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# An Analysis of Wi-Fi Based Indoor Positioning Accuracy

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***Abstract*** **– The increasing demand for location based services inside buildings has made indoor positioning a significant research topic. This study deals with indoor positioning using the Wireless Ethernet IEEE 802.11 (Wireless Fidelity, Wi-Fi) standard that has a distinct advantage of low cost over other indoor wireless technologies. The aim of this study is to examine several aspects of location fingerprinting based indoor positioning that affect positioning accuracy. Overall, the positioning accuracy achieved in the performed experiments is 2.0 to 2.5 meters.**

**Keywords – Indoor positioning, location fingerprinting, Wi-Fi, Wireless Ethernet**

## I. Introduction

The increasing demand for location based services inside buildings has made indoor positioning a significant research topic. The applications of indoor positioning are many, for instance, indoor navigation for people or robots, inventory tracking, locating patients in a hospital, guiding blind people, tracking small children or elderly individuals, location based advertising, ambient intelligence etc.

Although the Global Positioning System is the most popular outdoor positioning system, its signals are easily blocked by most construction materials making it useless for indoor positioning. This study deals with indoor positioning using the Wireless Ethernet IEEE 802.11 (Wi-Fi) standard that has a distinct advantage of low cost over other indoor wireless technologies – it has relatively cheap equipment and in many areas usually a Wi-Fi network already exists as a part of the communication infrastructure avoiding expensive and time-consuming infrastructure deployment.

Although Wi-Fi has not been designed for positioning, its radio signals can be used for location estimation by exploiting the Received Signal Strength (RSS) values measured in any off-the-shelf mobile device equipped with Wi-Fi facilities – and no additional special-purpose hardware is required. Such a positioning system can be relatively easily implemented for notebook computers, personal digital assistants (PDAs), smartphones, and other Wi-Fi enabled mobile devices.

Most of the proposed Wi-Fi indoor positioning systems use either proximity detection via radio signal propagation models [1] – [3] or location fingerprinting techniques [3] – [11]. Deriving an accurate propagation model for each Wi-Fi access point (AP) in a real-world indoor environment is extremely complex and therefore usually results in a relatively poor positioning accuracy [3], [11]. On the other hand, location fingerprinting techniques use empirical data to approximate a location. First, a so called radio map is constructed by measuring RSS at a number of known locations – calibration points. The location of the user is then determined by comparing the obtained RSS values to a radio map. This provides accurate positioning even in very complex environments while the modelling of the complex signal propagation is avoided. In addition, the fingerprinting techniques usually do not require knowing exact locations of APs.

An early example of a positioning system that uses fingerprinting is RADAR [12]. In RADAR, user's location is determined by finding a known fingerprint that is most similar to the actual RSS readings. Since then, many studies have been conducted that perform location estimation from a radio map employing Nearest Neighbours [3], [4], [9], [13], Artificial Neural Networks [13] – [15], Support Vector Machines [6], Decision Trees [5], [11], Bayesian techniques [9], [10], [16], or other techniques [2], [3], [7], [9]. In majority of these studies the Nearest Neighbours technique, in addition to its simplicity, turned out to be among the most accurate ones.

The aim of this study is to examine several aspects of Wi-Fi location fingerprinting based indoor positioning that affect the positioning accuracy.

*Making use of weakly-sensed APs*: It is considered to make use of (in many studies frequently ignored) weakly-sensed APs located further away, on other floors, and even in nearby buildings. It is demonstrated that the weak APs can provide additional information for at least a slightly more accurate positioning. Furthermore, also a situation, when in the entire building there would be no APs, is considered – the positioning system may use signal strength information from only those APs that are in other buildings nearby.

*Making use of the two different Wi-Fi frequency bands*: The use of either or both 2.4 GHz and 5 GHz Wi-Fi bands using IEEE 802.11b/g and IEEE 802.11a standards is examined.

*Making use of device orientation information*: In studies [9], [10], [12], [17], it is argued that the mobile device orientation information can have a significant effect on the RSS values and therefore on estimated location. This study examines the opportunity to improve positioning accuracy using device orientation information provided by a digital compass – a piece of hardware that is built-in in many newest handheld devices.

