LOCOSmotion: An Acceleration-Assisted Person Tracking System Based on Wireless LAN

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Abstract. Pervasive computing envisions seamless and distraction-free support for tasks by means of context-aware applications. Location information is a key component in many context-aware applications. This article describes the design, implementation and evaluation of LOCOSmotion, an acceleration-assisted WLAN-based tracking system. The basis of localization in LOCOSmotion is WLAN fingerprinting as proposed in RADAR [2]. In order to achieve high location update rates, it augments fingerprinting with dead-reckoning using acceleration measurements to capture movement. To evaluate the performance of LOCOSmotion, this article presents the results of a set of laboratory experiments as well as results of the EvAAL 2012 competition in Madrid. Based on the lessons learned from deploying and using LOCOSmotion during EvAAL, we identify future directions for possible optimizations.

Key words: Indoor Localization, Tracking, Pervasive Computing

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. This holds especially true for applications in the area of Ambient Assisted Living where it is often necessary to track the user's location in order to detect dangerous situations, abnormal behavior or to issue location-dependent reminders. In outdoor scenarios, the global availability of GPS can provide a suitable basis for tracking. However, the lack of GPS signals in many indoor environments makes this approach ill-suited for precise tracking in indoor scenarios. Thus, in recent years, a lot of research has been focused on developing alternative localization solutions.

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 devices. Smartphones – which are the fastest growing segment of computing devices [17] – are almost all capable of accessing WLAN. This presents a big 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 smartphones come packed with a plethora of other sensors such as accelerometer, magnetometer, gyroscope, lux sensors and more.

In this article, we describe the design, implementation and evaluation of LOCOSmotion, an acceleration-assisted WLAN-based tracking system. The basis of localization in LOCOSmotion is WLAN fingerprinting as proposed in RADAR [2]. In order to achieve high location update rates during tracking, it augments fingerprinting with dead-reckoning using acceleration measurements to capture movement. To evaluate the performance of LOCOSmotion, we present the results of a set of laboratory experiments as well as results of the EvAAL 2012 competition in Madrid. Based on the lessons learned from deploying and using LOCOSmotion during EvAAL, we identify future directions for possible optimizations.

The rest of this article is structured as follows; in the next section, we describe related work in the field of indoor localization. Section 3 describes the main design and development considerations, and thereafter the basic deployment and setup of LOCOSmotion. Section 4 presents an evaluation of the performance of the system both at our lab and at the EvAAL 2012 competition in Madrid. Based on these results, we present experiences and lessons learned in Section 5. Section 6 presents the next steps and future directions for improving LOCOSmotion and finally, we conclude the article with a short summary in Section 7.

2 Related Work

Many different systems have been developed for indoor localization and they employ different technologies to perform location estimation. There are vision-based systems [5], which make use of cameras and computer vision for location estimation. Other indoor localization systems have been developed on the basis of infrared light [19], ultrasound [20], or magnetic signals [8]. However, in this section, we will focus on RF-based systems since they are closest to our system in design.

2.1 WLAN

RADAR [2] is one of the earliest systems which uses WLAN signals for indoor localizaton. The system uses fingerprints where a fingerprint 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. Conceptually, our system is 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 other systems which seek to reduce the mapping effort by performing simultaneous localization and mapping [13] or using signal propagation models[10][21]. ARIADNE [10] 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 in [21] 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 modelling effort or they only consider some of the variables affecting the signal distribution which reduces their precision.

2.2 RFID

There are also several indoor localization systems based on RFID technologies. RFID is a technology for automated identification of objects and people [11]. An RFID system typically 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 [15] is an RFID-based localization system which uses reference tags. It uses multiple reference tags instead of multiple readers to mitigate cost. SpotOn [16] 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 sub-meter precision levels, but have the downside of requiring extra hardware and infrastructure to be acquired.

2.3 Others

Aside from WLAN and RFID, many other RF technologies have been used for indoor localization. For example, there are also IEEE802.15.4-based [4], Bluetooth-based indoor localization systems [1], Ultrawideband [9], 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 [14] and [6]. Most of these systems differ from our approach in that they require extra infrastructure to be purchased which can be sometimes expensive.

3 Design and Implementation

The primary goal in the development of LOCOSmotion is to be able to reuse existing WLAN infrastructure and low-cost off-the-shelf smartphones to enable tracking. In this section, we describe the key factors influencing our system design and how the resulting parts of the LOCOSmotion system fit together.

