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A multisource and multivariate dataset for indoor localization methods based on WLAN and geo-magnetic field fingerprinting

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***Abstract*—Indoor localization is a key topic for the Ambient Intelligence (AmI) research community. In this scenarios, recent advancements in wearable technologies, particularly smartwatches with built-in sensors, and personal devices, such as smartphones, are being seen as the breakthrough for making concrete the envisioned Smart Environment (SE) paradigm. In particular, scenarios devoted to indoor localization represent a key challenge to be addressed. Many works try to solve the indoor localization issue, but the lack of a common dataset or frameworks to compare and evaluate solutions represent a big barrier to be overcome in the field. The unavailability and uncertainty of public datasets hinders the possibility to compare different indoor localization algorithms. This constitutes the main motivation of the proposed dataset described herein. We collected Wi-Fi and geo-magnetic field fingerprints, together with inertial sensor data during two campaigns performed in the same environment. Retrieving sincronized data from a smartwatch and a smartphone worn by users at the purpose of create and present a public available dataset is the goal of this work.**

***Index Terms*—Indoor Localization, Geomagnetic Field, Fingerprinting, Dataset**[1]

I. Introduction

The community of makers is pushing the market of mobile devices toward a new era. As a matter of fact, the last decade have been characterized by a vibrant proliferation of embedded sensing technologies in mobile devices. Moreover, smartphones and in general other mobile devices are by their own nature ubiquitous, and applications able to leverage contextual information, such as location, become increasingly powerful. Indoor Localization Systems (ILSs) have proved to be essential in Ambient Assisted Living (AAL) scenarios [1], [2], [3], robotic applications [3], [4], and indoor navigation in large environments such as airports, malls, and campuses [5]. Beyond the widespread use of GPS location systems, which are incredibly useful outdoors, GPS signal is partially blocked, thus reducing precision in indoor environments.

In recent years, the development of ILSs has been under constant improvement, especially with the availability of new small and inexpensive sensors. There are several technological approaches that have been proposed for the design of indoor location systems. These include infrared light, ultrasonic sensors, WLAN, RFID, Bluetooth Low Energy, Ultra Wideband, ZigBee, and computer vision, among others [6], [7], [8], [9]. However, most of these technologies are not present in a mobile devices since require a dedicated infrastructure or higher processing capabilities, hindering the system's miniaturization and scalability. Therefore, some modern ILSs are based on the use of a variety of sensors and devices that are embedded in smartphones (e.g., accelerometer, gyroscope, magnetometer) [10], [11].

Although there are many papers in the literature trying to solve the indoor localization issue, the lack of a common dataset and frameworks to compare and evaluate solutions is the main drawback in this field. Each approach presents algorithms and results using its own dataset. Under these conditions, it is not possible to compare different solutions since experiments are impossible to be reproduced. The publication of datasets [12], [13], the organization of open competitions [1], [14], [15], [5], the proliferation of new benchmarking initiatives [16], and standards (i.e. the ISO/IEC DIS 18305 standard [17]) are overcoming the main drawback in the indoor localization research field. Although all these initiatives go towards a fair evaluation of ILSs, they not cover all possible environments. Indeed, each dataset covers a different environment and, therefore, it is not possible to compare different technologies in the same environment.

The dataset presented in this work addresses these issues by gathering, in the same environment, WiFi fingerprints, geomagnetic field, and inertial sensors. Moreover, together with the sensor data collected by the smartphone, we also gathered the synchronized sensor data coming from a smartwatch worn by the users during the same measurement campaigns. Therefore, as a matter of fact, by using the proposed dataset, it is possible to compare different technologies and algorithms in the same environment.

The main contribution of this work is the creation and presentation of a publicly available dataset, that could be used to make comparisons among different technologies in this field. It has been published on the public UCI Machine Learning Repository [2].

The dataset consists of 36795 continuous samples collected in a 185 m^2 indoor environment. The chosen environment

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[2]http://wnet.isti.cnr.it/software/Ipin2016Dataset.html

is composed by four hallways delimited by fire doors and three different rooms of the National Research Council area in Pisa. Each sample comprises a set of discrete captures taken along the indoor environment with a period of 3600 seconds with a fixed frequency of 10 Hz. There are almost 40000 magnetometer values, 6500 RSSs values obtained by the Wi-Fi interface, and 40000 accelerometer and orientation values for both smartphone and smartwatch worn by two users.

