Communication Technologies and their Applications beyond Communication

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Abstract

Wireless communication technologies are pervasive in today's everyday environment. Together with the ever-dropping cost for equipment relying on such technology, this abundance gives rise to a wealth of applications well beyond communication itself. Utilizing communication technologies in the context of mobile sensing seems to be an especially promising approach, as mobile phones and other personal handheld devices provide the capabilities to record, process and store sensor data.
In this paper, we focus on one main aspect of mobile sensing, namely the localization of mobile devices by means of different communication technologies. After a quick review of specialized localizing equipment like ultrasound or infrared-based systems, we are going to demonstrate how different communication technologies like GSM, WiFi, Bluetooth or ZigBee and their combinations may be applied in the context of position-finding.

1 Introduction

The penetration of mobile devices capable of wireless communication (i.e., devices using Bluetooth, GSM, UMTS, WiFi or similar technologies) has rapidly increased during the last few years and is still gaining momentum. According to Hermersdorf et al. (2006), 10 million Bluetooth radios were shipped every week already in 2006, resulting in an estimated 550 million devices shipped that year. The recently reached milestone of more than 4 billion GSM connections puts the global market on the path to reach 6 billion connections by 2013, thereby approaching a statistical penetration of 100% [11].
As virtually everybody owns a mobile phone or other personal handheld device, such devices have gained an important role as personal identifiers. Applications for handsets that act as personal IDs include proximity car locks, telemonitoring and telemedicine systems as well as personal tracking and localization.

1.1 Sensing in Rich Bluetooth Environments

In the above-mentioned survey [5], M.Hermersdorf et al. explored the potential of environments rich in Bluetooth-capable devices. They equipped mobile phones with an application that scanned for other Bluetooth devices in the vicinity approximately every thirty seconds and distributed those handsets to fourteen test subjects who were instructed to keep the phones with their own ones for the duration of the study. After having collected all the data, they succeeded in deriving complex behavioral patterns ("Reality Mining") and were even able to construct a probabilistic indoor locationing system that does not rely on fixed base stations but rather estimates the current location based on other Bluetooth devices close-by. Perhaps, one of their most noticeable results is the high number (1299) of *individual* Bluetooth addresses detected within four days and the high average number of Bluetooth devices detected on a single scan by a single phone (11.6). These numbers show that in certain environments the number of Bluetooth devices is already very high, although the authors admit that their test site "might not correspond to a typical office environment", but that the trend of increasing coverage of urban areas by short-range radios was obvious nonetheless.

Extraction of behavioral patterns

The authors were, as mentioned above, able to extract behavioral patterns – daily and weekly routines – from the acquired data. In the analysis of daily behavior, activity starts rising at around 8am, reaches its peak at around 14pm and decreases from 16pm onwards, while in the weekly data sets, five very comprehensible peaks (representing the working days) followed by a phase of low activity during the weekend occur (as shown in Figure 1). This result shows the potential of using mobile devices as personal identifiers.

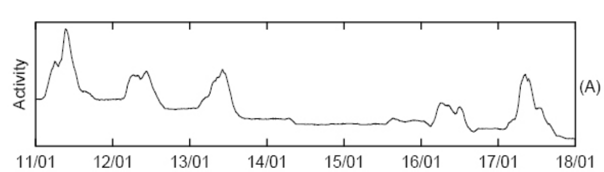

Figure 1: Weekly average Bluetooth activity pattern, each tic is set at 6am [5].

1.2 Location & Location Awareness

One of the most significant pieces of information we would like mobile personal handsets to be able to deliver is their location (and thereby the location of their holder). Information on the whereabouts of a person or device is very meaningful and significant – it may even be the case that a ubiquitously available localization system is the key missing technology that hinders a broad emergence of ubiquitous computing [3]. Furthermore, information on the physical location of mobile nodes can be of great help in urban search and rescue missions, as well as enable geographical routing in ad hoc multi-hop networks [15]. With the rapid deployment of GPS receivers in many current mobile devices, the problem of outdoor localization may already be successfully solved, but indoor locationing systems are an entirely different domain.
Most technologies that are currently in use for indoor localization – ultrasound (US) or infrared, to name just two – are heavily relying on specialized equipment. In order to set up an ultrasound-based localization system like Bat from the AT&T Laboratories Cambridge [1] (2001), one needs to mount US receivers on the ceiling in a regular pattern (see Figure 2), which adds considerably to the installation costs of such a system. Even so, ultrasonic ranging is currently one of the standard methods for indoor localization.

