Experimental Comparison of Bluetooth and WiFi Signal Propagation for Indoor Localisation

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Abstract. Systems for indoor positioning using radio technologies are largely studied due to their convenience and the market opportunities they offer. The positioning algorithms typically derive geographic coordinates from observed radio signals and hence good understanding of the indoor radio channel is required. In this paper we investigate several factors that affect signal propagation indoors for both Bluetooth and WiFi. Our goal is to investigate which factors can be disregarded and which should be considered in the development of a positioning algorithm. Our results show that technical factors such as device characteristics have smaller impact on the signal than multipath propagation. Moreover, we show that propagation conditions differ in each direction. We also noticed that WiFi and Bluetooth, despite operating in the same radio band, do not at all times exhibit the same behaviour.

1 Introduction

Positioning of people and resources has always been a necessity for society throughout human history. Indoor environments, however, still pose a challenge to the localisation paradigm and foster vigorous research by both academia and industry. Indoor spaces are typically characterised by restricted dimensions and multiple structure elements such as walls, doors, furniture. As a result, radio signals have stronger multipath components compared to outdoor scenarios. Moving human bodies are an additional complication. The combined effect of these factors challenges the pervasive application of a single positioning solution. While some authors, e.g., [8,18], try to find a solution based on a single wireless technology, others, e.g., [9,19], propose to combine multiple technologies. Still, the optimal choice of technology and localisation technique depends on the application requirements towards accuracy, cost and ease of deployment.

In the scope of the Location Based Analyser (LBA) project[1] we are interested in a positioning solution that is easy to deploy, is low-cost and scales well with the size of the indoor area. The application targets the support of Location Based Services (LBS) and statistical profiling for enterprises such as exposition centres, shopping malls or hospitals. We are interested in providing precision up

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to few meters in order to support variety of applications with different accuracy requirements. Furthermore, the positioning mechanism should be non-intrusive because we want to avoid placing dedicated software in the tracked devices and hence we cannot rely on their cooperation. Given these requirements, we decided to base the positioning mechanism on a radio technology such as Bluetooth or IEEE 802.11 (with the trade name WiFi). These technologies benefit from large support by personal devices and the radio signals being freely available.

As many other studies using similar approaches we stumbled upon the challenges of indoor signal propagation and its implications for a localisation system. Despite the large number of studies addressing radio-based indoor positioning, only few actually investigate the various factors that impact the localisation system. There are plenty of studies [2], proposing a novel propagation model but results are often not convincing or the model performs well only in a particular setting. Other studies take a more practical approach where propagation conditions are monitored in order to adapt the localisation scheme. For example, in some fingerprinting solutions one out of several radio maps is selected depending on periodically updated readings on humidity or temperature. Often, however, only a couple, if not a single factor is observed. To our knowledge, a detailed study, covering several factors and reflecting their impact on both Bluetooth and WiFi signals has not been conducted so far.

With this paper we aim to extend the state-of-the-art by investigating the impact of (1) device's technical characteristics, (2) manufacturing discrepancies and (3) device orientation. Without being exhaustive, we try to gain insights on the complex effects of each factor and the implications for indoor positioning. Our purpose is to identify which factors should be considered and which can be disregarded in the design of a positioning algorithm. The paper is, however, not concerned with the development or testing of such an algorithm.

The rest of the paper is structured as follows. In Section 2 we briefly summarise advances in indoor localisation and in radio-based solutions in particular. The following Section 3 introduces our monitoring system and the testing environment. Evaluation results are presented in Section 4. Finally, in Section 5 we draw conclusions and identify open discussion topics.