3.1 Design

The evaluation criteria for the EvAAL competition informed to a greater extent the design decisions made for LOCOSmotion. As described by the EvAAL competition guidelines, there are 5 main design goals that should be considered.

- *High Accuracy* – To be broadly applicable for various ambient assisted living applications, the accuracy provided by an indoor tracking system must be high. Consequently, LOCOSmotion uses WLAN fingerprinting as basis for localization since this approach is known to exhibit better performance than systems which use simple forms of signal propagation modelling [6]. More complex signal propagation models would require the consideration of additional variables such as the building materials, floor plan or access point locations – which may be hard to model accurately.
- *Low Installation Complexity* – To be cost efficient with respect to setup and maintenance, the installation complexity of an indoor tracking system should be low. This is especially true for tracking systems that target ambient assisted living applications since these must be often installed in the homes of the users. The users' homes may differ considerably with respect to size, room layout, materials, wiring of powerlines or available network connections, etc. Regarding the installation complexity, the use of fingerprinting is simultaneously beneficial and limiting. On the positive side, the use of fingerprinting solely requires a sufficiently dense deployment of WLAN access points. On the downside, it requires an on-site training phase where fingerprints are manually collected at several locations. In order to mitigate this, we decided to include a graphical user interface to speed up training.
- *High User Acceptance* – To be applicable for a broad range of users, the user acceptance of an indoor tracking system must be high. Especially, when considering that many users may not be technically inclined, the system should be easy to integrate in their daily activities. Furthermore, the total cost of ownership should be low. For this reason, we decided to use Android smartphones and off-the-shelf WLAN access points since they are broadly available, unobtrusive, and relatively affordable.
- *High Availability* – To be usable, a tracking system should provide high availability. This means that it quickly and reliably determines and provides the user location. This is especially beneficial for tracking moving targets. Due to measurement imprecisions, WLAN fingerprinting usually requires several measurements to accurately determine the location of the user. Thus, to meet the goal of achieving a location update rate of 2 Hz, we decided to combine fingerprinting with acceleration-based dead reckoning.
- *Interoperability* – To ease the integration with existing and future applications, a tracking system should be interoperable with respect to hardware and protocols. Towards this end, the decision to rely on unmodified off-the-shelf components simplifies the maintenance and upgradability of LOCOSmotion. In addition, in order to facilitate extensibility and to ease software integration, we decided to build LOCOSmotion using the NARF component system [7] 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. It allows the replacement of different software components while maintaining the interfaces to the other parts of a system.

3.2 Implementation

The LOCOSmotion tracking system comprises two parts: the mapper application and the localization subsystem. The mapper is an Android application which is used for collecting fingerprints to build a radio map during the training phase. The localization subsystem handles the tracking duties during the localization phase. It consists of a set of components that are built using the NARF component system. The overall software architecture of LOCOSmotion is illustrated in Figure 1. In the following, we discuss the functionality and implementation of both subsystems in more detail.

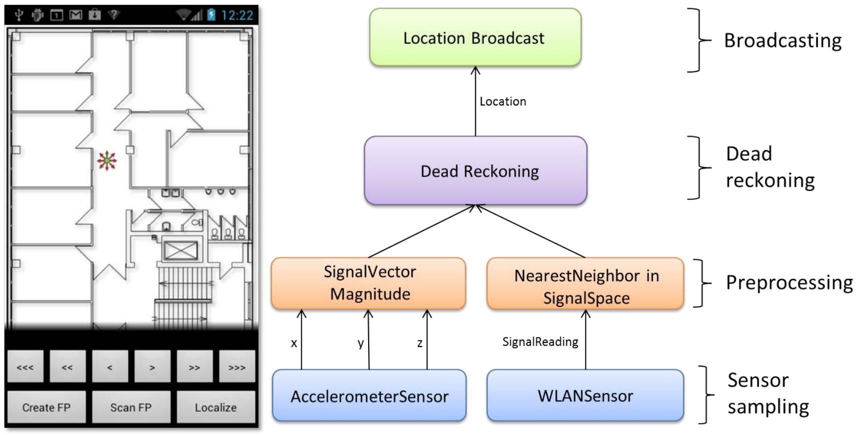

Fig. 1. LOCOSmotion Mapper and Localization Architecture

Training The training starts by setting up the application for a particular environment. This is done by loading a graphical 2D representation of the environment which is overlaid with a configurable Cartesian grid. The Cartesian coordinates defined by the grid are used internally to capture the location of fingerprints during training and they are also used as the output during the localization phase. Higher levels of abstraction such as areas of interest or rooms can be defined by combining multiple coordinates into a single output[1]. After this setup, the person performing the training can cycle through the different points of the grid in order to capture fingerprints with the device. At each point, the person must capture four fingerprints thereby facing four different directions (i.e. North, East, South, West). For each fingerprint, the mapper application memorizes the position as well as the received signal strength (RSS) of all access points that can be received there. The result is stored as a vector

[1] Note that these steps can be done offline given a map of the environment and a definition of the areas.

