Indoor location for safety applications using wireless networks

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Abstract—This paper presents the indoor positioning research activities carried out within the scope of the Liaison project. Most of the work has been performed on WiFi location. WiFi is nowadays widely deployed in buildings such as hotels, hospitals, airports, train stations, public buildings, etc. Using this infrastructure to locate terminals connected to the wireless LAN is expected to have a low cost. Methods presented in this paper include fingerprinting with particle filter constrained on a Voronoi diagram and TOA based on data frames and acknowledgments at the IEEE 802.11 MAC level. Other technologies have also been researched: A-GNSS to handle the transition between outdoors and indoors, UWB in ad-hoc mode to cope with possible lacks of infrastructure and inertial MEMS to increase the availability and robustness of the overall system.

1 Introduction

1.1 Location Based Services

Recently, there has been a growing interest on location-based services (LBS). LBS are addressed particularly to mobile networks. They can be defined as services that adapt to a user's location and situation: location is a crucial input for these applications. LBS explore the ability of technology to know where the user is and shape the information provided accordingly. Presently, many LBS have already been deployed and others that have been designed are ready for commercial implementation. A few of the most interesting ones are: information services, navigation, workforce management, demand-responsive transport, lone worker applications, children tracking, medical alert…

1.2 Indoor location

Outdoors is the typical scenario for GPS positioning and tracking. When the terminal to be located has an open view of the sky, GPS is expected to give good or even excellent accuracy. Difficulties with GPS positioning usually occur in urban canyons and indoors, where it is difficult or impossible to acquire the necessary satellites for a position computation. On the other hand, research has been performed on location systems that use the cellular network (GSM-GPRS, UMTS…) to provide the terminal's position, but the main drawback is that they provide not enough accurate positioning for many of the location based services. Given this situation, it is needed to research on alternative location techniques that are able to provide accurate location information of the user in medium to deep indoors, electrically noisy indoor scenarios, subterranean places (e.g. parking), etc, because in many of the location based services mentioned in the previous section the people to be located are in such environments. As WiFi is nowadays widely deployed in buildings such as hotels, hospitals, airports, train stations, public buildings, etc, it seems to be a suitable infrastructure to provide cost-efficient positioning solutions.

2 Fingerprinting in WLAN

2.1 Introduction

This technique aims at taking the major advantage of one of the available outputs of a standard WiFi card, which is the received signal strength (RSS) from each AP. Given this consideration, it is possible to get a list of the received power coming from all the APs covering the area where the mobile is moving. The simplest approach for locating a mobile device in a WLAN environment using this available information is to approximate its position by the position of the APs received at that position with the strongest signal strength, but its main drawback is its large estimation error. The accuracy is inversely proportional to the range of APs which is within 25 and 50 meters for indoor environments [3]. On the other hand, using a propagation model [1][2] to turn RSS measurements into distances did not provide satisfying results when introducing these ranges in a multilateration algorithm. [4] introduces a different approach for locating the device in indoor environments by using the radio signal strength fingerprinting.

Fingerprinting mainly consists in having some signal power footprints or signatures that define a position in the environment. This signature consists of the received signal powers from different APs that cover the environment. A first step, called training for profiling, is necessary to build this mapping between collected received signal strength and certain positions in the environment. This leads to a database that is used during the positioning phase. Building the footprint database can be done in two ways. A first method is to do on-site measurements for some reference positions in the building with a user terminal. An alternative approach is based on collecting limited on-site measurements and introducing them in an adjustable propagation model that would use them to fit some of its parameters. Then, this propagation model gives an extensive coverage map for each AP. However, the poor results obtained earlier with the use of the propagation model did not invite us to focus on such a model. Neural networks are another learning method for improving propagation models over time [5]. Ray tracing tools represent another solution to build such a database, but they are very complex. Moreover, a good knowledge of the radio environment (knowledge of the presence and position of all the APs is needed) to cope with the interfering issue. However, such information is not always available due to the fast growing emergence of this technology in indoor environments. It was decided then to carry on with the use of data collection to build the database.

