Geomagnetism for Smartphone-Based Indoor Localization: Challenges, Advances, and Comparisons

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Geomagnetism has recently attracted considerable attention for indoor localization due to its pervasiveness and independence from extra infrastructure. Its location signature has been observed to be temporally stable and spatially discernible for localization purposes. This survey examines and analyzes the recent challenges and advances in geomagnetism-based indoor localization using smartphones. We first study smartphone-based geomagnetism measurements. We then review recent efforts in database construction and computation reduction, followed by state-of-the-art schemes in localizing the target. For each category, we identify practical deployment challenges and compare related studies. Finally, we summarize future directions and provide a guideline for new researchers in this field.

CCS Concepts: • **Information systems → Mobile information processing systems**;

Additional Key Words and Phrases: Geomagnetism, indoor localization, smartphone, mobile computing

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1 INTRODUCTION

Localization was, is, and will be an interesting problem for mobile computing, services, and applications. Location-based service (LBS), and its related applications (like Pokemon Go which emerged in 2016), have recently created significant commercial and social attraction. The absence/weakness of Global Positioning System (GPS) signals in indoor environments (Lymberopoulos et al. 2015) has made indoor LBS (ILBS) an important problem for both industry and academia (Xiao et al. 2016).

Use of various signals has been explored for indoor localization, including Wi-Fi (Bahl and Venkata N. Padmanabhan 2000; Liu et al. 2007; He and Chan 2016), UWB (Gezici et al. 2005), RFID (Yang et al. 2014), FM (Yoon et al. 2016), inertial navigation system (INS) (Harle 2013; Yang et al. 2015), image (Tian et al. 2014; Huang et al. 2015; Chen et al. 2015; Zhang et al. 2016; Gao et al. 2016), magnetic field (Shu et al. 2015b; IndoorAtlas 2016), acoustics (Azizyan et al. 2009; Tung and Shin 2015), and visible light (Hassan et al. 2015; Zhang and Zhang 2016). Among all of the aforementioned signals, *magnetic field* (also known as *geomagnetism* or *earth magnetic field*) is very

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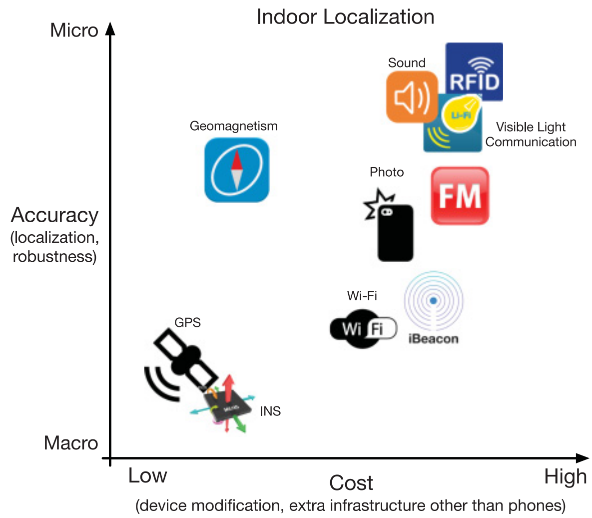

Fig. 1. Comparison of different signals for smartphone-based indoor localization according to the performance reported in literature.

promising due to its pervasiveness in indoor and outdoor environments.[1] Unlike the traditional localization schemes using RF signals (e.g., Wi-Fi), the geomagnetism-based scheme does not require deployment of extra infrastructure (Zou et al. 2016), while the interference and anomaly due to the indoor building structures leads to the discernibility of magnetic field for location estimation. In other words, a geomagnetism signal map is expected to outperform traditional Wi-Fi fingerprints in differentiating locations (Zhang et al. 2015). In the 2016 Microsoft Indoor Localization Competition, the scheme that fuses geomagnetism with Wi-Fi was reported to outperform many other schemes in terms of localization accuracy (Su et al. 2016). Recent studies (Wang et al. 2014; Shu et al. 2015a; Xie et al. 2016) have found that a main concern in finding signals for indoor localization is to achieve sufficient accuracy with minimal additional infrastructure (or dedicated device modification) cost. We have further identified the relative position of geomagnetism-based schemes in Figure 1 in terms of accuracy and cost in deployment/infrastructure (including device modification and extra infrastructure other than phones). Note that the closer to the upper left, the more cost-effective it would be in mobile settings. This figure shows geomagnetism to be more cost-effective for smartphone-based indoor localization.

According to the geo-science, we usually consider the geomagnetic field which encircles the entire earth as a huge "dipole magnet" (Storms et al. 2010). Given the earth's north and south poles, animals are believed to utilize the magnetic field to derive directional or even positional information from the anomalies of EMF (Mora et al. 2004). Leveraging such a magnetic field for navigation and orientation is not only an engineering practice but also the result from important biological evidences and studies.

Note that leveraging geomagnetism to determine direction (orientation) has long been studied (Zhou et al. 2014; Roy et al. 2014; Kok and Schön 2016), while extracting the positional information from magnetic field is more recent (Suksakulchai et al. 2000), especially for smartphone-based indoor localization. Each location inside a building may have a signature of geomagnetic fluctuations which can uniquely identify the location. The spatial anomalies in the measured

[1]In this article, we use "magnetic field," "geomagnetism," and "earth magnetic field" interchangeably.

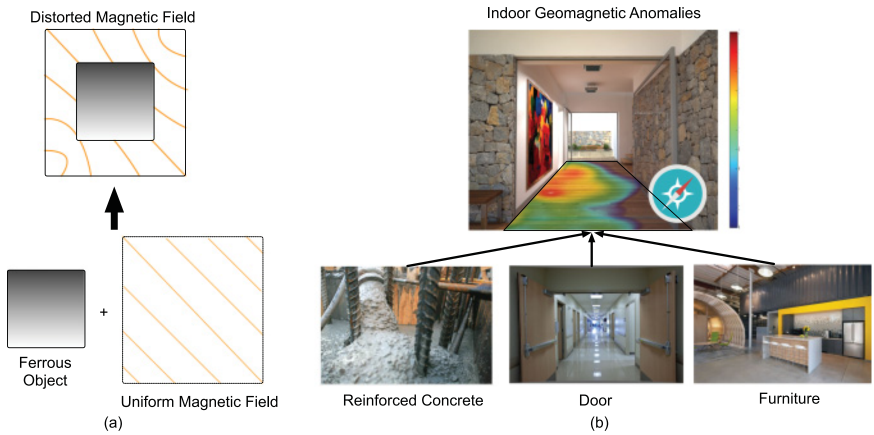

Fig. 2. (a) Illustration of a distorted geomagnetic field due to ferrous objects (Zou et al. 2016); (b) indoor geomagnetism anomalies due to building structures.

geomagnetism are usually introduced by the natural objects or artifacts (Figure 2(a)), where the local magnetic field is the combination of the primary geomagnetic field and a secondary one brought by the ferrous object (Zou et al. 2016). Figure 2(b) further illustrates three typical artifacts influencing indoor geomagnetism, including steel-reinforced concrete, metallic door frames, pillars, and furniture (Subbu et al. 2013). Other artifacts such as power lines and electric appliances may also influence the geomagnetic field (Shu et al. 2015a). These magnetic influences can be easily captured by a commodity smartphone's magnetometer, form the location *signatures* (or *fingerprints*) and support various ways of estimating indoor locations (Shu et al. 2015a).

Most existing surveys for mobile localization (Shang et al. 2015; Brena et al. 2017) focus on use of WLAN or RF signals (Gu et al. 2009; Yang et al. 2013; Maghdid et al. 2016; He and Chan 2016; Xiao et al. 2016; Vo and De 2016), and visible light (Pathak et al. 2015), and inertial-positioning (Harle 2013; Yang et al. 2015). Unlike these localization signals, recent advances in geomagnetism-based positioning (Xie et al. 2014; Shu et al. 2015a) make pervasive and infrastructure-less deployment of geomagnetism more likely. In fact, there have been increasing efforts in exploiting geomagnetism, including smartphone magnetometer readings, signal database construction, and localization (Xie et al. 2016). Despite various fragmented studies for geomagnetism-based indoor localization (Le Grand et al. 2012; Frassl et al. 2013; Xie et al. 2014; Shu et al. 2015a, 2015b; Xie et al. 2016), there does not exist any comprehensive survey of these recent smartphone-based systems, including their pros and cons. Furthermore, challenges and solutions for practical deployment of geomagnetism-based localization have not yet been adequately discussed. To fill this important gap, we conduct an extensive survey of geomagnetism-based indoor localization along with a qualitative comparison of existing results. Such a comprehensive survey will be a good reference for engineers as well as researchers in this interesting and promising research field.

Geomagnetism-based localization usually consists of three phases: *geomagnetism measurement*, *signal map and database construction*, and *target localization*. First, the geomagnetic signals are measured with the smartphone sensors (by engineers or crowdsourcing users). Then, in the phase of signal map and database construction, the ILBS constructs the corresponding signal map and the database (cloud or local). Finally, in the target localization phase, location queries are sent from the ILBS user. Related signals are processed by a certain algorithm and the corresponding location is returned to the target user. Figure 3 shows the flow of a basic system framework. Specifically,

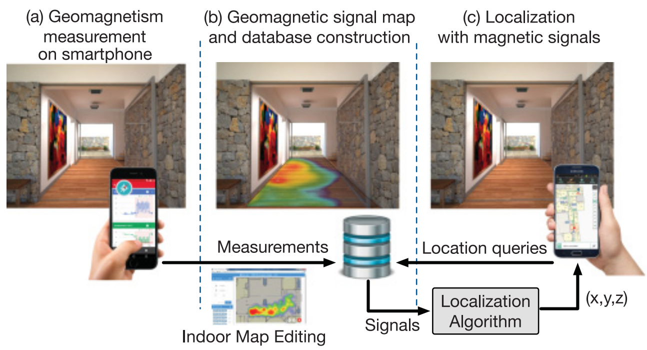

Fig. 3. The basic system workflow of indoor geomagnetism-based localization.

following the earlier phases, we will discuss the challenges and review recent advances (with the corresponding section titles) in three directions:

a) *Geomagnetism measurement on smartphones* (Section 2): The measured signals are important inputs for a geomagnetism-based ILBS system, determining its success of deployment with quality. However, the measurements can be noisy and device dependency may exist. Proximity to ferromagnetic materials, such as iron and nickel, may lead to reading anomalies in the smartphone magnetometer. Device calibration (including the smartphone orientation calibration (Roy et al. 2014; Zhou et al. 2014)) should be done before taking measurements.
b) *Geomagnetic signal map construction and maintenance* (Section 3): Signal map construction associates the indoor signal distribution with locations, and transforms the collected data to a heat map. Collection of the geomagnetic signals and their location labeling can be time-consuming and labor intensive. Data collected from smartphone sensors can also be voluminous, leading to large search scope and overhead for location estimation on resource-constrained smartphones (Galván-Tejada et al. 2013). The constructed signal map may change due to the dynamically changing indoor environment. For feasible and efficient deployment of geomagnetism-based ILBS, several ways of reducing survey, database update, and search efforts have recently been taken into account (Wahlström et al. 2013; Solin et al. 2015; Wang et al. 2016).
c) *Target localization with magnetic signals* (Section 4): While the geomagnetic measurements have been found to provide spatial discernibility and temporal stability, how to locate the smartphones in an indoor environment is still an open and non-trivial problem due to the dimensionless measurements (i.e., only three dimensions are recorded at each location point). Furthermore, low discernibility in an indoor open space may deviate the location estimation performance from the expected. In some earlier studies (Wang et al. 2012; Abdelnasser et al. 2016), geomagnetic anomalies are exploited as landmarks to indicate the target location. In more recent studies, spatial-temporal signal patterns (Zhang et al. 2015), and fusing geomagnetic field data with other sensors (including inertial measurement unit (IMU) (Xie et al. 2014) and Wi-Fi (Shu et al. 2015a)) has been proposed for the target location estimation.

One may also deploy artificially generated magnetic fields for localization (De Angelis et al. 2015; Pasku et al. 2017). Specifically, extra infrastructures like pre-deployed electric coils (Markham et al. 2012) are required beforehand to provide range measurements. The traditional trilateration or proximity detection algorithm can then be applied for location estimation (Blankenbach and Norrdine 2010). Despite the controllable signal measurements, the infrastructure and deployment cost may become high and limit their scalability. On the other hand, the geomagnetism introduced in indoor environments can be easily measured by handheld devices like smartphones. To support more pervasive deployment, we will focus on geomagnetism-based localization using smartphone sensors (Xie et al. 2014) (or emerging wearable devices (Markham et al. 2010; Abrudan et al. 2016)) for pervasive and mobile computing, which considers resource-constrained computation power, battery, and system deployment cost. Therefore, we will not consider existing magnetism-based localization schemes using external magnetic field infrastructures (Sheinker et al. 2013) or more advanced robot sensors (Suksakulchai et al. 2000; Navarro and Benet 2009; Pirkl and Lukowicz 2012).[2] Nevertheless, we will discuss their ideas when applicable or potentially helpful for smartphone applications.

