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FM radio for indoor localization with spontaneous recalibration

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ABSTRACT

The position of mobile users has become highly important information in pervasive computing environments. Indoor localization systems based on Wi–Fi signal strength fingerprinting techniques are widely used in office buildings with an existing Wi–Fi infrastructure. Our previous work has proposed a solution based on exploitation of a FM signal to deal with environments not covered with Wi–Fi signal or environments with only a single Wi–Fi access point. However, a general problem of indoor wireless positioning systems pertains to signal degradation due to the environmental factors affecting signal propagation. Therefore, in order to maintain a desirable level of localization accuracy, it becomes necessary to perform periodic calibrations of the system, which is either time consuming or requires dedicated equipment and expert knowledge. In this paper, we present a comparison of FM versus Wi–Fi positioning systems and a combination of both systems, exploiting their strengths for indoors positioning. We also address the problem of recalibration by introducing a novel concept of spontaneous recalibration and demonstrate it using the FM localization system. Finally, the results related to device orientation and localization accuracy are discussed.

1. Introduction

The myriad positioning techniques in existence today have enabled a number of interesting applications that require appropriate levels of precision. For a number of applications (e.g. outdoor navigation), GPS leads the way, while the picture is not as clear-cut when it comes to indoor positioning. A number of technologies for indoor positioning exists, varying in characteristics, methods used, precision and cost. Technology with the highest precision and lowest cost is the ultimate aim, however in practice typically there is a trade-off between the performance and the associated costs, such that a positioning technology becomes cost effective. Over the past number of years, a significant amount of work has been invested in the use of IEEE 802.11 (Wi–Fi) networks for the purpose of localization [1–7]. The cost-effectiveness lies in the fact that Wi–Fi networks are increasingly present in everyday life and a variety of mobile devices supports them.

The localization approach that these systems take is based on the fact that each point in the space has a unique fingerprint of signal parameters. In this approach, the location of a mobile unit is found by comparing the signal parameters observed from nearby access points (the *location fingerprint*) to the database which matches fingerprints with real coordinates. The acquisition of such a database (*calibration*) is a laborious and time-consuming process, since achieving a satisfactory localization performance requires the measurement of a large number of location fingerprints. Another drawback of the localization systems based on IEEE 802.11 wireless networks is that the electromagnetic field is prone to fluctuations due to various factors which can cause the degradation of the positioning accuracy [8]. Due to these fluctuations, the calibration process must be repeated periodically (*recalibration*) in response to performance degradation, which makes these

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systems inconvenient for practical use. A number of projects have addressed this problem using specific hardware capable of refreshing training set with updated measurements [8,5]. This approach is often costly due to additional hardware and increases the complexity and maintenance overhead of the system.

Moreover, while Wi–Fi coverage in large areas such as airports, enterprises and shopping malls is realized using multiple access points (APs) where localization might work well, in case of smaller areas such as private houses, these localization systems do not work, since a single access point (such as a Wi–Fi router for example) is not sufficient to localize a mobile device. In addition, use of Wi–Fi is prohibited in interference-prone environments, while FM signals are allowed. In these environments, the localization system cannot be built on the top of the pre-existing infrastructure; rather, such a localization system would require the acquisition of additional equipment.

Considering the above shortcomings, we have devised a FM-based localization system that has the ability to spontaneously recalibrate in response to signal degradation and in turn address the issues faced by other localization systems. The contribution of this paper is threefold: (i) further improvement of the FM positioning system we proposed in [9], (ii) a synergetic approach based on the combined advantages of FM and Wi–Fi positioning systems and (iii) the introduction and the proof of the concept of spontaneous recalibration for FM positioning.

The paper is organized as follows. The section that follows provides a critical review of the ongoing research work. Our methods and description of the experiments are provided in Section 3. In Section 4 we discuss the accuracy of FM and how it can be improved. Then, in Section 5, we compare performance of Wi–Fi versus FM positioning. In Section 6 we demonstrate the benefits of a combined, hybrid Wi–Fi + FM positioning system. In Section 7 we describe spontaneous recalibration and analyze obtained results. The impact of the user's orientation on the localization accuracy and estimation of user's orientation is examined in Section 8. Finally, we provide a discussion and summary in Section 9 and X respectively.

2. Related work

2.1. Localization

There is a spectrum of approaches to indoor localization that rely on different types of sensors and on different types of modeling the information obtained from an environment. The majority of indoor positioning systems are based on Wi–Fi [1,10,11], GSM [12], Bluetooth [13], RFID [14], ultrasound [15,16] and infrared [16,17]. To acquire user's location, such systems analyze the proximity of a mobile unit to a certain sensor, time of signal propagation or received signal strength, or both. Dedicated localization systems can provide high accuracy however they require expensive, specialized hardware, especially for large-scale deployments (e.g. [18]).

There are two general approaches to wireless localization: signal propagation modeling and signal fingerprinting. Propagation modeling techniques rely on the received signal strength indication (RSSI), the angle of arrival (AOA) or the time of arrival (TOA) measurements. Then, mathematical models are applied on these parameters to determine the location of the user [6]. Since all the characteristics of signal propagation are difficult to be considered within the same model, the propagation models usually have limited accuracy [2]. This is one of the main reasons why the research work has been more focused on fingerprinting techniques (e.g. [1,10,19]) or the combination of the two [4]. The fingerprinting approach is based on comparing the observed measurements at the unknown location with all known measurements, where the best match is returned as the estimated location.

The use of the IEEE 802.11 wireless infrastructure for localization has garnered significant interest over the past decade, due to the wide deployment and good coverage in urban areas. One of the first projects that employed the RSSI fingerprint technique was RADAR [6]. Both, propagation modeling and fingerprinting have been used and the authors reported 25th and 50th percentile errors of 1.92 m and 2.94 m respectively. In order to determine the mobile user's location, the k-nearest neighbors (kNN) algorithm was applied. Wassi et al. [2] studied the multilayer perceptron, generalized radial neural network and kNN algorithms applied to the signal strengths measurements recorded from three IEEE 802.11b access points in an indoor space. The experiments have been performed in the 75 m long corridor with a width of about 2.5 to 4.5 m; they reported a 2.4 m median error and demonstrated the kNN algorithm to slightly outperform the neural networks. Ferris et al. [1] designed Wi–Fi localization system using Gaussian processes in conjunction with graph-based tracking. They modeled users moving through the rooms on the same floor as well as more complicated patterns of moving such as going up and down stairs. When tested over the 3 km data in the three floor building with 54 rooms the average error was 2.12 m.