2 Indoor Localisation

Multiple technologies have been proposed to tackle the problem of indoor localisation some examples being infrared [22], ultrasound [16] and Radio Frequency IDentification [5]. Still, most research is dedicated to the usability of two technologies. Large number of papers, e.g., [10] and [23], argue that Ultra Wide Band (UWB) radio offers excellent means to determine one's location with high precision. Unfortunately, UWB-based solutions have longer deployment time and are expensive. Equally many studies campaign for the use of IEEE 802.11, e.g., [7,12], or Bluetooth, e.g., [14,19] since their ubiquitous support by personal devices is convenient for the quick, cost-efficient development of practical solutions.

2.1 Radio-Based Localisation

A radio-frequency technology can provide feedback on multiple parameters related to signal reception, which can be used for localisation. Some localisation mechanisms, see [11,17], use the Received Signal Strength Indicator (RSSI), which is derived from the received signal strength and should be therefore directly related to distance. Unfortunately, RSSI measurements are vulnerable to the strong multipath effects indoors. Other mechanisms, see [7,20], base the location estimate on Time of Arrival (TOA) or Time Difference of Arrival (TDOA) parameters. This approach, although more accurate, comes at a higher cost and requires intervention at the target devices. In [3] the Response Rate (RR) of a Bluetooth inquiry is introduced as the percentage of inquiry responses out of the total inquiries in a given observation window. The authors claim to achieve good positioning accuracy. We remain sceptical on the use of RR alone due to its vulnerability to the Bluetooth channel hopping and WiFi contention.

For our purposes we believe that the RSSI parameter is fitting. RSSI measurements are readily available and still can deliver satisfying accuracy, given that appropriate processing is applied. We should, however, account for the impact of radio propagation conditions on the RSSI values.

2.2 Radio Signal Propagation

Generally, radio signals are shaped by the transmitter, receiver and propagation environment. The transmitter and receiver affect the signal by their technical characteristics while the propagation channel's effects are related to path loss due to the propagation medium and any obstacles on the propagation path. Indoor environments make the reconstruction of signals more difficult due to their smaller dimensions and the significantly bigger number of obstacles on the signal path. These obstacles can be part of the indoor construction, e.g., walls and doors, as well as individual objects such as furniture and people. As a result, shadowing and multipath propagation exhibit strongly and multiple copies of the same signal, travelling over several paths. The signal reconstructed at the receiver is formed by all individual paths and is more difficult to relate to the actual distance between the nodes.

Characterising the indoor radio channel has been an active research area dating back to the early '90s, e.g., [13]. There are many works, such as [1,2,6,21], which study the radio channel in general and investigate the path loss distribution over distance or for different propagation scenarios, including line-of-sight or non-line-of-sight. Studies focusing on radio-based indoor positioning [4], examine the specific effects of the above factors - distance and obstacles - on radio signal parameters used for positioning. Other factors such as technical characteristics or orientation are also important but rarely studied in detail. To fill in the gap we investigate how a radio signal is affected:

- at the transmitter side by the technical specifications of different manufacturers and even models of the same type of device;

– at the receiver side by manufacturing discrepancies occurring during the production process;
– during propagation by the propagation path that a signal takes;
– by type of radio technology - Bluetooth or WiFi.

3 Monitoring Approach

Technology. In order to observe the impact of various factors on the received signal we deployed sensor nodes, which can scan for transmissions on two interfaces - one for Bluetooth and one for IEEE 802.11b/g.

In the context of Bluetooth we rely on the inquiry procedure, introduced in the Bluetooth's Core Specification 4 [15]. For an inquiry to be successful a Bluetooth device should only be discoverable. We prefer to work with the inquiry procedure due to several advantages. First, the RSSI reported by an inquiry procedure is not affected by power control and hence can be directly related to distance. Second, although long lasting - the inquirer needs to check all 32 Bluetooth radio channels - an inquiry procedure can monitor a large number of target devices. Last, we can gather measurements without requesting any privacy-sensitive information from the mobile devices.

In the context of WiFi the sensor nodes overhear WiFi signals from the target devices. Contrary to Bluetooth, there is no inquiry procedure defined in WiFi. A mobile device becomes visible only after it sends out a request to associate to an access point. In the associated state there is a periodic exchange of control messages. By overhearing these messages, or any potential data messages, a scanning sensor node can derive information on RSSI levels.