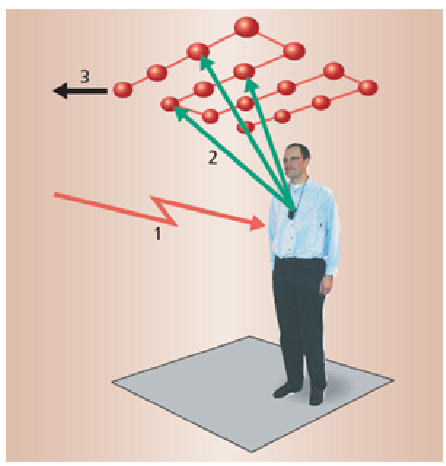

Figure 2: The Bat indoor localization system [1].

In order to tackle the problem of indoor position-finding, one starts to try and utilize existing infrastructures and technologies to achieve the same goal – There are attempts to implement indoor locationing using powerlines (PowerLine Positioning PLP, [12]) or, since room-level localization is enough for most applications, to exploit the movement of people between different rooms in a building by measuring differential air pressure in heating, ventilating and air-conditioning (HVAC) system ductworks [9].
It is important to bear in mind that the probability of widespread adoption of an indoor localization system depends to a very large extent on its setup costs and its ease of use concerning setup and day-to-day utilization. A system that is based on hardware already available to the user and familiar to him from his home environment gains a huge advantage when it comes to actual deployment. Zàruba et al. (2007) state that to facilitate location awareness for a vast number of devices and with minimal cost, it is important that localization can be performed using minimal infrastructure and with the signals generally available in today's networks [15].

2 Localization Technologies

In this chapter we are going to start with a quick survey of some methods used for localization, discuss their strengths and weaknesses and have a look at systems that apply these techniques. Subsequently, we will examine communication technologies that are either already ”in place” (i.e., are already present in people’s homes like GSM, WiFi or Bluetooth) or are promising technologies to be deployed in commercial settings (e.g. ZigBee). Specifically, we are going to investigate possible ways to apply these communication technologies in the context of localization. In the last section of this chapter, we will look at a specific project in greater detail: the Redpin system for indoor localization.

2.1 Localization Methods

2.1.1 Proximity Detection

Locationing by proximity detection is a very simple method to locate mobile devices in environments with high numbers of stationary receivers. The position of a device is estimated by observing which of these receivers are able to detect it and which are not at a given moment in time. The main fields of application for this approach are localization using Radio Frequency Identification (RFID) tags and localization based on infrared beacons, for instance the ”Active Badge” system developed by Want et al. (1992) at Olivetti Research [13].

2.1.2 Angle of Arrival (AoA)

In AoA-based systems, the location of a mobile device is calculated from the incident angles of signals submitted from different fixed base stations (”triangulation”). In order to pinpoint a device in two dimensions, a minimum of two base stations is required (3D: three base stations). AoA is widely used in aviation and in the GSM sector [7]. It can lead to very high localization errors in indoor environments due to multipath effects caused by reflection, refraction, scattering or diffraction, though.

2.1.3 Time of Arrival (ToA)

When applying the ToA mechanism (sometimes called Time of Flight, ToF), one calculates the location of a certain emitter from distances to various stationary receivers (”trilateration”). These distances are directly computed from the round-trip time (or, in some systems, the one-way time) of a signal between the mobile device and the receptor and its (known) speed (e.g. 343 m/s for sound waves – the lower the signal speed, the higher the localization accuracy). The ToA-approach is widely used in localization systems, most prominently in the Global Positioning System (GPS).

2.1.4 Received Signal Strength Indication (RSSI)

There are two different ways in which the measurement of received signal strength can be exploited for localization, namely ranging using RSSI and fingerprinting. Both suffer from general problems with signal strength measurements, for example their temporal instability – according to [3], the received signal strength of WiFi may fluctuate more than 50% within one hour. Moreover, Kuster and Balzano (1992) state in [6], that the RSSI of WiFi access points depends heavily on whether humans are in the line of sight or not, as the human body absorbs electromagnetic radiation quite well. Bolliger (2008) concludes that in rooms where the number of people is high and changes frequently, it seems unlikely that a localization accuracy of under two meters can be achieved using the signal strength values of WiFi access points [3].