In summary, this survey makes the following three contributions:

(1) The first comprehensive survey of challenges, approaches and insights in geomagnetism-based indoor localization in mobile environments;
(2) Identification and analysis of issues and approaches related to practical system deployment;
(3) Suggestion of future research directions for geomagnetism-based localization.

This article is organized as follows. We first discuss state-of-the-art geomagnetism measurements using smartphones in Section 2. We then summarize the approaches in building and maintaining a geomagnetism signal database in Section 3. Given the constructed database, we present several important localization schemes using the magnetometer readings in Section 4. Finally, this article concludes and summarizes future directions in Section 5.

2 MEASURING GEOMAGNETISM WITH SMARTPHONES

We review the challenges of magnetic measurement and existing approaches thereof. In Section 2.1 we first overview the basics of magnetic field measurements using smartphone sensors or off-the-shelf magnetometers. Then, in Sections 2.2 and 2.3, we discuss the device and usage/environment dependency in sensor readings, each of which is followed by the related magnetometer calibration techniques. Finally, we discuss and summarize these recent advances in Section 2.4.

2.1 Overview of Mobile Geomagnetism Measurement

To express mobile magnetism measurements, the strength of geomagnetic field is considered as a three-dimensional vector, $\mathbf{B} = [B_x, \quad B_y, \quad B_z]^T$. A magnetic field signal map is built relative to the earth coordinate regardless of how the smartphone is rotated (Zhou et al. 2014). The magnetic readings with respect to the mobile device are thus transformed in the coordinate for localization. Specifically, let $\mathbf{B}_p$ be the magnetic field readings at the smartphone coordinate system, and $\mathbf{B}_e$ be the environmental magnetic readings (the earth coordinate system). Given the smartphone's rotation, that is, yaw ψ, pitch θ, and roll ϕ, let $\mathbf{R}_x(\phi)$, $\mathbf{R}_y(\theta)$, and $\mathbf{R}_z(\psi)$ be the corresponding rotation matrices for the yaw, pitch and roll. We can then define the relationship between $\mathbf{B}_p$ and $\mathbf{B}_e$ in the two coordinate systems as

$$\mathbf{B}_p = \mathbf{R}_x(\phi)\mathbf{R}_y(\theta)\mathbf{R}_z(\psi)\mathbf{B}_e. \tag{1}$$

[2] Note that some of the existing studies in the field of robotics usually assume the sampling rate of the robot's magnetometer can be several hundred hertz, which may not be achievable on most commodity smartphone platforms like Android and iOS (less than 100Hz in practice) due to resource and energy constraints.

Table 1. The Magnetometers in the Recent Typical Smartphones (by Jan. 2017)

Device Model	**Year**	**Sensor Model**	**Measurement Range**	**Sensitivity**
iPhone 7	2016	Alps HSCDTD008A	$\pm$2,400μT	0.15μT/LSB
Samsung Note 7	2016	AKM AK09916	$\pm$4,912μT	0.15μT/LSB
Samsung S7	2016	AKM AK09911	$\pm$4,900μT	0.6μT/LSB
Google Pixel	2016	AKM AK09915	$\pm$4,912μT	0.15μT/LSB
Google Nexus 6P	2015	Bosch BMM 150	$\pm$1,300 ~ 2,500μT	0.3μT
Samsung Galaxy S6	2015	Willow YAS537	2,000μT	0.3μT/count
Samsung Note 5	2015	Willow YAS537	2,000μT	0.3μT/count
iPhone 6	2014	AKM AK8963C	$\pm$4,900μT	0.6μT/LSB

The magnetic readings contain external environment noises, including *hard iron offsets* as well as *soft iron deviation* (Gebre-Egziabher et al. 2006). Hard iron offsets come from the slowly time-varying magnetic fields (Gebre-Egziabher et al. 2006). Such fields are introduced by permanently magnetized materials, yielding a fixed magnetic deviation or offset upon the measurement. In other words, the offsets or biases are brought by the materials which exhibit a constant, additive field to the existing EMF, thereby generating a constant offset to the output at each magnetometer axis (Konvalin 2009). The hard iron effect remains constant for a given area. In an indoor environment, a speaker magnet, for example, can produce a hard-iron effect upon the nearby magnetometer (Konvalin 2009). On the other hand, soft iron effect stems from ability of a ferromagnetic object in supporting its internal magnetism (so-called *permeability*) when influenced by the external magnetic field (Gebre-Egziabher et al. 2006). From the magnetometer's perspective, it can be considered as the interfering magnetic field induced by the geomagnetic field onto the unmagnetized ferromagnetic components at the chip-set PCB. For example, iron and nickel, which do not necessarily generate a magnetic field themselves, can introduce a soft-iron distortion effect (Konvalin 2009). Thus, the soft iron effect is subject to the measurement environment, including location and nearby instrumentation.

Let $\mathbf{V}$ and $\mathbf{W}$ be the effect matrices imposed upon the readings by the hard and soft iron effects. Based on the preceding discussion, we can model the hard iron bias (offset) as $\mathbf{V} = [V_x, \quad V_y, \quad V_z]^T$, and the soft iron effect as $\mathbf{W} = [W_x^1, W_x^2, W_x^3;\ W_y^1, W_y^2, W_y^3;\ W_z^1, W_z^2, W_z^3]$. Considering the soft- and hard-iron effects, we may first model the geomagnetic measurement in Equation (1) as Ozyagcilar (2012):

$$\mathbf{B}_p = \mathbf{W}\mathbf{R}_x(\phi)\mathbf{R}_y(\theta)\mathbf{R}_z(\psi)\mathbf{B}_e + \mathbf{V}. \tag{2}$$

Besides the environmental influence, we can also consider the measurement error due to the magnetometer itself. The magnetic sensor introduces three sources of measurement errors: *device offset*, *scale factor error* and *sensor misalignment* (Gebre-Egziabher et al. 2006). For the same magnetic field signal, different measurement instruments may yield different readings because of varying sensitivity of the sensors to the magnetic field. Experimental studies have shown that a clear offset exists in magnetometer readings (magnitude) even on the same walking path, despite how the phone is posed. Table 1 lists several typical device models proposed over the last 5 years, their magnetometer models and corresponding vendors (based on iFixit (2017) and related sensor datasheets; LSB = Least Significant Bit). Despite the reading differences, one may also observe a great similarity in the sequence *shape* subject to some measurement noise or temporal distortion, which also matches the observations in Shu et al. (2015a). Mathematically, the device offset in the magnetometer readings can be modeled as $\mathbf{B}^{dev} = [o_x, \quad o_y, \quad o_z]$.

Scale factor and misalignment error mainly come from the installation imperfection of the sensors. In particular, with respect to different dimensions, we characterize the randomness in the reading magnitudes as the scale factor errors: $\mathbf{W}^{sf} = \mathrm{diag}(s_x, \quad s_y, \quad s_z)$. Furthermore, misalignment of the sensor exists, which can be further modeled as $\mathbf{W}^m = [\boldsymbol{\epsilon}_\mathbf{x}, \quad \boldsymbol{\epsilon}_\mathbf{y}, \quad \boldsymbol{\epsilon}_\mathbf{z}]^{-1}$, where $\boldsymbol{\epsilon}_\mathbf{x}$, $\boldsymbol{\epsilon}_\mathbf{y}$, and $\boldsymbol{\epsilon}_\mathbf{z}$ are three three-dimensional (3D) column vectors containing the orthogonality corrections.

Based on Equation (2) and the preceding errors, the measurement is finally modeled as

$$\widehat{\mathbf{B}} = \mathbf{W}^{sf}\mathbf{W}^m\left(\mathbf{W}\mathbf{R}_x(\phi)\mathbf{R}_y(\theta)\mathbf{R}_z(\psi)\mathbf{B}_e + \mathbf{V}\right) + \mathbf{B}^{dev} + \mathbf{N}, \tag{3}$$

where $\mathbf{N}$ is considered as a zero-mean white Gaussian noise.

Given the preceding background, we briefly summarize the recent feasibility studies of geomagnetism-based location estimation. A reliable location signature must have two important properties: *spatial differentiation* and *temporal stability* (Angermann et al. 2012; Frassl et al. 2013). The feasibility of constructing a geomagnetism-based location signature has recently been studied extensively (Haverinen and Kemppainen 2009; Li et al. 2012). They involve the time-varying nature and the spatial variation as discernibility (Solin et al. 2015). The indoor geomagnetism is shown to exhibit discernible spatial variations and stable temporal fluctuations, which can be used as location fingerprints (Subbu et al. 2013). Significant spatial variations have been reported, making magnetic field another source of positional information. Long-term studies (say, in days (Shu et al. 2015a) or weeks (Subbu et al. 2013)) on its temporal stability have also been reported, showing reasonably small variations within the measurement. In terms of mobile objects nearby, however, significant temporal changes have been observed, especially when the user is walking between metallic objects or in a moving elevator. Despite this, if the metallic objects are reasonably far away from the magnetometer (say, 1 m), the observations tend to be more stable (Shu et al. 2015a). Further challenges in device and usage dependency will be discussed next.

2.2 Device Dependency

As modeled earlier, different magnetometers might have different readings for the same magnetic field, leading to *device dependency*. In practice, the scale factor $\mathbf{W}^{sf}$ and misalignment $\mathbf{W}^m$ in the magnetometers are given, or hard to be calibrated at the smartphone application level (Xie et al. 2014), and hence most of the existing related studies focus on device calibration of $\mathbf{B}^{dev}$. Some of the recent studies (Zheng et al. 2014; Xie et al. 2014; Shu et al. 2015a) on mobile localization addressed the device dependency issue. The magnetometer information on some smartphone models has also been investigated (Subbu et al. 2013). Offline calibration that mitigates device heterogeneity might be useful, but it is inconvenient to ILBS users. To address this problem, the recent studies consider sequential measurements as locational signatures, and calculate the signal gradient between two neighboring data points instead of absolute values (Xie et al. 2014). This way, the inherent device offset is removed, thus avoiding the need for extensive device calibration.

Another method is to leverage the shape matching of geomagnetic sequence instead of raw value comparison, which has also been reported in Magicol (Shu et al. 2015a) and WaveLoc (Rallapalli et al. 2016). Specifically, one may collect a sequence of magnetic field readings along her/his walking trajectory. When a user is holding another device and walking along the same path in the same direction, a similar sequence shape in the time domain is expected, despite the differences of device dependency and measurement noise. Such sequence-shape similarity can be easily quantified with some existing signal processing schemes, which will be discussed in Section 4. This way, we can mitigate the effect of device dependency, and directly locate the user's walking path. However, the data along the walking path has to be accumulated before conducting localization, which introduces delay in making a positioning decision. Furthermore, the matching process has to be suspended and restarted once the user changes her/his walking direction in the middle. Making geomagnetism-based localization decisions therefore becomes more complicated than the traditional point localization.

2.3 Usage and Environment Dependency

Despite the device dependency, at the same indoor position, even the same mobile phone may experience distinct geomagnetic readings. It may be due to the soft-iron effect introduced by the nearby metallic objects, which affects the readings with respect to usage and environment. We term this *usage and environment dependency*.

Thus, the smartphone magnetometer needs recalibration whenever it is placed in a magnetically different environment. Traditional calibration of device magnetometer, or "compass swinging" (Apple's Developer Library 2016), has been widely applied on existing Android/iOS platforms. In these applications, the smartphone needs to be rotated in almost all possible orientations such that the local magnetic field can be compensated as much as possible.

Many of the earlier studies focus on industrial magnetometer calibration. Based on the difference in the calibration intuition, we can categorize these methods into three groups: *scalar checking* (difference minimization), *ellipsoid fitting*, and *maximum likelihood estimation* (Kok and Schön 2016). Scalar checking aims at minimizing the value difference between the sampled field and that of the local field (Alonso and Shuster 2002). For ellipsoid fitting approaches (Renaudin et al. 2010), a geometric formulation is usually considered. Specifically, if perfectly calibrated, the smartphone can measure the rotated version of the local geomagnetic field, which is considered as a sphere with radius equivalent to this field. In fact, due to the measurement noise, the "locus" of geomagnetic signal values (Renaudin et al. 2010) (i.e., the reading trace) converts to an ellipsoid. The ellipsoid of geomagnetic values is hence mapped towards a sphere via the calibration scheme, and finally the magnetometer gets calibrated.

