Analysis of RF-based Indoor Localization with Multiple Channels and Signal Strengths

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Abstract. In this paper, the influence and improvement of the localization accuracy achieved using a fingerprint database with information coming from different channels and radio signal strength levels is evaluated. This study uses IEEE 802.15.4 networks with different power levels and carrier frequency channels in the 2.4 GHz band. Experimental results show that selecting part of this information with a cleverer data processing can provide similar or better localization accuracy than using the whole database.

Keywords: Indoor location · Fingerprinting · IEEE 802.15.4

1 Introduction

The location information promises attractive services on future applications where determining the location of a target in a given environment triggers a set of actions related to it. For outdoor environments, Global Positioning System (GPS), complemented with the use of Cell-ID for cell phones, provides a precise location system for applications of mobile devices around the world. Neither of these technologies can be used in the case of indoor environments (there is not a GPS for indoors). In this case, radio frequency (RF) technologies as Wi–Fi and cellular signals, and RF signals from Wireless Sensor Networks (WSN) like ZigBee can be used for location and tracking purposes.

In outdoor applications, several analytic location systems can be used to calculate the distance between every beacon and the transmitter using the original signal strength and the propagation coefficient in the medium. However, in indoor environments the behavior of the RSSI (Received Signal Strength Indicator) can be harshly altered by the interactions with other electromagnetic waves and the obstacles around. To improve the analytic methods accuracy, fingerprinting techniques are used [2,8]. These methods start measuring the signal strengths in the

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chosen indoor area to create a database that will be used in the location phase to estimate the transmitter's real position. The main drawback of these methods is the time and effort needed to build the database. Additionally, the computing processes involved in the location need a large amount of memory and computational resources to carry out the location in real time.

This paper analyzes the information provided by network beacons using different channels and power levels, and how it can be taken into account to improve the location method. In the next section, some existing RF location and tracking techniques proposed until now for indoor applications are described. Section 3 describes the base RF location methodology using multiple channels and signal strengths. Experimental results showing the advantages of our approach are presented in Sect. 4. Finally, concluding remarks are given in Sect. 5.

2 Related Work

Many RF-based strategies have been proposed in the last decade for indoor location and tracking combining radio signal strength (RSS) and fingerprinting. This methodology is based on a first stage of training or preliminary exploration, in which the signal strength from all the beacons or base stations deployed in the localization scenario is obtained for a set of reference points. In the location stage, a metric to compare the signal strength of the test points with the collected information is applied. Around this idea, improvements to increase the location accuracy based on probabilistic techniques, pattern recognition, spatial filters, different number of beacons, etc. have been introduced.

One of the first approaches using RF signals was RADAR [3], which uses available WLAN based on Wi-Fi, and MoteTrack [4], which uses WSN based on IEEE 802.15.4. Some algorithms estimate the spatial position exploring the received signal strength information [1] improving the results presented in [3]. Statistical estimation methodologies for increasing the location accuracy have also been proposed [6].

The use of only one channel in RF-based location has been the norm in previous works. However, a very large number of carriers (500 channels) have been used in [7] for indoor location based on cellular telephony, where classification data has been carried out using Support Vector Machine techniques. This technique involves long training and higher computational complexity over previous methods, but good quality location results have been obtained. A recent proposal [5] uses the flexibility of current WSN with reconfigurable channels and RSS values to increase the amount of information available per location point in the fingerprint. Thus, by adding more information of channels and signal strengths more accurate locations may be achieved.

3 RF-based Localization Analysis

The location method presented in [5] relies on the flexibility of current WSN devices to configure the frequency channel and the signal strength involved in a packet transmission. Using several transmissions at different frequency channels and signal strengths, the total amount of information that is available during the location estimation is increased. The method consists of two phases: Training and Location estimation.