In our previous work [9] we presented preliminary results of FM positioning for indoor environments. In this paper we improve positioning results by considering different experimental setups and additional signal processing methods (described in the sections that follow). There are few other works dedicated to FM positioning. The first positioning system based on FM radio was presented by Krumm et al. [20]. It was an outdoors-only positioning system that employed a prototype wristwatch device featuring an FM receiver, to distinguish six districts of Seattle using the signals broadcast from public FM stations. They recognized the correct district in about 80% of cases. More advanced algorithms enabled the system to locate the user with 8 km median accuracy [21]. Recently, Fang et al. [22] presented a comparison of FM and GSM outdoor localization within 20 reference points on an area of about 1 km^2. With 6-channel fingerprints, GSM accuracy was better than that of FM. However, by employing more FM channels they were able to improve FM performance significantly. It can be seen, that the previous works focus on outdoor localization using broadcast FM signals and special

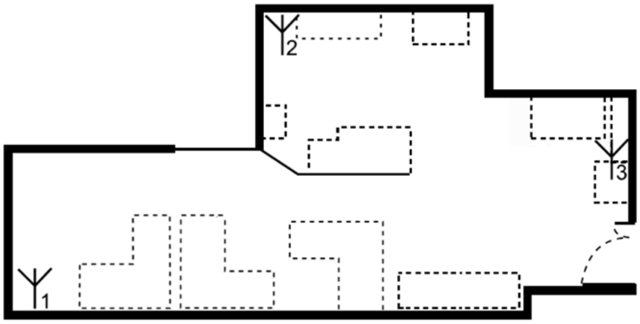

Fig. 1. Experimental layout.

receivers (prototype wristwatch or professional spectrum analyzer). This paper, in contrast, has a focus on indoor positioning with readily available consumer-grade devices.

2.2. Signal degradation

The laborious calibration process presents one of the major drawbacks of localization based on fingerprints. In addition, it is often necessary to update the training set, since the localization performance is prone to degradation due to changing conditions in the environment. To address these problems, some projects employ a variety of sensors that provide the system with updated fingerprints from pre-defined points in the area of interest. Yuan et al. [8] designed a positioning system based on IEEE802.11e that uses location sensors based on RFID, which provide the system with reference tags of known locations. Upon request, the sensors transmit their ID to the access point and the RSSIs from these locations are stored. Another approach was proposed by Oceana et al. [5], who used a robot capable of autonomously collecting Wi–Fi signal strength measurements in different locations. In addition, they proposed a number of strategies to reduce the calibration effort by optimizing the number of collected training samples, thus decreasing the time spent on calibration.

Our localization system, based on FM radio addresses the shortcomings of existing research work. In comparison to Wi–Fi, a FM positioning system is cheaper and consumes less energy on both, the mobile device and the stationary points. FM localization components are widely available off-the-shelf and in addition, FM can be used in environments where other signals, such as Wi–Fi or GSM are prohibited. In order to alleviate the recalibration effort, in response to signal degradation, we employ the concept of *spontaneous recalibration* to keep the fingerprinting set always updated, using no additional hardware. To the best of our knowledge, there are no other projects that employ either FM radio for indoor positioning or the concept of spontaneous recalibration.

2.3. Theoretical comparison of FM and Wi–Fi radio waves

There are intrinsic differences between FM and Wi–Fi, defined by the physical laws of wave propagation. From radio physics, it is known that the propagation of a radio wave in an environment with obstacles (such as indoors) depends on the relation between wave length λ and obstacle size α [23, p. 7]. When $\lambda \ll \alpha$, wave propagation can be approximated by geometric optics. In contrast, comparable values of λ and α represent a complicated case, where diffraction processes play a significant role and one must take into account the shapes of the obstacles. Finally, when $\lambda \gg \alpha$, the wave is scattered according to Rayleigh's law, and the shapes of the obstacles are insignificant.

The FM radio band spans from 88 to 108 MHz (76 to 90 MHz in Japan), while Wi–Fi operates at 2.4/5 GHz. These frequencies correspond to wavelengths of about 3 m and 0.12/0.06 m, respectively. Thus, in typical home/office settings FM radio waves will be diffracted on a few large obstacles, such as walls and furniture, and scattered by smaller objects. In turn, relatively short Wi–Fi waves will undergo diffraction on most objects in the environment. As mentioned above, the shape and positions of the obstacles are important for diffraction and insignificant for Rayleigh scattering. Thus, the propagation of FM radio waves in an indoor environment is determined by a few large stationary objects and thus is more stable and predictable than the distribution of Wi–Fi waves which is defined by many small objects.

3. Experimental setting and positioning approach

3.1. Experimental setup

The testbed room dimensions are 12×6 m; its shape, the locations of the access points and the furniture setting are shown in Fig. 1 and it is located in our Lab in [24]. Three short-range FM transmitters (König) and three collocated Wi–Fi stations (Cisco) shown in Fig. 2 serve as localization beacons.

Fig. 2. FM transmitter and Wi–Fi access points.

Table 1
FM and Wi–Fi RSSI.

Original FM RSSI	6-level FM RSSI	Wi–Fi RSSI
40–45	−50	Excellent
30–39	−60	Very good
20–29	−70	Good
10–19	−80	Low
1–9	−90	Very low
0	0	No signal

For localization data acquisition we used an HTC Artemis smartphone which features embedded FM receiver and a Wi–Fi module. The software has been written in C# using. NET Compact Framework. The FM tuner is controlled through a custom, low-level library written in C++, while Wi–Fi RSSI values are provided by OpenNetCF SDF library [25]. A standard HTC headset has been used to serve as a FM antenna.

The mobile device used in our experiments reports Wi–Fi signal strength through 6 different levels, due to the firmware design. On the other hand, the FM RSSI is represented with 45 levels. In order to ensure a fair comparison of these technologies, we reduced the precision of the acquired FM RSSI samples to 6 levels as shown in Table 1. Note that this conversion has an adverse effect on FM positioning accuracy and has been applied only for comparison with Wi–Fi.

While FM transmitters are distinguished by their frequency, different Wi–Fi access points are recognized by their MAC address. We assumed independence of RSSI received from different access points since the interference does not have an important influence on the system [10].

Besides FM RSSI, we also explored if FM stereo channel separation could be used for localization. The stereo FM signals are known to be more sensitive to noise than mono transmission. The frequency band from 0 to 15 kHz encodes the sum of left and right channels ($L + R$) to ensure compatibility with mono receivers, while the band from 23 to 53 kHz contains a differential signal ($L - R$). At the receiver side the differential signal is decoded using the pilot tone of 19 kHz [26], and any distortions of the latter result in a lower channel separation, so the signal transmitted for the left channel can be heard in the right one and vice versa.