The rest of the paper is organized as follows. Section II presents the related work. Section III illustrates the data acquisition process and the description of the collected dataset together with the characteristics of gathered data. Finally, the discussion and the most important conclusions arisen from this work are reported in Section IV.

II. Related work

In the literature, many works deal with geo-magnetic field- and RSS-based fingerprinting methods for indoor localization solutions. In this section, we focus on the datasets used for testing their own solutions and we also survey whether they are publicly available or not.

In [18], authors collect geo-magnetic field data in different environments. Data are collected in corridors, intersections of two squares, and rooms. Only geo-magnetic field values were collected, although the authors stated that WiFi may be used to avoid errors in the proposed localization solution. In [19], authors consider a 67x12 m^2 of environment, composed by a corridor, a lab, an office, and a library. Data are statically collected with 45 cm intervals and 10 seconds spent in each location. The created database consists of 350 samples from a 3-axes magnetometer. However, how the information has been collected is not described. In [20], authors show that, when all the three axes are considered, the geo-magnetic localization performs better. Three environments are considered: a suburban house, a city-centered apartment, and a university lab. However, they did not detail the number of samples. The geo-magnetic field in halls of a multi-level building has been evaluated by authors in [21] by using four different devices. The corridor was about 36 m long and 2 m wide. Samples were taken along the corridor at three different positions: centered, 60 cm left the corridor, and 60 cm right the corridor. However, very few samples have been collected in this work. In [22], authors present an indoor geo-magnetic based system using wearable devices. The proposed solution is tested in two environments: a 187 m corridor (37200 training samples and 310 test data points), and an atrium environment (40800 training samples and 408 test data points).They used a special device with four magnetometers for sampling the geo-magnetic fingerprints, exploiting vectors consisting of 12 elements. In [23], all the samples were taken in 260 m^2 laboratory, which is composed by 8 corridors, at Universitat Jaume I university campus. The 8 corridors and the 19 intersections were mapped in two different directions with a Google's Nexus 4 and Android 5.0.1. As a result, there were 54 different alternative paths. Sampling on every path was repeated 5 times, so that the database designed for training purposes is composed of a total of 270 different continuous samples. Data from magnetometer, accelerometer and orientation sensors is included in a public database [3].

Many papers, in the literature, deal with RSS-based methods for indoor localization [24], [25], [26], [27], [28]. In [24], the impact of the number of fingerprinting points, number of samples, user orientation, and the issue of tracking a mobile user have been investigated. The experiment has been tested in a 980 m^2 environment that includes more than 50 rooms, but the test were conducted only on the corridors. The test relied on an infrastructure of 3 deployed Wi-Fi access points. The mobile host was a laptop computer and RSSs from the 70 reference points, using four different user orientations, have been collected. In [25], authors describe a localization method based on a genetic algorithm. Four experiments have been conducted in two different environments: a small (27x18 m, 486 m^2) and a large one (140x90m,12600m^2). During the experiments, authors collected the fingerprints at grid locations with 1.5 m separation distance for the small environment and 3 m for the large environment, gathering up to 10000 measurements. The experiments presented in [26] were carried out at Tampere University of Technology (10000 m^2 approximately). The reference data were collected in 96 points and a mean of 30 RSS measurements were computed. Nokia N900 smartphone and a laptop were the devices used to collect data. The experiments in [27] were performed in two buildings at the University of Minho, Portugal. A laptop computer, equipped with three different network interfaces, was used to collect data during the calibration and operational phases. A total of 392 calibration points were established in the whole environment and 9358 calibration samples were taken. The experiments done in [28] followed the comprehensive benchmarking methodology developed in the EVARILOS Project [30], [31]. The authors deployed custom infrastructure and they used a MacBook Pro notebook as device. They performed the experiments in four different environments: small office, medium lab, big office, and open space. In the experiments, each training point consisted of 40 RSSI scans. In the small office, medium lab, big office, and open space they collected the reference fingerprints at 41, 56, 123, and 100 locations, respectively. In [12], authors present an available database of RSS values captured in the UJI University campus that covers a surface of 108703 m^2, including 3 buildings with 4 or 5 floors, depending on the building [29]. The number of reference points is 933, with 21049 sampled points: 19938 for training/learning and 1111 for validation/testing. Data were collected by more than 20 users using 25 different mobile devices [4].