In the training stage, a mobile node is placed at a set of reference points with coordinates (i, j) forming a grid that covers the location scenario. The mobile node takes RSSI samples exchanging packets with every network beacon (b) at different signal strengths (p) and frequency channels (c). Thereby, at every reference point a vector of $p \times c \times b$ components is conformed and stored in a centralized database. It should be noticed that each component contains two RSSI values taken at the two different elements involved in the packets exchange. One RSSI value is taken at the beacon, after the first packet transmission from the mobile sensor, and a second RSSI sample is acquired at the mobile sensor, when the beacon replies in the opposite direction. In order to avoid sampling errors, 5 five consecutive packets exchanges are performed providing a group of 10 RSSI values (5 RSSI values in each direction) that can be averaged later.

In the location estimation stage, a variation of the K-Nearest Neighbor (KNN) method [5] is applied. This algorithm (named Proposal Method or PM) has better average location accuracy, 2.09 m (meters), for the scenario described in the next section, in comparison with other alternative methods, such as: (a) Location Engine (system integrated in the CC2431 from Texas Instruments), 8.72 m, (b) the standard KNN algorithm, 2.59 m, and (c) a neural network based algorithm [5] implemented using a multilayer feed-forward network, 3 m.

The use of more channels increases the amount of information provided at each reference point. It is supposed that this increase allows more accurate locations, but some information may be redundant or it could even add more noise and degrade the location precision. The spacing of frequency channels used in WSN is small and there should be no significant differences between them. However, some channels can be affected by interferences from other RF waves present in the medium. As a consequence, the RSSI value can be altered and some channels can introduce an undesirable noise in the location process.

On the other hand, several studies show that the location accuarcy for points that are too distant or too close to a beacon depends on the signal strength. Weak signals have problems for distant points due to packet losses, although they provide more information for nearby points. In contrast, strong signals are little discriminant for close points, but they are very useful for distant points. Thus, the combination of different signal strengths can provide more information and increase the accuracy. However, this behavior may vary for different scenarios.

4 Experimental Results

In this section, experimental results using the case study shown in Fig. 1 are presented. The experimental setup includes a Zigbee subsystem implemented using Texas Instruments CC2431 circuits.

The beacons are placed at positions B1, B2, B3, and B4 (see Fig. 1) and the mobile sensor is moved and placed sequentially at each position in the set of

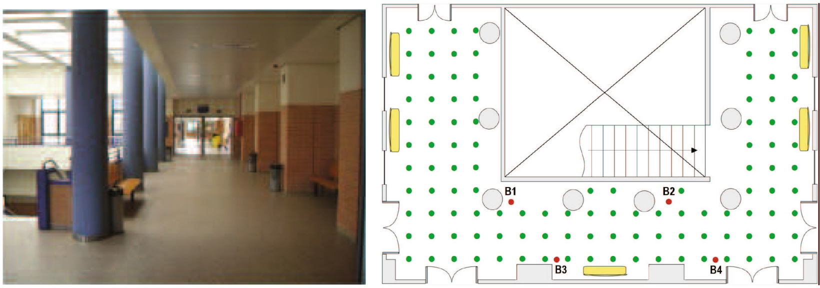

Fig. 1. Photograph and map of the testing scenario.

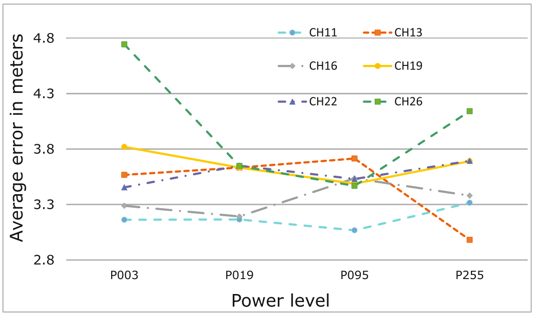

Fig. 2. Location accuracy for every channel and each one of the power levels.

122 reference points (with a distance of one meter between them) marked in Fig. 1. In the training, six channels: CH11, CH13, CH16, CH19, CH22, CH26 (frequencies (MHz): 2405, 2415, 2430, 2445, 2460, and 2480, respectively), and four power levels: P3, P19, P95, P255 (gains (dB): -25.2, -5.7, -0.4, and 0.6, respectively) were chosen. So, at each reference point the mobile sensor exchanges packets with the 4 beacons, using 6 different channels and 4 power levels. Thus, the system takes 192 RSSI samples at each reference point, since it saves the two RSSI values received at both sides (the mobile sensor and the beacon). All the information is saved in a database that contains 111,360 RSSI values.