When using **RSSI for ranging**, one should – as signal strength is correlated with distance – at least in theory be able to calculate the distance of a mobile device to a base station from the RSSI of the signal received from that base station. In practice, this endeavor proves to be very difficult due to effects like multipath (as mentioned in section 2.1.2, Angle of Arrival) or shadowing, both of which are very diverse in different environments [7]. Due to the non-injectivity of RSSI as a function of distance (i.e., the ambiguity of calculated distances), accurate localization based on this measure is very hard to achieve.

Localization using **RSSI fingerprinting** is based on a database of $<$*location, RSSI*$>$-tuples known a priori that allow to extract the most probable position of a mobile device given its current RSSI-measurements for one or multiple base-stations. The database is built using a training phase which may be conducted *explicitly* prior to public deployment (see for instance [15]) or *implicitly* when the system is already operational ([3]). Fingerprinting allows for better estimates because it takes into account the effects that buildings, solid objects or people may have on the signal [12].

2.2 Wireless Communication Technologies and Localization

Wireless communication technologies are ubiquitous these days: Some, like GSM, UMTS, WiFi or Bluetooth have already achieved widespread deployment and are very well-known in many regions of the world while others, e.g. UWB or ZigBee, are currently in the process of commercialization. In this section, we are going to discuss some of these technologies and give examples of localization systems based on them.

2.2.1 The Global System for Mobile Communication (GSM)

Originally created by the Groupe Spéciale Mobile in 1982 (agreement to design a pan-European mobile technology), the GSM system today is the prevailing standard for mobile phones in the world. GSM coverage is all but pervasive with the wide acceptance of cellular phones making them ideal conduits for the delivery of ubiquitous computing applications [8]. In addition, cellular phone networks are fairly stable – their infrastructure is rarely changed which means that GSM fingerprints should be pretty stable, too.
When trying to localize a mobile phone, various features of GSM can be used and combined [7]:

1. *Cell Identification/Cell of Origin (CoO)*: As the total coverage area of the GSM system is subdivided into cells each served by a base station, identification of the currently active cell of a mobile phone provides an easy way to estimate the position of the mobile device. Localization accuracy is dependent on the size of the current cell and ranges between a few hundred meters in urban environments and a few dozen kilometers in rural areas.

2. *Enhanced Cell Identification*: This method additionally considers the time between the start of a radio frame and the actual transmission of the mobile phone ("timing advance") to improve the localization

accuracy (especially in rural areas). The timing advance specifies at which precise moment a mobile phone is allowed to transmit in order to compensate for the different distances of mobile handsets from the base station. As its step size is approximately $3.7\mu s$, the timing advance value changes for each step of approximately 550m (round-trip time of the signal is $c \cdot \frac{3.7}{10^6} \approx 1100m$) [7].

3. If the currently active cell has directional antennae, it is additionally possible to determine the cell sector the mobile device is currently located in.

Accurate GSM Indoor Localization [8] The key idea Otsason et al. (2005) employed in order to build an indoor localization system based on GSM fingerprints that would achieve an accuracy comparable to a WiFi-based implementation, was to use "wide signal-strength" fingerprints that include the readings from up to 35 GSM channels (each GSM base stations gets assigned one or multiple channels at the discretion of the operator) – many of these channels are too weak for efficient communication, but can still be detected. In order to be able to compare different approaches, Otsason et al. (2005) implemented localization algorithms based on different types of fingerprints: (1) *"onecell"* uses the reading of the single strongest GSM cell in range, (2) *"cell"* uses readings of the six strongest GSM cells and (3) *"chann"* uses readings of up to 29 GSM channels additionally to the six strongest cells. In addition, a WiFi-based fingerprinting algorithm (*"802.11"*) was used to be able to directly compare GSM- and WiFi-fingerprinting approaches.
The authors have shown that it is in general feasible to achieve an accuracy comparable to a WiFi-based system using *wide* GSM fingerprints, especially when single-floor fingerprinting is used: Here, the *chann*-approach and an enhanced version of *chann* using geographical clustering match the accuracy of *802.11*. Furthermore, their results show that in a building having reinforced concrete floors, one is able to perfectly distinguish between different floors when using WiFi fingerprinting while *802.11* performs considerably worse in residential housing where it is massively outperformed by *chann*-fingerprinting on the same task.