Test-Bed. All experiments were set up in an indoor office with dimensions 6.90x5.50x2.60m. A schematic is shown in Figure 1. The office is equipped with desks, chairs and desktop machines. The sensor nodes (SNs) and mobile devices (MDs) hang at 0.50m below the ceiling and are at 1.50m above the tables. Such test environment allows us to judge the relevance of the tested factors for a positioning system under realistic propagation conditions.

Metrics. Our first challenge was to select the appropriate metric to compare performance. We considered four groups of metrics to characterise the RSSI, namely, instantaneous values, probability density function, mean and standard deviation, median and percentiles; as well as the response rate of a scan.

4 Evaluation

Below we evaluate the impact of each of the three factors: technical characteristics, manufacturing discrepancies and direction-specific multipath propagation. During the measurements collection in all experiments no humans were present in the test-bed area.

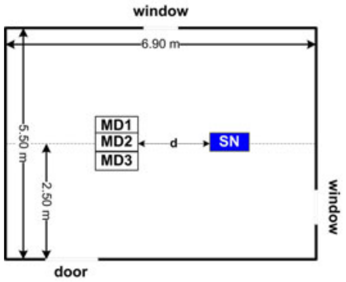


Fig. 1. Experiment A: Set-up

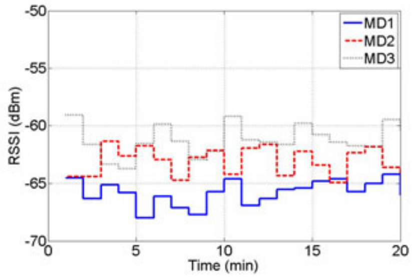


Fig. 2. RSSI time variation of three MDs

4.1 Technical Characteristics

The transmit power of a personal device is a result of propagation conditions and technical specifications but also of manufacturer preferences. Differences between manufacturers, or even between different models of the same manufacturer, could additionally (on top of multipath effects) aggravate the problem of localisation. In order to investigate how such differences affect the RSSI we performed *Experiment A*. The test set-up is shown in Figure 1. Three mobile phones by different manufacturers were placed at one and three meters away from the same sensor node. At each distance, measurements are gathered for 30 minutes, which allowed us to collect about 200 samples for WiFi and 400 for Bluetooth.

The choice of evaluation approach should be made carefully. By placing the mobile phones next to each other we try to minimise the spatial and temporal difference in their propagation paths. Yet, this rises some concerns on interference between the phones, which could be avoided by doing independent measurements. The latter approach, however, catches different temporal states of the propagation channel. Furthermore, we can choose between measuring (i) the transmitted signal at the antenna, which allows to isolate the impact of the propagation environment or (ii) the received signal, which is affected by the multipath propagation but shows how a real system sees different mobile phones. Since we are interested to develop an operational localisation system we looked at the second.

Instantaneous RSSI. Figure 2 shows the changes in time of the *instantaneous RSSI* of a Bluetooth signal at distance one meter. With instantaneous RSSI we refer to a single momentary RSSI value. The strong variations of the RSSI show that this metric is much affected by multipath propagation. Therefore, relying on instantaneous RSSIs for localisation can be misleading.

A better analysis would be based on metrics that can (partially) eliminate the impact of multipath propagation. The latter causes temporal, unpredictable RSSI variations. Evaluating a set of samples rather than a single value can isolate temporal changes and provide a more distinct main trend. We discuss the appropriate metrics in the coming three sections.

Probability Density Function. The *probability density function* (PDF) of the RSSI, constructed for each combination of mobile device and distance, is shown in Figure 3(a) for Bluetooth and in Figure 3(b) for WiFi. On the x-axis of a graph we plot the RSSI values whereas the y-axis plots the PDF.

