

ON THE USE OF VARIOUS POWER LEVELS TO IMPROVE WIRELESS LAN-BASED POSITIONING

Using Multiple Power Levels With Fingerprinting Algorithms

Hendrik Lemelson, Thomas King, Stephan Kopf and Wolfgang Effelsberg
Department of Computer Science IV, University of Mannheim, Germany

Keywords: Wireless LAN, positioning systems, fingerprinting, transmission power, context-aware applications, location-based services.

Abstract: When talking about location-based services, one of the key factors influencing the overall service quality is the positioning accuracy that the system can rely upon. Nowadays, wireless LAN hardware supports the variation of the transmission power in a wide range. In this paper, two novel algorithms suitable for extension of common wireless LAN-based positioning systems are presented. These novel algorithms exploit the additional information that can be gained by using one or more non-standard transmission power levels. Our findings indicate that the overall positioning accuracy and reliability can be increased with such an approach.

1 INTRODUCTION

In the past few years we have seen an on-going miniaturization and increase of features on mobile devices. This, in conjunction with increasing wireless bandwidth available on these devices, opens the door for new mobile applications. Especially in the research focus here is a new type of application where the user's device supplies additional information to create a more feature-rich and user-adaptive experience.

The application or service can vary its behaviour depending on the user's preferences, locational information or other context information such as weather data, available credit cards or simply, the time-of-the-day (Chen and Kotz, 2000). These kinds of applications are called "context-sensitive applications".

A subset of these context-sensitive applications are the location-based ones. Leaving all other context information aside, here, the service is only supplied with information about the current user location. This already increases the overall service quality a lot. Considerable research was done on location-based services in the past few years and many promising approaches were found.

One of the major challenges in this area is the accurate and reliable localisation of an object or user. When talking about outdoor scenarios, satellite-based systems such as GPS or Galileo (Kaplan and Hegarty,

2005) offer an almost optimal solution; however in the indoor scenario there is still room for improvement. Satellite-based systems fail to work here because the received signals are either too weak to be used or the time-of-flight measurements are very imprecise due to signal shading, reflection and multipath propagation. One of the more promising approaches, therefore, is the positioning based on wireless LAN access points.

Even though wireless LAN is already a well known technique, there is still much development done especially regarding the hardware. One of the new features that many up-to-date wireless LAN access points offer, is the possibility to vary the transmission power as needed.

Most promising positioning systems based on fingerprinting and using wireless LAN though still take the access points' transmission power as fixed. Our approach is to increase the amount of available information for positioning by using multiple transmission power levels. This paper describes the development of novel algorithms that benefit from this increase in available information. On the basis of several well-known wireless LAN-based fingerprinting algorithms we implemented novel fingerprinting algorithms according to our approach and evaluated these to confirm their advantages.

Fingerprinting algorithms are split into two phases. In the offline phase, data is collected at given reference positions. This data is used to create so-called “fingerprints” for these reference positions. They reflect the unique properties of the signals at each position. In the subsequent phase, called positioning, live, or online phase, collected live samples are compared to each fingerprint to estimate the position using an algorithm-specific metric. To sample the signal strength of access points the so-called active scanning approach is typically used (King et al., 2007).

The remainder of this paper is structured as follows: In Section 2, an overview of related projects in the area of positioning with wireless LAN and fingerprinting is given. Section 3 introduces the algorithm we used as a basis and describes the extensions that are necessary to use the algorithm with multiple transmission power levels. In Section 4, an overview of the evaluation testbed as well as the hard- and software used is given. The methodology of the evaluation is presented in Section 5. Finally, Section 6 concludes the paper and gives an outlook to our future work.

2 RELATED WORK

In the area of indoor positioning, much effort and work were done during the past few years (Want et al., 1992; Priyantha et al., 2000). One of the newer projects regarding this topic is the Landmarc positioning system (Ni et al., 2004). It uses RFID technology to estimate the position of objects that are equipped with RFID tags. One of the key ideas of this system is the use of several concentric reading ranges to determine properties of the signal space and to increase the accuracy of distance estimates using this information. The Landmarc system was the key motivation to develop and examine a wireless LAN positioning system that uses different transmission power levels.

Due to the bad signal propagation properties that wireless LAN signals show indoors (Rappaport, 2001), the general consensus is that a fingerprinting-based approach is a good solution for such a scenario. We chose to base our novel algorithms on the RADAR positioning system (Bahl and Padmanabhan, 2000) and the system described in (Haeberlen et al., 2004). Both positioning systems use wireless LAN and fingerprinting but utilize different metrics. To refer to the latter one, we use the name RICE for the remainder of this paper, even though this is not its official name.