2.2.2 Wireless Fidelity (WiFi)

The WiFi-Alliance (founded as Wireless Ethernet Compatibility Alliance WECA in 1999) is a global organization with the goal of driving the adoption of a single worldwide standard for high-speed wireless local area networking [14]. They do this by testing wireless equipment for interoperability and certifying wireless devices that implement the IEEE 802.11 specifications.
Every IEEE 802.11 access point (AP), together with all nodes accessing this AP, is called a Basic Service Set (BSS). Every BSS is uniquely identified by its Basic Service Set Identifier (BSSID) – a main feature when attempting to perform localization based on WiFi.
One main problem of WiFi-based localization are the temporal dynamics/fluctuations in signal strength described in section 2.1.4 on RSSI; other issues are related to the limited WiFi-coverage (especially in rural areas) and the instability of an IEEE 802.11 infrastructure which changes much more frequently than that of a GSM network. A major advantage of WiFi-based localization when compared to GSM is the higher accuracy (when given the same number of radio sources) of this technique due to its limited range.

In section 2.2.1, we have already looked at one indoor localization system based on WiFi fingerprinting and some of its properties. One very interesting project by Chen et al. (2005) is a sensor-assisted WiFi indoor localization system that is able to adapt to environmental dynamics, which we identified as one of the main problems causing fluctuations in signal strength in IEEE 802.11-based systems. Specifically, they take into account three dynamic environmental factors (people, doors, and humidity) that can interfere with radio signals and cause localization inaccuracy in WiFi-based locationing systems [4]. Using RFID and environment sensors, this locationing system automatically adapts to its environment which leads to a reduction of the localization error by an average of 2.6 meters in comparison to traditional non-adaptive position finding systems [4].

2.2.3 IEEE 802.15.1 Bluetooth

The Bluetooth-standard is a wireless short range radio standard which is developed and maintained by the Bluetooth Special Interest Group. Because of the widespread installation of Bluetooth radios on mobile devices (especially mobile handsets), a Bluetooth-environment is extremely unstable compared to WiFi or GSM. This deficiency is in part compensated by the abundance of Bluetooth devices in some environments that allows for probabilistic mapping as performed by Hermersdorf et al. (2006) in [5]. When compared to WiFi, Bluetooth provides a lower bandwidth; its operational range depends heavily on the power consumption of a device, ranging from 1m for Class 3 devices to approximately 100m for Class 1 devices. One main advantage of Bluetooth is its lower implementation cost when compared to WiFi-technology.

Indoor Locationing in Rich Bluetooth Environments [5] As we have seen in section 1.1, Hermersdorf et al. (2006) explored the potential of environments rich in Bluetooth devices. They hypothesized, that given enough Bluetooth devices, one might be able to use characteristic sets of devices at different locations as a surrogate for stationary base stations [5]. They used known Bluetooth beacons for training their localization model, while the actual testing was conducted without any knowledge of these beacons. The results obtained support their hypothesis (in 13 out of 15 places, the most frequent estimate was the correct one) and show that different locations can indeed be characterized by their Bluetooth surroundings, as many people share similar routines. These results also indicate that the applicability of this system depends heavily on the amount of Bluetooth-enabled devices in the surveyed environment – places where lots of data were collected (e.g., in the cafeteria) produced the best results. Hermersdorf et al. (2006) plan to fuse this Bluetooth information with data from a stationary camera in order to try and associate different people with their respective Bluetooth ”Identities”.

2.2.4 ZigBee

ZigBee is a low-power, low-bandwidth standard for wireless personal area networks (WPANs) based on the IEEE 802.15.4 standard that is targeted at applications requiring simple wireless connectivity, short distance and low cost, like home automation, industrial monitoring and remote controlling [10]. Its main advantages compared to the Bluetooth standard are the very long battery lifetime and the ability to connect to other devices in a very quick and flexible way: A ZigBee *Network Coordinator* node needs approximately 30ms to enumerate its *Slaves* and set up a topology, while a Bluetooth *Master* node requires at least two seconds (and sometimes around 30s) to perform the same task. The importance of this capability to couple/decouple with other devices in a fast way cannot be stressed enough, as it, among others, leads to battery lifetimes of 100-1000 days, compared to 1-7 days for GSM/Bluetooth and 0.5-5 days for WiFi-enabled devices [10].
Since the public deployment of ZigBee is only in its beginnings, there are few localization systems based on ZigBee wireless communication. Grossmann et al. (2007) have built a system that uses the link quality

indicator (LQI) already provided by the ZigBee specification itself to estimate distances from position-aware beaconing nodes. They conclude that although the system did not perform as accurately as desired, the most important advantage of ZigBee-based systems is the simplified implementation process due to already defined fundamental functions within the provided protocol suite of ZigBee [2].