A more recent study (Kok and Schön 2016) leverages the maximum likelihood (ML) and other inertial sensors (accelerometer and gyroscope) to map the ellipsoid towards the sphere. Calibration is done without knowledge of the sensor orientation. The heading estimation is reported to have been improved significantly. Furthermore, it does not require external equipment and can thus be operated by any magnetometer users. However, it formulates a non-convex optimization (Boyd and Vandenberghe 2004) problem to find the ML estimates, which may be computationally expensive for resource-constrained smartphones. Despite the algorithmic difference, the three categories of magnetometer calibration share the basic principle in magnetometer calibration: *to fit the measurement against the local magnetic field.*

With the fast development of the smartphone inertial measurement units (IMUs), smartphone-based algorithms have emerged for more advanced signal calibration. Some heading/orientation estimation of a smartphone (w.r.t. the earth coordinate) provides higher-level information than the traditional compass calibration (Abadi et al. 2015), mainly because it involves not only the compass direction detection but also the holding gesture classification problem in practice (Xie et al. 2014). Note that the knowledge of smartphone orientation is important for geomagnetism-based indoor localization. An ILBS system may leverage the magnetic anomalies as location pattern. Meanwhile, it has to detect the ground-truth of user heading for correct indoor map rotation. A^3 (Zhou et al. 2014) and WalkCompass (Roy et al. 2014) are two typical ways of addressing the smartphone's heading estimation problem.

A^3 in Zhou et al. (2014) leverages the gyroscope, accelerometer and magnetometer to estimate the smartphone's attitude. It proposes an automatic method called "opportunistic calibration" to differentiate the sensing modalities, select the best among them and find the attitude estimation which is the most accurate. It quantifies the calibration capabilities of each sensor based on their mutual consistency. For most of the time, the gyroscope reading is considered as the major heading

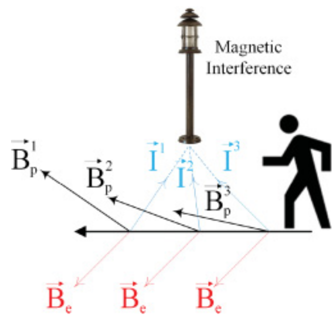

Fig. 4. Illustration of smartphone heading estimation via WalkCompass (Roy et al. 2014).

reference. If closely matched measurements in attitude change are made by both of the compass and gravity sensors, then A^3 resets the gyroscope from the new attitude base. Given mutual consistency of sensor readings, A^3 reduces the measurement error introduced by the individual sensors.

WalkCompass (Roy et al. 2014) also fuses different smartphone sensors to identify the walking direction of a target user. WalkCompass designs different techniques other than the aforementioned approaches, to locate, quantify and isolate the magnetic interference in the environment. Figure 4 illustrates the basic idea using WalkCompass for magnetometer calibration. Specifically, given a few walking steps, WalkCompass iteratively conducts magnetic *triangulation* to cancel the vector bias (say, $\vec{\mathbf{I}}^1$, $\vec{\mathbf{I}}^2$, and $\vec{\mathbf{I}}^3$ w.r.t. time in the illustration) introduced from outside metallic objects (say, a metallic pillar).

The details are as follows. Recall that the smartphone magnetometer readings $\vec{\mathbf{B}}_p^i = \vec{\mathbf{B}}_e^i + \vec{\mathbf{I}}^i$ (in the vector space), and the geomagnetic field with respect to the earth, $\vec{\mathbf{B}}_e^i$, is usually considered as static and constant. Based on this, WalkCompass iterates the values of $\vec{\mathbf{B}}_e$'s direction. Given the sequential measurement $\vec{\mathbf{B}}_p^i$'s, one can find $\vec{\mathbf{I}}^i$'s which coincide together (Roy et al. 2014) (minor deviation might be expected). As the user walks from one side to another, the source of magnetic interference (say, the metallic pillar) is discovered and the compass reading gets calibrated. Further fine-grained measurement correction can be made via crowdsourcing when multiple people walk along the same path and their heading readings can be combined (Abadi et al. 2015).

Despite the measurement and calibration accuracy, WalkCompass needs dynamic walking trace for orientation estimation, which is in practice inconvenient for many compass applications. If the user is static or the mobile system is at a cold start, then WalkCompass does not receive sufficient readings for calibration and may not fully address the compass error.

2.4 Summary and Comparison

Table 2 summarizes the existing studies of geomagnetism calibration and measurement, comparing their deployability in terms of:

(1) *Calibration Accuracy*: including calibration performance on *device dependency*, *smartphone heading*, and *noise filtering*.
(2) *Robustness to Measurement and Environmental Noise* (or *Robustness to Noise*): The sensor measurement contains noise due to the magnetometer fabrication imperfection or the user mobility. Environmental noise exists due to indoor environment changes. Both may influence the performance of the final measurement.

Table 2. Typical Schemes for Device and Usage Calibration

Category	Scheme	Calibration Accuracy	Robustness to Noise	Battery Consumption	Limitation in Practical Deployment
Device Calibration	Direct DTW @LocateMe (Subbu et al. 2013)	Low	Low	Low	Only suitable for 1D trace matching
	DTW-based Time-Normalization &Clustering @Groping (Zhang et al. 2015)	High	High	High	Computationally high with affinity propagation clustering; many samples required
	Mean Removal @Magicol (Shu et al. 2015a)	Medium	Medium	Low	Error-prone to biased magnetic field
	Differential Fingerprint @MaLoc (Xie et al. 2014) @FollowMe Shu et al. 2015b)	Medium	Medium	Low	Require activity detection for walking direction
Usage and Environment Calibration	Ellipsoid Fitting (Renaudin et al. 2010)	Low	Low	Low	Prone to sensor measurement noise
	ML Estimate (Kok and Schön 2016)	Medium	Medium	High	Non-convex optimization is formulated
	A^3 (Zhou et al. 2014)	Medium	High	Low	Depends on gyroscope quality
	Walk-Compass (Roy et al. 2014)	High	Medium	High	Dynamic walking is required

(3) *Battery Consumption*: If different smartphone sensors other than the magnetometer are extensively used without proper optimization, then energy consumption would be high, draining the smartphone battery quickly.
(4) *Limitations in Deployment*: Some proposed systems may rely on important assumptions or hypotheses which may not hold in different application scenarios. Based on our deployment experience, we summarize their potential limitations and provide some insights on their practical applications.

From Table 2, one can observe that measuring indoor geomagnetism still has some open issues, and how to practically deploy it is still critical for indoor LBSes. One must know the advances in the magnetometer and smartphone applications, including automatic hard-iron effect compensation (Android Sensor Document 2016) and system-level calibration for compass. However, in the practical application level, we still need to consider better filter design, noise source identification and energy-efficiency for the geomagnetism measurement (Shu et al. 2015a).

3 CONSTRUCTING GEOMAGNETISM DATABASE

Given the measurements, constructing a signal map is critical for location estimation in ILBS systems. The signal map construction should be fast and convenient, and adapt to environmental changes. Furthermore, due to the smartphone's high sampling rate, the amount of sensed data at the target site can be huge. The signal map construction should therefore support efficient query of the current user's location. This section is organized as follows. We first review the signal map and database construction (Section 3.1). Then, we discuss the search scope reduction for computational efficiency (Section 3.2), followed by the survey reduction and signal map studies (Section 3.3). Finally, we discuss and summarize the recent advances in addressing these issues (Section 3.4).

3.1 Signal Map and Database Construction

We mathematically describe the forces from magnetic objects and electricity currents as *magnetic field*. In the data management point of view, a *signal map of geomagnetism* usually comprises many

<magnetic readings (say, in μT), location coordinates (say, in pixels on a map or in meters)> tuples. Its construction process associates the spatial coordinates at an indoor site with the magnetic measurements in the signal space.

Clearly, the atomic element of a signal map is the geomagnetic reading. Different forms of geomagnetic readings may be applied in the database management. Three types of magnetic readings have recently been applied (Xie et al. 2014): *direct usage of 3D readings*, *signal magnitude*, and *horizontal and vertical components*. We elaborate these next.

Direct usage of 3D readings ($\mathbf{B}_p$ and $\mathbf{B}_e$): which directly leverages $\mathbf{B}_p$ at the smartphone coordinate system as the geomagnetic fingerprints (Chung et al. 2011). It can be easily implemented for traditional robot navigation, as the robot heading (say, an automated robot car) may be considered as fixed with respect to the moving path. In contrast, as the smartphone heading can be random in the earth coordinate system (similar problems may happen in the indoor unmanned aerial vehicles (Brzozowski et al. 2016)), readings at different headings have to be explored at each location (Xie et al. 2014), which, however, is both labor intensive and error prone due to the measurement noise.

An alternative and more intuitive approach is transforming the measurement vector $\mathbf{B}_p$ to that at the earth coordinate $\mathbf{B}_e$ to directly reflect the environmental signal properties. Nevertheless, as the smartphone orientation needs to be measured before the transformation can be conducted, how to mitigate the potential measurement noise and synchronize the sensor readings (i.e., magnetic data and rotation matrix) becomes challenging.

Magnitude as fingerprints ($|\mathbf{B}_p|$): Instead of $\mathbf{B}_p$, one may record the magnitude of $\mathbf{B}_p$ (i.e., $|\mathbf{B}_p|$) as the fingerprints despite the smartphone orientations and placements (Subbu et al. 2013). Besides earlier attempts in robot navigation, this pattern has been widely leveraged in many recent geomagnetism-based smartphone localization systems (Wang et al. 2012; Zheng et al. 2014).

However, it is dimensionless with much less spatial uniqueness during the signal comparison than using the 3D vector $\mathbf{B}_p$. Clearly, some positional information with respect to each magnetometer axis is filtered out as a consequence of magnitude calculation, leading to potential spatial ambiguity. Therefore, for those location estimation studies on magnitude measurement, geomagnetism is more or less considered as a supplementary measure to RF (say, Wi-Fi), rather than a major location indicator (Zheng et al. 2014). If a particle filter is applied for fusion-based localization (Frassl et al. 2013), then it may take longer to converge towards the correct location than using all the three dimensions in practice (Xie et al. 2014).

Horizontal and vertical components ($\mathbf{B}_h$ and $\mathbf{B}_v$): If the tilt information of the smartphone is available, then we can convert the geomagnetic field at the device coordinate system into the components on the horizontal (denoted as $\mathbf{B}_h$) and vertical (denoted as $\mathbf{B}_v$) planes (Li et al. 2012). These two components are independent of the user's walking directions. It provides more positional features for localization than using only magnitude $|\mathbf{B}_p|$.

Despite the preceding advantages, as the motion during walking may influence the gravity readings, the components $\mathbf{B}_h$ and $\mathbf{B}_v$ may not provide robust measurements for locating mobile users. Recent schemes like MaLoc (Xie et al. 2014) combine $|\mathbf{B}_p|$, $|\mathbf{B}_h|$, and $|\mathbf{B}_v|$ together to form a 3D vector for indoor localization. This way, the influences of user mobility and fingerprint ambiguity can be jointly considered and mitigated. Similarly, some recent studies (Abadi et al. 2015) utilize the international geomagnetic reference field (IGRF) for the spatial representation. IGRF utilizes the magnitude $|\mathbf{B}_p|$, horizontal element $\mathbf{B}_h$ and the inclination angle ($I = \tan^{-1}(B_z/B_h)$) to form the geomagnetic vector (Thébault et al. 2015).

Table 3 summarizes the preceding forms of geomagnetism measurements applied in recent geomagnetism-based systems. We discuss the representative schemes, along with their implementability, robustness to measurement noise, and location discernibility (qualitative comparison).

Table 3. Typical Geomagnetism Measurement Forms

Measurement Form	Typical Schemes	Easiness for Implementation	Robustness to Noise	Location Discernibility	Comments
Direct Readings	(Chung et al. 2011)	Easy	Low	High	Exploration of different headings and orientations
Coordinate Transformation	(Bilke and Sieck 2013)	Difficult	Low	High	Error-prone to orientation measurement noise
Magnitude	LocateMe (Subbu et al. 2013)	Easy	High	Low	Regardless of user heading and phone placement
Horizontal & Vertical Components	Feasibility studies (Li et al. 2012); MaLoc (Xie et al. 2014)	Medium	Medium	Medium	Error-prone when the user is walking; better when fused with magnitude (Xie et al. 2014)

We also show the potential issues in their implementation. As discussed in the table, the magnitude can be the most robust readings against measurement noise due to its least dependency on smartphone orientation. However, as it is dimensionless and less informative in labeling location, additional sensing information is needed to make the signature more discernible (Xie et al. 2016).