*Testing the accuracy on devices with different RSS measuring characteristics*, i.e. different ranges of possible RSS values and different RSS measurement precisions. In this study, it is done using three different devices – a PC notebook,

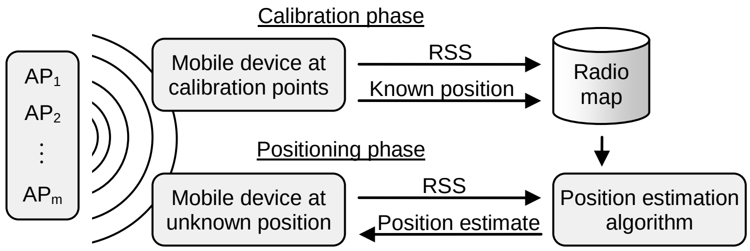


Fig. 1. The two phases of location fingerprinting

a smartphone, and a Pocket PC PDA.

In many existing studies, to perform the positioning experiments, (usually) three to six APs are carefully distributed across the area of interest specifically for the purposes of the experiments. Therefore, it should be noted that in the experiments of this study no additional APs were deployed and no existing APs were moved – the experiments are performed using an already existing infrastructure with APs that have been deployed for maximum Wi-Fi internet availability.

The remainder of this paper is organized as follows: Section 2 outlines location fingerprinting, describes Weighted k-Nearest Neighbours algorithm and sketches the idea of the usage of device orientation information. Section 3 describes the developed software. Section 4 describes the performed experiments and presents experimental results and findings. Finally, Section 5 concludes the paper.

## II. METHODOLOGY

### *A. Location fingerprinting*

Location fingerprinting based positioning systems usually work in two phases (see Fig. 1): calibration phase (also called offline phase) and positioning phase (also called online phase or run-time phase). In the calibration phase, a mobile device is used to measure RSS values (in dBm) from several APs at the chosen calibration points in the area of interest. Each of the $n$ measurements becomes a part of the radio map and is a tuple $(\mathbf{q}_i, \mathbf{r}_i)$ $i = 1,2,\ldots,n$ where $\mathbf{q}_i = (x_i, y_i)$ are the geographical coordinates of the $i$th location and $\mathbf{r}_i = (r_{i1}, r_{i2}, .. r_{im})$ are the $m$ RSS values from $m$ APs at that location. Usually, an average of several samples recorded per location is stored.

In the positioning phase, a mobile device measures the RSS values in an unknown location and applies a location estimation algorithm to estimate its current location using the previously created radio map. As indoor environments have unique signal propagation characteristics, it can be assumed that each location can be associated with a unique combination of RSS values.

### *B. Weighted k-Nearest Neighbours*

A general Weighted k-Nearest Neighbours (WKNN) algorithm for location fingerprinting can be described as a two step process. First, find within the radio map the $k$ indices $i_1, i_2, \ldots, i_k$ whose $\mathbf{r}_{i_1}, \mathbf{r}_{i_2}, \ldots, \mathbf{r}_{i_k}$ values are nearest (according to Euclidean distance in the signal space) to the given vector $\mathbf{r}$ measured at the unknown location. In the second step, calculate the estimated location $\mathbf{q}$ (for each coordinate separately) as an average weighted by the inverse of the RSS distances:

$$\mathbf{q} = \sum_{j=1}^{k} \frac{w_j \mathbf{q}_{i_j}}{\sum_{l=1}^{k} w_l}, \tag{1}$$

where all weights are nonnegative $w_j = d(\mathbf{r}_{i_j}, \mathbf{r})^{-1}$ and $d$ is the Euclidean distance between the $m$-vectors. Note that there is a special case when the distance is zero; then as the estimated location just the one with the zero distance is taken without fully computing (1). The reasoning behind this algorithm is that the calibration point with the shortest distance in signal space also has the shortest distance in physical space, and as such acts as a proper location estimate.