2.3 Redpin - Adaptive, Zero-Configuration Indoor Localization through User Collaboration [3]

The above discussion – especially section 2.2.1 makes it clear that more accurate measurements can be achieved if as many different sources as possible are read. Bolliger (2008) took it one step further by taking into account measurements of GSM, Bluetooth and WiFi when designing his hybrid zero-configuration fingerprint-based indoor localization system *Redpin* for mobile phones. More precisely, he uses:

1. The signal strengths of all WiFi access points in range

2. The Bluetooth identifiers (Bluetooth Device Address, BD_ADDR) of all non-portable Bluetooth devices (which can be distinguished from their mobile counterparts using the major and minor device class specifier)

3. The cell ID of the currently active GSM cell (the current version of Symbian's Telephony application programming interface only provides information about the currently active cell).

Through the simultaneous use of multiple wireless technologies, the author tries to increase robustness, accuracy and flexibility of the localization system. Additional design goals were to enable easy setup and maintenance through a zero-configuration approach, to use hardware that everyone already has and to be able to adapt to changes in the environment.

2.3.1 Adaptability and Zero-Configuration properties

The Redpin system requires no configuration or training phase before being actively used to locate mobile handsets, but rather lets its users create and manage the locations in a collaborative way. Bolliger (2008) believes that this approach is feasible as people like to participate and contribute in folksonomy-based systems (like Wikipedia, to name the most prominent example for such a system) "because of ideological reasons and even more so, because it is fun" [3]. This approach also adds to the adaptability and flexibility of the system, as users can always correct the location if Redpin provided a wrong identifier.

2.3.2 Localization using Redpin

Once a user starts the Redpin application on his or her handset, the system performs the following steps:
First, the device measures the signal strengths of the currently active GSM cell and all WiFi access points and acquires the BD_ADDR of all non-portable Bluetooth devices in range (*Sniffing*). Next, the measurement data is sent to a central server that tries to locate the device based on all known fingerprints: If the localization is successful, the server will return a plan of the current floor and display the device's current location on this plan. If the system cannot locate the device, it will inquire the user to specify his current

location and indicate its position on one of the known floor plans. If the system returned a wrong location, the user may correct this information.
The localization algorithm (running on the server) computes the distance between two different fingerprints using a very simple distance measure, namely a straightforward account model [3]: Every matching unique identifier adds to the account, while each difference causes a diminution. For every matching pair of identifiers, an additional contribution or diminution is calculated based on the measured signal strengths. If a fingerprint can be found whose distance to the currently measured fingerprint is below a certain threshold, the location associated with this fingerprint will be returned. If multiple fingerprints are found, the system returns the best match. It is possible to adjust the localization algorithm to suit the actual environment by adapting the respective weights of the Bluetooth-, WiFi- and GSM-fingerprints.

2.3.3 Results

Bolliger (2008) evaluated the system by conducting several experiments in his office building: The fingerprints of 26 rooms chosen at random were added to the database (see Figure 3) in order to investigate the success rate of the system. The tests were repeated several times, during working hours as well as in the night. The results show that the localization was, on average, correct in 90% of the cases. According to the author, the remaining 10% can be explained by the strict threshold values used and the simplicity of the distance measure and the locator algorithm [3].

Figure 3: Measurements to evaluate the performance of the Redpin system [3].

Another survey showed that the floor plan had been completed after one day (with 10 people actively contributing). The time it takes to get at least one fingerprint for every room is of course room-dependent – rooms that are used more frequently are added much faster. However, it should be noted, that the testing was performed in a laboratory-like environment (i.e. an office building of the departement of computer science) with an expected density of Bluetooth- and WiFi-capable devices much higher than in ”everyday” environments and with people sharing a professional interest in this subject of whom a higher willingness can be expected to actively contribute to such a system.
Bolliger (2008) plans to enhance the system by exploring more sophisticated locator algorithms and states that they might even be able to use an automatic learning approach to infer and tag locations of importance based on the gathered data.