Although we presented several state-of-the-art works, the related datasets used by authors are not completely available or detailed regarding the use cases and the environments analyzed. Only two works [29], [23] present publicly available datasets.

[3] http://archive.ics.uci.edu/ml/datasets/UJIIndoorLoc-Mag
[4] http://archive.ics.uci.edu/ml/datasets/UJIIndoorLoc

TABLE I: Comparing the datasets in the literature.

Paper	Infrastructure	Spaces	# of features	# of samples	# of reference points	source	available
[18]	N.A.	1D and 2D	magnetic	125	-	smartphone	no
[19]	N.A.	1D	magnetic	350	-	smartphone	no
[20]	N.A.	2D	magnetic	-	-	smartphone	no
[21]	N.A.	2D	magnetic	29	-	smartphone	no
[22]	N.A.	2D	magnetic	78000	-	smartphone	no
[23]	N.A.	1D	magnetic, accelerometer, orientation	40159	270	smartphone	yes
[24]	based	2D	RSS	-	280	smartphone	no
[25]	free	2D	RSS	10000	167	smartphone	no
[26]	free	2D	RSS	-	96	smartphone	no
[27]	free	2D	RSS	9358	1176	smartphone	no
[28]	based	2D	RSS	-	320	smartphone	no
[29]	free	2D	RSS	21049	933	smartphone	yes
Proposed dataset	**free**	**2D**	**RSS, magnetic, accelerometer, orientation**	**36795**	**325**	**smartphone, smartwatch**	**yes**

The proposed dataset, instead, contains more information including:

- 36795 continuous samples over two measurement campaigns of one hour at 10 Hz (resulting in 6500 discrete samples in 325 reference points);
- we do not only consider corridors, but also combinations of two connected corridors (turns changing corridor);
- we gathered data from accelerometers, orientation sensors, RSSs received from Wi-Fi access points, and gemagnetic field by two different set of devices: a smartphone and a smartwatch.

Table I shows a comparison of the surveyed datasets available in the literature with respect to the proposed dataset, highlighting differences and key features. In particular, we can see that the dataset presented in this paper is the only one providing information coming both from smartphone and smartwatch.

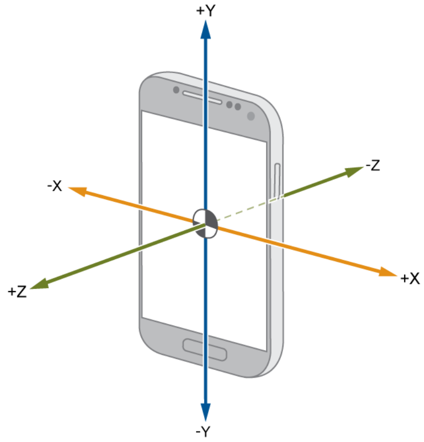

Fig. 1: Axes orientation on Android based smartphones.

III. Dataset Description

A. Data acquisition

The data acquisition process involved two campaigns performed at the first floor of the Institute of Information Science and Technologies (ISTI), inside the Italian National Council (CNR) building. Both datasets collected cover a surface of 185.12 m^2 (Figure 2). The data acquisition campaign has been performed by wearing two devices simultaneously: a smartphone and a smartwatch. The smartphone model is the Sony Xperia M2, while the smartwatch is the LG W110G Watch R. Both devices were running the Android OS with dedicated apps developed to collect the data [32]. Data gathered during the study comprises both physical parameters and Wi-Fi access points information. In details, the devices log data regarding:

- force applied to a device on all three physical axes (x, y, z) expressed in *m/s*^{2}, including the force of gravity;
- ambient geo-magnetic field for all three physical axes (x, y, z) expressed in μT;
- orientation or degrees of rotation that a device makes around all three physical axes (x or pitch, y or roll, z or azimuth) expressed in °;
- device's rate of rotation around each of the three physical axes (x, y, and z), expressed in *rad/s*.

The axes orientation on every Android based device is shown in Figure 1. During the acquisition, the smartphone was kept at the chest level with the screen facing up. Every time the user was on a predefined location, the device recorded the following additional data concerning the detected Wi-Fi access points (APs):

- WiFi network name;
- AP MAC address;
- AP Received Signal Strength Indication (RSSI) expressed in *dB*.

The reference time used by the smartwatch is synchronized with the smartphone before starting each data acquisition session. Every time sensors or Wi-Fi data are recorded, an entry is written to a file together with the acquisition timestamp.