Due to these properties of FM, we expected a gradual increase of channel cross-talk as the noise increases as a consequence of increased distance. However, in our experiments we did not observe a gradual decrease of the channel separation level; instead, the FM receiver automatically switched to mono mode as soon as the noise level reached a certain threshold. This can be explained by the fact that most of the current FM receivers have special circuitry that tries to maintain the best signal quality. This is done by automatically switching the reception from stereo to mono mode that is more robust to noise [27,28]. Due to these results, only the RSSI level has been used in the FM-related experiments that follow. It should be noted, however, that a gradual decrease of channel separation may still be observable by other receivers, which have a programmable mono to stereo switching threshold.

3.2. *Classification and regression for positioning systems*

Whether the target is continuous or discrete, the problem of learning can be classified as regression or classification respectively. In the case of localization, one may require a mapping from the observed RSSI either to one of locations, predefined by the training process (discrete target), or to one of locations from the infinite set that contains all possible positions in the space (continuous target). Hence, localization can be considered both as a classification and a regression problem, thus providing strong motivation to compare both techniques.

We chose k-nearest neighbors (kNN) classification and Gaussian Process (GP) regression because kNN is a simple yet powerful method, widely used in fingerprinting-based localization systems (e.g. [2,3]), while GP regression provided interesting results in a number of applications [1,29]. Ferris et al. [1] specifically emphasize GP regression method for the localization based on signal strength because of the following properties: (i) GP does not require a discrete representation of an environment, (ii) as a non-parametric approach it is suitable for approximation of a very wide range of non-linear functions, (iii) GP provides uncertainty estimates for predictions at any set of locations and (iv) the parameters of GP can be learned from training data via well-known algorithms. Therefore the results that follow will reflect the performance of the localization system using kNN and GP. However, initially we provide a short description of each technique.

3.2.1. K-nearest neighbors

K-nearest neighbor (kNN) is one of the simplest classification methods. Given a test point to label, the algorithm evaluates the distances from this item to already labeled points, and selects k nearest ones. From these k labels, the most frequent one is returned as the classification result [30]. The algorithm works with any suitable distance measure; in our experiments we used the Euclidean distance:

$$d(x, y) = \sqrt{\sum_i (x_i - y_i)^2}.$$

The method has one parameter — k, the number of considered neighbors. The optimal value of k is task-specific. In our experiments, the optimal $k = 1$ was found by leave-one-out cross-validation. Although low values of k make the classifier more sensitive to eventual outliers, in our experiments $k = 1$ resulted in a minimal positioning error.

3.2.2. Gaussian processes regression

GP regression is non-parametric machine learning technique for probabilistic modeling [31].

We consider output values (coordinates in our case) as $y_i = f(x) + \varepsilon$, where x are input values (RSSI), ε is Gaussian noise with zero mean and variance σ_n^2, since we do not have access to function values but only to noisy observations. These observed outputs are jointly Gaussian:

$$y \sim N(0, K + \sigma_n^2 I) \tag{1}$$

where K is the matrix of covariance functions. The covariance function or kernel reflects the underlying idea of GP that the function values at different points are correlated. There are many different covariance functions and we chose the most commonly used, the squared exponential:

$$k(x_p, x_q) = \sigma_f^2 \exp\left(-\frac{1}{2l^2}|x_p - x_q|^2\right) \tag{2}$$

where l is the length-scale, σ_f^2 is signal variance. The free parameters l, σ_f^2 and σ_n^2 are called hyper-parameters and have a strong influence on the smoothness of the estimated functions [31].

Taking into account training data X, y one can write the joint distribution of the target values y and the function values f_* for a new input vector x_* as:

$$\begin{bmatrix} y \\ f_* \end{bmatrix} \sim N\left(0, \begin{bmatrix} K(X, X) + \sigma_n^2 I & k(X, x_*) \\ k(x_*, X) & k(x_*, x_*) \end{bmatrix}\right). \tag{3}$$

The optimization of hyper-parameters is performed by the algorithm which is based on maximizing the log likelihood [31]. The learned parameters are not identical to the ones that would completely correspond to the process because we can get only limited information about the process from a training set [32]. Hence, an increase of the number of training points would improve the hyper-parameter estimation [32]. We found that for the training set with a grid of 1 m the improvement of the system's accuracy was possible by further adjusting the parameters manually, that is changing them by hand until they yield improvement in the result. This was less likely when the extensive data set with the grid of 0.5 m was used, which indicates that the more information about the process is available, the more accurate automatic hyper-parameter estimation will be.

3.3. Experimental procedure

Both, Wi–Fi and FM signal measurements were carried out on each accessible point in the room (see Fig. 1), initially following a grid of 1 and then switching to 0.5 m step for the second data acquisition set. Since not all points were accessible in the room, these data sets contain 40 and 140 points respectively. The person, who was performing the experiment, was always facing the same direction. However, in Section 8 we discuss the accuracy of location estimation when four directions are considered; that is, the person performing the experiment was facing North, South, East and West.

The system's accuracy was tested using all the 100 signal samples per point initially; then, we repeated the same procedure for only 20 samples per point. The comparison yielded no notable degradation, thus leading us to the conclusion

Table 2
Reference comparison of localization systems.

Project	RADAR [6]	Wassi et al. [2]	Ferris et al. [1]	Chan et al. [7]	Our system
Error calculation method	CDF (50%)	CDF (50%)	Average error	Trajectory estimation error	CDF (50%)
Data analysis method	kNN	MLP, GRNN, kNN	GP	kNN	GP, kNN
Error in meters	2.94	2.4	2.12	1.1	0.93

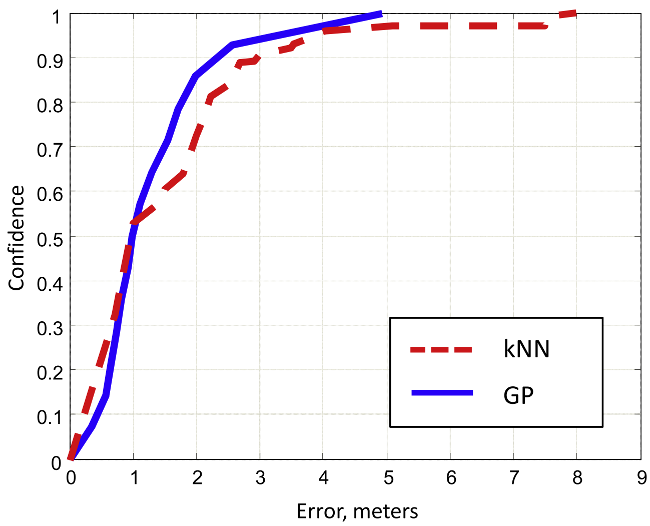

Fig. 3. The accuracy of the FM localization system using kNN and Gaussian processes.

that both FM and Wi–Fi signals exhibit a relatively stable behavior and 20 signal samples sufficed without performance degradation.