$V_{training} = (X, Y, O, RSS(AP_1), RSS(AP_2), ..., RSS(AP_N))$ whereby X, Y and, O are determining the position and orientation and $RSS(AP_1)$ to $RSS(AP_N)$ are capturing the signal strength of the corresponding access points. In order to cycle quickly through the different locations and orientations, the mapper application provides a graphical user interface that shows the next location and controls the capturing process.

Localization The localization phase starts by starting a localization application on the smartphone. The application consists of a simple user interface to start and stop the localization subsystem that continuously computes and broadcasts the current user location using the set of components depicted in Figure 1.

To compute the current location, the smartphone continuously performs WLAN scans using a WLANSensor component. The component produces a new vector $V_{localization} = (RSS(AP_1), RSS(AP_2), ..., RSS(AP_N))$ roughly every 1.4 seconds. Once a new vector is produced, the NearestNeighborInSignalSpace component matches it against the corresponding parts of all vectors $V_{training}$ captured during the training phase. The output is a distance d between $V_{localization}$ and all instances of $V_{training}$ that is computed as the Euclidean distance $d = \sqrt{\sum (RSS(AP_{training}) - RSS(AP_{localization}))^2}$. When computing the distance, special care is taken to handle the fact that not all access points are visible at all locations. Thereby, the vectors are dynamically extended with adequate values to handle the non-visible access points. The resulting distances are then used as an input into a k-nearest-neighbor classifier which eventually outputs the location in terms of X and Y coordinates of the nearest vectors of $V_{training}$.

Given such a fingerprinting, it is possible to compute a new location update roughly every 1.5 seconds. Furthermore, due to possible measurement and aggregation errors in $V_{localization}$, consecutive location updates might exhibit high physical distances. To mitigate both issues, LOCOSmotion includes a AccelerometerSensor component that also captures measurements using the built-in accelerometer of the smartphone. The measurements are used to compute the force in the SignalVectorMagnitude component which is then forwarded to the DeadReckoning component. Using the force, the DeadReckoning component computes an approximate movement speed of the user by estimating the footstep frequency as described in [12]. The resulting speed is then used for dead reckoning and scoping. Dead reckoning estimates intermediate location updates by computing the trajectory between the last two updates and extrapolating the next location using distance estimates from the footstep frequency. Scoping corrects location updates by reducing the set of possible consecutive locations to those locations that exhibit a sufficiently close proximity to the last known location. Together, this results in a higher update rate as well as fewer false positives.

Once a new location has been computed, the LocationBroadcast component sends it out over WLAN such that the location can be received and used by other applications.

4 Evaluation

To evaluate LOCOSmotion, we present the results of a number of laboratory experiments as well as the results of the EvAAL 2012 competition in the following. In the lab, the evaluation was performed offline - meaning a set of fingerprints were collected and used for testing the performance - rather than online which would be time consuming. The EvAAL competition performed the evaluation online by having a person actively using the system.

4.1 Lab

For evaluating the performance of the LOCOSmotion system, we set it up on the 5th floor of our research building. The floor was logically divided into 2×2 meter cells with one coordinate in each cell. Using a smartphone, multiple training fingerprints were collected for 8 different orientations at each cell. After the completion of the training, a second set of fingerprints were collected with to perform the offline evaluation of the performance of the system.