3 Summary and Outlook

The main advantage of using communication technologies to achieve tasks beyond communication is that they are "already there", i.e. that one is able to avoid the installation of additional hardware.
In this paper we have discussed novel approaches to mobile sensing that arise from the widespread use of wireless communication technologies, especially concerning techniques for indoor localization. After arguing that mobile handsets have begun to act as personal identifiers, we have outlined current and oncoming methods for mobile communication, reviewed their properties with respect to localization and given examples for locationing systems based on them. In the last section we have covered the Redpin system that provides indoor localization using a combination of fingerprints of different wireless communication technologies in greater detail.
The merger of multiple communication technologies to enable accurate indoor locationing ([3]) has proven a success and we are most likely going to see more systems based on this approach, those incorporating newer technologies like ZigBee. As there is a trend towards including communication technologies in everyday objects ("The Internet of Things", [7]) localization systems based on these will furthermore have to strive for more energy efficiency.

One important aspect of mobile sensing that we have chosen to neglect in this discussion is the issue of privacy — sensing with the help of mobile, personal handsets allows extensive activity monitoring and greatly simplifies intrusions into the privacy of holders of such devices. As an example, consider the architecture of the Redpin system: To facilitate the quick sharing of knowledge about locations and to enable quick mapping of a building, every mobile device transmits its measured fingerprints to a central server, thereby revealing its current location (in 90% of the cases, at least). The issue of location privacy will be covered in this course's talk on the implications of ubiquitous sensing on 7th of April 2009.

References

[1] M. Addlesee, R. Curwen, S. Hodges, J. Newman, P. Steggles, A. Ward, and A. Hopper. Implementing a Sentient Computing System. *Computer*, 34(8):50–56, 2001.

[2] J. Blumenthal, R. Grossmann, F. Golatowski, and D. Timmermann. Weighted Centroid Localization in Zigbee-based Sensor Networks. *IEEE International Symposium on Intelligent Signal Processing, WISP 2007*, 2007.

[3] P. Bolliger. Redpin - Adaptive, Zero-Configuration Indoor Localization through User Collaboration. In *MELT '08: Proceedings of the first ACM international workshop on Mobile entity localization and tracking in GPS-less environments*, pages 55–60, New York, NY, USA, 2008. ACM.

[4] Y.-C. Chen, J.-R. Chiang, H.-h. Chu, P. Huang, and A. W. Tsui. Sensor-Assisted Wi-Fi Indoor Location System for Adapting to Environmental Dynamics. In *MSWiM '05: Proceedings of the 8th ACM international symposium on Modeling, analysis and simulation of wireless and mobile systems*, pages 118–125, New York, NY, USA, 2005. ACM.

[5] M. Hermersdorf, J. Perkiö, H. Nyholm, V. Tuulos, J. Salminen, and H. Tirri. Sensing in Rich Bluetooth Environments. In *Proceedings of WSW'06 at SenSys'06*. SenSys'06, 2006.

[6] N. Kuster and Q. Balzano. Energy Absorption Mechanism by Biological Bodies in the Near Field of Dipole Antennas above 300 MHz. *IEEE Transactions on Vehicular Technology*, 41(1):17–23, 1992.

[7] F. Mattern. Lecture Notes, Ubiquitous Computing, ETH Zurich. 2008.

[8] V. Otsason, A. Varshavsky, A. LaMarca, and E. de Lara. Accurate GSM Indoor Localization. In *proc. of UbiComp 2005*, pages 141–158, 2005.

[9] S. N. Patel, M. S. Reynolds, and G. D. Abowd. Detecting Human Movement by Differential Air Pressure Sensing in HVAC System Ductwork: An Exploration in Infrastructure Mediated Sensing. In *Pervasive 2008*. ACM, 2008.

[10] O. Riva. Lecture Notes, Advanced Computer Networks, ETH Zurich, 2009.

[11] M. Simmons. Mobile World Celebrates Four Billion Connections. http://www.gsm.org/, 24.2.2008.

[12] E. P. Stuntebeck, S. N. Patel, T. Robertson, M. S. Reynolds, and G. D. Abowd. Wideband PowerLine Positioning for Indoor Localization. *UbiComp '08: Proceedings of the 10th international conference on Ubiquitous computing*, pages 94–103, 2008.

[13] R. Want, A. Hopper, V. Falcão, and J. Gibbons. The Active Badge Location System. *ACM Trans. Inf. Syst.*, 10(1):91–102, January 1992.

[14] WiFi-Alliance. Get to Know the Alliance. http://www.wi-fi.org/about_overview.php, 24.2.2008.

[15] G. V. Zàruba, M. Huber, F. A. Kamangar, and I. Chlamtac. Indoor location tracking using RSSI readings from a single Wi-Fi access point. *Wirel. Netw.*, 13(2):221–235, 2007.