Fusion of magnetic and WiFi fingerprints for indoor positioning

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***Abstract*—WiFi received signal strength (RSS) and magnetic field intensity are common measures for indoor localization because they are readily available on most mobile devices. There is a vast literature on smartphone positioning using RSS and it has been widely implemented in real-world scenarios in the last two decades. There is much work done on localization aided by magnetic field measurements. We have recently evaluated the accuracy of RSS-based positioning applying state-of-the-art algorithms to measurements in a well-controlled experimental setup. In this paper, we extend this work to assess the accuracy improvements achievable by fusing WiFi and magnetic field information. We show that accuracy improvements of up to 30% are possible.**

***Index Terms*—Indoor Positioning, Fingerprinting, Magnetic based localization, RSSI based localization.**

I. Introduction

Research on indoor localization has been very popular in the last two decades. Different technologies have been used for positioning purposes (see, e.g., Brena et al. [1]). In this work, we focus on fingerprinting based on WiFi received signal strength (RSS) and magnetic field ($\vec{B}$) measurements. The use of these signals is attractive because they are readily available on most smartphones and it has even been incorporated into some commercial products.

One of the most common positioning methodologies is called fingerprinting, which consists of two phases. In the offline or calibration phase, the indoor environment is surveyed to build a database of *fingerprints* for a number of known locations. Each fingerprint is a collection of measurements of one or more signals (e.g., WiFi RSS). In the online or positioning phase, new measurements at an unknown location are collected and the system estimates the position based on the previously observed fingerprints. Indeed, the use of these signals for localization has already been explored in the literature (see, e.g., [2]–[4] and references therein)

In a previous study [5], we evaluated the accuracy of positioning systems based only on WiFi fingerprints. Although there is a vast literature on the subject, we found it difficult to compare results from different researchers on a fair ground. For this reason, we applied the state-of-the-art positioning algorithms on our own set of measurements taken under a careful experimental setup. One of the main conclusions was that WiFi RSS alone is not sufficient to achieve an accuracy of less than a meter. In this paper, we extend our previous work and incorporate measurements of the magnetic field, evaluating the effect of $\vec{B}$ in the accuracy.

The remaining of the paper is organized as follows. In Section II, we overview some of the related work. In Section III, we describe our experimental setup and in Section IV we present the results. Finally, we close the paper with some conclusions in Section V.

II. Related work

Universality, spatial representativeness, and time invariance are the desirable properties for fingerprinting localization [6]. Compliance of $\vec{B}$ with these properties has been evaluated for instance in Refs. [7], [8]. Likewise, WiFi large deployment and its distance depending propagation [9] makes it a suitable measure for indoor positioning. Indeed, the use of WiFi for positioning has been an active research area for about twenty years (see, e.g., [10]–[12] and references therein).

Subbu et al. [8] analyzed magnetic signatures inside buildings. They found that indoor magnetic measurements are a combination of the Earths magnetic field and the fields from ferromagnetic objects, such as pillars, doors, and elevators. The impact of these structures becomes dominant as the distance to the observation point decreases since magnetic field magnitudes are known to be inversely proportional to the cube of the distance.

In this work, variations of the magnetic field $\vec{B}$ were measured on fixed locations. However, magnetic signatures are commonly taken in an offline stage by a surveyor walking by pre-designed trajectories in which $\vec{B}$ variations are measured at determined time intervals. Later, online tracking is made using tools such as particles filters [6], [13], [14] or extended Kalman filters [15]. In this sense, the fingerprints are signatures of trajectories instead of stationary, fixed-position, measurements. A notable exception to this approach of trajectory signatures is [16]

Xie et al. [17] described different ways of using magnetic field measurements. One possibility is to use the three axis components directly, based on the local mobile devices coordinates. In this case, the training cost increases rapidly and, according to Xie and colleagues, the accuracy reduces as the sample space becomes large. Alternatively, it is possible to estimate phone orientation and transform $\vec{B}$ to the earth coordinate system ($\vec{B}_e$) following [18]. However, this is error-prone because orientation estimation usually contains errors. A third possibility is to use the magnitude of the magnetic field as the observation. $\|\vec{B}\|$ avoids errors due to the rotation and the signature is stable in time. However, the elements in each fingerprint will drop from three to one, reducing the uniqueness of each fingerprint. Finally, Xie et al. propose to extracting the horizontal and vertical components of $\vec{B}$. The gravity sensor on smartphone provides the direction of gravity (i.e., the vertical direction). Although the gravity sensor reading is very precise when the user stands still, noise will be introduced when the user moves, resulting in decreasing of precision or even localization failure.