We estimated the localization accuracy through tests based on leave-one-out method of sequentially selecting one point from the dataset as a test point while excluding the rest of the measurements that correspond to this point from the training set. We then repeated this procedure for the entire set and we calculated the errors as a Euclidean distance between the location estimation and the ground truth. The cumulative distribution function (CDF) of the error is plotted and used as an indicator of the system's performance.

4. FM positioning system accuracy

In this section we demonstrate the overall accuracy of our FM localization system. In order to test the performance accuracy we initially considered different sizes of a grid in the training set. Wassi et al. [2] showed that using smaller grid spacing, that is more points in the training set, improves the performance. However, after a certain threshold the accuracy starts to level off or even degrade [2]. In our experiments we tested the grid size of 1 m and 0.5 m (40 and 140 training points respectively) and found the latter to provide a median error 30 cm lower.

As mentioned before, the number of training points directly affects the accuracy of the algorithm for inferring GP regression hyper-parameters. When the grid of 0.5 m has been used, maximizing the log likelihood resulted in a more accurate estimation of the parameters than in the case of using the grid of 1 m. The manual adjustment of parameters did not improve the performance anymore.

Lastly, applying pre-processing based on relations between signal strengths on the input data also improves the accuracy of the system, especially when the test is performed a certain period of time after training (described later in Fig. 6). We will discuss this in more detail in Section 7.

Fig. 3 shows the cumulative distribution function of the distance error when kNN and GP methods are applied, using the training set with a grid of 0.5 m, pre-processed only for GP. The median estimation error (50th percentile) of the system is 0.97 m for GP and 0.93 m for kNN while 95th percentile error is 2.65 m for GP and 3.88 m for kNN. These correspond to 8%, 7%, 22% and 32% of the largest dimension of the testbed (12 m).

In general, it is difficult to compare different indoor positioning systems considering the fact that the performance is dependent on the physical parameters including size, furniture, layout of walls and partitions and beacon positions. However, with these issues in mind, Table 2 provides a reference overview of the accuracy of different indoor positioning systems.

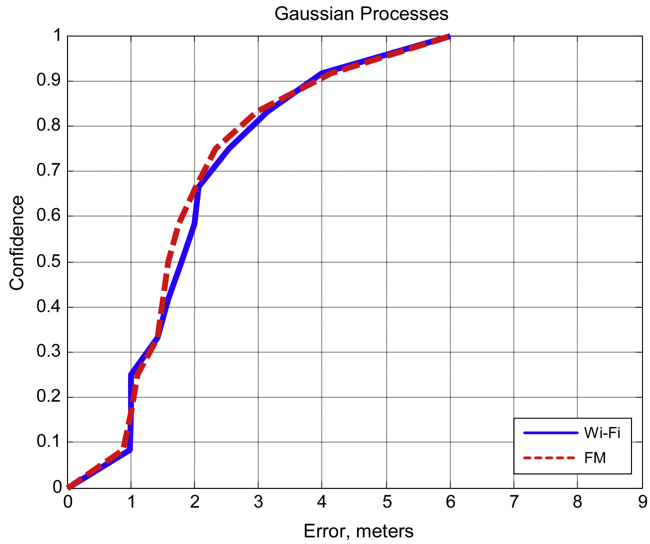

Fig. 4. FM vs. Wi–Fi localization systems.

In order to understand how FM performance relates to other techniques, and to ensure a fair comparison, we have performed another set of experiments, thus evaluating FM and Wi–Fi positioning systems simultaneously using the same testbed.

5. Performance results of FM versus Wi–Fi positioning

As previously discussed, Wi–Fi localization systems have gained in popularity because of cost-effectiveness, especially when utilizing an existing infrastructure. Our work is in a similar line with numerous projects that exploit Wi–Fi technology for the purpose of localization with certain differences, mainly in using a FM radio signal for the fingerprinting method. Hence, we chose a Wi–Fi localization system to compare FM with.

On Fig. 4 we juxtaposed cumulative distribution functions of error for Wi–Fi and FM positioning systems, by applying two machine learning algorithms, namely kNN and GP. As it has been mentioned above, our test device reported Wi–Fi RSSI in coarse-grained manner due to firmware limitations. To ensure fair comparison of the two methods, we mapped the FM signal strength to a scale similar to Wi–Fi (see Table 1). Under these conditions, Wi–Fi and FM systems demonstrate very similar performance (Fig. 4).

From the comparison of the two graphs, one can note that a classification approach provides slightly better median accuracy, but it is more prone to distant outliers, which increases the error for high confidence levels. Regression, in contrast, is more suitable for applications that require high reliability of position information. Also, it should be noted that the nature of the classification method makes it impossible for kNN to provide any estimation with an error smaller than the dimension of grid used (in this experiment it was 1 m) while this is not the case for GP regression.

5.1. Advantages of FM

Considering the applications that are intended for usage in homes, hospitals or other environments, where a Wi–Fi infrastructure with multiple access points is not expected to be already available, the FM positioning system has a number of advantages. First, FM transmitters are cheaper while also widely available off-the-shelf. Second, FM is much more energy efficient; on average Wi–Fi consumes around 300 mW, while FM receivers consume around 15 mW [33,34]. Finally, a Wi–Fi signal belongs to a radio frequency range of 2.4/5 GHz that is shared with many other electronic devices (e.g. cordless phones [35], microwave ovens [36]) which makes Wi–Fi more prone to interference than FM, in addition to the fact that in sensitive environments, Wi–Fi transmissions are prohibited, which is not the case for FM radio.

Therefore, since the results show that FM localization system performs comparably to Wi–Fi, it is reasonable to use FM in cases when a Wi–Fi infrastructure is not available or not allowed. FM makes an especially compelling case for home use, where a single Wi–Fi router is not sufficient for localization.

6. Performance results of combined FM + Wi–Fi positioning system

Previous work on positioning methods has demonstrated that the systems performing a fusion of different localization technologies usually have better accuracy than any of these technologies in isolation [37]. In this section we present the performance results of a combined FM + Wi–Fi positioning system.