TABLE II: Parameters collected for each device

	Phone	Watch
WiFi APs	X	-
Accelerometer	X	X
Geomagnetic	X	X
Gyroscope	-	X
Orientation	X	X

Sensors output is sampled with a frequency of 10 Hz. Table II shows the data collected for each type of device used in the experiment. The place in which the data collection was carried out is an indoor office environment composed of two rooms, two corridors and one small entrance hall. The overall map is shown in Figure 2. Each dot in the map corresponds to a detection point and for each of them, two samples of each parameter were collected. The points were equally spaced by 60 cm in both directions in order to uniformly cover the interested area.

B. Dataset description

The records of both datasets have been captured on 325 different places. These places are shown as bullets in Figure 2. Local coordinates are given considering the X-Y axis origin on the bottom-left corner. By this point, each bullet is 0.6 meters far from another since each tile is $0.6m*0.6m$. Table III shows the main characteristics of the proposed datasets.

Each dataset contains the following elements:

- Place ID;
- AccX, AccY, AccZ;
- MagneticFieldX, MagneticFieldY, MagneticFieldZ;
- Z-Axis Angle (Azimuth), X-Axis Angle (Pitch), Y-Axis Angle (Roll);
- GyroscopeX, GyroscopeY, GyroscopeZ;
- Timestamp.

Regarding the Wi-Fi dataset, it also contains:

- Place ID;
- RSSIs collected from the different SSIDs observed.

The database also contains the mapping between the coordinates of the reference points used during the campaigns, identified by the relative Place ID, and local Cartesian coordinates - according to Figure 2. As example, Table IV shows coordinates of the 25th Place ID.

The follows two sub-section provides details about WLAN dataset and geo-magnetic dataset.

1) WLAN dataset description: The whole proposed WLAN dataset contains 650 records, 325 records retrieved during the first campaign and 325 during the second one.

In particular, Place ID is the unique point identifier for the different places acquisition points. During this phase, the operator who performed the campaign moves from a point to another. Above each points, one second of data sensors was retrieved by smartwatch and smartphone and stored into the database. SSID contains the Service Set Identifier (SSID) retrieved by the smartphone and stored for each Place ID of the campaign. In the proposed dataset, 10850 AP-MAC addresses are retrieved during the first campaign (127 uniques) and 10945 AP-MAC addresses during the second campaign (132 uniques). RSSI contains the most important information for Fingerprint-based techniques. For each WAPs identified, the equivalent single measurement of RSSI intensity level values, measured in dBm, is stored. In each different Place ID, for WAPs not detected on the single point, the RSSI was stored with the -100 artificial value. Generally, RSSI values fall into a range of $-90dBm$ for weak signals received and $0dBm$ for strong signals. The average number of different unique SSIDs detected in each Place ID is 10.17. Furthermore, Figure 3 shows, for every Place ID the number of SSID detected. This number ranges from 0 to 16.

Figure V shows an example of WLAN dataset entry stored during the first campaign.

2) Geo-magnetic dataset description: The proposed geo-magnetic dataset has been split into two different tables. Smartphone sensors table contains data retrieved by the smartphone, while smartwatch sensors table contains data retrieved by the smartwatch. Each record is related to a single capture, as previously described.

Data collected from both devices are structured as shown in Table VI.

The data, coming from two different sensor sources, are provided as raw data and collected at 10 Hz. Two different users, equipped with the same technology, performed a zig-zag trajectory for the purpose of covering the entire map.

The information provided by the magnetometer are not completely useful for users orientation change detection. For this reason, also the raw data from the orientation sensor was recorded. The orientation sensor provides the direction vector and the values are measured in degrees. Moreover, a data-fusion process with smartwatch data recorded may be useful for this purpose. Please note that, for both campaigns, the user was walking at an average pace of ~ 0.6 m/s.

IV. Discussion and conclusions

In this paper we presented a multisource and multivariate dataset that can be used for developing and testing novel approaches to the indoor localization problem. The multi-source characteristic is supported by the presence of two different devices collecting, simultaneously, data from the surrounding environment: a smartphone and a smartwatch, respectively. Each device collects multivariate data represented by their inertial parameters (i.e. acceleration, orientation, and gyroscope), geo-magnetic field, and received signal strengths from Wi-Fi access points. This multisource and multivariate aspect can be easily exploited by ILSs fusing different data. Several examples are available in literature focusing on hybrid methods [33], [34] and information fusion frameworks [35], [36], these systems can now be tested on real world data, publicly available to researchers.