WKNN has one tuning parameter, the number of nearest neighbours considered $k$, which is used to control the locality of the location calculation. When $k = 1$, the algorithm acts as a simple look-up table. For larger values, the location can also be estimated to be somewhere in-between the calibration points. Reference [18] recommends using $k = 1$ only if the density of the radio map is high. However, $k$ should also not be too large as then the location estimates will be too much influenced by calibration points far away. In this study the number is fixed experimentally to $k = 2$.

### *C. Making use of device's orientation information*

The study in [9] showed that the positioning accuracy significantly benefits from varying rotation of the measuring device during the calibration phase. This is mostly because of the radio irregularity caused by the direction of a mobile device antenna, existence of some reflector of the wireless signal, or user's body due to the high proportion of water in human body absorbing wireless signals [10], [17]. Device rotation can level out or equalize the impact of its orientation to measure more reliable fingerprint compared to the fingerprint that is measured only for one direction.

In [10], during the calibration phase RSS values were recorded in four different orientations while in the positioning phase device orientation was estimated and employed for a more accurate positioning. It was shown that, when the user movement consists of mostly straight lines, positioning accuracy can be improved. However, if the orientation of the device is estimated incorrectly, the positioning accuracy decreases.

Theoretically, the availability of orientation information from a built-in digital compass can improve the positioning accuracy by using radio map data of only the specific orientation. This study examines the potential to improve positioning accuracy using device orientation information provided by a digital compass.

## III. DEVELOPED MOBILE SOFTWARE

To perform the experiments, a prototype of an indoor positioning system that works entirely on the user's device (without requirement to have a back-end server) was developed. The software allows determining the position of the device using a prepared radio map and device built-in Wi-Fi chipset. The software works in the two location fingerprinting phases – calibration phase and positioning phase. Fig. 2 shows a screenshot of the software for handheld devices with Microsoft Windows Mobile operating system.

In calibration phase, the available Wi-Fi access point RSSs are measured in different positions in the building. In each point RSS of all available APs are measured for a defined period of time and after that the average value is calculated and written into radio map.

In positioning phase, the software determines the actual position. RSS values of all the sensed APs are measured and compared to the ones in the prepared radio map so that a number of nearest neighbours (in the signal space) are selected and used for position estimation. While the first phase is usually done by the system maintainers, the second phase is the one that is actually performed by the end-user.

In calibration phase, the software has the following functionality: 1) load and view map of the building; 2) view list of all available APs and their current RSS in the current position; 3) perform fingerprinting by tapping on the current position in the map. Functionality in the positioning phase: 1) load and view map of the building; 2) estimate position (in form of coordinates as well as a point on the loaded map).

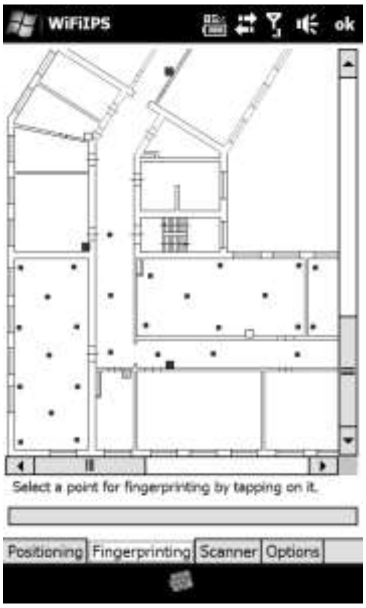


Fig. 2. „Fingerprinting" tab

## IV. EXPERIMENTAL STUDY

### *A. Experimental testbed and data collection procedure*

The experiments were performed on the fifth floor of a five-storey building of the Faculty of Computer Science and Information Technology, Riga Technical University.