Next, a study about the location accuracy for different channels and RSSI strengths is presented. Results are obtained using the algorithm from [5]. These results point out which channels and strengths provide better information. The location error at every testing point of the grid in Fig. 1 is calculated comparing the location result with the real testing point position. Figure 2 shows the average error when the location algorithm uses a combination of only one channel and one power level. As it can be noticed, lower channels (e.g., 11 and 16) present a lower average error that is quasi constant independently of the power level. It can be also drawn that power level P3 provides a more stable behavior.

Figure 3 (left) shows the average error for each power level and different combinations of channels. Notice that, as the number of channels increases, the

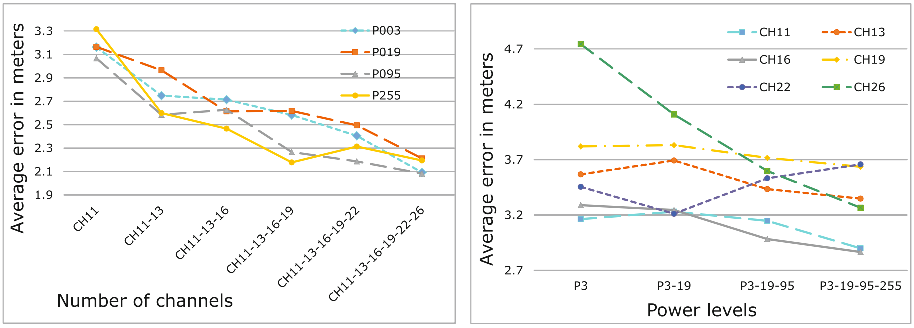

Fig. 3. Location accuracy for: (left) one power and a different number of channels; (right) one channel and an increasing number of power levels.

Table 1. Average localization accuracy for different algorithms.

PM(11)	PM(11,13)	PM(11,13,16)	PM(all)	NM(11,13,16)
3.16	2.75	2.71	2.09	2.05

error decreases. This is because of the number of points in the database to compare is higher and this aggregation decreases the average error. Figure 3 (right) depicts the average error for individual channels when more power levels are combined. Now, the average error usually decreases as the number of power levels is increased, but this effect is less significant than in the case of adding channels.

Thus, it can be concluded that it is not necessary to include all the channels and power levels for improving the location accuracy. Table 1 shows the average error for the algorithm PM considering only power level P3 with three different combinations of channels: (a) CH11, b) CH11-CH13, and (c) CH11-CH13-CH16. These values are compared to PM with all the database, PM(all), and a new variation of the PM algorithm, named NM (New PM), with only channels CH11-CH13-CH16 and the power level P3.

The NM algorithm starts with the 8 candidates that the PM algorithm provides for channels CH11-CH13-CH16. Then, NM applies the following conditions:

- if the first two candidates for CH11 are inside a radium ($r_p \leq 2d$) and the difference with the first candidates of CH13 and CH16 are inside a distance radium ($r_g \leq 2r_p$), the average between the two first candidates is taken.
- if the first three candidates for CH11 are inside a radium ($r_m \leq 1.5r_p$), the average among the three first candidates is taken.
- otherwise, the average of the eight candidates from the three channels is taken. If the average provides a location outside the fingerprint area, the most frequent coordinate among the candidates is taken.

5 Concluding Remarks

In this paper we conclude that, although the use of more channels increases location accuracy, a previous analysis and a clever selection of them can provide a similar location accuracy but with less computational requirements. The use of more power levels has a minor effect in the location accuracy. Additionally, lower levels of signal strength provide more significant information, but this effect may vary for different scenarios. Finally, a selected subset of all the available channels can provide the same or better location accuracy using an improved location algorithm, but this is a subject that requires further studies.

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