3.2 Search Scope Reduction for Computation Efficiency

Given the high sampling rate from the smartphone sensors (e.g., 100Hz on commodity smartphones), the granularity (density of fingerprints) of the geomagnetic signal map can be much higher than that of RF fingerprint map (say, Wi-Fi). However, such high granularity in practice does not necessarily lead to high localization accuracy, while the highly redundant signal data set significantly increases the search scope in location estimation. For practical deployment in spacious indoor sites, the search scope should be carefully reduced before performing location estimation.

Down-sampling of the signal map: Down-sampling the signal map may still provide sufficient information for localization. For example, FollowMe (Shu et al. 2015b) triggers the sequence sampling with respect to the step detection to improve the computation efficiency. Specifically, as a pedestrian walks, each step triggers one geomagnetism measurement. In other words, the geomagnetic sequence can be further discretized into multiple data points. Thus, the resultant sample size and the density can be much smaller. Some researchers (Wang et al. 2016) propose multiscaling and construct a database in different levels of granularity, thus reducing computation and increasing resilience to noise.

GROPING (Zhang et al. 2015) proposes clustering via so-called affinity propagation to choose appropriate fingerprint that represents each walking path segment. By using the affinity propagation, GROPING finds the *exemplar* magnetic fingerprints which can best represent the segment. In this way, when localizing the target walking path, only a few signals need to be compared and the computational complexity is significantly reduced. Due to the sophisticated clustering process, the offline computation and preprocessing complexity is increased as the price to pay.

Hierarchal location estimation: Besides the down-sampling, multi-layered or hierarchal location estimation can be applied to reduce the localization computation overhead at resource-constrained smartphones (or embedded systems). For example, the target can first be located within a floor or even a room via the magnetic field patterns. Given the geomagnetic signal map in that space, we may further execute the fine-grained geomagnetism-based localization, such as MaLoc (Xie et al. 2014) or Magicol (Shu et al. 2015a)). With such an area classification mechanism, the final search scope and power consumption can be significantly reduced, especially for those sophisticated machine learning algorithms (Shu et al. 2015a).

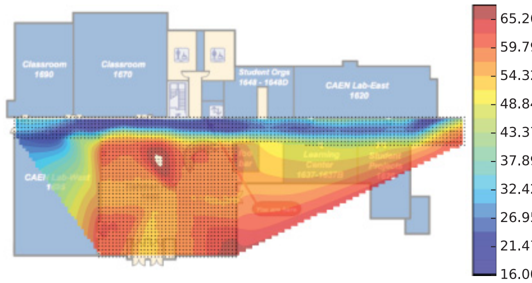

Fig. 5. Illustration of the constructed geomagnetic signal map at the ground floor of an office building. The warmer the color is, the higher the geomagnetic magnitude (in μT) is.

Sensor fusion for search scope reduction: Note that in a practical deployment trial, leveraging other sensors helps reduce the search scope in addition to improving localization accuracy. For example, opportunistic detection of Wi-Fi (Shu et al. 2015a), GPS (Chintalapudi et al. 2010) or iBeacon (Conte et al. 2015; Martin et al. 2014) can help pinpoint the location and narrow down the search space of geomagnetism-based localization. Furthermore, if the sensors can be dynamically and adaptively initiated for localization in different environments, the energy consumption due to computational search can also be greatly reduced (Zhang et al. 2015).

Discussion: It is important to reduce the search scope for indoor LBS as low computational efficiency degrades the quality of service and the user experience. It is also critical for real-time computing and signal processing systems. The preceding approaches should be applied with care as each of them has a trade-off in their deployment.

Down-sampling the geomagnetic signal map definitely leads to a smaller dataset. However, the signal map down-sampling may also miss important locational information, potentially lowering the quality of signal map (Shu et al. 2015b). Hierarchal location estimation requires proper area division and granularity design with respect to each layer applied in the map processing phase. Besides, if the location estimation is wrong during a coarse phase (i.e., the target location is mapped to incorrect areas), the user experience is much worse than applying the traditional localization algorithms. Sensor fusion often requires more sophisticated schemes and sensing techniques, which may also increase system complexity and energy consumption (He and Chan 2016). One should optimize and combine the preceding measures to achieve more real-time localization performance and better user experience.

3.3 Survey Reduction for Deployment Efficiency

Building a signal map is important and necessary for indoor localization in a complex environment (Akai and Ozaki 2015). Figure 5 shows a typical signal map of the geomagnetic distribution in an academic office building. We collected more than 6, 500 data points with the Samsung Galaxy Note 7 to construct the signal map. Note that traditional fingerprinting for indoor localization is often expensive and labor-intensive, which is infeasible for ubiquitous and global localization (He and Chan 2016). Therefore, researchers attempted to make the signal map construction accurate and efficient. Specifically, we discuss the following three phases for geomagnetic field signal map construction: *signal and location labeling*, *data cleaning (washing)*, and *signal map construction/reconstruction*.

Signal and location labeling: Ground-truth location labeling is important for signal map construction. Explicit manual labeling is simple yet intrusive to users. More advanced approaches consider using inertial sensors or external tracking devices, which may function transparently to ILBS users. Based on how the signals are collected and labeled with locations, we discuss in the following two categories: *user bootstrapping and crowdsourcing*, and *sensor-assisted data collection*.

- *User bootstrapping and crowdsourcing*: With the power of crowdsensing (Howe 2006) and the era of emerging Big Data (Laurila et al. 2012), a signal map can be constructed via crowdsourcing to scale for large indoor sites. In some existing geomagnetism-based localization systems (Xie et al. 2014), crowdsourcing has been mentioned to improve the scalability in spacious sites. One may apply an organic fingerprinting method (Park et al. 2010) using explicit user location inputs. It may be often annoying to explicitly prompt users for signal collection, but we can provide some practical incentives (say, shopping coupons or monetary rewards) to motivate the users for contribution. While interesting problems may have been widely studied for mobile crowdsourcing, with its benefits how to boost forward the ILBS system deployment is still an open question for geomagnetism-based localization.
- *Sensor-assisted data collection*: One may deploy additional sensing infrastructures to help label the crowdsourced signals with locations and calibrate the parameters in the signal map. The cross-modality learning work in Papaioannou et al. (2017) proposes use of image/vision-based tracking to locate the target users and construct the geomagnetic signal map. The proposed system utilizes the site-wide closed-circuit television (CCTV) to monitor and track the targets. Meanwhile, CCTV labels the locations of the target w.r.t. the magnetometer readings, and hence the signal map can be constructed.
  Different from the earlier work, Travi-Navi (Zheng et al. 2014) utilizes only the smartphone sensors (smartphone camera and inertial sensors) to label the magnetic field data with the indoor locations. During the signal collection, the geomagnetic field along the trace is recorded. The magnetometer readings are associated with the photos and Wi-Fi signals. Their combination (or cross-labeling) is then used as the reference for later users' navigation. More advanced studies in mobile robotics utilize the Light Detection And Ranging (LIDAR) and particle filter for magnetic field collection (Akai and Ozaki 2015). Given the measured signals and the trajectory, they also apply a Gaussian process for signal map construction. However, its deployment cost is high (especially using LIDAR) and it is still far from large-scale deployment.

  Though sensor-assistance improves the location labeling accuracy of the magnetic map, some deployment restrictions may exist before the devices other than smartphones can be deployed. Issues like infrastructure costs, extra sensor calibration efforts and occlusions in images should be carefully considered.

Data cleaning/washing: Crowdsourced signals will likely contain measurement error and noise. Sometimes even malicious/erroneous feedbacks may be included in the measurements, thus severely degrading the quality of stored heat map. Given a significantly large data set, the influence from minor erroneous inputs can be filtered out (e.g., via some the majority voting or random sampling consensus (Fischler and Bolles 1981; He and Chan 2016)). Further data washing can be conducted via unsupervised learning (e.g., clustering (Park et al. 2010; Wang et al. 2012)) and other statistical analysis tools widely applied in crowdsourcing (e.g., partial least squares (Wu et al. 2015), support vector machine and minimum covariance determinant).

Unsupervised machine learning infers a function to describe the hidden structure in unlabeled data, and hence is a good tool for indoor localization without site survey (Chintalapudi et al. 2010; Yang et al. 2012). Unsupervised learning (Bishop 2006) with clustering has been widely studied for data washing and preprocessing. According to the concept of signal fingerprint, one can expect that similar geomagnetic signatures which tend to cluster in the signal space would lie at physically close locations (Wang et al. 2012). Schemes like GROPING (Zhang et al. 2015) utilize the *affinity propagation clustering* to find the most representative magnetic fingerprints for each path segment where the target has walked. The clustering process also filters away some unnecessary erroneous fingerprints (or *outliers*) before location comparison, which can serve as a good means of data preprocessing and cleaning.

However, when given only a limited amount of user feedback, it is difficult and inaccurate to conduct simple majority voting and statistical analysis. Therefore, in the initialization of the ILBS, more labor-intensive but more accurate fingerprint collection is often needed before the ILBS system can function satisfactorily.

Signal map construction and reconstruction: At the output stage, the construction/reconstruction of a signal map is non-trivial for geomagnetism-based indoor localization. The crowdsourced signals may be sparse at sites with limited coverage. The geomagnetic signals at the unexplored locations need to be estimated, introducing the so-called "*construction*" problem. On the other hand, given the stored geomagnetic signal map, regular maintenance is required to keep it up-to-date, which becomes the "*reconstruction*" problem. In either case, we need to estimate or adapt the signals given only the crowdsourced data.

Below we briefly discuss the three methods for signal map construction/reconstruction: (1) *Geomagnetic field interpolation*: Given sparse geomagnetic measurements, we can interpolate them to estimate the missing signal values at unexplored locations. Different linear or nonlinear interpolation (regression) methods can be applied (Bishop 2006). For example, one may apply the Gaussian kernels for geomagnetic interpolation. Let $\mathbf{B}_e^i$ be the magnetic fingerprint at location i, and $\widehat{\mathbf{B}}_e$ be the signal to be predicted at an unexplored location, which is given by $\widehat{\mathbf{B}}_e = (\sum_i \omega_i \mathbf{B}_e^i)/(\sum_i \omega_i)$. The weight ω_i can be calculated as $\exp(-d_i^2/\sigma^2)$, where d_i is the fingerprint-to-target distance while σ represents the sensitivity. In other words, the closer the two locations, the more correlated their signals in the signal space. The geomagnetic map shown in Figure 5 is generated based on the preceding kernel-based interpolation. However, the interpolation based on signal values rather than the inherent geomagnetic properties may not sufficiently reflect features of the signals, potentially introducing errors in missing value prediction. (2) *Learning-based signal map prediction*: The preceding (traditional) interpolation usually focuses on some explicit or implicit relationship in signal space. However, indoor geomagnetic anomalies are often complicated due to the complex environment, despite the formulation of a mathematical relationship between the generated field and the source (Jackson 2007). If fully parametric characterization of the geomagnetic anomalies is difficult, then one may resort to the *nonparametric* algorithm for better description or less over-fitting.

Early works (Vallivaara et al. 2010) used the Gaussian process (GP) for geomagnetic signal map construction. However, they only leveraged the squared exponential GP priors for the signal map interpolation. Physical properties correlated with the EMF itself have not yet been considered in their GP for better signal prediction accuracy. The work in Wahlström et al. (2013) proposes using the Gaussian process (Rasmussen and Williams 2006) to model the geomagnetic field. GP has been widely applied for signal map modeling in indoor localization (Ferris et al. 2007; Atia et al. 2013; Herranz et al. 2016). It considers the magnetic signals to be spatially correlated with a Gaussian distribution. This scheme first calculates the hyper-parameters from the training signals (e.g., crowdsourced from mobile users in the target site). These parameters determine the closeness between two locations in geographical and signal spaces. Given the learned hyper-parameters, the system can predict the signals at unexplored locations with these samples.