Once this prerequisite step is accomplished, it is necessary to perform the reverse operation, which will deliver the position associated to an instantaneous collected tuple of received signal strengths. Different techniques can fit these requirements. One of the simplest ones is the k-closest neighbours algorithm, which goes through the database and picks the *k* referenced positions that match best the observed received signal strength tuple. The criterion that is commonly retained is the Euclidian distance (in signal space) metric. The estimated position of the mobile is considered to be the barycentre of those *k* selected positions. The main advantage of this method is its simplicity to set it up. However, the accuracy highly depends on the granularity of the reference database [6]. A better accuracy can be achieved with finer grids, but a finer grid means a larger database what is more time-costly. However, in both techniques, the signal strength fluctuations introduce many unexpected jumps in the final trajectory. Removing those jumps can be done by using a filter. Kalman filter and particle filter are often used in parameter estimating problems and tracking. This last filter will be introduced in the next section, and the benefits using such a filter will be presented.

2.2 Improving WiFi positioning with a particle filter constrained on a Voronoi diagram

Nowadays, maps of most public or corporate buildings are available in digital format (dxf, jpeg, etc). The key idea is to combine the motion model of a person and the map information in a filter, in order to obtain a more realistic trajectory and a smaller error for a trip around the building. In the following, it will be considered that the map available is in bitmap format. So, no other information is available except for the pixels in black and white which depict the structure of the building. The particle filter, based on a set of random weighted samples (i.e. the particles), represents the density function of the mobile-position. Each particle explores the environment according to the motion model and map information. Their weights are updated each time a new measurement is received. However, the free particle filter is not fit for handset based applications, as the computations are quite heavy. At each time step, it is necessary to check if a particle crossed a wall or not in order to introduce the architecture of the building in the filter. An approach to reduce this computation complexity is to limit the space the particles need to explore. Another representation for the building is a graph. These sets of edges and nodes make the skeleton of the building. Constraining the particles to move on this representation of the building is really interesting, as it is not necessary to check if particles crossed a wall or not.

The particle filter tries to estimate the probability distribution $\Pr\left[X_k \middle| Z_{0:k}\right]$ where X_k is the state vector of the device at the time step k, and $Z_{0:k}$ is the set of collected measurements until the $(k+1)^{th}$ measurement. When the number of particles $\left(\text{positions } x_k^i,\ \text{weight } \omega_k^i\right)$ is high, the discrete probability density function of presence can be assimilated to:

$$\Pr\left[X_k \left| Z_{0:k}\right.\right] = \sum_{i=1}^{N_s} \omega_k^i \cdot \delta\left(X_k - X_k^i\right) \tag{1}$$

This filter comprises several steps:

- Prediction: During this step, the particles propagate within the building given an evolution law that assigns a new position for each particle with an acceleration governed by a random process. New positions for all the particles are predicted.
- Correction: When a measurement (n-uplet of RSS) is available, it must be taken into account to correct the weight of the particles in order to approximate $\Pr\left[X_k \left| Z_{0:k}\right.\right]$. As the measurement is signal strength and given that particles are characterized by their position, the RSS n-uplet must be transformed into a position. The mapping between the position and the signal strength is performed thanks to the empirical database. Then it is possible to estimate $\Pr\left[Z_k \left| X_k\right.\right]$. Once defined all the necessary probabilities to update the weight of a particle, it is just needed to combine them to find the new posterior distribution.
- Update of the weights: The weight update equation is the one used in [4][5]. To obtain the posterior density function, it is necessary to normalize those weights. After a few iterations, when too many particles crossed a wall, just a few particles will be kept alive (particles with a non zero weight). To avoid having just one remaining particle, a re-sampling step is triggered.
- Re-sampling: The re-sampling step is a critical point for the filter. The basic idea behind the re-sampling step is to move the particles that have a too low weight, in the area of the map where the highest weights are. This leads to a loss of diversity because many samples will be repeated. Various re-sampling algorithms are proposed in [7]. We chose the simple SIS (Sequential Importance Sampling strategy).