In this paper, only the results regarding the RICE positioning system are presented due to the limited space available.

The RICE positioning system adopts a probabilistic approach. The fingerprints for the reference positions contain either histograms of the collected signal strengths of each access point or values for average and standard deviation of the signal strengths computed from the histograms. The values represent a normal distribution with these parameters. For both variants, in the positioning phase a value is computed for each reference position using the collected live sample and the corresponding fingerprint. This value reflects the overall probability to be at that position. The algorithm then selects the reference position with the highest probability. We use the variant based on the Gaussian distributions in our evaluation.

As the RADAR system offers a feature called K-Nearest-Neighbors (Bahl and Padmanabhan, 2000) that was not available in the original implementation of the RICE algorithm we extended the RICE system to support this feature as well for comparability and fairness. How the extension works in detail is explained in Section 3.2.

3 ALGORITHMS

The following sections provide a brief overview over the original implementation of the RICE algorithm, the K-Nearest-Neighbors extension and our two novel algorithms that use multiple transmission power levels.

3.1 Original Algorithm

The original RICE algorithm that was taken as a basis for some of our novel algorithms uses normal distributions to describe the distribution of the received samples’ signal strengths. In contrast to the one using histograms, this variant is more robust and requires a reduced amount of offline samples to compute the fingerprints.

In the positioning phase a sample is collected and compared to all stored fingerprints using the following metric:

The probability $P_{r,ap}(s_{ap})$ to receive the signal of a certain access point ap with a certain signal strength s_{ap} at a given reference position r is defined by:

$$P_{r,ap}(s_{ap}) = \int_{s-0.5}^{s+0.5} df(avg_{r,ap}, stdddev_{r,ap}) \quad (1)$$

where df is the density function of the normal distribution with the average $avg_{r,ap}$ and the standard deviation $stddev_{r,ap}$ for the access point ap . These values are taken from the fingerprint for position r . Because the probability for a single value is zero by definition, we consider the probability for an interval

of $s \pm 0.5$ instead. The interval of $s \pm 0.5$ is used to map the discrete signal strength values received from the hardware (-102dB to 0dB) to the continuous numberspace of the normal distribution.

The overall probability computed for one reference point is now defined by:

$$P_r(s) = \prod_{i=1}^n P_{r,ap_i}(s_{ap_i}) \quad (2)$$

Hereby, n is the number of access points that are found in the collected live sample, s_{ap_i} is the signal strength collected for the access point ap_i and r is the current reference position of which the fingerprint is taken as a comparator.

After having compared the collected sample to the fingerprints of all reference positions, the algorithm selects the reference point as the estimated position that has the highest overall probability.

3.2 K-Nearest-Neighbors

As mentioned earlier, we have extended the RICE algorithm by a feature called K-Nearest-Neighbors taken from the original RADAR positioning system. The details of this modification are described in (King et al., 2006). Such an approach was necessary to ensure a fair comparison between our novel and the existing algorithms.

The K-Nearest-Neighbors extension not only uses the best matching reference position to make a position estimate but takes the K best matches into consideration. The coordinates of these K best matching reference positions are averaged and the result of these computations is taken as the position estimate. Sensible values for K are 2 to 4, according to the authors of RADAR.

3.3 Power Level Aware Algorithms

Using the RICE or RADAR algorithms with a single transmission power level that simply differs from the stock one does not require any modifications as long as the fingerprints and the live samples are collected using the same transmission power level.

Using more than one transmission power level though, requires some changes to the way the algorithm handles the multiple samples and results. The first thing to mention here is, that of course for each used transmission power level the algorithm has to be supplied with a fingerprint database for that power level. Furthermore, if a power level is used multiple times, the algorithm should be given a distinct fingerprint database for each occurrence.

In the positioning phase, the algorithm has to be supplied with live samples for each used transmission

power level or occurrence of a transmission power level as well. Afterwards, for each reference position and sample a probability is computed using the sample itself and the corresponding fingerprint.

$$P_{r,tx}(s_{tx}) = \prod_{i=1}^n P_{r,ap_i}(s_{ap_i,tx}) \quad (3)$$

Here, n is again the number of access points that are found in the collected sample for power level tx , $s_{ap_i,tx}$ is the signal strength collected for ap_i in power level tx and r is the current reference position whose fingerprint is taken as the comparator.