Fig. 3 displays the layout of the floor where the experiment was performed. The area has five APs installed, which have been deployed for maximum Wi-Fi internet availability, and can be sensed in at least a third part of the area. The largest left-out part of the fifth floor (upwards in the figure) has some additional APs that can be barely sensed from some nearest locations. Furthermore, some APs from the fourth and even third floors can also be sensed in some small areas. This sums up in locally-situated 14 APs. Most of the local APs are Enterasys devices RBT-1002 and RBT-4102 operating in both IEEE 802.11a and IEEE 802.11b/g modes at the same time, allowing getting RSS readings for both 2.4 GHz and 5 GHz Wi-Fi frequency bands. Additionally, there are a total of 43 APs in the nearest buildings, each of which can be sensed in at least one small location. Note that no additional APs were deployed and no existing APs were moved – the experiments were performed using an already existing infrastructure. The measurements were done mostly in working hours with people walking around and the Wi-Fi internet being used.

Two experiments were performed. The first experiment involved a PC notebook with an internal wireless card. The area of the testbed in this experiment is approximately 860 $m^2$ in (displayed in Fig. 3). The second experiment involved HTC Touch HD smartphone and Fujitsu-Siemens Pocket Loox N560 Pocket PC device both using Microsoft Windows Mobile operating system. The area of the testbed in this experiment was smaller (for technical reasons) – approximately 460 $m^2$ (the lower horizontal part of the building in Fig. 3). Note that the handheld devices have less sensitive Wi-Fi chipsets (they only sensed about 19 APs of the nearest other buildings) as well as they do not support IEEE 802.11a mode.

The RSS measurements were collected by a human operator using one of the mentioned devices with internal wireless card. The devices were used for both calibration and positioning phase.

For the first experiment a total of 82 calibration points were defined, while the second experiment involved 46 calibration points. In the classrooms, the points were placed near the walls and corners, as the walls are responsible for fast drop of signal strength while in the free space the signal strength drops much slower, especially further away from an AP. On average, the distance from one calibration point to the nearest other point is 3.7 m within the same room and 2.6 m when also the points from other rooms are considered. The number of APs that could be sensed from a location ranges from 2 to 13 with average of 7.

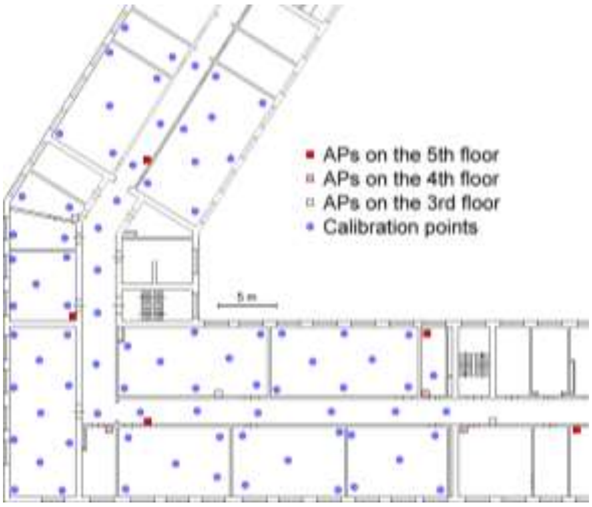


Fig. 3. Layout of the testbed environment with calibration points

To be able to test the usefulness of device orientation information, for each calibration point the RSS readings were collected in four directions (facing north, east, south, and west), while for each direction a total of 30 RSS samples were collected over a time span of 30 seconds. The readings were then averaged for each direction separately as well as for all the directions combined, resulting in five different average RSS values, each for a separate radio map.

Finally, a test set of 68 points for the first experiment and 25 points for the second experiment was created (see Fig. 4). The placement of the testing points mimics a person walking following the route through classrooms and hallway. The route starts at one point and finally ends at the same point, visiting a number of different locations where each location is visited two times, each time facing a different direction. The measurement process, apart from that it is performed for only two orientations, is the same as for the calibration points.

For PC notebook device averaged RSS values range from -99 dBm (used when the AP is not present) to about -33 dBm in close proximity to an AP. For smartphone device it is from -99 dBm to -40 dBm, for the Pocket PC device it is from -99 dBm to -50 dBm. Additionally it is important to note that RSS measurements of the Pocket PC device could only be done in steps of 10 measurement units, while the other two devices allowed steps of 1 unit. Here, a question rose – how much worse will the results of the Pocket PC device be? The outcome of the measurement session can be downloaded at http://www.cs.rtu.lv/jekabsons/.