The presence of Wi-Fi RSSs and geo-magnetic field values, together with the map of the monitored environment, opens various possibilities for fingerprinting-based ILSs, helping researchers in the off-line collection phase. As we can see

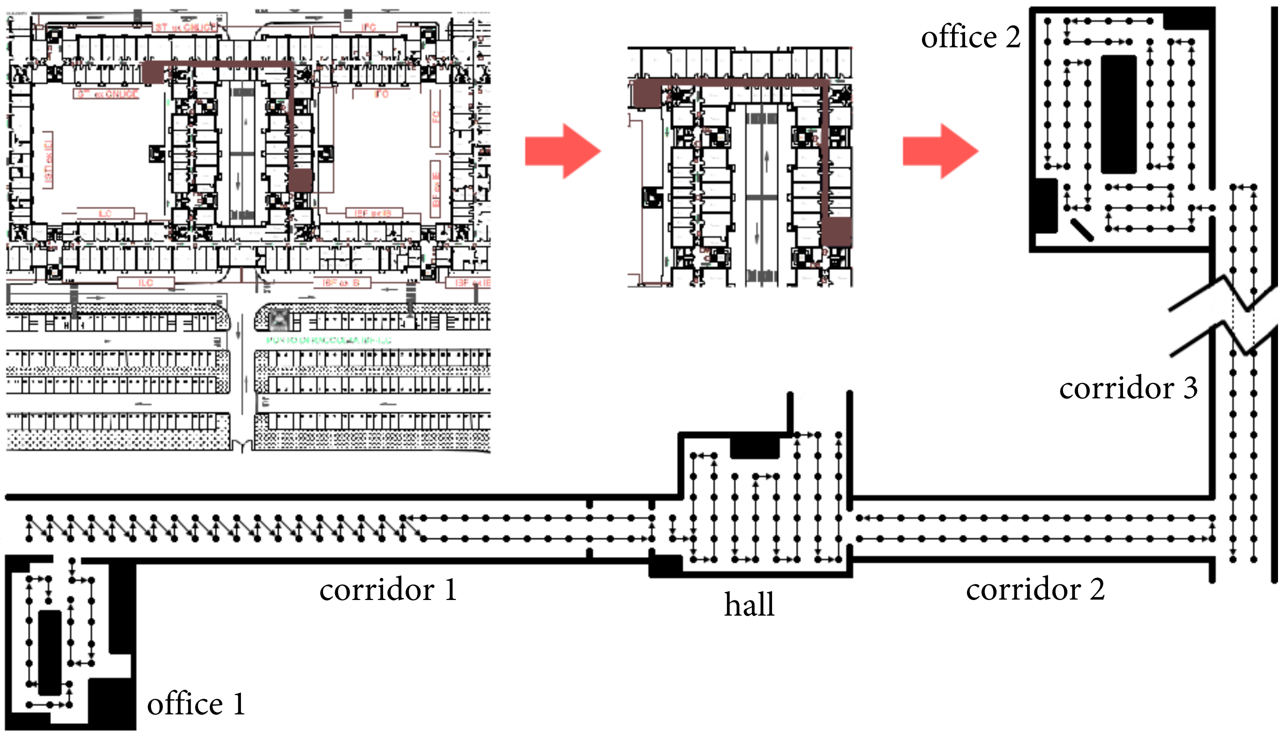

Fig. 2: Map of the data collection environment.

TABLE III: Main characteristics of proposed dataset: Number of Campaign (N), Number of buildings (N_B), Surface, Number of floors, Number of places, Number of WLAN Samples, Number of WAPs, Number of Geomagnetic Samples, Number of devices

N	N_{Bu}	N_{Fl}	N_{Su}	N_{Pl}	N_{Ws}	N_{Wa}	N_{Ge}	N_{De}
1	1	1	185 m^2	325	10850	127	7500	2
2	1	1	185 m^2	325	10945	132	7500	2