When the algorithm has finished the computation of the probabilities for all transmission power levels, there are several ways to handle these results.

3.3.1 Distinct

One way is to handle each probability independently from the others. For each power level, the reference position with the highest probability is selected using the computed probabilities for that power level. This results in one position estimate for each power level. Since these estimated positions for the single power levels can differ from each other, they have to be post-processed afterwards to produce one final result. This can be done by computing the centroid over all position estimates like it is done by K-Nearest-Neighbors for example.

The advantage of this approach is that no changes to the core algorithm itself are necessary. Only the surrounding logic that supplies the algorithm with the fingerprint databases and the live samples and that processes the results has to be adapted. It has to supply the corresponding samples and fingerprint databases for each power level and to handle the multiple results in an appropriate manner.

The direct benchmarks for this algorithm developed by our team in Mannheim is the RICE algorithm extended by the K-Nearest-Neighbors feature. Using a similar approach, our algorithm still has the advantage of using K times the most probable position estimate instead of using the K best position estimates.

3.3.2 Combined

A second possible way of handling the various sub-probabilities is to merge them into one final probability per position. In this case, all sub-probabilities for each reference position are multiplied, thus resulting in one final probability per position. The goal of this approach is to exploit interference effects between the single transmission power levels in such a way that some power levels can absorb outlying values of another power level. This is similar to supplying more than one live sample to the original algorithms, again

with the major difference of using different transmission power levels and fingerprint databases in our approach:

$$P_r(s) = \prod_{tx=tx_1}^{tx_n} P_{r,tx}(s_{rx}) \quad (4)$$

When given a sample set s , the overall probability $P_r(s)$ to be at the reference position r is the product of all sub-probabilities for the transmission power levels tx_1 to tx_n occurring in the sample set to be at that reference position (also see Equation 3).

4 EVALUATION SETUP

In the following, we briefly describe the setup of the evaluation.

4.1 Evaluation Environment

The evaluation environment is the second floor of the building A5,6 B at the University of Mannheim in which the offices of our department of Computer Science are located. The area is split up into two hallways, several offices and three smaller rooms in the middle of the hallways (see Figure 1). The two hallways are measured 30 x 6 meters and 15 x 4 meters respectively covering an area of approximately 240 square meters.

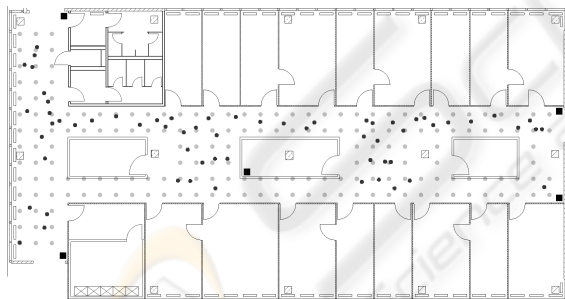


Figure 1: Floor plan of the evaluation environment.

4.2 Hard- and Software

To build up the wireless LAN infrastructure, five WRT54GL V1.1 access points manufactured by Linksys/Cisco are used. They are spread over the evaluation environment as depicted by the black squares in Figure 1. These access points do not support the variation of the transmission power per se. But as their firmware is based on Linux and is Open Source, several alternatives to the manufacturer's firmware exist. In addition, some of these do support the variation of the transmission power. We

decided to use the firmware DD-WRT v23 RC1 developed by the DD-WRT project¹. It offers the possibility to vary the transmission power in 1 mW steps from 1 mW to 251 mW and can be controlled using a web interface or via ssh and telnet.

To collect the offline as well as the live samples, we used an IBM Thinkpad R51 laptop computer running Suse Linux 10.1. Due to driver limitations, we could not collect our data with the internal Intel 2200bg network card. It was therefore switched off and a plug-in Lucent Silver PCMCIA card was utilized instead.

On the software side, the samples were collected with the LocEva framework (King and Kopf, 2007) which is available in Java. The application to collect the samples uses the Java Native Interface and a small wrapper written in C to interact with the operating system kernel's wireless extensions interface by system calls. This makes it possible to request the communication parameters and connection information from the wireless LAN card's driver.

Regarding the variation of the access points' transmission power levels, the application used to collect the samples was extended by the ability to switch all access points simultaneously to one transmission power level. This is done by sending commands to the web interface of the devices using HTTP requests and monitoring the status replies to verify the successful execution. As the wireless link was occupied for sensing, we used a wired ethernet link to communicate with the infrastructure.