Although the PDF shapes are similar for the three mobile devices, the maximum RSSI value is not the same, suggesting that the impact of the technical characteristics of the device should not be underestimated. Further, as it can be expected, RSSI values are lower at three meters due to larger path loss. Also, we notice that at distance one meter (upper row) the graphs are more compact whereas at three meters (lower row) the PDFs are generally wider, i.e., the set of observed RSSI values is larger. This can be explained by the stronger effect of multipath propagation as distance increases. Another consequence of multipath propagation is the slight asymmetry of the PDF with longer tail towards lower RSSI values.

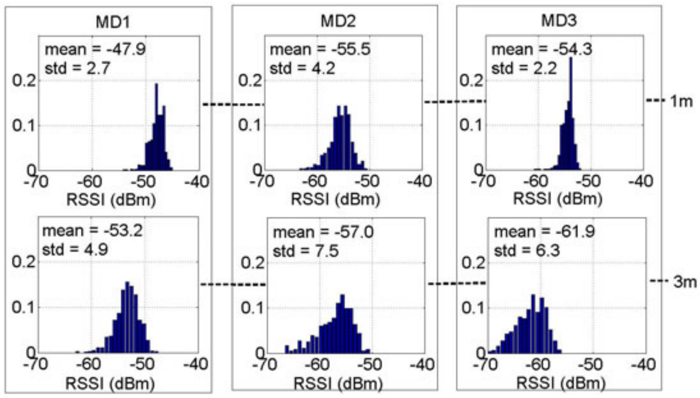
Differences between Bluetooth and WiFi are minor: WiFi signals have by default higher transmit power and subsequently stronger multipath components, which causes higher deviation of the RSSI signals, i.e., broader PDF shape. This is also the reason for the generally weaker received Bluetooth signals. For MD2 we could not identify the reasons for the little effect of distance on its WiFi signal.

Median and Percentiles. An alternative to a PDF representation is a *boxplot*, which depicts a population's median, lower and upper quantiles, minimum and maximum, and outlier samples. Using boxplots makes it easier to identify the main concentration of the RSSI values and how much the RSSI deviates. Another advantage of a boxplot is that outliers are visible; they are difficult to spot in a PDF due to their low probability.

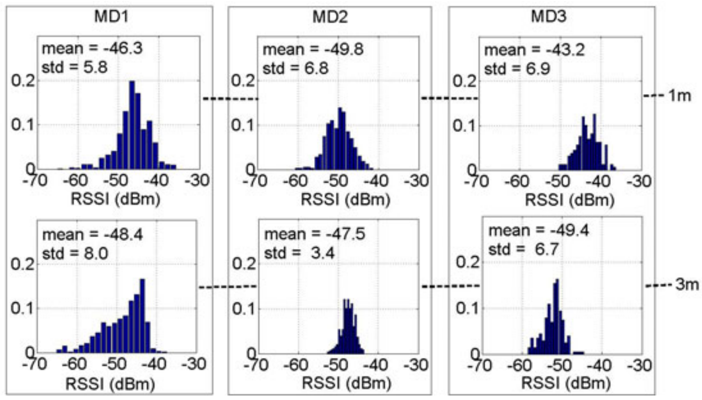
The boxplots corresponding to the PDF curves for both Bluetooth and WiFi are shown in Figure 4. Along with differences in the behaviour of mobile phones, we can directly observe a much larger deviation of RSSI values at three meters than at one meter. We also observe that WiFi signals are less robust to deviation than Bluetooth signals.

Mean and Standard Deviation. Although PDFs and boxplots are very descriptive, they require the collection of many samples (corresponding to long observation periods). Their use in a real-time positioning system, where samples are evaluated every few seconds, is challenging. An easier to derive set of metrics is the *mean* and *standard deviation*. The corresponding metrics for each PDF graph in Figure 3 are shown in the upper left corner.