2.2.1 The Voronoi diagram

The Voronoi diagram [8] has been used for a long time in the robotics community to model the environment in which a device is evolving. The Voronoi diagram is a set of edges that are equidistant to all the walls. The first stage is to automatically design this Voronoi diagram from a bitmap picture. A routine has been written to perform this task (figure 1). With such a representation it is possible to limit the moves of the particles. Now they are constrained to move on the edges of the oriented graph. This reduces the processing cost at each time step. There is no need to check if a particle crossed a wall or not. As they have a reduced area to explore, it is possible to cut down the number of particles. In our simulations, only 200 particles were used to track the device. Indeed, the particles move on a graph which is a one dimensional space, whereas in the previous case, the particles were moving in a two dimensional space.

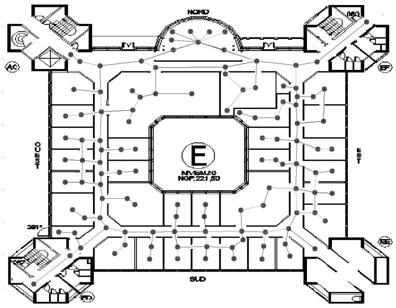

Figure 1: Voronoi diagram for a building (set of edges and nodes)

2.3 Experiments

To experiment with all those techniques and estimate their capabilities and accuracy to localize a device, a demonstrator has been built. It is made of a set of four 802.11g Linksys WAP54g APs placed at each corner of the 35×35 m building. The mobile device (PDA) is evolving in an indoor office environment. Both, a laptop and a Compaq iPAQ 4700 PDA were used for the measurements. The database is built with one measurement in each room, and a measurement every two meters in the corridor. The single floor problem is considered. The criterion to define the error is the mean error over a trip in the building. A walk around the building was made for the test. Some real measurements were collected along this path and then reused to estimate the performances of the positioning technique. Here, the measurements frequency is 3.33 Hz and the handheld device computes itself its own position.

Obtained results show that using the raw fingerprinting it is not possible to recognize the path followed by the mobile moving across the building. As expected, it is necessary to filter information over the time to be able to obtain a coherent trajectory. The particle filter (with 200 particles) constrained on the Voronoi diagram has been used to find the trajectory of the mobile. The estimated trajectory along the corridor is shown on figure 2.

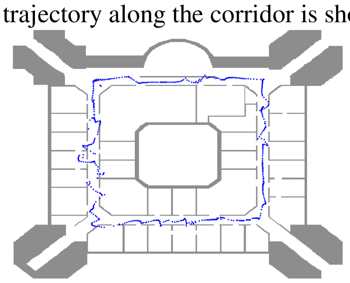

Figure 2 : Trajectory obtained with the particle filter constrained on a Voronoi diagram

It can be seen that the estimated trajectory fits the real one. After some few time steps, the filter starts tracking the device correctly. The obtained results show an achievable accuracy of less than 2 m of error for the 66% of the cases with a low infrastructure. Increasing the density of APs improves the performance, however such deployment does not appear to be realistic. Hence, the particle filter constrained on a Voronoi diagram appears to be a good trade off between complexity (computation time of a measurement) and performance, as the performance of this filter are similar to the one achieved with the particle filter with particles freely moving.

3 TOA with IEEE 802.11 MAC frames

3.1 Introduction

The research challenge corresponds to achieve an indoor location system capable to provide accurate positioning using the existing WLAN infrastructure and devices with minor changes, avoiding the need of synchronization between APs and long manual system pre-calibrations (i.e. build of fingerprinting database), while presenting robustness to environmental changes (i.e. furniture reorganization). Following this direction, a new WLAN location technique is presented, which can be divided into the ranging (distance estimation) and the positioning subsystem. The former estimates the distance between the MT and the AP from TOA estimation and the latter calculates the MT position using the distances estimated from the MT to 3 APs and the APs' known positions.