4.3 Data Collection

To get a sufficient amount of data for the evaluation and to achieve stable statistical results, 186 reference points were laid out in the evaluation environment using a grid of one meter side length (see the grey dots in Figure 1). The samples collected at these positions are the foundation for the fingerprint databases in our evaluation.

Additionally, 63 live points were randomly spread over the hallways (see the black dots in Figure 1). The samples collected at these positions are used to emulate a user requesting a position estimate.

The selected transmission power levels for the evaluation are 3 mW, 13 mW, 23 mW, 33 mW, 43 mW, 53 mW and 63 mW. The lower boundary 3mW was chosen due to some fluctuations in the signal strength we observed below that transmission power level. As we can see in Figure 2, the signal strength decreases from 0 mW to 3 mW and only afterwards begins to

¹DD-WRT Project Website: <http://www.dd-wrt.com>

increase almost monotonically. The upper boundary for our measurements was selected to stay below governmental regulations regarding the maximal allowed EIRP (Effective Isotropic Radiated Power) for devices using the 2.4 GHz band in Germany. Finally, the stepsize of 10 mW was chosen to get noticeable differences between adjacent power levels.

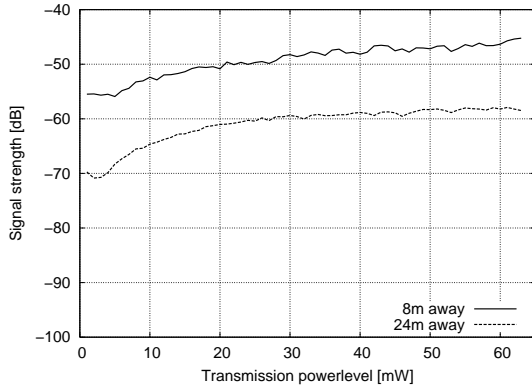


Figure 2: Irregularities regarding the signal strength.

During the data collection phase, 110 samples per power level were collected for each reference position and live position. Hereby, the application switched all access points to the next power level automatically after having collected 110 samples. This was repeated until all power levels had been processed.

The collected samples contain a timestamp, the MAC address of the collecting wireless LAN card, the current position, the current transmission power level, and for each received access points the MAC address, the channel and the RSSI (received signal strength indicator) value. All samples were stored in a logfile for easy reference during the following evaluation.

5 EVALUATION

In this section, the results of the evaluation of our novel algorithms are presented.

The key questions for this evaluation was whether a combination of several different power levels or at least the multiple use of one non-standard power level would outperform the others. For this reason, we evaluated different combinations of transmission power levels, namely 127 different permutations of the selected seven power levels as well as 49 doublets. A doublet in this context means that one power level was used not only once but up to seven times by supplying the algorithm with multiple samples and fingerprint databases for a given transmission power level.

For each permutation and doublet, a total of 500 runs were performed for each algorithm. For each run

the algorithms were given 20 randomly selected samples per power level and reference position to build the fingerprint database. Afterwards, one sample per power level and live position was supplied to compute a position estimate. The difference between the estimate and the real position, called positioning error, was calculated and stored for later reference and analysis. In addition, the average positioning error as well as an error distribution was computed and stored.

5.1 Number of Power Levels

This section summarizes the results on the influence of the total number of used power levels on the accuracy of the position estimate. As we can see in Figure 3, the number of transmission power levels has a considerable influence on the average error.

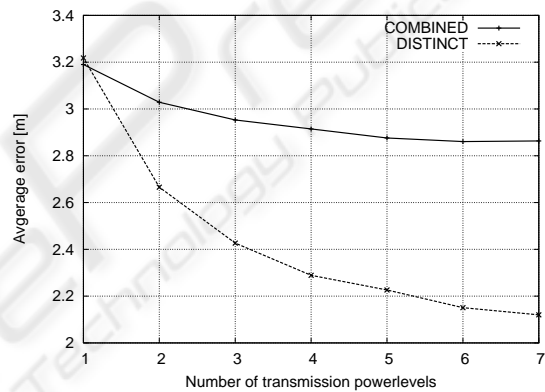


Figure 3: Influence of the number of transmission power levels.

The more power levels are used, the better the results are due to the higher amount of data available for positioning. This can be compared to feeding more than just one online sample to the original variants of the algorithms.