WiFi fingerprinting has been tested in many scenarios and using different algorithms. Usually, each research group that comes up with a new positioning algorithm creates a new experiment in a new scenario, making it difficult to compare the results of other groups. In order to attack this issue, some researchers have tested several algorithms in a common scenario, e.g. Khalajmerabadi et al. [19] and Grisales et al. [5]. Other efforts that enable a fair comparison of systems are localization competitions like EvAAL-ETRI [3] and Microsoft's IPSN [20]. There are also some standards like ISO/IEC DIS 18305 [21] which try to identify the appropriate metrics and evaluation procedures for localization and tracking systems focusing primarily on indoor environments. We must remark that the focus of this paper is not a general comparison of state-of-the-art positioning systems, but we aim at assessing the highest achievable accuracy.

Torres-Sopreda et al. [3] mention some of the pros and cons of both WiFi RSS and $\vec{B}$ and they highlight that no infrastructure needs to be installed and that good accuracy can be achieved. Pasku et al. [22] mention some of the advantages of the magnetic field over WiFi, for instance localization systems based on the magnetic field are not affected by multipath fading, while Subbu et al. [8] highlight the time stability of the magnetic field fingerprints. Bai et al. [2] analyze how WiFi and $\vec{B}$ propagate in a typical indoor environment while Li et al. [16] found an improvement of 23% of using WiFi power and magnetic field measurements over using only WiFi.

A common approach is to use WiFi RSS to reduce the search space and then use the magnetic field measurements for fine localization [6], [23]. In particular, this refinement led to a 22% improvement over WiFi-only localization in Ref. [23]. However, the authors claim that it is not clear how to determine the size of the search space given by WiFi and this is selected based on experience.

III. Setup and Equipment

Our aim is to assess the a highest achievable accuracy of positioning systems that use WiFi RSS and magnetic field measurements. For this reason, we carefully designed an experiment that, although it is conducted in a realistic environment, it alleviates some of the problems found in real world scenarios. As an example, WiFi fingerprinting can be affected by the presence and movement of people [24], but we reduce this factor at a minimum in our data acquisition stage. Measurements were taken in an large and almost empty room (see Fig. 1) used for motion capture experiments at one of ITBAs buildings. We used a Lenovo Yoga Tablet 2 and developed a simple Android application to handle measurements. The Lenovo tablet was placed on a short stool.

Fig. 1. Experimental setup.

We set up a measurement grid on the floor. A coarse, 1×1 meter measurement grid, was refined with several intermediate points, as shown in Fig. 2. Exactly 20 measurements of WiFi RSS and $\vec{B}$ were taken at each location. In order to get line-of-sight signals, we placed three access points (APs) on the same room, at heights similar to that of the tablet or slightly higher. These APs were based on RaspBerry Pi running a Linux variant. We must note that an analysis of the resulting radiomaps suggested that the antennas on these access points were far from isotropic. Besides the three APs placed inside the room, the tablet recorded information from other APs. A set of nine access points was detected at all measurement locations. These APs transmitted beacons on the following frequencies: 2412, 2417, 2437, 2462 and 5745 MHz. RSS measurements ranged from -85 to -18 dBm. The mean standard deviation of the RSS of every AP at each point is shown in Table II. As it can be observed, received power from some APs has large variations.

Disassembly of the tablet [25] reveals that it uses a Broadcom BCM43241 chip. Its datasheet [26] summarized the accuracy of the RSSI measurements at a 95 % confidence level as shown in Table I. Although it is not clear the nature of the

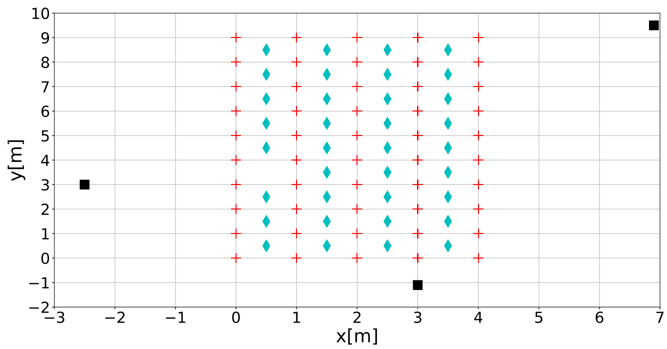

Fig. 2. Simplified measurement setup. Crosses and circles mark measurement locations. Crosses form a 1×1-meter grid. Filled squares mark the location of the three access points placed inside the room.

measurement errors, say, random errors in a single device or measurement differences among devices, a standard deviation of $\sim$ 2.5 dB is found for the lower power range under a normality assumption.

TABLE I
RSS ACCURACY.