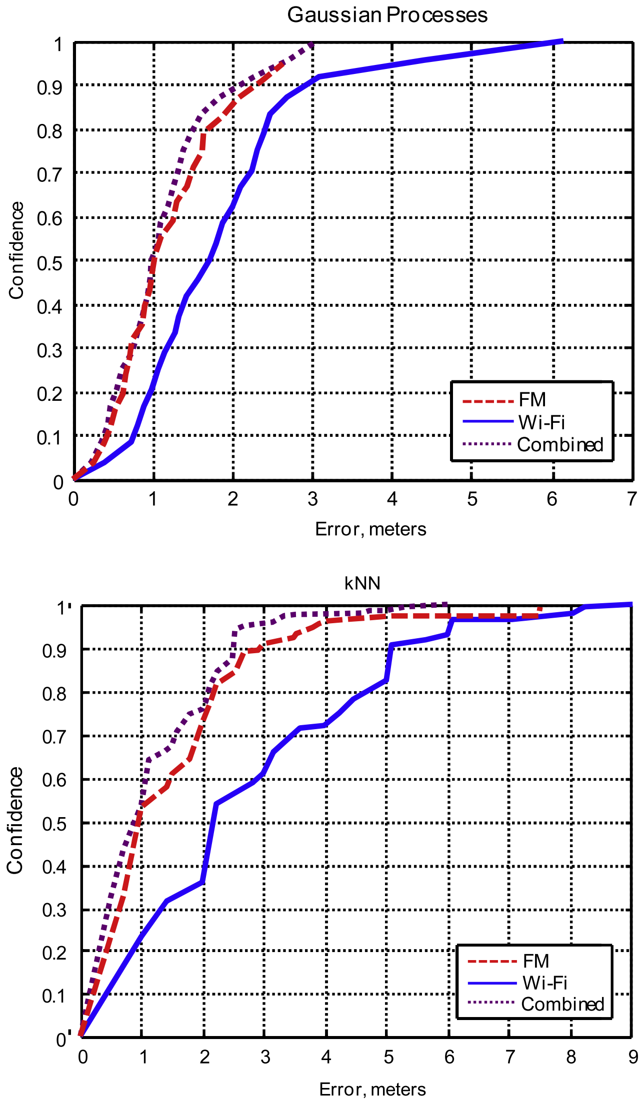

Fig. 5. Combined FM + Wi–Fi localization system.

The data fusion has been done by combining FM and Wi–Fi fingerprints into wider FM+Wi–Fi fingerprints. Despite the simplicity of such a data fusion approach, it has been previously demonstrated to improve the performance of a positioning system [38,28]. In our experiment, each wide fingerprint included 6 RSSI values, 3 for FM and 3 for Wi–Fi. FM data were of full precision, without conversion to 6-level values.

The positioning accuracy of the combined FM+Wi–Fi system is presented in Fig. 5. As it can be seen, for both processing methods the combined system outperforms each of the underlying technologies alone. While for GP the difference is minor, in the case of kNN even low-precision Wi–Fi fingerprints can significantly improve the positioning accuracy of the pure-FM approach. Fusion of FM and Wi–Fi positioning technologies improves the positioning accuracy by up to 22% (0.85 m at 95th percentile for kNN).

Combining Wi–Fi and FM positioning systems also has a number of other advantages. In the environments with existing Wi–Fi infrastructure, the positioning accuracy can be improved by installing additional FM transmitters, which are more cost-effective than Wi–Fi access points. FM can also be employed to provide positioning in areas not well covered by Wi–Fi (e.g. passages and hallways). In sensitive or mixed environments, devices can transparently switch between WiFi + FM, Wi–Fi-only (when no FM available), and FM-only positioning (where Wi–Fi is banned or non-existent). Finally, switching between precise Wi–Fi + FM positioning and power-effective FM technology enables smart power management and enhances battery life, due to FM's lower power requirements.

Given that many mobile devices today come already with an embedded FM receiver, the users can benefit from better positioning accuracy and coverage without any hardware changes.

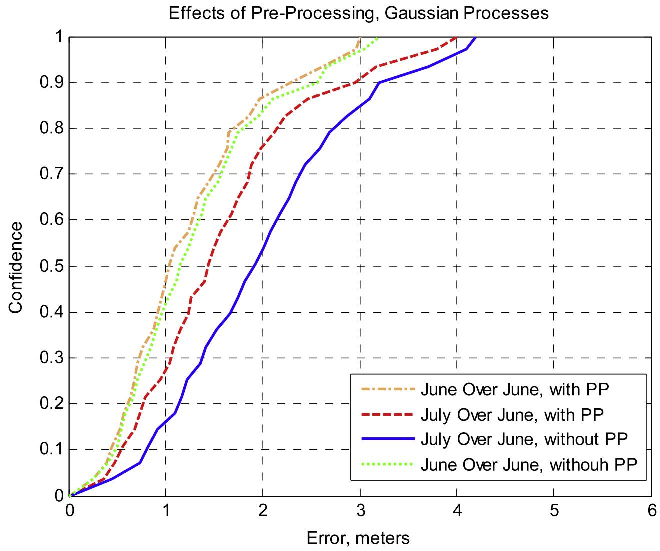

Fig. 6. Effects of the pre-processing algorithm on the system's accuracy.

7. Spontaneous recalibration

In general, radio signal propagation suffers from a number of factors in an indoor environment that can cause signal fluctuation and subsequently localization accuracy degradation [11]. Any change of the electromagnetic field in the area of interest will cause changes in the fingerprint map thus degrading localization performance. We performed the train and test procedure several times during the period of seven months, from December 2008 till July 2009. Unexpectedly, the test that was performed in July using the set of fingerprints measured in June showed more degradation in comparison to the tests in June and July using the training set acquired in December. Such results point to a conclusion that fluctuations in the electromagnetic field that affect fingerprints, are derived from a random processes influenced by numerous factors that are difficult to predict.

Undoubtedly, the best way for tackling degradation is to repeat the calibration for all points; that is, taking a whole new set of signal measurements. However, a huge disadvantage of this approach is that it is a labor-intensive process that requires expert knowledge and cannot be carried out often, without incurring high maintenance costs. To address this issue, a number of projects relies on additional hardware (e.g. RFID or dedicated robot) [8,5,39] to obtain new measurements from well known points. However, this adds additional cost and maintenance overhead. The approach that we have adopted does not rely on any additional hardware.