Also visible is the advantage the DISTINCT algorithm takes by computing a single position estimate for each power level and merging these afterwards to one final result. Instead of using all the data to compute just one position at the end, this approach produces better results and a later saturation of the gain.

At first, when several position estimates are computed by using several live samples, it is likely that the estimated positions are located somewhere around the real position. The error vectors of the single position estimates therefore are likely to point into different directions. If these vectors are merged, the intermediate errors interfere with each other resulting in a reduction of the overall error (Bahl and Padmanabhan, 2000).

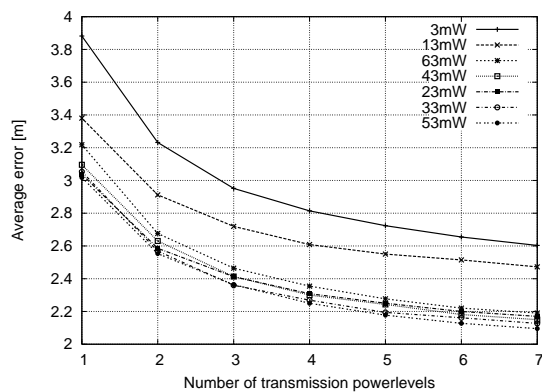


Figure 4: Influence of the transmission power level. when increasing the number of power levels.

Secondly, averaging several position estimates makes it possible to also reach positions in between the grid points that would not be accessible by simply matching to grid positions. This has a smoothing effect on the overall error distribution because of the finer granularity of the possible positions (see Figure 6).

5.2 Selection of Power Levels

The selection of power levels clearly influences the results as well. As we recognise in Figure 4, some of the power levels perform far better than others, no matter if a transmission power level is used only once or up to seven times.

While it might not be surprising that the very low settings perform worse due to their very unstable signals, a mere raising of the transmission power is clearly also not the best strategy. According to our evaluation, the best results can be achieved by using a transmission power level of 53 mW. A further increase of the transmission power reduces the accuracy again (see Figure 5). The reason for this behavior are the low fluctuations the signals have in that power level and the good differentiation between different reference positions in signal space. These fluctuations are also the reason for the unexpected good result of the powerlevel 23 mW. In this power level the standard deviation of the signal strengths was lower than those of the adjacent power levels such resulting in a better position accuracy.

Of course, this can not be generalized based on our test environment as e.g. hardware properties as well as the structural environment could influence the results. To verify the general validity, tests using different hardware as well as a different testbed are necessary.

From our collected results, it is clear, that the use of different power levels performs worse compared to

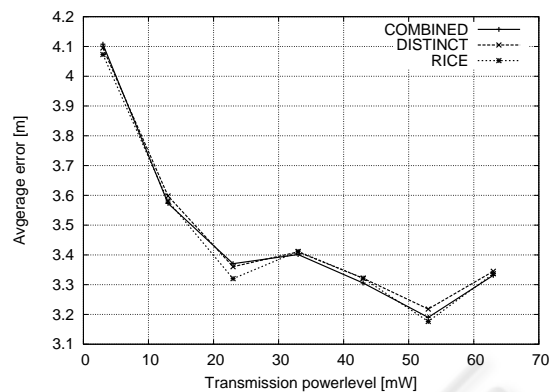


Figure 5: Influence of the transmission power level.

using the best power level several times. The 53mW doublet of a certain size n outperforms all the permutations of the same size regardless of their composition in nearly all setups. The reason here is that using only the best intermediate results leads to a better estimate than taking worse estimates into consideration, which is done when using different power levels. Additionally, no exploitable synergies between different power levels are visible that could absorb this disadvantage.

5.3 Advantages of Different Power Levels

When comparing the original algorithm to our novel algorithms, only minor differences in the accuracy of the position estimates are detectable. Using the same power level, the results of the original algorithm given 20 samples per reference position to build the fingerprint database and s samples during the online phase are - leaving statistical fluctuations aside - the same as those of the COMBINED variant using the power level s times (see Figure 6). This suggests that the use of several different fingerprint databases for the same power level does not make much sense if the number of samples used for each fingerprint is high enough to create stable values. In this case, the fingerprints in the different databases for the same power level are very similar, making more than one database obsolete.