Mathematically, the traditional Gaussian process (Rasmussen and Williams 2006) is written in the form of $f(x) \sim \mathcal{GP}(0, \kappa(\mathbf{x}, \mathbf{x}'))$, where $y_i = f(\mathbf{x}_i) + \epsilon_i$, $\epsilon_i \sim N(0, \sigma_n^2)$. The task of

Table 4. Typical Schemes for Geomagnetism Signal Map Construction/Reconstruction

Type	Scheme	Signal Map Construction	Geomagnetism Measurement	Sampling Density	Limitations in Deployment
Inter-polation	3D Mapping (Le Grand et al. 2012)	Linear interpolation	Full 3D vector measurement	7 m between collection line	Sampling with high directions; labor-intensive; linear-interpolation is error-prone
	Maloc (Xie et al. 2014)	Interpolation	Magnitude Vertical Horizontal	0.1 m × 0.1 m	Sampling with high density; labor-intensive
	Magicol (Shu et al. 2015a)	Interpolation Extrapolation	Magnitude	Step length	Error-prone to step detection error
Learning-based	GP (Vallivaara et al. 2010)	Squared exponential GP	Full 3D vector measurement	High	Geomagnetic physical properties not considered
	GP+ Physical properties (Solin et al. 2015)	Gaussian process	Full 3D vector measurement	High	Computationally expensive

geomagnetism interpolation with GP is to characterize the hyper-parameters in the covariance function (relationship in signal space) between the locations $\mathbf{x}$ and $\mathbf{x}'$ (Solin et al. 2015). We can then find the function $f(\mathbf{x}_i)$ so given each input location $\mathbf{x}^*$ to be predicted, we may find the corresponding signal estimation y^*.

Despite the prediction accuracy reported, this scheme uniformly applies the hyper-parameters estimated from all input data in the entire site. It is problematic in complex indoor environments with various characteristic length scales and signal amplitudes in different regions of the space. More recent work (Akai and Ozaki 2015) divides the entire spatial map into multiple subareas for more fine-grained training, which is more adaptive and accurate in performance.

(3) *Signal map update*: To adapt the stored geomagnetic signal map to a dynamic environment, one may implement interpolation- and learning-based techniques for reconstruction or update. One key challenge is how to distinguish between the transient (due to moving metallic objects) and permanent changes (due to building structure changes) in the dynamic signal map. An immediate patch may not be necessary for transient fluctuations while it is imperative for permanent signal changes (He and Chan 2016). To better differentiate between them, the site monitor may leverage the long-term consistency check (outlier detection (He and Chan 2016)), data aggregation or majority voting (truth discovery (Jin et al. 2017)) on the crowdsourced signals.

Table 4 summarizes different schemes mentioned earlier for geomagnetic signal map construction/reconstruction. We also qualitatively compare their pros and cons in practical deployment, including signal map density and limitations in database construction. From deployment point of view, one should balance between implementation efficiency and signal accuracy. Small sites like an office room may be easier for validation of sophisticated learning-based methods due to less difficult characterization of parameters in these models. This may also account for the lack of testing related methods under spacious environments in these works. On the other hand, for spacious sites like airports or supermarkets, inherent factors affecting the signals may be enormous. Traditional interpolation can be more efficient to be implemented, from which fine-grained granularity may not be expected. Such trade-off highly depends on the actual deployment demand.

Table 5. Signal Map/Database Construction for Geomagnetism-based ILBS Systems

Scheme	Data Washing & Cleaning	Signal & Location Labeling	Signal Construction & Reconstruction	Signal Construction Reconstruction Accuracy	Adaptivity towards Environment	Computation Efficiency	Deployment Cost	Limitaions in Deployment
3D Mapping (Le Grand et al. 2012)	N/A	Manual	Interpolation	Low	Low	High	Medium	Data-intensive preprocessing
MaLoc (Xie et al. 2014)	N/A	Manual	Interpolation	Low	Low	High	Medium	Data-intensive preprocessing; no data washing
Magicol (Shu et al. 2015a)	N/A	Manual+ IMU/INS	Interpolation & Extrapolation	Medium	Low	Medium	Medium	Inertial sensor labeling contains errors
GRPOING (Zhang et al. 2015)	Clustering & Exemplar Selection	DTW-based Segment Matching	N/A	Medium	High	Low	Low	Clustering is computationally expensive
LIDAR+GP (Akai and Ozaki 2015)	N/A	LIDAR & SLAM	Gaussian Process	High	Medium	Low	High	Gaussian process is computationally expensive
Cross Modality Training (Papaioannou et al. 2017)	Particle Filter Parameter Estimation	Particle Filter & CCTV	Regression	High	Low	Medium	High	CCTV monitoring is error-prone to none-line-of-sight measurement

3.4 Summary of Approaches and Comparisons

We summarize the recent approaches applied in geomagnetism-based systems, and qualitatively compare them based on our own deployment experience. The summary and comparison of these schemes are based on the following metrics:

(1) *Signal Construction/Reconstruction Accuracy*: the accuracy of different construction/reconstruction schemes or systems based on our deployment experience, including the prediction error and robustness to noise.
(2) *Adaptivity towards Indoor Environmental Changes*: including wall decoration, building renovation, structure reconstruction or even human mobility, which may introduce new anomalies in the collected geomagnetism.
(3) *Computational Efficiency*: To achieve fast and scalable deployment, one may need a computationally efficient scheme for the signal map and database construction. Otherwise, the ILBS systems may not adapt to the dynamic market demand and indoor environments.
(4) *Deployment Cost*: Extensive site survey inside the target area is labor-intensive and costly. Furthermore, one may also deploy additional infrastructures besides smartphones for more accurate signal map monitoring, which may introduce extra deployment cost. The engineers for geomagnetism-based ILBS should make a feasible decision in selecting a construction scheme.
(5) *Limitations in Practical Deployment*: including other pressing issues which may be specific to each of the schemes discussed, and the assumptions which may degrade the generalizability of the algorithms.

Table 5 summarizes and compares the differences in recent signal map and database construction approaches. From this table, we can observe that most existing schemes have not thoroughly considered data washing and cleaning, because their proposed schemes have not fully leveraged crowdsourcing for data collection. The works in Le Grand et al. (2012) and Xie et al. (2014) usually consider controlled signal fingerprinting rather than the layman ILBS users, thus not requiring extensive data washing. The deployment cost for the geomagnetism-based localization is often claimed to be smaller than traditional Wi-Fi fingerprinting-based localization. However, advanced sensors like LIDAR and CCTV may increase the system deployment cost.

4 SMARTPHONE LOCALIZATION WITH GEOMAGNETISM MEASUREMENT

Given the constructed signal database and the online magnetometer readings in the query, the ILBS needs to find the corresponding location in the map. Here we consider how to locate the target given smartphone geomagnetism measurements. After overviewing location inference methods (Section 4.1), we discuss how to leverage the local geomagnetic anomalies at landmarks to pinpoint the target location (Section 4.2). We then discuss how to exploit the spatial-temporal geomagnetic patterns for location matching (Section 4.3). We then study the location estimation via sensor fusion (Section 4.4) and discuss the problem of joint localization and mapping (Section 4.5). Finally, we discuss and summarize the state-of-the-art location estimation (Section 4.6).

4.1 Overview of Geomagnetic Location Inference

We first overview the existing algorithms and techniques for geomagnetism-based smartphone localization. Based on the patterns leveraged, we categorize them as *landmark-based* or *spatial-temporal sequence*. Despite the difference of their geometric and semantic representation in signal space, they share common properties of the positional signatures (Suksakulchai et al. 2000) including (1) minimum/maximum signals or bot, (2) ignoring flat signatures that are less informative, and (3) increasing the number of dimensions by combining or adding features. Specifically, the landmark-based schemes leverage the local anomalies in geomagnetic magnitude to identify the locations, while the spatial-temporal sequence matching focuses on the sequential magnetic measurements to identify the walking path (trace). Clearly, the latter may retrieve more abundant signal-location mapping information than the former. Due to lack of dimensions, using only geomagnetism for indoor localization is difficult in practice. To address this, many recent studies focus on sensor fusion with other signals. Besides the preceding pattern matching techniques, we will also discuss how to fuse the magnetic signals with other sensors (say, Wi-Fi (He and Chan 2016) or Bluetooth (Mirowski et al. 2013)) to further enhance the localization scalability and accuracy. Different fusion models, including Hidden Markov Model and particle filter, will be discussed along with some recent state-of-the-art approaches.

4.2 Local Magnetic Anomalies as Landmarks

Local magnetic anomalies can be exploited to pinpoint specific indoor locations, hence forming indoor "landmarks." A pioneering approach, UnLoc (Wang et al. 2012), followed by more recent SemanticSLAM (Abdelnasser et al. 2016), has proposed use of unsupervised learning to extract indoor geomagnetic field anomalies (including the variance of magnetic field within a sliding time window) while the user is walking. Using unsupervised clustering, the algorithm extracts the indoor magnetic field anomalies which can uniquely identify locations, and pins them on the map for navigation. Such an unsupervised-learning approach reduces reliance on the traditional signal fingerprinting, and hence facilitates cost-effective deployment. Some recent efforts like MapCraft (Xiao et al. 2014) also consider the magnetic field anomalies along a corridor for location indication/identification. They form the "peak point in a map" to pinpoint the target location, and hence the search scope can be narrowed further. Figure 6 illustrates the process of landmark-based indoor localization, where the landmark is generated by the geomagnetic anomalies. Given the thus-discovered geomagnetic anomalies, the estimated trajectories are corrected by comparing them with those without landmark information.

Geomagnetic anomalies have also been applied for indoor/outdoor detection. IO-Detector (Li et al. 2014) utilizes the geomagnetic anomalies to determine whether the LBS user is indoor or not. Recall that both the indoor electric instrumentation and the metallic building structures generate geomagnetic anomalies. Distinct features can be identified when one travels between outdoor

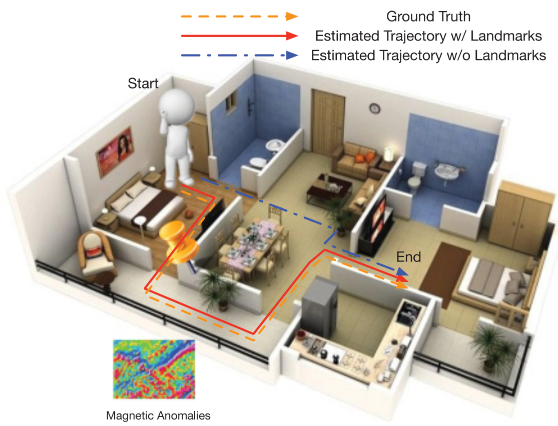

Fig. 6. Illustration of the geomagnetism landmark-based localization and trajectory matching. The discovered geomagnetism anomalies can be used as "pinpoint" to correct the trajectory mapping.

and indoor with smartphones. Hence, IO-Detector sets a certain threshold for the magnetometer readings as the decision boundary. Besides the geomagnetic field measurements, the IO-Detector also combines the readings from cell and the light sensors to further improve the overall detection accuracy. Note that simple thresholding may not be able to deal with significant environmental variations, which has also been shown in some following studies (Li et al. 2014; Radu et al. 2014).

Simple location information can also be retrieved for context awareness. More recent studies have also considered use of the magnetic field measurement change to identify the rooms of the target (Galván-Tejada et al. 2013), or detect the door opening (Zhao et al. 2015). The former considers the extraction of spectral and temporal magnetic features for room classification. Their evaluation shows that the temporal state features are more suitable for signal behavior characterization, given the higher identification accuracy. Based on the immediate magnetic change when passing a door, LMDD in Zhao et al. (2015) leverages a "kernel-based edge-preserving filter" for detection, and uses the cross-correlation function to mitigate the influence of measurement error. Specifically, a Gaussian kernel is proposed to detect the rising/falling edge in the sensor readings. Hence, the environmental white noise is mitigated. To reduce the false detection of door opening (e.g., when the smartphone is approaching other metallic objects), LMDD exploits the following cross-correlation function to preserve only the regular door information and filters out the irregularities:

$$c_{xy} = \frac{\sum_{i=1}^{n} (B_x(i) - \mu(B_x)) \left(B_y(i) - \mu(B_y)\right)}{\sqrt{\sum_{i=1}^{n} (B_x(i) - \mu(B_x))^2 \cdot \sum_{i=1}^{n} \left(B_y(i) - \mu(B_y)\right)^2}}, \tag{4}$$

where n and $\mu(B_x)$ are the size and the mean of a sliding window, respectively. LMDD considers only the x-axis and y-axis readings of the magnetometer. If the cross correlation exceeds a predefined threshold, then the signals will be filtered out to prevent the false door detection. Despite its accuracy reported in their environmental settings, LMDD may likely fail to recognize a glass door with little metallic elements inside.