7.1. Lessening the causes of degradation

The first step of our approach to address performance degradation is to lessen the causes of degradation through pre-processing the input data. Assuming that all FM transmitters follow the same pattern of signal change over time, we processed data of perceived signal strengths of each of three FM transmitters that constitute the input matrix in the following way: first we constructed a new matrix by subtracting the columns ($ss1$-$ss2$, $ss1$-$ss3$, $ss2$-$ss3$) that refer to the signal strength difference of each FM transmitter. Then, we divide each column by its maximum value and finally center the values in each of the columns around zero, by subtracting their mean values. The idea is to mitigate the change of signal strengths over time and to make new inputs less dependent on their absolute values. Such a pre-processing algorithm has even further degraded the system's performance in the case of using kNN. However, with Gaussian Processes regression, pre-processing had a positive effect even when the system was trained and tested with the same set (Fig. 6). Applying GP regression on pre-processed data proved our initial assumption that all transmitters generally follow the same pattern of change or exhibit same degradation levels and our method of pre-preprocessing prevented the system from degradation to a certain extent. As a result, we got an improvement in the median error from 2 to 1.45 m (Fig. 6).

7.2. Spontaneous recalibration approach

The second step of our approach, the *spontaneous recalibration*, is based on having pre-defined locations in the environment where the position of the mobile unit is known automatically and fingerprints can be acquired without having any additional hardware intended for that purpose as it is the case with other systems. These known locations are mobile phone cradle, wall charger, night stand and other locations where a mobile phone typically remains stationary. The advantage of

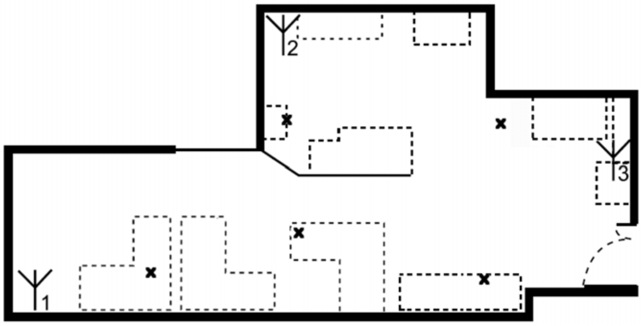

Fig. 7. Positions of the points used for spontaneous recalibration.

our approach is that these known locations can be easily identified (for example, when an event is produced by the mobile phone once the charger is plugged in). As such, our system exploits these well-known locations in order to counter the accuracy degradation by adjusting the corresponding points in the training set. Each time an event occurs, such as mobile phone placed on the charger, the localization system receives the known signal's fingerprint at that location and compares it with the fingerprint it currently has. If they are different, the current signal's fingerprint will be updated with the received fingerprint. In our experiment we have defined *five* such points (Fig. 7), and these five points were sufficient for the recalibration process.

Only with minor constrains of having fixed locations for charger, cradle or computer and placing the phone during the night, the training set gets updated efficiently, without increasing the cost or complexity of the system. Once the point is updated, the change is applied to adjacent points accordingly; by applying the following propagation model [4,6,7]:

$$P(d)[\mathrm{d}Bm] = P(d_o)[\mathrm{d}Bm] - 10n\log\left(\frac{d}{d_0}\right)[\mathrm{d}Bm] - X[\mathrm{d}Bm] \tag{4}$$

where n is the path loss exponent, $P(d_o)$ is the signal power at the reference distance d_o and d is the distance from the unknown point to the transmitter. X is a component which reflects the sum of losses induced by each wall between the transmitter and receiver.

Solely propagation models are rarely used for localization because of the existence of multipath signal propagation and other phenomena that are difficult to predict [2]. However, our approach of applying the propagation model only on the points closest to the reference point (neighboring points) in a training set is more likely to result in good estimations because of lack of obstacles between these points that affect signal propagation. We have found empirically from the initial training set that the best suited value for the coefficient n is 2 (see (4)), while for X is zero (there are no walls between adjacent points). For each spontaneously calibrated point we have adjusted eight neighbor points, by applying the propagation model. Therefore, 45 points in total were adjusted (5 directly calibrated from well known locations, plus 5×8 updated due to being neighboring points).

Adjustment of these points resulted in the improvement of the median error from 1.45 to 1.2 m (Fig. 8(a)). To evaluate the spontaneous recalibration approach, we compared the achieved result with the performance when the test and train procedures are performed on the same set with the leave-one-out method (Fig. 8(b) — "July Over July") which corresponds to the situation where all the points are calibrated again. Results depicted in Fig. 8(b) show very similar performance of the two (only 12 cm difference in the median error). This means that using only 5 known points that can be easily recognized in an environment (5 reference points in our case, out of 140 points) the system can be calibrated often with no effort from the user's side and no additional hardware for recalibration. These results show that we achieved the result close the same localization accuracy as if all points were updated.

The effect of the number of known points used for recalibration, on the system's accuracy is shown on Fig. 9. We selected one point randomly 100 times, applied the described procedure for recalibration and calculated the 50th and 95th percentile errors. We repeated the same with two, three, four and five points and compared the results using a box-and-whisker diagram (Fig. 9). In the diagram, thick horizontal lines correspond to median values, bottom and top of each box correspond to the first and third quartiles of distribution, and the whiskers extend up to 1.5 times the interquartile range (IQR). Small circles represent outliers.

It can be seen that as the number of reference points increases, so does the variance of the positioning error of recalibrated system. This demonstrates that specific sets of reference positions are more effective than the others, and by carefully selecting the reference points one can significantly reduce the negative effect of accuracy degradation. The graphs also show that the accuracy of recalibrated system generally improves as the number of reference points grows. Therefore, the accuracy gain can be further increased by carefully selecting the reference locations, however in our setup we were constrained by the physical location of the known points.