Several contributions existed in the scope of the proposed technique, but none of them fulfilled the degree of desired accuracy, simplicity and flexibility. In [9], a new approach is proposed to ranging in IEEE 802.11, without the requirement of initial synchronization between transmitters and receivers. Ranging is achieved by using a high precision timer in order to measure TDOA from two GRP (Geolocation Reference Point). The authors also propose to take advantage of the IEEE 802.11 data link frames for measuring TOA (time-of-arrival), but they do not give more insight to this matter. In [10], a system which can estimate TOA using IEEE 802.11 link layer frames is proposed, but the RTS (Request-to-Send)/CTS (Clear-to-Send) mechanism is required. In [11], a method to estimate TOA between WLAN nodes without using extra hardware is presented, but the achieved accuracy (error of 8 metres) is not enough for most safety related applications.

3.2 Ranging system

3.2.1 RTT estimation

TOA is estimated from *RTT* measurements in order to avoid the need to synchronize the MT with the APs. *RTT* is the time a signal takes to travel from a transmitter to a receiver and back again, in our case from a MT to a fixed AP. As can be seen in figure 3, we estimate the *RTT* by measuring the time elapsed between two consecutive frames under the

IEEE 802.11 standard: a link layer data frame sent by the transmitter (it is the MT) and the reception of the correspondent link layer acknowledgement (ACK) from the receiver (it is the AP). Other link layer frames would be also suitable [10].

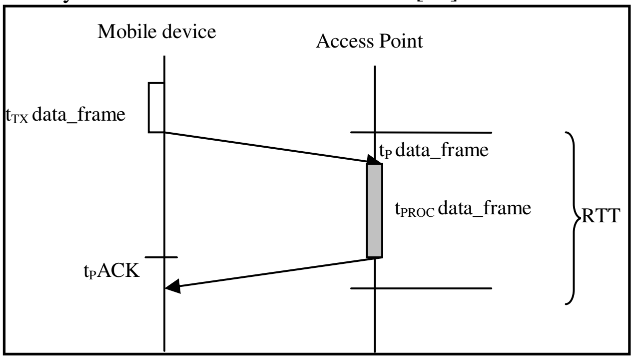

Figure 3: RTT measurement using IEEE 802.11 data/ACK frames

As the overall (i.e. propagation plus processing) *RTT* is expected to be in the order of microseconds, measuring it with software as in [11] leads to a significant lack of accuracy. Therefore, we propose to measure the *RTT* through a simple hardware module that starts counting cycles of the built-in 44 MHz clock from the WLAN card when it detects the end of transmission of a data frame, and it stops when the corresponding ACK frame arrives**.** Then it sends its value (i.e. slotted in 44 MHz periods) to the laptop PC. A lab prototype implementing this has been build, based on a laptop with an IEEE 802.11b PCMCIA card and the additional connected hardware module.

The *RTT* is time-variant due to constraints such as the variability of the radio channel multipath [12], the 44 MHz clock quantification errors [11], delays due to the electronics of the hardware module and the relative clock drift. If we only considered the quantification errors, a distance estimation error of 7 m should be present. In order to mitigate these errors this paper proposes to deal with *RTT* as a random variable: performing several (n) *RTT* measurements (i.e. samples) and using a proper *RTT* estimator over the *RTT* samples. The chosen *RTT* estimator was the average *RTT* value (η, measured in number of clock cycles) obtained from all the measurements, since among all tested choices this value provided the best *RTT* estimation. Other choices, such as the half range *RTT*, the *RTT* mode, the average of n minimum *RTT* values and η- β times the standard deviation were also tested, but they did provide lower accuracy and are not reported.

3.2.2 Distance estimation

First, a *RTT* estimation at zero distance between the MT and the AP is obtained (the propagation times t_p is zero), in order to calibrate the processing time in the AP. The figure obtained is assumed to be the $t_{proc\ data\_frame}$ part in Fig. 1, so that it can be used as an offset for measurements at a non-zero distance. Consequently, by applying the offset obtained, it is possible to find the ΔRTT , it is the pure propagation time of the *RTT*:

$$\Delta RTT = RTT_a - RTT_0 \tag{2}$$

Once the ΔRTT is calculated -and being aware that a 44 MHz clock was used for the measurements and that the average RTT is used as estimator (η, measured in number of clock cycles)- the distance d (in meters) between the transmitter and receiver can be obtained as:

$$d = ((\eta_a - \eta_0) \cdot 3 \cdot 10^8)/(2 \cdot 44 \cdot 10^6) \tag{3}$$

3.2.2.1 Empirical coefficient

During the development process, it was observed that all the distances estimated were longer than the actual distances; therefore, the estimated distance had to be divided by an empirical coefficient to correct the estimated value. This coefficient is justified by the different sources of error commented before, which can increase the theoretical expected *RTT*. To estimate that coefficient, linear regression lines were traced for several distances relating the estimated distance obtained following the method described above with the actual distance. The obtained coefficient was k=0.694. Therefore the corrected formula for calculating the distance is:

$$d = ((\eta_a - \eta_0) \cdot 3 \cdot 10^8 \cdot k)/(2 \cdot 44 \cdot 10^6) \tag{4}$$

3.2.3 Experimental Test Bed and Measurements

The first experimental test bed consists of several distance estimations in the laboratory (indoors) in LOS situations between the lab prototype and the AP, for distances from 0 to 30 meters. The obtained mean distance estimation error taking into account all the tested distances was 0.81 meters. In a second set of measurements, the probability distribution of the distances estimated by the ranging system was obtained. This set consists of 450 distance estimations (450*300 *RTT* measurements) at a fixed distance of 10 metres, after the initial calibration at 0 metres. Ideally, all the distances measured should be 10 metres; however, due to several error sources, the ranging system obtains distances from 8.80 metres to 12.80 metres. The known probability distribution that best fitted it was found to be a Gaussian distribution, with $\mu = actual\_dist + 1.12$ and $\sigma = 0.84$.

3.3 Positioning System

3.3.1 Introduction

The MT position can be estimated once the distance estimations from a set of AP are obtained and the APs coordinates are known. The simplest option is to use a pure triangulation algorithm, but higher accuracy can be achieved if tracking is applied, because it takes advantage of the past trajectory followed by the MT. Specifically, a Kalman-based tracking algorithm has been designed due to its simplicity and potential performance features. For a detailed description of the Kalman filter see [13] and [14].

3.3.2 Experimental Test Bed: Simulations

Simulations have been carried out in order to evaluate the performance of the positioning system using the Kalman-based approach. Furthermore, the Non Linear Least Squares (Newton) trilateration algorithm has also been implemented in order to evaluate the advantage of tracking results versus pure positioning techniques. For this evaluation it was desired to obtain the Cumulative Distribution Function (CDF) of the absolute positioning error. The observables that feed the filter (i.e. in the correction step) on every position estimate correspond to the distance estimations from the MT to the three nearest APs, using ranging statistical distribution presented before. A large number of routes (5000) with bad GDOP zones and probable changes of direction were generated following a motion model as similar as possible to a real behaviour of a pedestrian. The scenario is composed by a squared area of 50x50 m^2 with an AP in every corner. The positioning step *T* is set to 1 second.

3.3.3 Results

The obtained CDF of the absolute positioning error for the algorithms shows that the Kalman-based algorithm provides a high accuracy of less than 0.9m. of absolute positioning error for the 66% of the cases (one sigma), and less than 1.4m. for the 90%. Comparing it with Newton, the improvement seems to be noticeable, because it provides 1.2 metres and 1.8 metres for 66% and 90% respectively. Figure 4 shows an interval of one of the generated MT's trajectory and the estimated ones obtained with Newton and the Kalman-based algorithms. It can be easily appreciated that the later provides an erratic path whereas the former is able to achieve a smoothed trajectory very similar to the actual one.

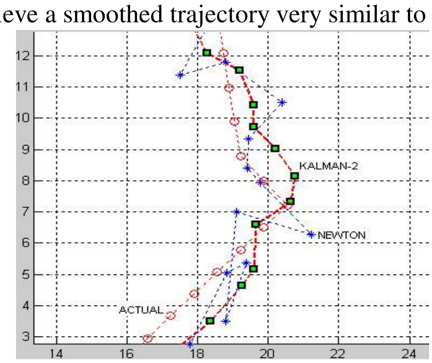

Figure4: Actual and estimated trajectories

4 Other technologies

4.1 Ultra Wide Band (UWB)

The work on UWB-based positioning focused on the analysis of the potential ranging and positioning accuracy of future LDR UWB systems compliant to the IEEE 802.15.4a standard, currently under development. The analysis took into account the characteristics of the UWB propagation channel (in terms of both communication range and impact on the ranging accuracy) as well as the MAC strategy to be adopted in the 802.15.4a standard, based on Aloha, and the impact of Multi User Interference.