5.4 Advantages of Multiple Power Levels

Another interesting observation is the high benefit of computing several independent position estimates and averaging these afterwards in comparison to summarizing the computational results for all online samples and then making one position estimate. The first method achieves far better and more stable results. As

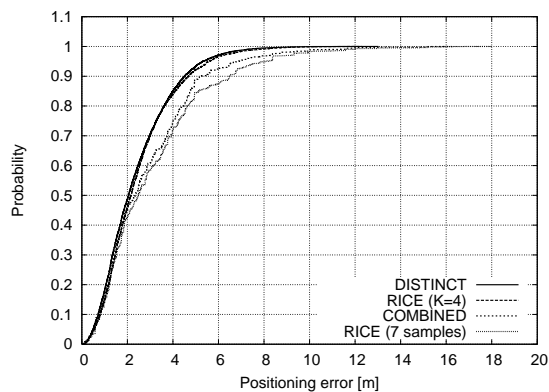


Figure 6: Similar results regarding the COMBINED Variant and the original algorithm given 7 samples, and the DISTINCT variant and the original algorithm merging the 4 best matches respectively.

already mentioned earlier, when merging the position estimates for each power level, the probability of the error vector pointing to different directions is quite high.

A good strategy to define the parameters for a wireless LAN based positioning system based on fingerprinting would thus be the following: At first, a well suited transmission power level should be selected. In our case, this would be 53 mW as this transmission power level produced the best results (see Figure 5).

Secondly, as the gains in position accuracy by increasing the amount of samples tend to fade out at higher amounts, it seems to make sense to supply up to three live samples per position estimate to the algorithm (see Figure 3).

Keeping in mind that the merging of several position estimates highly increases the accuracy, at least two to four position estimates should be computed and merged afterwards. In opposition to the original approach, a further increase of the number of computed neighbors would not decrease the overall position accuracy as the single estimates are calculated in independent runs.

Finally, the fingerprints stored in the database should be computed using enough offline samples to allow the values to stabilize.

6 CONCLUSIONS

In this paper, we presented novel algorithms using multiple transmission power levels for fingerprinting-based positioning with wireless LAN.

We experimentally verified that the usage of multiple different transmission power levels for our wireless LAN positioning algorithms has minor advantages. In addition, the use of multiple fingerprint

databases has almost no positive influence on the achieved results when using one transmission power level.

We further demonstrated that the selection of a special non-standard transmission power level has a remarkable influence on the positioning accuracy and that the merging of several independently computed sub-estimates helps to increase the quality of the results significantly. We presented a strategy for a good selection of the number of supplied live samples as well as the number of sub-estimates that leads to an overall gain in accuracy and stability.

REFERENCES

- Bahl, P. and Padmanabhan, V. N. (2000). RADAR: An In-Building RF-Based User Location and Tracking System. In *Proc. of the 19th IEEE InfoCom*.
- Chen, G. and Kotz, D. (2000). A Survey of Context-Aware Mobile Computing Research. Technical Report TR2000-381, Dartmouth College.
- Haerberlen, A., Flannery, E., Ladd, A. M., Rudys, A., Wallach, D. S., and Kavraki, L. E. (2004). Practical Robust Localization over Large-Scale 802.11 Wireless Networks. In *Proc. of the 10th ACM MobiCom*.
- Kaplan, E. and Hegarty, C., editors (2005). *Understanding GPS: Principles and Applications*. Artech House Incorporated, second edition.
- King, T., Haenselmann, T., Kopf, S., and Effelsberg, W. (2007). Overhearing the Wireless Interface for 802.11-based Positioning Systems. In *Proc. of the 5th IEEE PerCom*.
- King, T. and Kopf, S. (2007). Loelib - A Location Library. Website: <http://www.informatik.uni-mannheim.de/pi4/lib/projects/loelib/>.
- King, T., Kopf, S., Haenselmann, T., Lubberger, C., and Effelsberg, W. (2006). COMPASS: A Probabilistic Indoor Positioning System Based on 802.11 and Digital Compasses. In *Proc. of the 1st ACM WiNTECH*.
- Ni, L. M., Liu, Y., Lau, Y. C., and Patil, A. P. (2004). LANDMARC: indoor location sensing using active RFID. *Wireless Networks*, 10:701–710.
- Priyantha, N. B., Chakraborty, A., and Balakrishnan, H. (2000). The Cricket Location-Support System. In *Proc. of the 6th ACM MobiCom*.
- Rappaport, T. S. (2001). *Wireless Communications: Principles and Practice*. Prentice Hall PTR, second edition.
- Want, R., Hopper, A., Falcao, V., and Gibbons, J. (1992). The Active Badge Location System. *ACM Transactions on Information Systems*, 10(1):91–102.