### B. *Experimental results*

Table 1 summarizes the positioning errors for the first experiment (using the PC notebook device).

*Making use of weakly-sensed APs:* The results suggest that indeed the positioning accuracy can be at least slightly improved if the list of the used APs consists of not only the strongest APs (average positioning error of 2.43 m) but also the weakly-sensed APs located further away, on other floors, and even in nearby buildings as well (average positioning error of 2.19 m).

Additionally, an interesting result is that if in the entire building there would be no APs and the positioning system could use signal strength information from the 'outside' APs only – those of the other buildings nearby, the average positioning error would still be a decent 7.14 m. This suggests that such a positioning system could still be useful, especially if used together with some supplementary positioning or tracking technology while walking through hallways in the middle of the building (where, in this experiment, the positioning error is the largest).

*Making use of the two different Wi-Fi frequency bands:* Signals from eight of the local APs were strong enough for the measuring device to be able to detect them in both bands, 2.4 GHz (IEEE 802.11b/g) as well as 5 GHz (IEEE 802.11a). It turned out that in addition to 2.4 GHz RSS, using also the 5 GHz RSS (as if they came from additional eight APs) always increased the average positioning accuracy by at least 10%. Apparently, despite the sharply dropping 5 GHz signal strength, the RSS values are still useful for extracting additional information for positioning.

*Making use of device orientation information:* For this experiment, four different radio maps where created – one for each orientation. The location estimation for each testing point was done using corresponding orientation of the radio map nearest to the actual orientation of the measuring device at the time of measurement.

While theoretically the availability of orientation information could increase the positioning accuracy, in practice there was no improvement. The reason for this could be the evident signal strength fluctuations, i.e. the noise in the data might be higher than the useful orientation-specific information. Nevertheless, it should be noted that the positioning accuracy significantly benefited from the RSS readings averaged over all four orientations, for example, while using all local APs and both frequency bands, the positioning error decreased from 2.85 m, when RSS information from only the north orientation was used, to 2.10 m, when all four orientations were used.

Finally, the impact of varying the number of used APs was studied in more detail and without regarding the origin of an AP (see Fig. 5). The list of all APs was sorted by their overall RSS variance in the full radio map and for each number of used APs only those with the largest variance were used. As expected, the positioning error is not a linear function of the number of APs: the decreasing rate of positioning error gradually slows down and at some threshold it is evident that only little benefit is achieved by further increasing the number of APs. Here, the best results are achieved mostly using about 20 APs. However, the fluctuations of the curves suggest that a better criterion for sorting the APs or a better algorithm for finding the best subsets of the APs could be used delivering smaller subsets with the same or even slightly better positioning accuracy.

TABLE I

TEST SET ERROR (IN METERS) DISTRIBUTION FOR EXPERIMENT WITH NOTEBOOK: MEAN, MEDIAN, AND PERCENTILES

| | Mean | Median | 75th | 90th | 95th |
|---|---|---|---|---|---|
| 5 strongest local APs | | | | | |
| 2.4 GHz | 2.56 | 2.35 | 3.60 | 4.64 | 5.56 |
| Both freq. | 2.28 | 1.87 | 3.40 | 4.24 | 5.36 |
| Both freq. + orientation info. | 2.45 | 1.88 | 3.76 | 4.70 | 5.50 |
| All local APs (14) | | | | | |
| 2.4 GHz | 2.33 | 2.16 | 3.17 | 3.99 | 5.12 |
| Both freq. | 2.10 | 1.67 | 3.12 | 4.18 | 5.41 |
| Both freq. + orientation info. | 2.40 | 1.61 | 3.26 | 5.03 | 7.23 |
| All sensed APs (57) | | | | | |
| 2.4 GHz | 2.44 | 2.32 | 3.58 | 4.62 | 5.10 |
| Both freq. | 2.02 | 1.62 | 3.04 | 4.22 | 4.52 |
| Both freq. + orientation info. | 2.11 | 1.71 | 3.10 | 4.08 | 4.96 |
| Only the ‘outside’ APs (43) | 7.14 | 6.51 | 10.02 | 13.64 | 14.55 |

The results of the second experiment (with the handheld devices) are shown in Fig. 6 (for the smartphone device) and Fig. 7 (for the Pocket PC device). The dependence of average positioning error (in meters) on the choice of the method (WKNN versus *k*-Nearest Neighbours, KNN which is the same WKNN method but without the weighting) and selected number of nearest neighbours *k* is shown (from 1 to 10).