Range [dBm]	Accuracy [dB]	
	Minimum	**Maximum**
-98 to -30	-5	5
$>$ -30	-8	8

TABLE II
DISPERSION OF WIFI RSS MEASUREMENTS

AP	σ **[dB]**
1	7.52
2	2.78
3	7.78
4	2.81
5	4.81
6	2.70
7	5.45
8	3.46
9	3.20

Yoga Tablet 2 has a ST 3-axis Magnetic Fields Sensor by STMicroelectronics. Although we do not know the exact model, some specifications, collected by a sensor app on the tablet, are shown in Table III. We saved the three components of the magnetic field at each location. In order to avoid artificial changes in the magnetic field, we preserved the orientation of the tablet at each location. Moreover, we tried to preserve the same orientation at all locations. The mean standard deviation of every component of $\vec{B}$ at each point is shown in Table IV. Note that the dispersion is $\sim$ 8 times (almost an order of magnitude higher than) the resolution. This means that measurements are not perfectly stable and are affected by unaccounted for variations.

IV. RESULTS

As in Ref. [5], our approach to assess the maximum achievable accuracy was to apply state-of-the-art algorithms to the

TABLE III
MAGNETOMETER

Resolution [μT]	0.44
Max. Range [μT]	810.0

TABLE IV
DISPERSION OF MAGNETIC FIELD MEASUREMENTS

Component	σ **[μT]**
B_x	3.32
B_y	3.03
B_z	3.42

experimental measurements. We selected the algorithms based on popularity, representativity and ease of implementation. Algorithms implemented were k Nearest Neighbors(kNN), Kernel Ridge, Least Absolute Shrinkage and Selection Operator (LASSO), Ridge, Support Vector Machines (SVM) and Kernel Density Estimation (KDE). A detailed description of the algorithms used can be found in Refs. [5], [10], [19] and references therein.

All algorithms were implemented in Python, using Scikit-learn [27], SciPy [28], NumPy [29], Pandas [30] and Matplotlib [31]. We used PyPy [32] to speedup the calculations.

We randomly chose 80% of the reference points for training and the remaining 20% for testing. In Figure 3 we report median localization error (in meters) based on 10000 random partitions in order to average out the effects of a particular training and testing datasets. kNN, Kernel Ridge, LASSO and Ridge hyper parameters were tuned using cross validation. In the case of SVM regression, we used a radial basis function kernel with parameters set on a trial-and-error basis. For KDE we used parameters proposed by Kushki et al. [33].

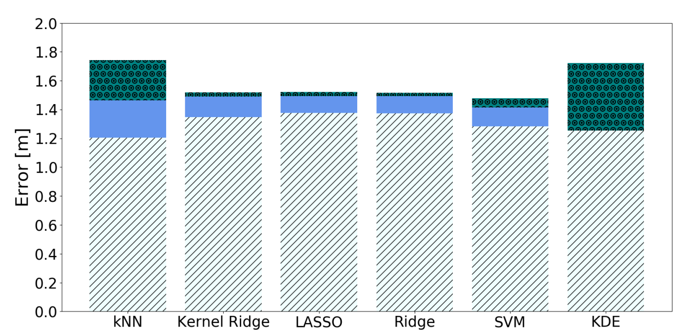

Fig. 3. Median localization error for different algorithms: WiFi RSS and $\vec{B}$ (lines), WiFi RSS and $\|\vec{B}\|$ (dots), and WiFi RSS only (no pattern).

We ran tests with only WiFi RSS, WiFi RSS and $\|\vec{B}\|$ and WiFi RSS and $\vec{B}$. Fig. 3 we present the median error for each each type of fingerprint and for each of the studied algorithms. As it can be observed, adding the information of the magnetic field always improves the localization performance. Moreover, the gain in performance appears to be more significant for those algorithms that have a poorer performance when only WiFi RSS fingerprints are used. The performance improvement is also summarized in Table V.

Fig. 3 also reveals that there is some loss when information of the magnetic field is summarized by its total intensity. It may be the case that, using only $\|\vec{B}\|$ may reduce the fingerprint uniqueness as argued by Xie et al. [17]. We must note that we do not show any results of the use of WiFi RSS and the magnetic field intensity for the KDE approach because we found some numerical problems in the density estimation.