We note that the mean is often off-set at 1-2dBm from the median, see Figure 4. These differences are caused by the asymmetry in the PDF distribution - the mean and standard deviation take into account all samples, including outliers, while the median excludes them. All other observations are consistent with previously made ones.

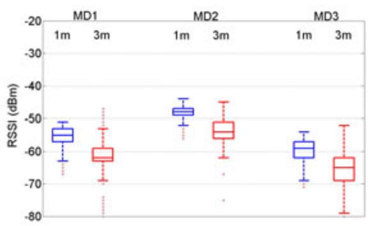


(a) Bluetooth

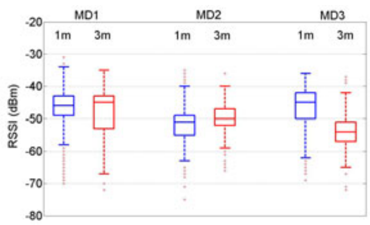


(b) WiFi

Fig. 3. PDF of the RSSI levels for three mobile devices measured at the same sensor node; distances one and three meters



(a) Bluetooth



(b) WiFi

Fig. 4. Boxplots of three MDs, RSSIs measured by the same sensor node; distances one and three meters

Table 1. Experiment 1: Response Rates

	Bluetooth			WiFi		
	MD1	MD2	MD3	MD1	MD2	MD3
1 m	12.9	6.8	11.3	23.3	12.9	14.2
3 m	13.6	6.0	10.8	18.8	5.2	5.1

Table 2. Experiment 2: Response Rates

	WiFi			Bluetooth		
	SN1	SN2	SN3	SN1	SN2	SN3
1 m	20.6	16.2	19.7	43.4	30.1	41.0
3 m	15.4	16.8	16.3	37.8	20.3	55.5

Response Rate. While RSSI-related metrics are vulnerable to multipath propagation, the *response rate* (RR) of a device is not and has potential for localisation. The response rate is defined as the average number of times per minute that a device (i) responded to an inquiry procedure in Bluetooth or (ii) was overheard in WiFi. By comparing the RRs of the same device at several anchor nodes one can derive conclusions on the devices location.

Results for the RR of both Bluetooth and WiFi for all studied scenarios are shown in Table 1. We see that the RR of Bluetooth varies in an incoherent way making it difficult to relate it to distance. Frequency hopping in Bluetooth causes the RR to depend on channel synchronisation and obstructs its use for positioning. No such discrepancies are observed in the case of WiFi, where the RR is a function of the distance. Although values among devices differ, the changes in RR in distance are consistent.

Concluding Remarks. In terms of evaluation metrics we conclude that the choice of metric depends on the time granularity needed by the localisation algorithm. Probability density functions and boxplots are more representative but they also require the collection of many RSSI samples. They are better used in positioning applications whose main purpose is the collection of long-term statistics. When a quick evaluation is desired, e.g., as in real-time systems, the mean of a group of samples is more convenient to handle. In all cases using a single instantaneous RSSI value is not recommended.

In terms of performance we conclude that mobile devices show significant difference in performance. This fact should be considered in the development of a localisation algorithm. One possible approach to compensate for these differences is to relate a device's measurements from several scanning nodes.

4.2 Experiment B: Manufacturing Discrepancies

In order to observe the impact of manufacturing discrepancies on signal reception we designed *Experiment B*. We placed three sensor nodes of the same manufacturer and model (Gumstix Overo Fire) but different manufacturing runs according to the experiment set-up in Figure 5. The sensor nodes are at virtually the same spot (sensor's dimensions cause some displacement) at distance one and three meters of a mobile device. At each distance measurements were collected during 30 minutes. Based on the conclusions of Section 4.1 we selected as evaluation metrics the median and percentiles (depicted by a boxplot diagram) and the response rate.