Two different scenarios were selected for this analysis in order to represent the different application scenarios expected to be served by the new IEEE 802.15.4a standard. The first scenario was characterized by a centralized controller determining the position of fixed or mobile nodes based on the distance estimations provided by a set of fixed reference nodes. A Time Difference Of Arrival approach adopting a Least Square Error minimization was used for estimating the position of the terminals at the central controllers. An indoor environment characterized by both LOS and NLOS links was considered. Simulation results show that the positioning error is potentially very low in the case of LOS links between nodes, and remains acceptable even in presence of a significant percentage of NLOS links.

The second scenario addressed the case when no external infrastructure is available, and relative position information must be built from scratch within the network. The scenario was characterized by a network of terminals that build a coordinate system exchanging distance and position information by means of a distributed algorithm derived from the Self Positioning Algorithm (SPA) [15]. In this scenario the results indicated that, for a network with high enough terminal density, a distributed protocol combined with an IEEE 802.15.4a UWB physical layer can potentially provide accurate position information even in absence of any external infrastructure, despite the potentially high MUI interference caused by the strong signalling overhead in the construction of the common coordinate system required by the SPA algorithm. Further information on the results of UWB research activity within LIAISON can be found in [16], [17] and [18].

4.2 Inertial Navigation Systems

Inertial Navigation Systems (INS) are commonly used in the naval and aviation fields. While pedestrian navigation is based on the same underlying principles, i.e. measure of accelerations and angular velocities, the quality of the sensors employed differ quite significantly from the "traditional" inertial systems. Due to constraints on ergonomics (weight and size), power consumption and price, the sensors used in pedestrian navigation are based on Micro-Electro-Mechanical Systems (MEMS) technology [19]. The Liaison research activities in this domain of MEMS based location focus on two primary axes:

- Research of algorithms for real-time implementation to detect and characterize human physical activities, encompassing both body postures (lying, sitting and standing) and body displacement (distance travelled and azimuth of travel).

- Coupling of MEMS derived body displacement with absolute positioning information provided by other positioning technologies (e.g. A-GNSS or WiFi-based).

With respect to the first point, a novel approach in the context of pedestrian navigation is being pursued that consists on placing sensors in different parts of the human body, specifically the trunk, thigh and shank. With this architecture it is possible to determine the real posture of a pedestrian. This information is not only useful to infer about his safety condition, but also to adjust the navigation algorithms to certain specific movements of the professional users (e.g. crawling or walking squatted) [18] A few first tests have been performed under less stringent conditions, both in terms of movement complexity (postures and displacement) and environmental conditions. The results obtained show a rate of success of better than 95% in posture detection and 90% in detecting the type of displacement (forward, backward, lateral movement, stairs climbing and descending). As for the quantification of the actual displacement, the errors observed are less than 5% of the distance travelled and 1 degree in orientation (in magnetically free environments) [18]. Validation of these results under more severe conditions is planned for the near future. Future research activities on this axis will contemplate the adaptation to the project's test cases specific movements and context, and also the online calibration in order to reduce the effect of large bias and noise levels typical of these sensors.

Regarding the second research axis pursued under Liaison, work is currently undergoing to hybridize MEMS based positioning with other positioning technologies, namely A-GNSS and WiFi TOA/Fingerprinting. Besides increased availability of the overall system, this approach allows the correction of certain systematic errors on the MEMS side (i.e. step length and orientation errors), improving positioning accuracy [20][21].

5 Conclusion

Indoor location with WiFi allows using the existing infrastructure and devices widely deployed in buildings such as airports, train stations, hotels, etc. The two approaches presented in this paper provide a good accuracy. UWB (in adhoc mode) and INS can be used in extreme cases such as fire when infrastructure is disconnected.

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