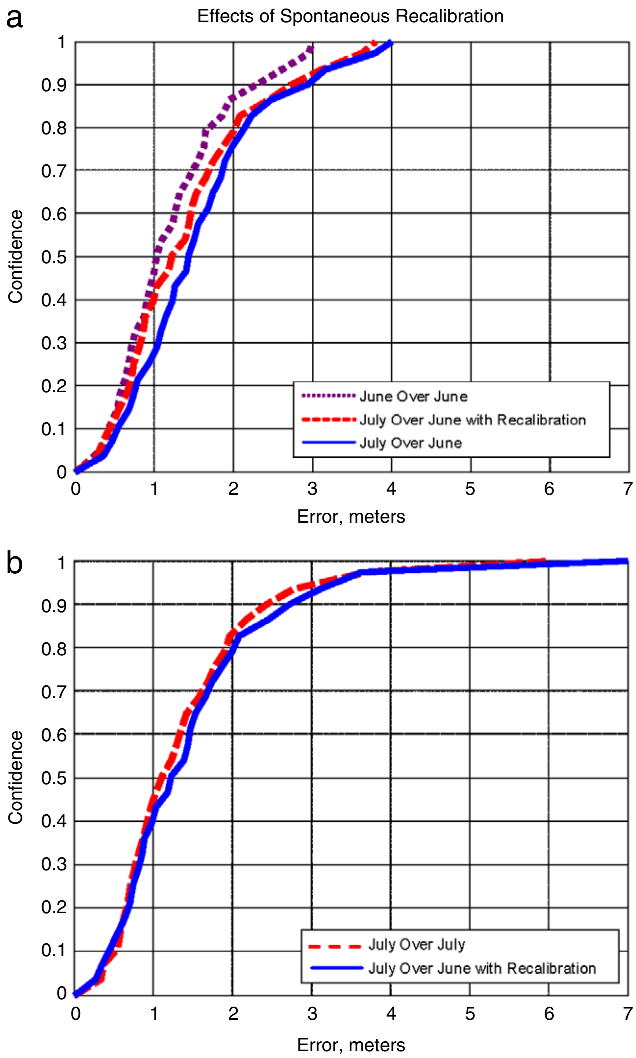

Fig. 8. Effects of the spontaneous recalibration.

8. The impact of orientation on FM radio localization system

The orientation of a user has a significant impact on the observed signal strength and consequently on the localization accuracy. The reasons lie in the direction of mobile unit's antenna, reflections of the radio signals and the fact that components of the mobile unit can partly shield signals from certain directions [40]. A considerable factor for instability of signal strengths with respect to the orientation is the human body that is 70% composed of water [6]. Given that water absorbs radio signals, changing the direction of mobile device will result in the change of received signal strengths, even if the position remains fixed. RADAR project [6] investigated the case in which the training set points are acquired while facing a single direction, while the test samples corresponded to the other three directions. Their results showed significant degradation in the accuracy of prediction of position, where the degradation was up to 67%.

In this section we examine the following: (i) the accuracy of our FM positioning system considering the orientation, and (ii) if changes in signal strengths due to orientation change can provide means of detecting user's orientation, similarly to the manner in which the location is estimated.

8.1. Localization accuracy using different orientations

As we discussed above, the user's orientation while measuring the signal strength can significantly affect the fingerprinting map. Therefore, having a training set that contains only one orientation would affect the real life application accuracy. In order to overcome this problem we considered two possible solutions. The first solution consists of having four different training sets (for each orientation). To estimate the user's location one of these sets would be used depending on the user's

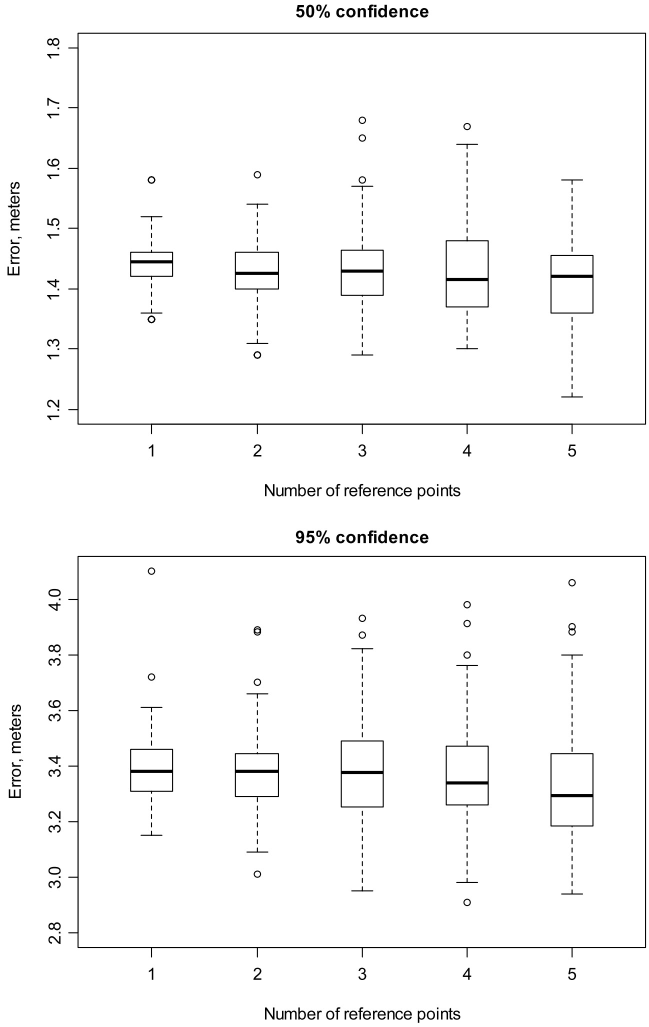

Fig. 9. The number of recalibrated points and the system's accuracy at 50% and 95% confidence levels.

orientation at any given time. The current orientation would be detected using an additional sensor, such as a compass. The second solution is based on using one extensive training set that is composed of signal strengths from the three FM beacons for all four orientations in each physical point. We tested these two approaches to verify whether having an additional sensor for orientation is an acceptable trade-off, concerning accuracy.

Following a grid of 1 m we performed measurements in 40 physically accessible points in our Lab (Fig. 1). In each point 20 samples are taken for all four directions i.e. facing North, South, East and West. This resulted in four training sets, one for each direction. The first approach assumes that the orientation is given, so to estimate the user's position one of the four training sets is used accordingly. We tested the accuracy for each orientation, applying leave-one-out method on four training data sets separately (North, South, East and West graphs on Fig. 10). Note that the mobile device may be oriented in between of two orientations, such as between North and West for example. In this case, the closest of the four orientations is taken as the actual user's orientation and the corresponding training set is used. This means that 45° is the maximal error, which we found does not significantly affect the change of signal strengths. In order to compare this approach with the second approach, we performed the leave-one-out test on the set that is composed of previously used four data sets containing North, South, East and West orientations, merged In each physical point leave-one-out method is performed with all samples (for all four orientations) while leaving out from the training set all measurements that belong to the current physical point. The results are presented on Fig. 10, applying both Gaussian Processes (a) and kNN (b).

From the obtained results it can be seen that one extensive training set containing measurements for all four orientations provides similar localization accuracy as in the case when the user's orientation is fixed and the corresponding training set is used. For example, the graphs show that localization accuracy of using the merged training set with four orientations is very similar to the result of fixed orientation training sets North and West for GP and West and East for kNN (Fig. 10).