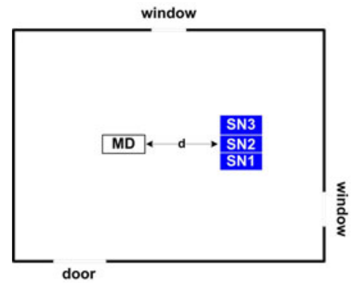
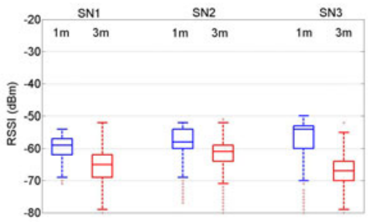
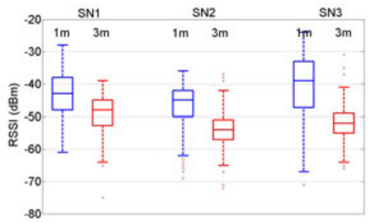


Fig. 5. Scenario B: set-up



(a) Bluetooth



(b) WiFi

Fig. 6. Boxplots of three SNs measuring the RSSI values of the same mobile device; distances one and three meters

The boxplots in the case of Bluetooth signals are shown in Figure 6(a). The median of different sensor nodes changes in the order of 2-3dBm. This is much less than the 10-15dBm registered by different mobile devices in Figure 4(a); the RSSI deviation for sensor nodes is also lower. In the case of WiFi, see Figure 6(b), the differences between the median values of sensors increases to 5-6dBm coming close to the results for device specifics of Section 4.1. Other observations on the RSSI deviation and behaviour of Bluetooth and WiFi signals, already made in Section 4.1, continue to hold.

The response rate RR of both Bluetooth and WiFi signals calculated at each sensor node is shown in Table 2. Two observations are worth noting. First, the RR of different sensors is similar, given the same technology and distance. This leads us to believe that manufacturing tolerances have little impact on the response rate. Second, the RR is difficult to relate to distance for Bluetooth signals but can be helpful in WiFi.

Concluding Remarks. Given that measurements were made in a realistic environment and not a well controlled one, it is difficult to pinpoint the cause of the RSSI degradation to only manufacturing tolerances or only multipath propagation. Still, we can observe that for the same propagation environment, although at different time instants, manufacturing tolerances seem to show smaller impact on the RSSI than device characteristics. Therefore, we claim that in the development of an indoor localisation system the designer can assume that all receiving devices have the same behaviour, given they are from the same model.

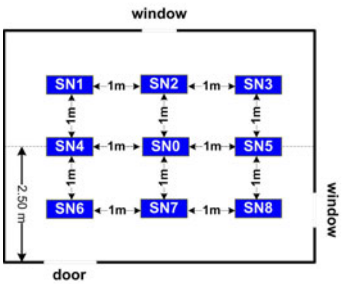


Fig. 7. Scenario C: set-up

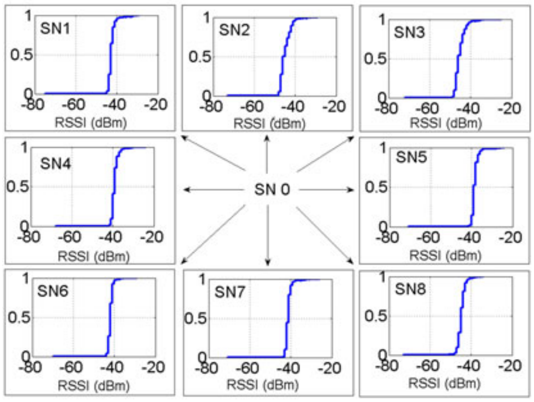


Fig. 8. CDFs in eight communication directions

4.3 Experiment C: Propagation Paths

Depending on the locations of sender and receiver the signal between the two traverses propagation paths of different length through different obstacles. Many studies have shown that the orientation of the device indeed has a strong impact on the propagation and should be taken into account. This is particularly relevant for fingerprinting-based localisation solutions. Majority of these studies, however, only perform short-term measurements, which makes them vulnerable to temporal variations in the propagation channel. We are more interested in the long term behaviour of the propagation channel in different direction such that to allow drawing conclusions relevant for the creation of radio maps. Therefore, we performed *Experiment C* based on the set-up of Figure 7.