From the results, it can be seen that at first increasing the *k* value decreases the positioning error. But already starting form $k = 2$ (the best value for the used Pocket PC device) or $k = 3$ (the best value for the used smartphone device) the error starts to increase. It can be seen that fewer calibration points that are nearer in the signal space are actually more useful for position estimation than more calibration points taken from a larger radius. More calibration points from further away actually dilute the useful information.

The smallest positioning error in this experiment was 2.35 meters using WKNN method. The best result of KNN was 2.48 meters. This experiment also demonstrates that in practice the WKNN method is expected to be more accurate than KNN. The only difference between those two methods is that WKNN also takes into account the signal space distances to calibration points. Note also that these results are very similar to the results performed by a PC notebook, which has at least slightly more sensitive Wi-Fi chipset.

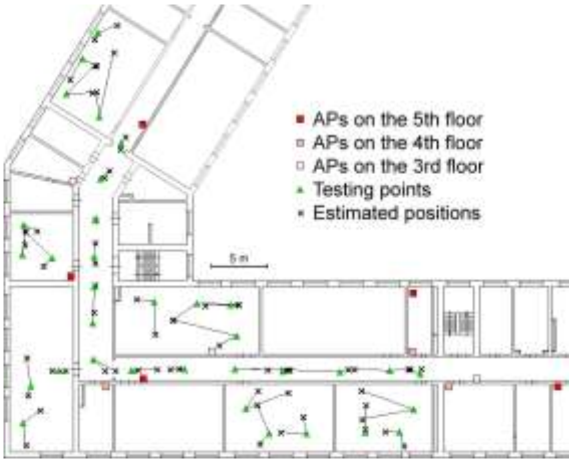


Fig. 4. Testing points and their corresponding estimated locations

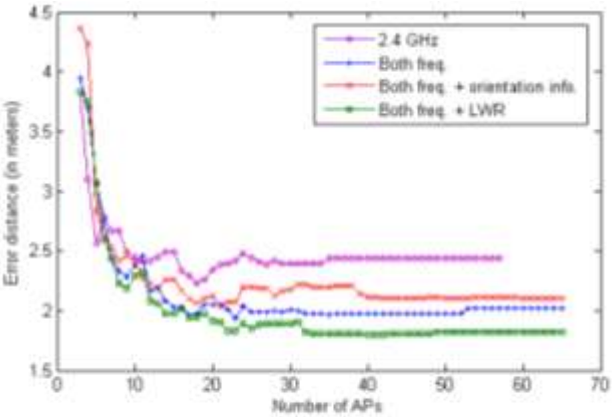


Fig. 5. Positioning performance with different numbers of APs

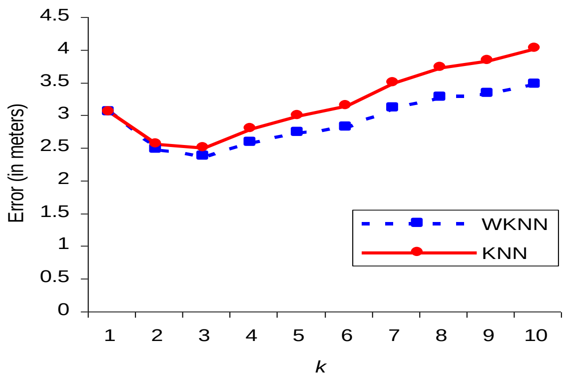


Fig. 6. Average positioning error dependence on *k*, smartphone device

Finally, the experiment showed that the Pocket PC device with significantly lower RSS measurement precision still performed surprisingly well – the results are almost the same for both handheld devices. Similarly to the uselessness of the orientation information, this can be explained by the evident signal strength fluctuations – the noise in the data might be higher than the useful information from the more precise measurements. This can be seen also as good news because this means that we can achieve reasonably high positioning accuracy with rather cheap Wi-Fi chipsets.