Discussion: While the aforementioned methods are simple and efficient to implement, their geomagnetic field measurements are not fully utilized in practice. In their settings, only point-wise magnitude (i.e., the strength or intensity) of the magnetic field is usually recorded, which may not be sufficient for large-scale location identification. Such a dimensionless representation provides very limited location information, thus limiting the generality of different and complex environments (e.g., various thresholds for different sites). As a result, these approaches often consider fusing the landmark information with other sensor readings for better decision-making (Radu et al. 2014), which will be thoroughly discussed next.

4.3 Spatial-Temporal Sequence Patterns

In the context of localization, the spatial-temporal sequence refers to successive measurements of signals at multiple locations (He et al. 2015). These temporal readings are inherently correlated in the signal space, exhibiting a pattern to represent a certain location. Besides geomagnetism, the spatial-temporal sequence matching has recently been studied for localization with other signals (He and Chan 2016), including the RF RSS in Walkie-Markie (Shen et al. 2013) and WarpMap (Ye et al. 2016). While its basic principle might be similar, the sequence matching on geomagnetism is different from that on traditional RF (like Wi-Fi) signals in the following two aspects.

(1) For the same smartphone, the sampling rate of magnetometer sensor is often much higher than that of its COTS RF (like Wi-Fi) sensing, for example, 100Hz (Shu et al. 2015a) vs. 1Hz (He and Chan 2016)). Given such large data size and search scope, conducting dynamic sequence matching (e.g., via maximum string matching (Leiserson et al. 2009)) can be computationally costlier than traditional Wi-Fi.
(2) For Wi-Fi fingerprinting, a Wi-Fi sample dumped from Android API may consist of RSSIs from multiple access points (APs), forming an RSSI vector. In many indoor environments, the number of detected APs can easily exceed 10. Each sample point within the Wi-Fi measurement sequence can thus support location estimation with fine granularity. In other words, one may further leverage the RSSI vectors to find the specific point on the trace. In contrast, sequential magnetometer readings are a trace or trajectory which is composed of only 3D values. If similar signal readings exist, then obtaining a more accurate location point beyond the roughly matched trace (Rallapalli et al. 2016) will be more challenging (Ye et al. 2016).

The basic principle used in many recent studies leveraging the spatial-temporal geomagnetic sequence can be summarized as follows. A *sequence/string-matching-like problem* is first formulated based on intuitive observations (Shu et al. 2015a). Then, different matching algorithms, including dynamic programming (DP) (Shu et al. 2015a) or dynamic time warping (DTW) (Rallapalli et al. 2016), are applied. To satisfy the specific application requirements (e.g., low-cost navigation), more advanced system modes like the *leader-follower mode* are then applied (Shu et al. 2015b). Details of each phase are discussed next.

Sequence/string matching: When the user is walking indoors, her/his mobile device can acquire a sequence of geomagnetic readings. Given the signal values within the temporal sequence, one may consider formulation of a sequence matching problem (Leiserson et al. 2009; Rallapalli et al. 2016), which has been studied widely and extensively in the field of natural language processing (NLP) (Weikum 2002; Liddy et al. 2007). Specifically, given these temporal geomagnetic measurements with respect to a walking trace, one may model them as a sequence of strings for further trace matching (Shu et al. 2015a). Sequence matching of the user motion and magnetometer readings along the walking path can be easily solved with traditional string matching and DP.

However, the traditional sequence matching based on DP is still computationally expensive. A longer sequence length may lead to higher matching accuracy, but suffer from inefficiency and high energy consumption, thus creating a practical trade-off in deployment (Paek et al. 2011). In the context of geomagnetic localization, even with some noisy signal measurements, one may find

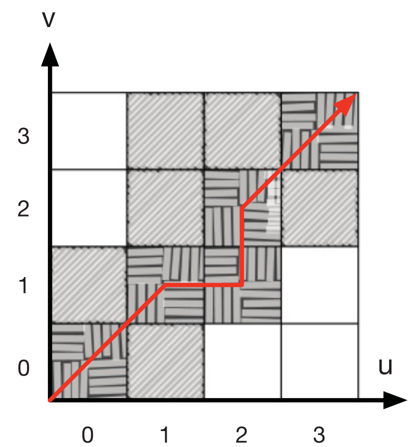

Fig. 7. A typical example showing the dynamic time warping path.

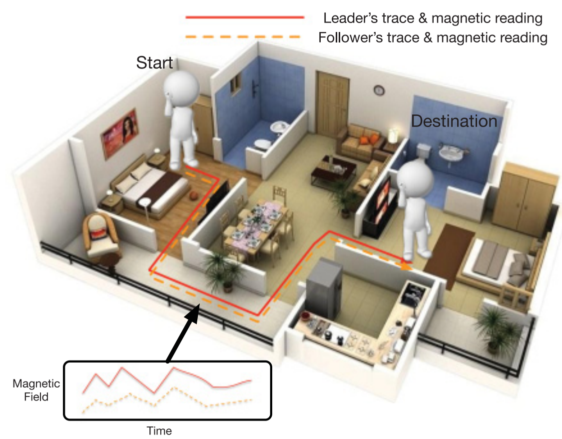

Fig. 8. Illustration of leader-follower mode in the FollowMe system (Shu et al. 2015b).

that a long data sequence does not necessarily lead to more accurate location matching. Besides DP, one may apply more advanced probabilistic schemes including the Hidden Markov Model (HMM), Sequential Monte Carlo (particle filter) method (Shu et al. 2015a) and conditional random fields (CRFs) (Xiao et al. 2014), to solve the matching problem. As these schemes usually involve further sensor fusion, we will detail them in Section 4.4.

Dynamic Time Warping (DTW) (Subbu et al. 2011; Shu et al. 2015a): DTW measures and aligns the similarity in temporal shape between two given time series (Berndt and Clifford 1994; Senin 2008). Specifically, DTW maps each element within a given temporal sequence against one or several entries of another time series. In the geomagnetism-based localization, the algorithm with DTW maps the target's magnetic data (in a sequence) against the preloaded ones in the reference trajectory.

Specifically, DTW considers compressing or stretching the time axis of geomagnetic sequences to better align them (Müller 2007; Subbu et al. 2011), that is, finding the *warping path* with the minimum difference between the magnetic sequences. To solve this, two sequences are usually compared based on the dynamic programming (DP) (Leiserson et al. 2009) to find the warping path. During the search, DTW considers the constraints of *index monotonicity*, *bounded traversal* and *continuous index browsing* (Subbu et al. 2013). Based on these requirements, at each iteration, DTW finds the minimum values among the cumulative differences of neighboring entries, and the distance accumulated (Subbu et al. 2011) in the discovered path so far.

However, in practical deployment, directly applying traditional DTW is computationally infeasible and unscalable (Shu et al. 2015b) for three reasons. First, the user's walking trace dynamically increases as he walks. Traditional DTW works offline upon two given sequences, which is nevertheless not scalable to online streaming data. Second, the quadratic cost function using Euclidean distance incurs high computational overhead. Third, the traditional quadratic cost function compares two sequences based on the absolute values, which is not scalable to device and usage heterogeneity (Section 2.2). Clearly, practical adaptation on DTW should be considered.

Figure 7 shows a typical warping path example of DTW between two sequences **u** and **v**. The red line indicates the minimum warping path. In Shu et al. (2015b), a slight modification has been made to the traditional DTW. That is, after computing the costs of neighboring entries, the system only searches within a specific range along the row v and the column u (Shu et al. 2015b) and

Table 6. Typical Geomagnetism Localization Systems Using DTW

Scheme Name	DTW Type	Cost Function Adaptation	Efficiency Enhancement	Other Adaptations	Limitations
Localization with DTW (Subbu et al. 2011)	Sliding windowed DTW	Absolute value; l2-norm	Sliding windowed	Hallway comparison	Device and usage heterogeneity not considered
LocateMe (Subbu et al. 2013)	Sliding windowed DTW	Absolute value; l2-norm	Sliding windowed; short signature	Short signature comparison	Device and usage heterogeneity not considered
FollowMe (Shu et al. 2015b)	Step-constrained trace synchronization	Differential magnetic information	Step detection constraint	Adaptive search band change	High latency compared with traditional schemes
WaveLoc (Rallapalli et al. 2016)	Enhanced DTW	l1-norm; weighted function	Wavelet coefficient; short-term memory; incremental feature	Hierarchical localization; first trace & then point	Device dependency not considered;

finds the minimum matrix elements. A similar efficiency enhancement has also been proposed in Marshall (2015), where the matching is done within a regional window of each data point. This way, the computation and search scope of DTW can be reduced.

To address the device dependency, one can use differential values during the sequence comparison (Shu et al. 2015b). One may also apply the cosine similarity instead of Euclidean distance. Specifically, the distance at a warping path can be computed by the inverse of cosine similarity (Zhang et al. 2015), which compares the relative shape of 3D vectors. If the shape is closer, then the cosine similarity is greater, leading to a smaller difference (distance).

Since many recent studies proposed different ways of adapting DTW for geomagnetism-based localization, we summarize and compare their properties in Table 6, including computational efficiency and adaptivity to random noise. The basic studies of DTW algorithms focus on how to make the comparison more efficient and adaptive. This table lists several studies adapting DTW to more real-time and localization scenarios. We summarize the DTW type, cost function or adaptation, efficiency enhancement, and deployment limitations according to our own experience.

Leader–Follower mode: Leader–follower mode, or *leader following*, has been widely used for robot navigation (Stein et al. 2016). Basically, a lead agent (not necessarily a robot (Stein et al. 2016)) traverses the target environment. It measures signal–location mapping properties (including the geomagnetic field) and reports them to other following agents (robots). Then, a following agent tries to find the path of the most similar measurement sequences to the leader's (Storms et al. 2010). In terms of ILBS application, such a mode is useful when the ILBS has little knowledge of the indoor map information, and time-consuming extensive bootstrapping is not needed for smart scale deployment (Shu et al. 2015b). Figure 8 illustrates a typical scenario of the leader–follower mode in indoor localization. The system finds the leader trace (the red line) whose geomagnetism matches the most with the follower's temporal sequences (the orange dashed line).

However, as stated in the beginning of this section, such a mode is tailored to some specific application (e.g., temporary or plug-and-play (Shu et al. 2015b)) scenarios. Conversely, if the indoor site is spacious with complex signal properties, the leader–follower mode may achieve no better performance than the traditional localization systems (Bahl and Venkata N. Padmanabhan 2000; Youssef and Agrawala 2005). To support more general long-term ILBS deployment and maintenance, given map information of the large target site, the system still requires full knowledge of indoor map and signal collection. However, with a proper combination of adaptation and optimization, we can build a more ubiquitous localization system with a hybrid mode.

4.4 Location Estimation via Sensor Fusion

As the geomagnetic landmarks may be less informative given noisy or complex environment, many of recent studies focus on fusing the magnetic field with the pedometer (motion information) or the RF signals to further improve localization accuracy and deployability. Discussed later in the text are several directions of geomagnetism fusion along with some deployment issues.

(1) Fusing with the pedometer (step counter): As the user walks, the accelerometer, gyroscope and magnetometer inside his smartphone can jointly measure the walking steps. The repetitive step patterns are detected via the step counter. If the step length is provided or calculated, and then fed to the step counter, then we may derive the walking distance and constrain the location estimation. We may apply the existing state-of-the-art RF-pedometer fusion algorithms (Rai et al. 2012; Xiao et al. 2014), replace the RF signals with geomagnetism, and then apply them similarly. The difference lies in that the geomagnetism is sampled at a much higher frequency, and therefore, the search space can be much larger than that in traditional RF-based fingerprinting algorithms.

However, fusing with the pedometer requires extensive calibration of the step detector and the stride length estimator (He et al. 2015). Recent approaches like MaLoc (Xie et al. 2014) applies the *augmented particle filter* (each particle is also associated with various step lengths and heading values for resampling) to estimate the potential step length and heading without requiring explicit calibration. Anomalies in user behaviors (such as shaking smartphones abnormally) may also influence the motion detection accuracy of inertial sensors (Brajdic and Harle 2013). Instead of inflexible thresholding for motion detection, one may design more advanced model-based classification algorithms, including support vector machine (SVM) (Lau et al. 2008) and principal component analysis (PCA) (Brajdic and Harle 2013), to identify the true walking behaviors.

We have observed that the inertial motion sensors are more suitable for offline site survey (Wu et al. 2013) than for online (real-time) localization, mainly because more accurate or "clean" data can be collected from professional engineers or dedicated users—if a proper incentive is given—than from the inertial sensors or IMUs. However, in case of practical online localization, the user behaviors are much less controllable. It is also intrusive and inconvenient to constrain the user behaviors for motion data collection. Handling diverse motion behaviors, on the other hand, makes the deployment of inertial motion sensing on smartphones much more difficult.

