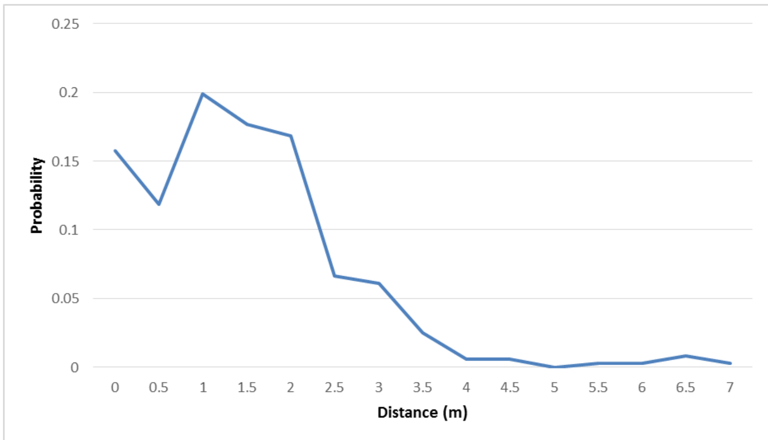

Fig. 3. Probability Distribution of Errors

The average error from the evaluation is 1.6m, the median error is 1.5m and the maximum error is 7m. The curve is a Gaussian distribution which is shifted by 1m. This is a result of the fact that for localization, we do not collect a single fingerprint for localization, but rather multiple scans are performed and smoothed and the result is used to generate a location estimate. The resulting fingerprint at each point is therefore not an absolute fingerprint at that position, but rather an aggregation of a multiple fingerprints depending on the speed at which the user is moving. We are therefore not always localizing the person where they are, but rather where they were approximately 2 seconds ago (average human walking speed is 1.4 m/s). For a user who would be running, the shift would be even greater.

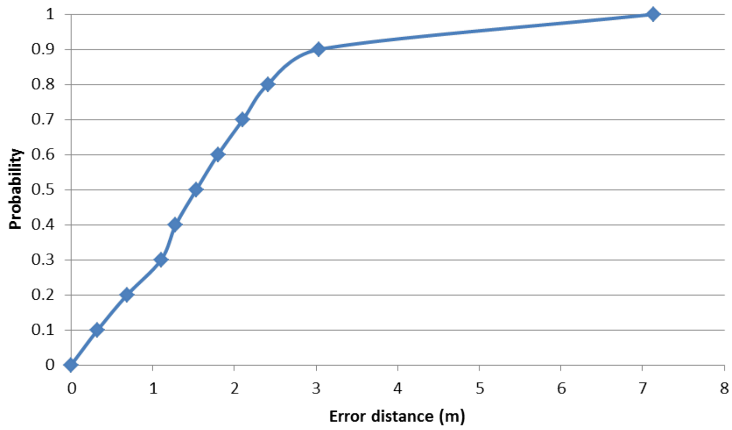

Fig. 4. Cummulative Probability Distribution of Errors

Likewise, the precision measures the success probability of location estimates with respect to the accuracy. Figure 4 shows the cumulative probability distribution of the localization system. From the figure, we can read that 60% of the location estimates have an error of 2m or less which increases to 90% at 3m. Only 10% of the values are between 3m and 7m. This is an improvement over the results from the first LOCOSmotion paper where only 34% of the time the result was within 2 neighboring cells (each of dimension 2x2m), and 83.8% of the time within 4 neighboring cells. It is obvious that the new fingerprinting method leads to dense fingerprinting which improves accuracy and precision.

Calibration Effort The total time needed for the calibration of the entire 5th floor of our office building was 11.5 minutes. In the first iteration of LOCOSmotion, we overlaid a grid over the floor resulting in 90 locations where fingerprints were to be collected for 8 different orientations. The IEEE 802.11 standard requires that all channels be scanned during a WiFi scan. There are typically 14 WLAN channels in use and with most commercial access points broadcasting for 100ms on each channel[18], it requires a total of 1.4 seconds to perform a complete WLAN scan. Combining this with the 8 orientations and 90 points in the building, it took a total of 1.4 hours to create a complete scan of the whole floor using the previous implementation.

The new mapping system represents an over 86% reduction in (pure scanning) time required to create a fingerprint radio map. The new system also has the advantage of eliminating unnecessary points which result from a grid system and focusing on the areas and paths where people are usually found in the first place. This leads to better coverage of the areas and faster deployment times for the LOCOSmotion system.

6 Conclusion

In this paper, we presented improvements to the LOCOSmotion indoor localization system. LOCOSmotion enables indoor localization by combining WLAN fingerprinting with speed estimations gathered from acceleration measurements and relies on standard off-the-shelf hardware which makes it very cost-efficient. The improvements proposed to the system increase its accuracy while simultaneously reducing the installation effort. Consequently, we think that it is a suitable candidate for supporting the development of many pervasive computing applications that require person tracking. At the present time, we are investigating further drive down the cost of installation and increase accuracy by making use of signal transmission properties and propagation modeling.

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