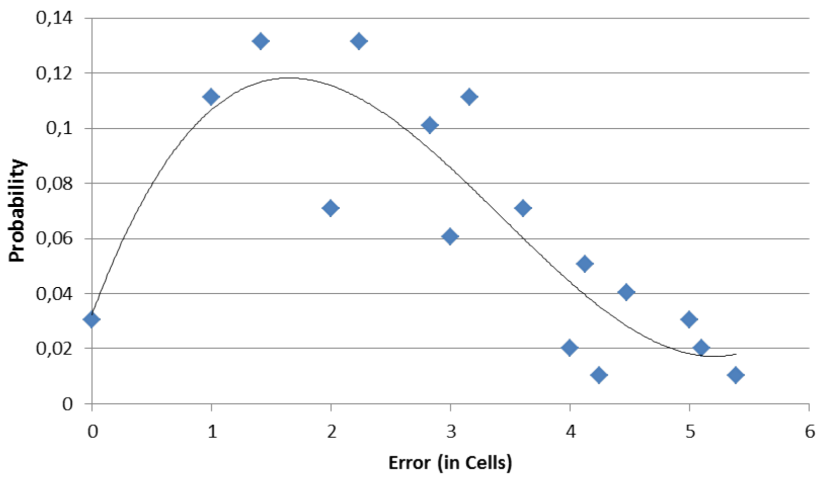

Fig. 2. Localization error probability distribution in the lab

For the evaluation, we compute the location of each individual fingerprint in the evaluation set by comparing it to all fingerprints in the training set. Figure 2 shows the resulting probability distribution for the error of the system over the whole evaluation set. The diamond points represent the actual values whereas the line represents the best polynomial fit of them.

The error with the highest probability is between 0 and 3 neighboring cells with an average distance error of 2.6 cells. The system can locate the user correctly within 2 neighboring cells 34% of the time and 4 neighboring cells 83.8% of the time. The maximum error recorded is 5.3 cells. For most office environments, this places the subject in the worst case scenario in a neighboring office.

For tracking, we set out to build a pedometer whose outputs are used to augment the location update frequency. In order to achieve this, we studied the movement pattern of several users in order to determine the patterns in the accelerometer data generated by someone who is walking. We placed the phone in the pocket of multiple test subjects and had them walk around at different speeds while the phones collected accelerometer readings for all the three axes. Later on, the three data points from each axis were combined to give the magnitude and the data was then analyzed. Figure 3 shows an example from one of the participants.

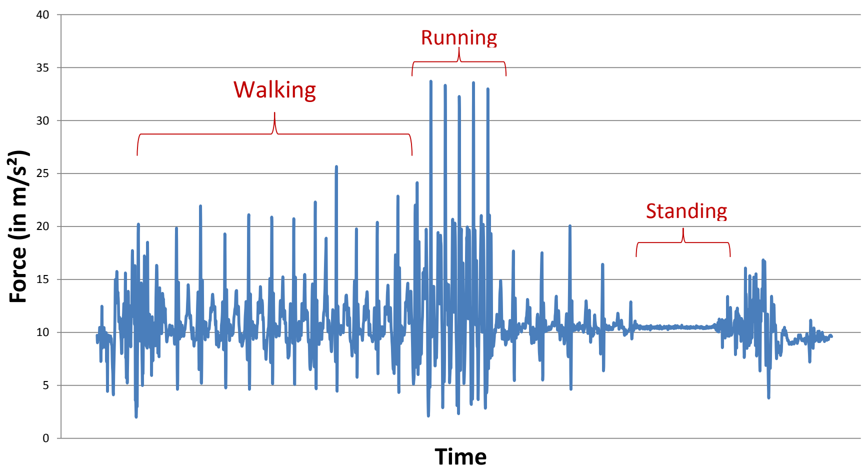

Fig. 3. Movement pattern example

The base reading of the signal magnitude of the accelerometer when the phone is held still is 1g (approximately 9.8 m/s^2). When the person starts moving, it can be observed that the value jumps to about 2g. The exact value of the magnitude varied from person to person depending on the gait, weight, height and force of movement. However, the values were all above 1.6g when the person was in motion. Thus, we selected this value as the threshold for when to consider the person as moving. Once the person is considered as being in motion, the number of measurements exceeding the threshold were counted. Looking closely at the values for each step, it is recognizable that there are approximately three peaks for each step. Hence the number of peaks is divided 3 for each step and then multiplied by a constant factor to account for the distance. This simple approach worked well across all participants in the laboratory setting.