(2) Fusing with Wi-Fi: Wi-Fi (including traditional trilateration (He and Chan 2016), angle of arrival (Kotaru et al. 2015) and fingerprinting (He and Chan 2016)) has recently been studied extensively. Using existing WLANs, one may easily deploy an indoor LBS. Fusing the geomagnetic field with Wi-Fi has recently attracted considerable attention (Li et al. 2015). When applied with a particle-filter-based system, Wi-Fi signals can be used as the distribution constraint on the particles (or as the initial location input). Similarity between measured Wi-Fi signals and the fingerprints can also be used to adjust the particle weights (Shu et al. 2015a), or find the confidence level assigned to candidate locations (Xiao et al. 2015). Furthermore, Wi-Fi supports large-scale localization across multiple areas and floors, which can help reduce the search scope and improve computational efficiency (Li et al. 2015).

Despite the aforementioned advantages, traditional Wi-Fi RSSI fingerprinting still suffers from expensive survey cost (Wu et al. 2013), vulnerability to multipaths (Kotaru et al. 2015) and high energy consumption (Constandache et al. 2009; Subbu et al. 2014). A simple combination of Wi-Fi and geomagnetism without careful adaptation or optimization may offset the benefits brought by both signals.

(3) Cross-modality fusion: Beyond Wi-Fi and other traditional RF signals for indoor localization, many other modalities including image (Papaioannou et al. 2017), Bluetooth (Mirowski et al. 2013), cell (Li et al. 2014) and visible light (Kuo et al. 2014; Zhang and Zhang 2016) have been applied,

or can be easily fused with geomagnetism for improving localization accuracy and deployability. A cross-modality system was proposed in Papaioannou et al. (2017) where image, radio signals and geomagnetism were used jointly for learning site environments. Specifically, given some image and inertial sensor tracking information, the system utilizes the particle filter to estimate the parameters of a geomagnetic signal map. Based on the learned geomagnetic field database, the system then can track the target if its camera does not function properly. These signals or sensing techniques have strengths and weaknesses when applied in complex indoor environment. For example, image-based tracking does not perform well given occlusion between the target and the camera (Papaioannou et al. 2017). For more pervasive deployment, sensor fusion is essential to achieve increasingly ubiquitous localization.

Given the extra signals to be fused, different machine learning models have been explored to improve the localization accuracy. Traditional Bayesian models have been studied widely for the purpose of fusioning, including the typical Bayesian filters like HMM (Rabiner and R. 1989), Kalman filter (Welch and Bishop 2001), and particle filter (Arulampalam et al. 2002). Finally, we will discuss the *Conditional Random Field* algorithms (Sutton and McCallum 2010).

Hidden Markov Model: HMM is a well-known probabilistic sequential model. It provides a scoring mechanism to determine the compatibility between state labels X (locations in our problem) and sensor observations S (Wi-Fi (Seitz et al. 2010) or geomagnetic field measurements). It has been widely studied for indoor localization with sensor fusion, including fusing pedometer with geomagnetism. In HMM, the joint probability distribution between the states and observations (Rabiner and R. 1989) is $p(x_{0:T}, s_{1:T}) = p(x_0) \prod_{t=1}^{T} p(x_t|x_{t-1})p(s_t|x_t)$, where $p(x_t|x_{t-1})$, $p(s_t|x_t)$, and $p(x_0)$ represent the probabilities of transition, emission and the initial (prior) distribution, respectively. The objective of HMM is to determine the optimal hidden state sequences of the maximum joint probability among all possible combinations given the observation sequence. To solve this problem efficiently, the basic assumption for HMM is that the next state depends only upon the previous one (constrained interaction between X and S is formed), which achieves high computation efficiency. The authors of Park et al. (2014) use HMM for indoor multi-modal trajectory matching. Via HMM, the system in Park et al. (2014) finds the indoor path which is the most "compatible" (maximum joint probability) with the measured motion and magnetometer readings (Lee et al. 2013).

More recent studies (Ma et al. 2016) leverage *backward sequences matching algorithms* (BSMA) to further improve the HMM-based algorithm. A single magnetometer reading was considered as low discernibility due to little dimensional information for indoor localization. To address the preceding problem, the authors of Ma et al. (2016) proposed a system, called *Basmag*, by optimizing the HMM framework. The intuition behind Basmag is that instead of focusing on a specific data point, it further conducts backward search to consider the geomagnetic field measurements in a vectorized form. Based on the adapted HMM formulation, Basmag finds the trace of the target with higher accuracy and efficiency.

One common property shared by these HMM-based schemes is that they often discretize the indoor space into multiple cells, each of which is represented by the geomagnetic readings inside. State-space discretization benefits the HMM implementation, and makes the entire location estimation efficient. Such discretization has also been applied in other localization scenarios, including outdoor cell-based LBS.

Discussion: Despite the efficiency of location estimation, the assumption of HMM, that is, the conditional independence, may not provide sufficiently accurate location information. If additional noise exists, then the location estimation accuracy may deteriorate due to the incorrect state indication. It has been shown in Wen et al. (2013) and Xiao et al. (2014) that jointly considering multiple temporal sensor signals can improve the localization accuracy with noisy measurements. Furthermore, when the indoor space is discretized into cells, the size of each cell needs to be determined carefully according to the size of environment, accuracy requirement, user walking speed, and so on.

Kalman filter: Like HMM, Kalman filter has also been studied for tracking and localization problems in many fields including robotics (Welch and Bishop 2001). From the magnetometer's perspective, Kalman filter has been applied in the sensor fusion to mitigate the measurement noise (Beravs et al. 2014). In terms of indoor localization, Kalman filter, including its extended version (nonlinear state estimation), has been applied to mitigate the location error (Zhao and Wang 2012).

Specifically, the Kalman filter models the location estimation problem under an interactive framework between *predictor* and *corrector* (Zhao and Wang 2012). In the prediction phase, the location is estimated based on the previously known position and the state transition modeled by pedestrians' walking. Then, measurements from sensor readings including geomagnetic field are fed and the location estimation is corrected or updated on the weighted observations. The Kalman gain characterizes the weight assigned for the observation corrections.

Discussion: Kalman filter cannot fully address the location estimation problems based on geomagnetism and pedometer due to the complex indoor signal properties (Xiao et al. 2014). The traditional Kalman filter is based on the Gaussian noise assumption and might not accurately represent the realistic measurements. Furthermore, Kalman filter works the best given fusion of different sensor readings (Xiao et al. 2014). If some of the fused signals are missing or removed, then its performance may degrade significantly. Therefore, to achieve more accurate and general localization, most of the recent work is based on the particle filter.

Particle filter: The particle filter has been widely applied for indoor localization. Multiple particles are spread to indicate the potential locations (sometimes including the candidate headings and step lengths), and travel through the indoor site according to the pedestrian motion (Rai et al. 2012). Given the wall constraints brought by the corridors and rooms, incorrect candidate locations that violate the constraints can be filtered out via particle re-sampling (Arulampalam et al. 2002).

Specifically, each particle in the filter is associated with potential locations of the target (other motion information like heading directions, step length, and relative direction changes may be also included) and a weight function describing its importance for location estimation. These weights quantify the degree of consistency between the predicted and the measured states (locations). Initially, the weights are assigned uniformly or according to some external hints. Given geomagnetism measurements (say, similarity comparison or probability distribution) and motion estimation, the particles move accordingly within the target site. Meanwhile, their weights are updated dynamically. For a sensing modality A, let d_A be a certain similarity metric between signals in the target side and a reference location in the signal map (i.e., the larger d_A, the more similar) (Shu et al. 2015a). The weight of a particle p can be given empirically by

$$\kappa_p = \exp\left(-\frac{d_{\text{mag}}^2}{\sigma_{\text{mag}}^2}\right), \quad \text{or} \quad \kappa_p = \exp\left(-\frac{d_{\text{mag}}^2}{\sigma_{\text{mag}}^2}\right) + \sum_k \exp\left(-\frac{d_k^2}{\sigma_k^2}\right), \tag{5}$$

if there is any other specific signal k involved in the fusion. A more advanced weight assignment may be applied. Note that σ_A determines the specific sensitivity to specific signal A. The system may normalize all the weights and perform "re-sampling" (Arulampalam et al. 2002). Particles of better consistency with the external signal correction have heavier weights (importance), making them more likely to be re-sampled and appear in the next round, while others may be less important (or even perish due to low sampling possibility). The location estimation (represented by the weighted average of the particle locations) is expected to converge to the ground truth, given continuous accurate sensor measurements.

Discussion: The particle filter (PF) and its adaptation have been widely studied for geomagnetism-based localization. Despite the ease of implementation and soundness in the performance reported, it is still challenging to determine the particle weight, number of particles, and weight update. Improper setting of particle weight and its update may lead to slow convergence and less robustness to external signal noise. Moreover, the number of particles may also influence the estimation accuracy, robustness and convergence speed. Due to its ease of implementation for localization and potentially high accuracy, researchers proposed numerous ways to improve the PF fusion performance further (He and Chan 2016). For example, the authors of Hilsenbeck et al. (2014) propose discretization of a continuous indoor map into a graph of connected edges to constrain the particles, reduce the search space and overhead, and improve PF robustness. A two-pass bidirectional particle filter was also proposed in Shu et al. (2015a) to improve the fusion accuracy.

EConditional random fields (CRFs): The concept of CRFs has recently become popular for "structured prediction based on undirected graph" (Klinger and Tomanek 2007). Besides indoor localization, it has also been widely used, for example, to analyze human languages or activities. Some researchers (Park et al. 2014) propose using CRFs to model the trend changes in compass azimuth. CRFs in conjunction with other sensor readings are then used to predict the user's walking path. The basic idea of CRFs is to find the sequence of locations, that is, a trajectory, which best matches the sensor (including geomagnetism and motion) measurements. The existing HMM requires the observations induced by an action (say, a stride) which depends only on that state (under the naive Bayes assumption). In contrast, CRFs allow a feature function to associate a chain of sensor observations with one or more states (Xiao et al. 2014). This way, instead of considering one single snapshot of signal measurement, CRFs can jointly consider a sequence of readings and mitigate random errors. A more recent approach, called MapCraft (Xiao et al. 2014, 2015), implements CRFs with Wi-Fi (or magnetic field disturbance map, if exists) and inertial motion sensors for indoor map matching.

The localization scheme based on CRFs has been shown to outperform the traditional HMM in noisy environments as multiple temporal measurements are considered together for making location decisions (Xiao et al. 2014).

Discussion: However, traditional CRFs require extensive training for the hyper-parameters in the maximum entropy framework (Wallach 2002). Especially when new training samples are provided (e.g., newly collected geomagnetism and motion data in the site), the high computational complexity makes it difficult to retrain the models (Sutton 2008). Hence, it is still challenging to scale CRFs in dynamic indoor environments, especially in the context of ubiquitous localization and navigation. In indoor LBS application, if some new measurement traces which are not considered in the training phase appear, the under-trained CRFs may not perform well.

4.5 Addressing Simultaneous Localization and Mapping (SLAM) Problem

SLAM is a critical problem for indoor mobile robot and smartphone localization. In the traditional SLAM problem, the mobile (a robot/smartphone) neither knows the indoor map information nor possesses the site fingerprints. Therefore, dead-reckoning is often required to capture the target's walking trajectory. As odometer- and pedestrian-based dead-reckoning degrades in location accuracy over time, external ambient signals are needed to correct both location estimation and constructed map. The basic idea of solving SLAM is to *simultaneously update the target location and map information to achieve their joint maximum likelihood.* Investigation of geomagnetic SLAM problems has recently begun after Wi-Fi and other SLAM systems (Huang et al. 2011; Herranz et al. 2016) have been studied widely. The authors of Vallivaara et al. (2010) propose fusing geomagnetic field and robot odometer to construct indoor maps. Specifically, they exploit Rao-Blackwellized particle filter (Arulampalam et al. 2002) to find the potential locations and filter out the incorrect odometer measurements. Meanwhile, a Gaussian process (Rasmussen and Williams 2006) is implemented to model the spatial relationship of geomagnetism. Using this fusion, the system finds the target's location while constructing the indoor map.