Eight sensors in scanning modes (SN1-8) are organised in a grid around a central sensor (SN0) that periodically sends out WiFi beacons. The scanning nodes SN1 to SN8 collect RSSI measurements of SN0's beacons. The experiment was run for 24 hours in order to collect a reliable number of samples per SN (ten thousands), which allows us to construct a stochastic profile of the radio channels in each direction. Grid step size is one meter. Sensor nodes' antennas are omnidirectional.

The Cumulative Distribution Functions (CDFs), constructed by the scanning sensors, are shown in Figure 8. The position of the CDF graph in the figure corresponds to the position of the scanning sensor, e.g., the CDF graph at position left-middle corresponds to SN5.

Our main conclusion is that no two nodes have the same distribution of the RSSI values, which is expected and explained with the distinct propagation conditions of each path. Despite the differences there are certain similarities. CDF curves of nodes on the diagonals to SN0 (SNs 1, 3, 6 and 8) have a 5dBm lower mean and a larger variance than SNs 2, 4, 5 and 7 as a result of different path lengths. Interestingly, SN6 is an exception with higher RSSIs, which we attribute to the node's location. A SN near a corner receives stronger reflected signals from the near walls than a SN in the centre of the room. Nodes from opposite directions also show similar behaviour - SN4 and SN5 have RSSI values mainly spread between -40 and -30dBm, while the CDFs of SN2 and SN7 are in the range of -45 to -33dBm. Although the specific causes for such behaviour are hard to determine, we explain it with the asymmetric shape, i.e., rectangular, of the room and the consequences of that on signal propagation.

Concluding Remarks. The propagation path-specific distribution of the RSSI, besides reconfirming the observations of others, has given us the idea to base our positioning algorithm on a ratio-based approach. This approach is similar to fingerprinting but instead of characterising an indoor location by the absolute RSSI values heard by anchor nodes we can use proportions of the RSSI readings.

5 Conclusion

This paper presented an investigation on the impact of technical characteristics of mobile devices (targets for localisation), manufacturing differences of sensor nodes (used for localisation) and direction-specific multipath propagation. Our main conclusions are: (i) signal strength varies less between sensors of the same type than between mobile devices from different manufacturers; (ii) multipath propagation seems to have strong effect on signal strength; (iii) radio signals experience distinct propagation conditions in different directions.

In parallel, we analysed the usability of four signal metrics, namely, instantaneous values, probability distribution, median and percentiles, mean and standard deviation, as well as the signal's detection rate. We show that the choice of evaluation metric depends on the time-granularity of localisation, i.e., mean values are convenient for real-time positioning while probability distributions may be better for off-line processing.

Based on our findings as a next step we envision to develop a localisation system for indoor applications that can compensate for the specific behaviour of different personal devices and their orientation in a flexible, on-the-fly manner.

References

1. Ahmed, I., Orfali, S., Khattab, T., Mohamed, A.: Characterization of the indoor-outdoor radio propagation channel at 2.4 ghz. In: 2011 IEEE GCC Conference and Exhibition (GCC), pp. 605–608 (February 2011)
2. Akl, R., Tummala, D., Li, X.: Indoor propagation modeling at 2.4 ghz for IEEE 802.11 networks. In: Sixth IASTED International Multi-Conference on Wireless and Optical Communications. IASTED/ACTA Press (2006)
3. Bargh, M.S., de Groote, R.: Indoor localization based on response rate of Bluetooth inquiries. In: Proc. of 1st ACM International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments, MELT 2008, pp. 49–54. ACM (2008)
4. Bose, A., Foh, C.H.: A practical path loss model for indoor wifi positioning enhancement. In: 2007 6th International Conference on Information, Communications Signal Processing, pp. 1–5 (2007)