4.2 EvAAL

For the EvAAL 2012 competition held at the Living Lab of the Polytechnic University of Madrid in Spain, we used our own equipment to setup LOCOSmotion. We deployed 8 access points (Netgear WNR-3500L) to enable localization using WLAN fingerprinting. Furthermore, we used a smartphone (Nexus S) for training and localization. The access points were placed at different locations in the Living Lab, with at least one access point per room. In rooms with multiple access points, one access point was placed toward the center of the room in order to provide a more characteristic fingerprint. The layout of the Living Lab as well as the exact placement of the access points is depicted in Figure 4)

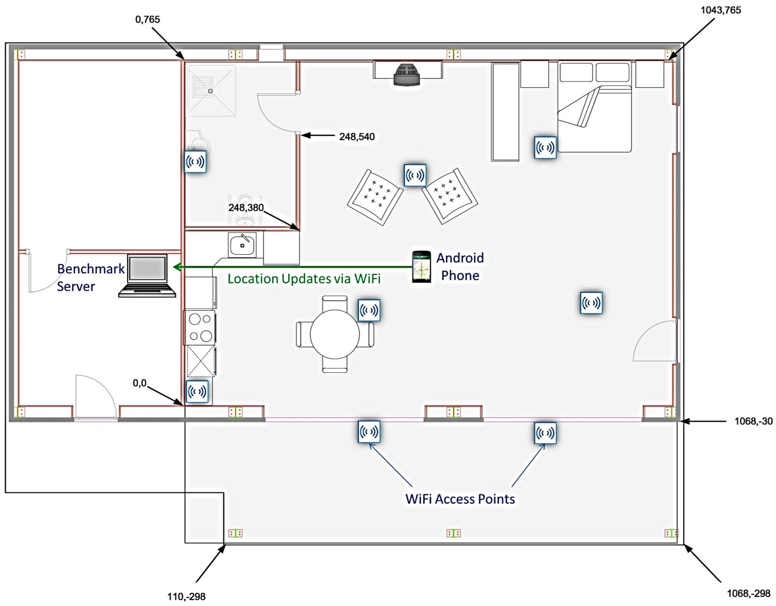

Fig. 4. Basic Deployment

To perform training, we overlaid a 2×2 meter grid on the floor plan of the Living Lab. For each of the cells in the grid, we collected several fingerprints for 4 different orientations. Deploying the access points and performing all the measurements for the complete environment took a single person 51 minutes which was within the 60 minutes threshold defined by the competition.

During the competition, the smartphone was put in the trousers pocket of the person performing the evaluation. The person then proceeded to move along several predefined paths while LOCOSmotion continuously computed and broadcast the person's location. The broadcast were then picked up by a benchmarking PC which used the values to compute performance scores. In the following, we describe the results:

Accuracy The system's accuracy is measured as the error distance between each computed localization sample and the reference position. It accounts for 15% of the overall performance score. During the competition, the person follows a pace-setting sound so that the speed of movement is the same for all the contestants. However, for our system, we noticed that this caused the pedometer to miscalculate the distance covered by the person. Due to the long slow steps, the location was over-projected leading to rather low accuracy scores. The aggregate results of the paths walked during the EvAAL competition is shown in Figure 5.

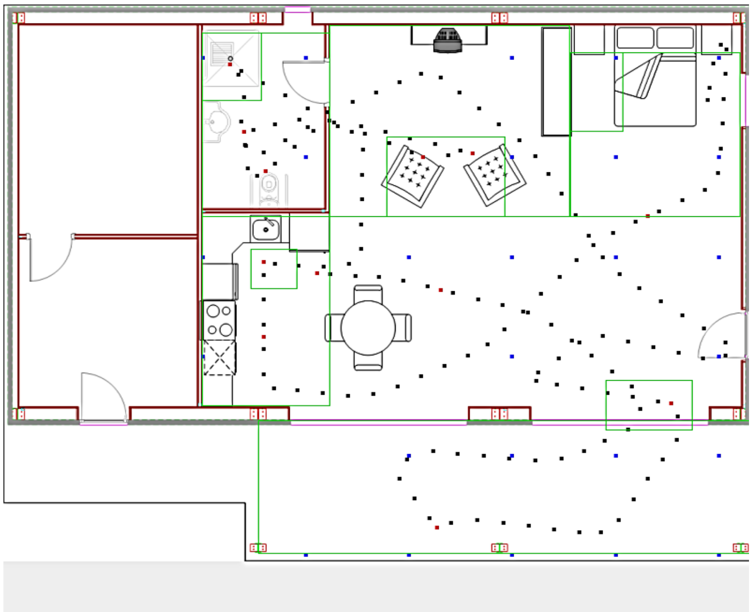

Fig. 5. Aggregate path localization results

The green lines represent the logical partitions of the space, which are the areas of interest. The black dots represent the ground truth location of the person and the blue dots are the corresponding location estimates by our system during the online evaluation. It can be observed that the using the WLAN location results, the location is predicted within the path of the person, then over-projected before being corrected again. This happens repeatedly, driving the overall accuracy score down to 8%.