Discussion: Despite its proof-of-concept prototype in the field of robotics, SLAM can also be applied to smartphone-based localization, only with step counter and device heading estimation. On the other hand, introduction of vision/image or even LIDAR processing may improve accuracy at the cost of additional system overhead. Therefore, smartphone-based SLAM needs to make good use of raw sensor data to balance between mapping accuracy and system overhead. Some recent studies (Huang et al. 2011) have shown that solving the joint optimization in SLAM problems is often computationally expensive due to simultaneous map calculation (Smith et al. 1990). To address this, FastSLAM (Montemerlo et al. 2002), followed by Robertson et al. (2013), was proposed to recursively estimate the posterior distribution of landmarks, and scales w.r.t. their number in a *logarithmic* manner. Efficient GraphSLAM (Huang et al. 2011)—which reduces the sophisticated optimization problem to the *least-squares* problem—was also proposed to improve the system scalability. To summarize, with proper taming over incoming data and the algorithm design, SLAM-based approaches can be efficiently deployed on smartphone platforms.

4.6 Summary of Approaches and Comparison

Based on recent reports (Xie et al. 2014; Shu et al. 2015a; Xie et al. 2016), we briefly discuss the performance of geomagnetism-based smartphone localization in practical application scenarios. Given localization algorithm and mobile device, diverse location estimation accuracy has been examined for different users and environments. In terms of user dependency, the reported estimation accuracy may vary marginally with different users (say, less than 10% (Shu et al. 2015a)), relative smartphone locations to the user body or with similar phone holding positions (Xie et al. 2014; Shu et al. 2015a), while the user step length, diverse walking frequency and user behavior anomalies may in practice markedly influence the motion sensor estimation. Taking MaLoc (Xie et al. 2014) as an example, we have observed that deliberate phone shaking while walking may cause up to 30% degradation of accuracy. Besides user dependency, the same scheme may show significantly different localization accuracies at sites like parking lots, corridors and shopping malls. Change of nearby metallic objects, diverse degrees of freedom in user mobility and crowds at a site may easily influence the localization performance (Shu et al. 2015a). For example, in terms of mean localization error, Magicol (Shu et al. 2015a) may achieve approximately 3.1m and 4.5m at a complex office building and a premium supermarket, respectively, which are almost twice the degradation of accuracy compared to a narrow and constrained environment (1.85m). Like many other localization schemes, how to mitigate the user and environment dependencies is still a major challenge for the geomagnetism-based localization.

We further summarize the approaches and compare them according to our own deployment experience based on the following aspects:

(1) *Localization accuracy*: Location estimation error is the key metric in evaluating the ILBS systems. Here we focus on the "mean localization error" or "classification accuracy." These metrics may depend on the testing environments and hence we list the values for reference only.
(2) *Sensor deployment/infrastructure cost*: Some schemes may rely on additional infrastructures or sensors for further location estimation, which may be expensive in practical

Table 7. Typical Geomagnetism-based Localization Systems for Mobile Devices

Types	Scheme	Location Estimation Algorithm	Additional RF Signals Used (Y/N)	Reported Accuracy (eg. Mean Localization Error)	Sensor Deployment/ Infra-structure Cost	Robustness to Environmental Noise	Smartphone Computation/ Energy Consumption	Limitations/ Restrictions in Practical Deployment
Landmark (Local EMF Anomalies)	UnLoc (Wang et al. 2012)/ SemanticLoc (Abdelnasser et al. 2016)	Landmark Matching (bending coefficient)	Y	1-2 m	Low	Low	High	Orientation detection & device dependency not fully addressed;
	IODetector (Li et al. 2014)	Joint Thresholds	Y	82%-90% in Indoor/Outdoor Detection	Medium	Low	High	Require cell link; thresholding in geomagnetism is not robust
	MapCraft (Xiao et al. 2014) (Xiao et al. 2015)	CRFs	Y	<2 m	Low	High	High	Heavy training overhead in CRFs
Spatial-temporal Sequence Matching	LocateMe (Subbu et al. 2013)	DTW	N	3.5 m	Low	Low	Low	Error-prone to electro-magnetic inference
	FollowMe (Shu et al. 2015b)	DTW	Y	<2 m	Low	Medium	Medium	Leader following mode fits low-cost small-scale deployment
	GROPING (Zhang et al. 2015)	DTW/ Bayesian	Y	<5 m	Low	High	Medium	Require incentives for extensive and high-quality crowdsroucing
	WaveLoc (Rallapalli et al. 2016)	DTW	Y	<1.5 m indoors; 10 m outdoors	High	Medium	Medium	Require CSI information with extra cost
Fusion with Motion (Signal Value Compari-son)	BasMag (Ma et al. 2016)	HMM	N	1 m	Low	Low	Medium	Error-prone to multiple noisy measurements
	Motion Compatibility (Park et al. 2014)	CRF/HMM	Y	<5 m	Low	Medium	Medium	Error-prone to user motion anomalies
	MaLoc (Xie et al. 2014) (Xie et al. 2016)	Particle Filter	N	<2 m	Low	Low	Medium	Particle convergence; computation power
	Travi-Navi (Zhang et al. 2016)	Particle Filter	Y	<2 m	High	High	High	Require camera support; applied to navigation only.
	Magicol (Shu et al. 2015a)	Particle Filter	Y	<4 m	Low	High	High	Particle convergence; computation power

deployment. In contrast, only leveraging geomagnetic sensing (combined with other inertial sensors) would incur much lower deployment cost.

(3) *Robustness to environmental noise*: The environmental noise includes measurement errors due to the participants in crowdsourcing, indoor structure changes and electrical appliances (like an elevator motor), all of which may influence the magnetometer readings at nearby smartphones.

(4) *Computation/energy efficiency*: The computation time determines the response rate of location estimation with respect to each localization query. Meanwhile, a long query time means high computation and power consumption for the algorithms running offline. Therefore, for better user experience of LBS, one might prefer a scheme with higher computation efficiency.

(5) *Limitations/restrictions in practical deployment*: including different scenarios or practical issues which may limit the performance of the proposed algorithms. We will also consider their reproducibility and generality in deployment.

Table 7 summarizes recent smartphone-based systems using geomagnetism. It also provides their qualitative comparison based on the preceding aspects. This table indicates that modeling the magnetic signals during the user's walking for sequence matching has been studied extensively. Various related algorithms that compare sequences have been applied and promising

Table 8. Comparison of Geomagnetism with Other Signals for Smartphone-based Indoor Localization

Smartphone-based Sensor Signal	Reported Accuracy	Extra Infra-structure Cost	Deployment Scalability	Energy Consumption
Wi-Fi	5–10m	WLAN	Medium	High
Bluetooth	3–10m	iBeacon	Micro	Medium
GSM	5–50m	Cellular Network	Macro	High
Camera	2–5m	No	Micro	High
FM	2–10m	FM Radio Chipset	Macro	Medium
Acoustic	<1m	No	Micro	High
Inertial Sensor	5–20m	No	Macro	Medium
Geomagnetism	1–5m	No	Medium	Low

micro-location estimation results have been reported. Despite their technical merits, a few of them have identified their limitations in static user localization, floor identification and context awareness for a more spacious indoor area where users might have much higher mobility. For example, fusing geomagnetism with the image requires line-of-sight photos (Papaioannou et al. 2017). Occlusions from walls or furniture may degrade the tracking performance. For the step-counter measurement (Xie et al. 2014), the step readings may be noisy due to abnormal user gestures. These will all limit the generality of the proposed localization algorithms. Due to the requirement of accumulated signals, existing systems may not fully address the "cold start" stage of the ILBS, given no historical sensor records, that is, "where am I right now" when one launches the LBS application for the first time. The initial location hints by Wi-Fi and iBeacons might be needed before more ubiquitous localization can be done (Shu et al. 2015a). This may also increase the complexity, energy consumption and infrastructure cost.

Finally, Table 8 compares geomagnetism with other available signals for smartphone-based indoor localization. These schemes are evaluated in terms of localization accuracy, extra infrastructure cost, deployment scalability and energy consumption. For deployment scalability, we consider three levels: micro (~20m^2), medium (~200m^2), and macro (~1,000m^2). Traditional RF signals (including Wi-Fi, Bluetooth, and GSM) are more likely to provide large-scale site deployment. However, their accuracy and energy consumption on mobiles may not be as satisfactory as non-RF signals. Geomagnetism-based schemes are found to achieve reasonably high localization accuracy with low energy consumption, and do not rely on extra infrastructures, making geomagnetism a signal with potentials for smartphone-based indoor localization.

5 CONCLUSIONS AND FUTURE WORK

Use of various signals has been explored for indoor localization, and of them, geomagnetism has emerged as promising for numerous practical reasons. In particular, geomagnetism is pervasive, does not require any additional infrastructures, and its fingerprint has been observed to be temporally more stable and spatially more discernible than commonly seen Wi-Fi fingerprints, enabling accurate localization.

In the context of smartphone-based computing, we have investigated the recent advances in geomagnetism-based indoor localization. We first discussed the emerging issues with the geomagnetism measurements using smartphones. We then examined the recent approaches to

Table 9. Several Commercialized Geomagentism-based ILBSes for Mobiles (By Late 2016)

Company	Year Founded	Reported Accuracy	Other Sensors	Extra Features
Indoor Atlas (IndoorAtlas 2016)	2012	1–2m	GPS	Map creator for layman users
GIPStech (GIPStech 2016)	2013	1m	Wi-Fi, iBeacons, Augmented GPS	Different IoT devices
indoo.rs(Indoo.rs 2016)	2010	2m	iBeacon	SLAM
Compathnion (Compathnion Technology 2016)	2015	1m	Wi-Fi; iBeacon	Crowdsourced signal map update
Ubirouting(UbiRouting 2016)	2013	1–2m	Wi-Fi; iBeacon	Map creator

constructing and updating a geomagnetism database (or signal map). We surveyed ways to reduce the data-collection effort and location-search computation. Given a constructed magnetic field database, we then reviewed the ways of localizing a target, including pattern matching and sensor fusion algorithms. We have also identified challenges and presented insights into this research field for new researchers and engineers. Based on this comprehensive survey, we summarize the fundamental limitations and potentials, and provide some future research directions as follows.

Improving Magnetometer Calibration: Although researchers have studied how to utilize geomagnetism for indoor localization and navigation, few of them have fully addressed the problem of calibrating the smartphone magnetometer for more accurate localization. The magnetometer readings may change significantly when the smartphone is close to electric appliances (e.g., microwave oven) or placed with metallic objects. In a complex environment with strong electromagnetic interference, the magnetic field measurements may show a different shape than the fingerprints, leading to potential localization error (Gao and Harle 2015). To fully address these issues, further sensor fusion and more advanced sensor filtering are needed.

Enhancing Ubiquitousness and Localizability: From Table 8, we also observe that the deployment of magnetism may not be as scalable as other RF-based signals. Existing localization schemes based on geomagnetism largely rely on the local anomalies introduced by some indoor building structures. The available information of plain geomagnetic fluctuations in some areas may not suffice to distinguish different locations. How to identify the floors or buildings is also critical for ubiquitous geomagnetism-based localization. Therefore, the ubiquity and localizability of the geomagnetism system often varies with environment, making its pervasive deployment challenging. How to cooperatively fuse geomagnetism with other signals (Bai et al. 2016) for better ubiquity and localizability is also an interesting topic to explore.

Updating Geomagnetic Signal Map: Complex indoor magnetic environments make it difficult to characterize and predict geomagnetic distribution. Unlike relatively sparse RF-signal measurements with long coherence lengths (Gao and Harle 2015), the geomagnetism pattern degrades more quickly with distance from metallic objects. Knowledge of neighboring sampling points may not necessarily lead to accurate characterization of local measurements (Xie et al. 2014). The massive amount of sampled data also makes regressing and updating the entire constructed magnetic signal map potentially labor intensive (Gao and Harle 2015). To enable its practical deployment, it is critical to accurately and efficiently update the magnetic signal map.

To show the current status of deployment, we review the recent commercialized systems in geomagnetism-based smartphone localization. According to Research and Markets (2016), the global ILBS market is expected to grow at a Compound Annual Growth Rate (CAGR) of 43.44% during 2016–2020. Table 9 lists several existing commercialized ILBS engines which have reported use of geomagnetism for localization. Note that for Apple iOS platforms geomagnetism may outweigh Wi-Fi fingerprinting, as Apple has not yet provided authorized Wi-Fi RSSI fingerprinting service on iOS devices. As of late 2016, commercial trials using Wi-Fi and iBeacon still outnumbers those using geomagnetism, due mostly to the challenges mentioned thus far. Bridging the gap between research and deployment is still very challenging. Table 9 also shows the current trend of fusing geomagnetism with other RF signals. Despite disadvantages in energy consumption and fingerprint stability, existing RF (like Wi-Fi) fingerprints still provide higher dimensionality and larger coverage of location information if properly leveraged. To support more ubiquitous LBS, one may need to fuse geomagnetism with multiple sensing modalities (Xu et al. 2016).

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