We must also remark that results in Fig. 3 correspond to the best case, that is, when an optimal number of APs was considered. We measured the effect of using different numbers of APs along with the three components of $\vec{B}$ and with $\|\vec{B}\|$ to test if the effect of adding information on the magnetic field is similar to the effect of using more or less WiFi APs. Some results are presented in Figs. 4-6. The APs are added sequential according to its relevance as predicted by the Fisher criterion (see [19]). We found an improvement in every case when $\vec{B}$ is added. However, for kernel ridge regression, LASSO and ridge regression, the addition of information summarized by the **intensity** of the magnetic field showed almost no gain over using only WiFi RSS (see, for instance, Fig. 6). From Figs. 4-6, it can also be observed that there are at least two different behaviors. While in the case of k-nearest neighbors there is no significant gain by considering more access points (even some loss can be observed when information of the magnetic field is added), the remaining algorithms always show an improvement when more APs are taken into account.

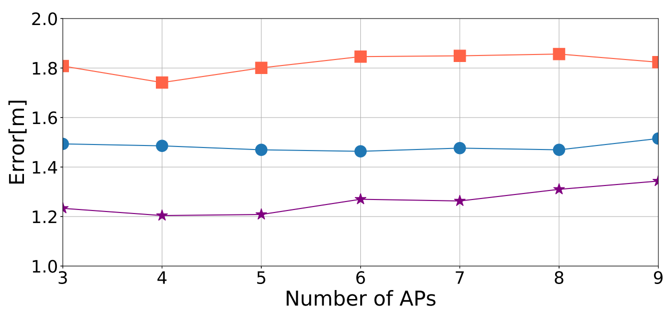

Fig. 4. Median error for kNN: WiFi RSS (squares),WiFi RSS + $\|\vec{B}\|$ (circles), and WiFi RSS + $\vec{B}$ (stars).

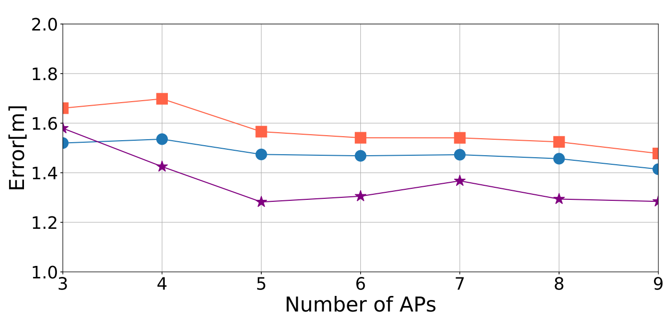

Fig. 5. Median error for SVM regression: WiFi RSS (squares),WiFi RSS + $\|\vec{B}\|$ (circles), and WiFi RSS + $\vec{B}$ (stars).

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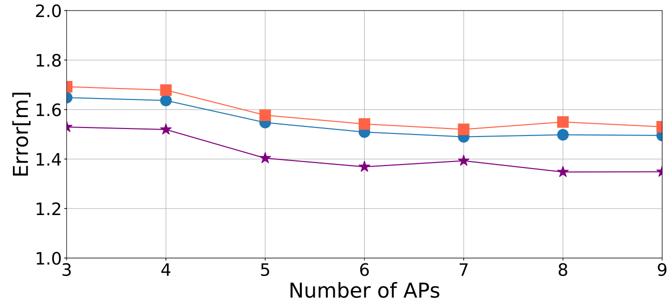

Fig. 6. Median error for kernel ridge regression: WiFi RSS (squares),WiFi RSS + $\|\vec{B}\|$ (circles), and WiFi RSS + $\vec{B}$ (stars).

TABLE V
ACCURACY GAIN

Algorithm	**WiFi + $\|\vec{B}\|$**	**WiFi + $\vec{B}$**
SVM	4%	13%
LASSO	2%	9%
Ridge Regression	2%	9%
Kernel Ridge Regr.	2%	11%
KDE	–	27%
kNN	16 %	31%

V. CONCLUSION

In this paper, we focused on the question of the attainable accuracy of localization algorithms based on WiFi received power and magnetic field measurements, using off-the-shelf hardware. In order to answer this question, we obtained measurements from a carefully planned experiment and we tried several state-of-the-art localization algorithms. We found that using both signals together achieves better accuracy than using only WiFi and the improvement is remarkable with algorithms like k-nearest neighbors and kernel density estimation. However, we cannot obtain errors below 1 m. Indeed, the best performing algorithm gave a median error of 1.20 m.

In real-world scenarios, the use of the three components of the measured magnetic field is complicated by orientation changes of the mobile device. An alternative is to use only the intensity of the magnetic field. We found that, indeed, some performance improvement can be obtained by adding information of the magnetic field on this form, but is much smaller than when the full $\vec{B}$ is considered.

Although we do not present the results here, we also tried approaches that used information on the magnetic field to refine the position estimated on the basis of WiFi RSS measurements. We did not obtained significant performance improvements and more work needs to be done to evaluate the convenience of these approaches.

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