Installation complexity Installation complexity represents a measure of the effort required to install the localization system in the Living Lab and makes up 15% of the total score. LOCOSmotion relies only on the presence of WLAN access points and the availability of a radio map. We were able to setup the access points and map the entire floor within 51 minutes with just one person resulting in an installation complexity score of 13.25%.

User Acceptance User acceptance expresses how much the localization system is invasive in the users daily life and thereby the impact perceived by the user. In the EvAAL 2012 competition, user acceptance make up 25% of the total score. LOCOSmotion relies solely on off-the-shelf consumer electronics, and works with Android phones which are the fastest growing phone category as of today. This means that the chances that the user of the system already has one are high. WLAN access points are also common in most homes. Given that the localization system runs on a smartphone which fits in a user's pocket, the user acceptance of LOCOSmotion was rather high, coming it at 90.35%.

Availability Availability is the fraction of time the localization system was active and responsive. Availability comprises 20% of the total score. LOCOS-motion uses WLAN to connect to the benchmarking PC and broadcast location updates. Thereby, the dead-reckoning keeps the location updates coming in at rates of at least 2Hz. As a result, the system had a 100% score on availability which is critical for tracking applications.

Integrability in AAL Integrability in AAL evaluates the degree of interoperability of the solution in terms of openness of the software, adoption of standards for both software and hardware, replaceability of parts of the solution with other ones. It makes up 15% of the total competition score. LOCOSmotion makes use of off-the-shelf hardware components that can be easily upgraded or replaced. Furthermore, it uses the NARF component system in order to be easy to maintain and extend. With respect to this evaluation criterion, LOCOSmotion achieved a score of 50%.

Overall, LOCOSmotion got a score of 5.23 out of 10 at the EvAAL competition. It performed really well in most of the metrics, except for localization accuracy due to unanticipated movement patterns of the person and the installation complexity. In the next section, we describe the lessons learned from the laboratory experiments and the participation in the EvAAL competition.

5 Lessons Learned

Based on the results of our laboratory experiments and the results of the experiments performed during the EvAAL competition, there are several interesting lessons to be learned with respect to the suitability, the calibration as well as the performance of the system. In the following, we discuss each of them in more detail.

5.1 Suitability

With respect to the suitability of LOCOSmotion in an AAL context, both, our initial laboratory experiments as well as the results of the EvAAL competition indicate that the system is applicable to a broad range of scenarios. Due to the use of off-the-shelf hardware such as smartphones and access points, it is very cost efficient when compared to other alternatives that employ specialized hardware. With an average cost of approximately €60 for an access point and roughly €300 for a smartphone, the cost for a typical deployment stays well below €1000. Moreover, in cases where the user already owns an Android-based smartphone or is using WLAN at home, the cost even drops further. In addition, due to the use of a single smartphone to perform all measurements and computations, LOCOSmotion is very convenient to set up and use. With a weight of approximately 130g and a size of $63 \times 123,9 \times 10,88$ mm, the smartphone running the localization system can be easily placed in a trouser pocket, thus, allowing the user to freely pursue his normal daily routine.

5.2 Calibration

With respect to the calibration procedure and effort, we found that LOCOSmotion's reliance on signal strength fingerprinting can be both, an advantage as well as a limitation. On the positive side, fingerprinting does not require a special wiring or placement of WLAN access points, thus, allowing us to easily adapt the deployment to any typical home environment that exhibits a sufficient number of power outlets. Furthermore, there is no need to manually generate a precise map of the deployment which minimizes the off-site preparation effort. On the negative side, however, WLAN fingerprinting requires an on-site training phase during which we collect a number of fingerprints for different locations. Ideally, this number should be large and the collection procedure should closely reflect the usage scenario. With LOCOSmotion's user interface collecting a large number of fingerprints can be done quickly. However, since the user interface is visual, it requires the person performing the calibration to hold the smartphone in the hand. Consequently, the location of the phone differs during calibration - where the phone is held in the hand - and usage - where the phone is placed in the pocket - which can introduce inaccuracy.