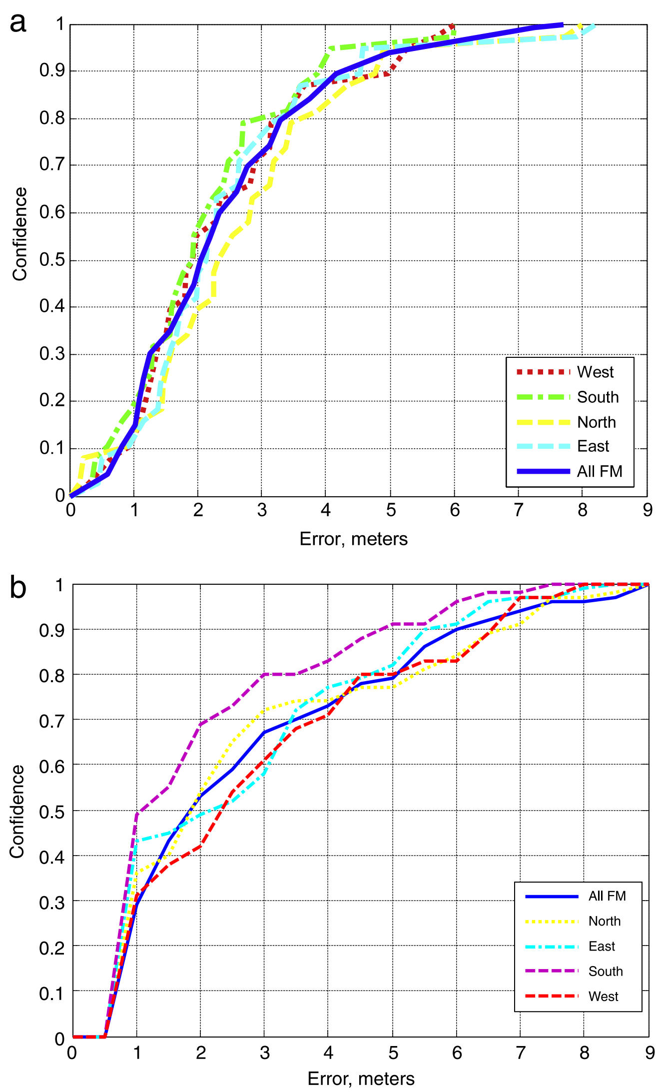

Fig. 10. System's accuracy depending on orientation.

Intuitively, having different signal strength fingerprints associated to one physical point (four in our case, for each orientation) would result in decreased localization accuracy, since there is a higher probability of having similar fingerprints in two or more physical points (for example, facing North in one point has an indistinguishable signal strength fingerprint with facing West in another point). However, despite this the accuracy degradation for our localization system is very small when all the directions are considered. This may be due to insignificantly small influence of human body on the propagation of radio waves in the FM band (88–108 MHz). Our results have shown that impact of orientation of the user on the localization accuracy is minimal when using the training set that includes measurements for four basic orientations, thus providing a good basis for a real-time localization system.

8.2. Detection of user's orientation

Considering that signal strengths received from emitters change in accordance to user's orientation prompted our investigation into the possibility of estimating the orientation. To investigate whether the correlation between signal strengths and orientation is sufficient to estimate user's direction, we used two data sets acquired by two different people. Out of these data sets, one was used as the training set and the other as the test set. Both data sets are composed of measurements in 40 physical points following a grid of 1 m, including four orientations. As with our previous measurements, we applied both kNN and Gaussian Processes regression algorithms. For kNN classification there were four classes, one for each direction, while for GP regression we annotated different orientations with angles (0° for North, 90° for East, 180° for

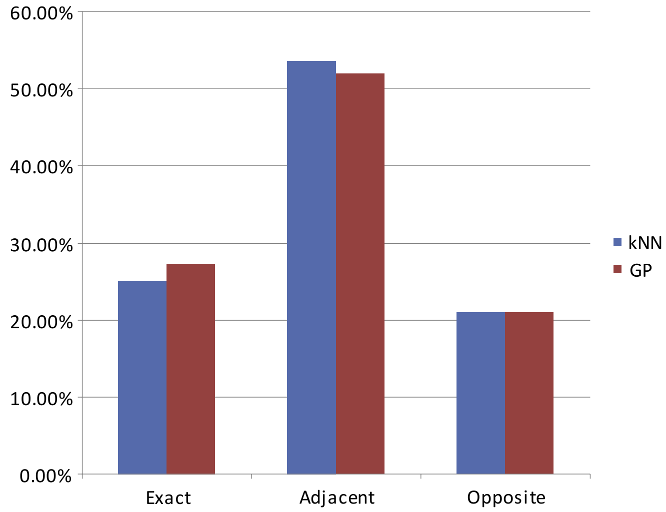

Fig. 11. Orientation detection results.

South and 270° for West). Estimated angle can belong to one of the ranges $0° \pm 45°$, $90° \pm 45°$, $180° \pm 45°$ or $270° \pm 45°$, which is subsequently classified to one of the four orientations, North, East, South and West respectively.

The obtained results are shown in Fig. 11. In reference to the figure, *Exact* describes the results when the estimated orientation matches the ground truth; *Adjacent,* the estimated and real orientation are adjacent (North is estimated, however the user is facing West); *Opposite*, the estimated and real orientation have opposite directions. It can be seen that the results are the same as random orientation prediction; around 25% for the accurate estimation, around 50% for one of two adjacent orientations and almost 25% for the opposite directions. Therefore, the correlation between signal strengths and orientations was not proved to be enough for detection of orientation in our experiments.

9. Conclusion

We presented a FM indoor positioning system that is cheap, energy-efficient and convenient for installation in various environments. When tested in the same setting, the system provided very similar performance to Wi–Fi localization system. In the space with the size of 50 m^2, we achieved the median error of only 0.93 m which is significant accuracy for systems based on the fingerprinting method. Also, we demonstrated that an already existing Wi–Fi localization system can benefit in increased accuracy by combining it with the cost-effective FM radio system.

In addition, we described the concept and the results pertaining to spontaneous recalibration that prevents the degradation of localization accuracy, which occurs due to changing conditions in electromagnetic field. The main advantage of such design lies primarily in the fact that specific equipment does not need to be added for achieving continuous adjustment of training set in response to accuracy degradation. We demonstrated that the degradation can be also prevented to the certain extent by applying pre-processing algorithms on the input data. Our experiments also showed that taking into account different orientations, has a minimal impact on the localization accuracy. However, in our experimental setup we have not found a sufficient correlation between the signal strength and device orientation to reliably estimate user's orientation.

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