TABLE IV: Mapping table - First campaign

Place ID	**X Axis**	**Y Axis**
25	20.4	4.8

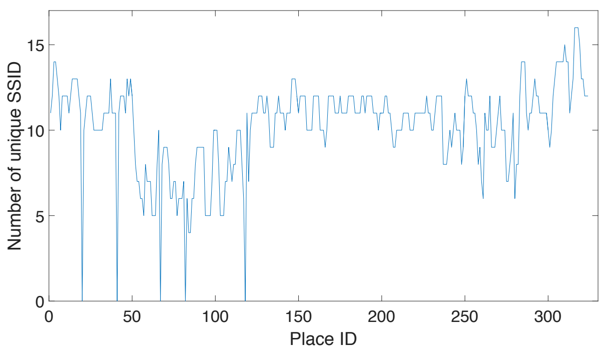

Fig. 3: Number of uniques SSIDs detected on different Place IDs.

in Figure 4, the space granularity offered by the geo-magnetic field survey campaign (heat maps shown in Figures 4a, 4b, and 4c) is less than the one offered by the RSSs from Wi-Fi access points (heat maps shown in Figures 4d, 4e, and 4f), that can be used to enhance the overall localization accuracy in hybrid methods.

On the other hand, the geo-magnetic field can be used to lower the effort in rebuilding the off-line Wi-Fi RSSs map, since it does not differ between different campaigns. It is a known fact that only significant magnetic disturbances in indoor environments impact on the geo-magnetic field map [18], [22], while for Wi-Fi based fingerprints it is very easy to be affected by environmental changes. This often leads to refining phases of the off-line map or to the development of self refining maps [37]. In this regard, Figures 5a and 5b show the recorded magnetometer values from one smartphone during two acquisition campaigns (in X, Y and Z axis) and the magnitude as root of the components squared sum. It can be observed that the magnetometer values are similar for the two campaign. In both cases, the curve is very similar with small variations in the magnitude measured in each location.