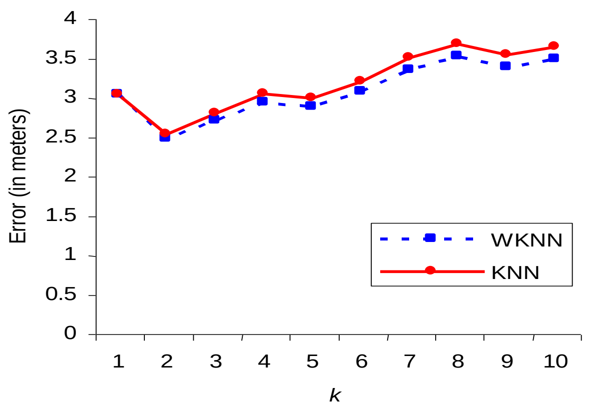


Fig. 7. Average positioning error dependence on *k*, Pocket PC device

## Conclusion

This paper examined several aspects of Wi-Fi location fingerprinting based indoor positioning that affect the positioning accuracy. Based on the experimental findings, the following conclusions can be drawn.

It was observed that a positioning system can benefit from the availability of additional weakly-sensed APs as well as APs working in 5 GHz frequency band (using IEEE 802.11a/n). RSS readings from these APs gave a notable improvement in positioning accuracy. In fact, in this study, using exclusively the APs from other buildings nearby, the positioning error was still a decent 7.14 m.

Nevertheless, it must be noted that the benefit from adding more and more weakly-sensed APs quickly decreases and after a certain number of APs, the accuracy actually can deteriorate. This is especially true for sparse radio maps. One of the future work directions here could be consideration of some kind of automatic subset selection technique to filter out the irrelevant APs. While this may not bring much additional accuracy, at least the size of RSS fingerprint database could be significantly reduced (see Figure 5 where it can be observed that the system can reach about the same accuracy using about the third of all the available APs).

The results also have shown that the performance of the handheld devices with less sensitive Wi-Fi chipsets actually was very similar to the performance of the PC notebook with more sensitive chipset. Furthermore, the Pocket PC, which in fact offers only six gradations of signal strength, still performed very well.

In this study, the availability of orientation information could not increase the positioning accuracy. The reason for this could be the evident signal strength fluctuations. However, as this result appears to contradict with some other studies, it should be investigated more extensively with different experimental setups.