5.3 Performance

Due to the combination of WLAN-based localization as well as acceleration-based dead reckoning, LOCOSmotion is able to score high with respect to availability, meaning that it is able to produce localization results quickly. In addition, during laboratory testing, we found that it can also increase the accuracy. Unfortunately, with our current implementation of LOCOSmotion, we were not able to replicate the positive results of our laboratory measurements during the EvAAL competition. In fact, in many cases the acceleration-based dead reckoning even reduced the overall accuracy of the localization. This issue can be attributed primarily to the simplicity of our dead reckoning algorithm. Instead of trying to determine the distance that a person was actually walking, our prediction of upcoming locations were solely based on the number of steps taken by the person. In our laboratory setup, we then experimentally determined the typical distance of a step and integrated the resulting constant into the code. However, during the EvAAL competition, the person performing the evaluation was following a pace setter which resulted in an atypical movement pattern. Consequently, our dead reckoning algorithm frequently overestimated the person's speed which dramatically worsened the system's performance.

6 Next Steps

Based on our experiences with LOCOSmotion, we are currently improving the system regarding both, the calibration procedure as well as the accelerometer-based dead reckoning.

With respect to calibration, we are integrating two optimizations. First, to closely mimic the localization procedure - where the phone is placed in the user's pocket, we are using Android's headset APIs to enable the remote triggering of calibration measurements using the volume keys. Second, in order to further speed up the calibration process, we have extended LOCOSmotion to use multiple phones - placed in different pockets. The phones are set to continuously capture measurements. To combine their fingerprints with the locations provided via the headset triggers, we ensure that they are time-synchronized. This, in turn, allows us to perform a simple time-based aggregation. Clearly, the use of multiple phones slightly increases the hardware cost during calibration. However, it also significantly reduces the time required at the target site and thus, reduces the personnel cost. Given that mobile phones are comparatively inexpensive we believe that this trade-off will likely reduce the overall system cost even further.

With respect to the accelerometer-based dead reckoning, we are currently extending the simple pedometer with a more realistic model for movements. As indicated by the performance of LOCOSmotion during the EvAAL competition, the walking mode has a significant impact on the length of individual steps. For example, when looking at the left side of Table 1 – which shows the number of steps that different persons require for walking a certain (fixed) distance in different modes – it becomes apparent that the step length can more than double when comparing slow walking with fast running.

As hinted in Figure 3 and on the right side of Table 1, both, the force as well as the step frequency can provide a good indication for the walking mode. Thus, instead of solely considering the number of steps, we also consider the actual frequency as well as the force per step in order to determine the walking mode which we then use to estimate a step length. Or initial experiments show that this approach allows us to predict the walking distance with an 80 percent accuracy. This can be further increased to 88 percent when considering the height of the person. Given these initial results, we are convinced that the improved version

	Number of Steps				Frequency in Hz			
	Walking		Running		Walking		Running	
	Slow	Fast	Slow	Fast	Slow	Fast	Slow	Fast
Person 1	276	255	159	135	1,60	1,96	2,58	2,61
Person 2	289	249	183	159	1,67	2,04	2,74	2,87
Person 3	319	299	174	150	1,70	2,21	2,64	2,73

Table 1. Step count and frequency for different persons and walking modes when walking the same distance.

of LOCOSmotion will exhibit a considerably higher localization performance during the next EvAAL competition.

7 Conclusion

Pervasive computing envisions seamless and distraction-free support for tasks by means of context-aware applications. Location information is a key component in many of them. LOCOSmotion enables indoor localization by combining WLAN fingerprinting with speed estimations gathered from acceleration measurements. Given the fact that LOCOSmotion relies solely on standard off-the-shelf hardware, it is very cost efficient and a typical installation will be well below €1000. Consequently, we are convinced that it is a suitable candidate for supporting the development of many pervasive computing applications that require person tracking in indoor scenarios.

Our experiences during the EvAAL competition provide a clear indication for the high applicability of LOCOSmotion to AAL scenarios. However, they also show that accelerometer-based dead reckoning requires a more sophisticated model for movement prediction in order to work well outside the laboratory environment. Based on our initial experiments, we assume that by considering the step frequency as well as actual acceleration force we will be able to improve the results presented in this article significantly.

At the present time, we are working on the improvements to the calibration procedure and the accelerometer-based dead reckoning. Thereafter, we are planning to investigate how to effectively integrate other sources of signals such as GSM [18] in order to improve the resulting localization accuracy and to reduce the training effort.

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