5. Byoung-Suk, C., Joon-Woo, L., Ju-Jang, L., Kyoung-Taik, P.: Distributed sensor network based on RFID system for localization of multiple mobile agents. In: Wireless Sensor Network, vol. 3-1, pp. 1–9. Scientific Research (2011)
6. Cherukuri, J.: Comparative study of stochastic indoor propagation models. Technical report, The University of North Carolina at Charlotte (2004)
7. Ciurana, M., Barceló-Arroyo, F., Cugno, S.: A robust to multi-path ranging technique over IEEE 802.11 networks. Wireless Networks 16, 943–953 (2010)
8. Fang, S.-H., Lin, T.-N.: Projection-based location system via multiple discriminant analysis in wireless local area networks. IEEE Transactions on Vehicular Technology 58(9), 5009–5019 (2009)
9. Fuchs, C., Aschenbruck, N., Martini, P., Wieneke, M.: Indoor tracking for mission critical scenarios: A survey. Pervasive Mobile Computing 7, 1–15 (2011)
10. Gezici, S., Zhi, T., Giannakis, G.B., Kobayashi, H., Molisch, A.F., Poor, H.V., Sahinoglu, Z.: Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks. IEEE Signal Processing Magazine 22(4), 70–84 (2005)
11. Gwon, Y., et al.: Robust indoor location estimation of stationary and mobile users (2004)
12. Haeberlen, A., Flannery, E., Ladd, A.M., Rudys, A., Wallach, D.S., Kavraki, L.E.: Practical robust localization over large-scale 802.11 wireless networks. In: Proc. of 10th Annual International Conference on Mobile Computing and Networking, MobiCom 2004, pp. 70–84. ACM (2004)
13. Hashemi, H.: The indoor radio propagation channel. Proceedings of the IEEE 81(7), 943–968 (1993)
14. Hay, S., Harle, R.: Bluetooth Tracking without Discoverability. In: Choudhury, T., Quigley, A., Strang, T., Suginuma, K. (eds.) LoCA 2009. LNCS, vol. 5561, pp. 120–137. Springer, Heidelberg (2009)
15. `https://www.bluetooth.org/Technical/Specifications/adopted.html`
16. `http://www.cl.cam.ac.uk/research/dtg/attarchive/bat/`
17. Kotanen, A., Hannikainen, M., Leppakoski, H., Hamalainen, T.D.: Experiments on local positioning with bluetooth. In: International Conference on Information Technology: Coding and Computing [Computers and Communications], pp. 297–303 (2003)
18. Liu, H., Darabi, H., Banerjee, P.: A new rapid sensor deployment approach for first responders. Intelligent Control and Systems 10(2), 131–142 (2005)
19. Mahtab Hossain, A.K.M., Nguyen Van, H., Jin, Y., Soh, W.S.: Indoor localization using multiple wireless technologies. In: Proc. of Mobile Adhoc and Sensor Systems, MASS 2007, pp. 1–8 (2007)
20. Martin-Escalona, I., Barcelo-Arroyo, F.: A new time-based algorithm for positioning mobile terminals in wireless networks. Journal on Advances in Signal Processing, EURASIP (2008)
21. Perez-Vega, C., Garcia, J.L., Lopez Higuera, J.M.: A simple and efficient model for indoor path-loss prediction, vol. 8, p. 1166 (1997)
22. Want, R., Hopper, A., Falcão, V., Gibbons, J.: The active badge location system. ACM Trans. Inf. Syst. 10, 91–102 (1992)
23. Zhang, G., Krishnan, S., Chin, F., Ko, C.C.: UWB multicell indoor localization experiment system with adaptive TDOA combination. In: IEEE 68th Vehicular Technology Conference, VTC 2008-Fall, pp. 1–5 (2008)