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**Gints Jēkabsons, Vadims Kairišs, Vadims Žuravļovs. Wi-Fi sakņotas pozicionēšanas precizitātes analīze**
Kaut arī globālās pozicionēšanas sistēma ir vispopulārākā pozicionēšanas sistēma, tās signāli tiek bloķēti ar lielāko daļu ēku konstrukciju materiālu, padarot to nederīgu izmantošanai iekštelpu pozicionēšanai. Šis pētījums ir veltīts iekštelpu pozicionēšanai, izmantojot bezvadu interneta tehnoloģiju Wi-Fi (Wireless Ethernet IEEE 802.11), kas sniedz tādu priekšrocību kā zemāka cena, salīdzinot ar citām bezvadu tehnoloģijām, kuras ir iespējams izmantot iekštelpās. Iekārtas, kuras izmanto Wi-Fi tehnoloģiju, ir salīdzinoši lētas, kā arī daudzās vietās Wi-Fi infrastruktūra jau ir uzstādīta, tādējādi tas palīdz arī izvairīties no dārgas un laikietilpīgas infrastruktūras ierīkošanas. Pieaugošais pieprasījums pēc „atrašanās vietā sakņotajiem pakalpojumiem" (Location Based Services, LBS) iekštelpās ir padarījis iekštelpu pozicionēšanu par svarīgu izpētes jautājumu. Šī pētījuma mērķis – izpētīt dažādus Wi-Fi sakņotus LBS iekštelpu pozicionēšanās aspektus, kas ietekmē pozicionēšanas precizitāti, izmantojot signālu „pirkstu nospiedumu" (fingerprinting) metodi. Rakstā ir aplūkoti šādi aspekti: signālu stiprumu datubāzes izmēri, signālu stipruma mērījumu skaits vienā mērījuma punktā, vāji uztveramo piekļuves punktu izmantošana, dažādu Wi-Fi tehnoloģijai pieejamo frekvenču izmantošana, ierīces orientācijas informācijas izmantošana, kā arī pozicionēšanas precizitātes atkarība no ierīces mērījumu precizitātes. Praktiskie eksperimenti tika veikti, izmantojot trīs tipu ierīces: PC portatīvo datoru, viedtālruni un Pocket PC ierīci. Pamatojoties uz eksperimentiem, tika izdarīti šādi secinājumi. Wi-Fi pozicionēšanas sistēmas var iegūt augstāku pozicionēšanas precizitāti, papildus tuvu esošajiem Wi-Fi piekļuves punktiem, izmantojot arī attālinātākus vāji uztveramus piekļuves punktus. Iegūtā pozicionēšanas kļūda bija aptuveni 2 metri. Pie tam, eksperimenti parādīja, ka, pat izmantojot piekļuves punktu signālus tikai no citām apkārtesošajām ēkām, pozicionēšanas kļūda bija tikai aptuveni 7 metri. Precizitāte uzlabojās, bez 2.4 GHz frekvences signālu mērījumiem, papildus arī izmantojot 5 GHz frekvences signālu mērījumus (izmantojot IEEE 802.11a/n standartus) – kļūda samazinājās par aptuveni 10%.

**Гинтс Екабсонс, Вадим Кайриш, Вадим Журавлев. Анализ точности позиционирования внутри помещений, основанного на технологии Wi-Fi**
Хотя система глобального позиционирования и является самой популярной системой позиционирования, ее сигналы с легкостью блокируются большинством материалов конструкций, делая ее бесполезной для позиционирования внутри помещений. Данное исследование посвящено позиционированию внутри помещений с использованием технологии беспроводного интернета Wi-Fi (Wireless Ethernet IEEE 802.11), которая обладает несомненным преимуществом в виде низкой цены по сравнению с другими беспроводными технологиями, используемыми внутри помещений. Оборудование, применяемое технологией Wi-Fi, является относительно дешевым, а также во многих помещениях сеть Wi-Fi уже обеспечена, являясь частью инфраструктуры телекоммуникаций. Все это позволяет избежать дорогой и трудоемкой работы по установке инфраструктуры. Растущий спрос на «услуги, связанные с местоположением» (Location-Based Services, LBS) внутри помещений сделал позиционирование внутри помещений важным предметом исследований. Цель данного исследования – рассмотреть различные аспекты Wi-Fi LBS позиционирования внутри помещений с использованием метода «отпечатков пальцев» сигналов (fingerprinting), которые влияют на точность позиционирования. В статье рассмотрены следующие аспекты: размеры базы данных сил сигналов, количество измерений силы сигнала в каждой точке измерения, использование точек доступа со слабой силой сигнала, использование различных доступных для технологии Wi-Fi диапазонов частот, использование информации об ориентации устройства, а также зависимость точности позиционирования от точности измерения устройства. Для проведения экспериментов были использованы три устройства: ноутбук, устройство смартфон и Pocket PC. Основываясь на результатах эксперимента, были сделаны следующие выводы. Система позиционирования может достичь большей точности, используя в дополнение к доступным точкам доступа точки доступа со слабой силой сигнала. Полученная при проведении эксперимента ошибка позиционирования равна 2 метрам. При этом эксперимент показал, что при использовании точек доступа только из соседних зданий ошибка позиционирования равна 7 метрам. При использовании точек доступа на частоте 5 ГГц (использующих стандарты IEEE 802.11a/n) в дополнение к точкам доступа, работающим на частоте 2.4 ГГц, точность позиционирования увеличилась на 10 процентов.