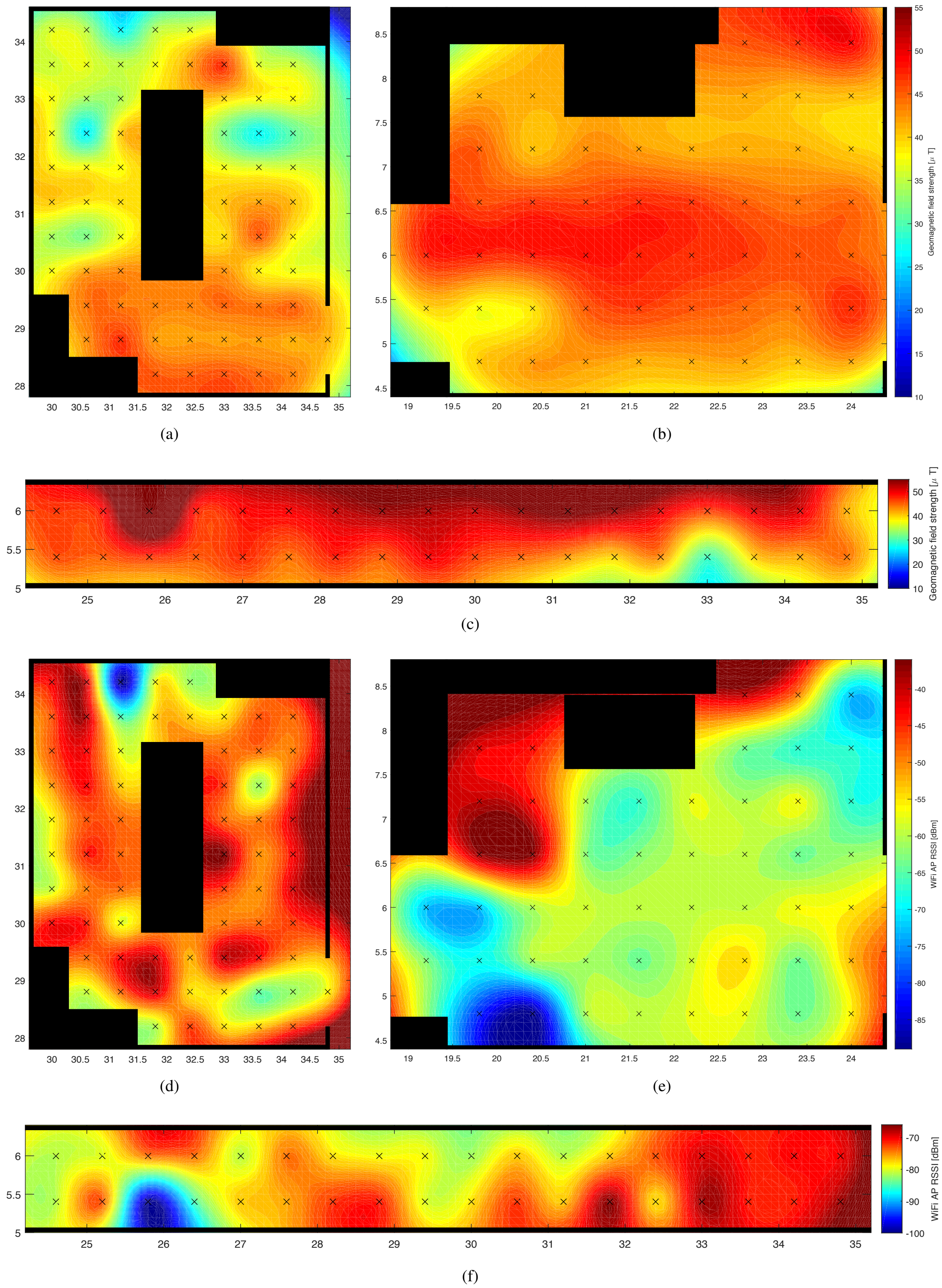

Fig. 4: Heat maps showing the data collected in different parts of the covered environment from: the smartphone's magnetometer ((a) office 2, (b) hall, and (c) corridor 2) and the smartphone's Wi-Fi antenna ((d) office 2, (e) hall, and (f) corridor 2).

TABLE V: WLAN dataset - smartphone Wi-Fi Table - example of data entry

$PlaceID$	WAP_{001}	...	WAP_{125}	...	WAP_{127}
2	Nan	...	-59	...	Nan

TABLE VI: WLAN dataset - smartphone sensors Table - example of data entry

timestamp	AccX	AccY	AccZ	MagnX	MagnY	MagnZ	Azimuth	Pitch	Roll	GyroX	GyroY	GyroZ
1422629495219	0,34	2,832	9,049	-16,4	12,3	-28,2	37,36	-17,358	2,041	0	0	0

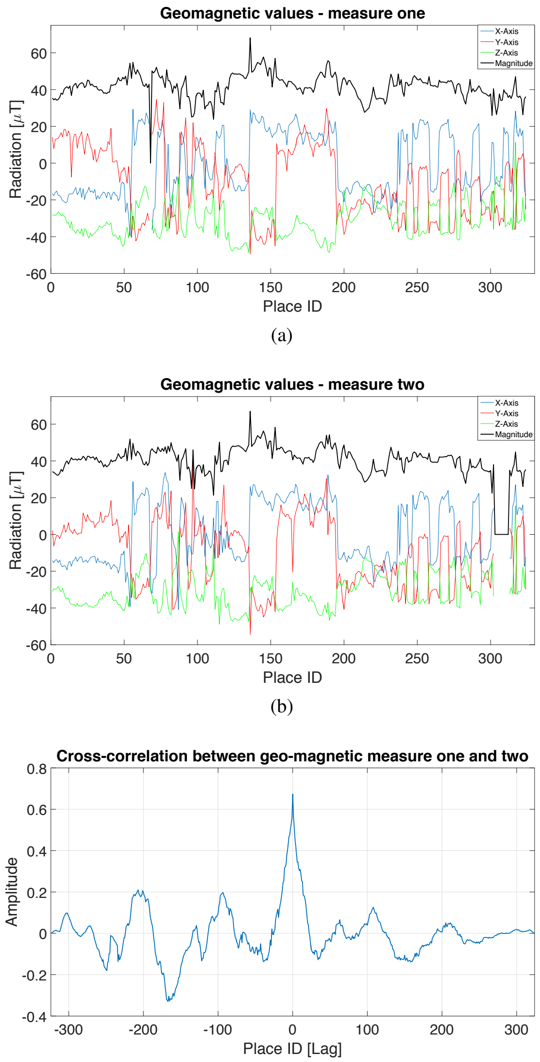

Fig. 5: The magnetic field values (on the X, Y, and Z axis) and their magnitude retrieved during the (a) first and (b) second campaign. The cross-correlation function between the two magnitude signals of all place IDs is shown in (c).

This is confirmed by the cross-correlation plot shown in Figure 5c, highlighting that the magnetic field of all place IDs measured in the same environment remains almost constant over different campaigns.

Future works will focus on exploiting the collected dataset to develop state-of-the-art indoor localization systems in order to compare how different techniques can benefit from fusing information coming from diverse sources and different kind of available data.

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