Evaluation of Geomagnetic Matching Algorithms for Indoor Positioning

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Abstract

Geomagnetic fingerprinting is a promising technology for supplying smartphone indoor navigation algorithms with infrastructureless and to some extent stable local position information. Geomagnetic disturbances in buildings impose a characteristic magnetic signature which can be detected by the phones magnetic sensor. A common approach is to create a database by recording reference fingerprints for example along a predefined known path. In the positioning phase, magnetic data is recorded along a certain time- or path length of the unknown path. The live data can be analyzed and compared against the prerecorded reference fingerprints. This magnetic matching procedure differs considerably from WiFi fingerprinting, where WiFi data from discrete points is compared. The main difference is that the described approach uses data recorded as time series. The matching has to consider not only the signal amplitude but also temporal- or spatial matching. In this paper several magnetic matching algorithms are evaluated for usage in an indoor positioning system. A public database is used as data source allowing comparison of the results with other works.

1. Introduction

Smartphone Indoor positioning is a technology which allows position determination with a smartphone in indoor environments. As no reliable GNSS signals are available in buildings, other technologies are needed. Numerous information- and communication technology groups are performing research on the topic. WiFi RSSI (received signal strength indicator) indoor positioning is a commonly applied approach and has been investigated since 2001 [1]. The most widely used algorithm is RSSI fingerprinting. However there are more methods, for example radio tomography, multilateration, centroid, proximity and more. These are a choice in cases when no radio map is available. An advantage of Smartphone WiFi based localization is the fact that it may be applied even if the WiFi installation has not been specifically prepared for that use case and, for example, characteristics and positions of the WiFi access points are unknown. The obtainable accuracy for WiFi based positioning is in the meter range for typical scenarios [2, 3, 4], as for example observed at Indoor localization competitions like the Smartphone-based Off-Line Indoor Location Competition at IPIN 2016 [5] or the EvAAL-ETRI 2015 competitions on indoor localization in large environments [6].

To enable more accurate results, data from all available sensors of a smartphone may be employed. This includes inertial measurement data from gyro- and acceleration sensors, compass

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data, as well as barometric- and magnetic data. The obutained accuracy may then be increased for example by Kalman filtering or application of a particle filter [7, 8, 9].

The paper focuses on using the geomagnetic field for indoor positioning [10, 11], in particular on the topic of geomagnetic matching along certain path [12]. An agent who wants to know his position records a trace of the magnetic field along his route. By comparing the trace with prerecorded traces which are stored in a database in many cases a position estimate can be performed. Reference records may be collected by walking the possible paths and calibrate these measurements to ground by enriching the records with true ground information at predefined reference points. In the paper several magnetic matching algorithms are tested for applicability in an indoor positioning system.

In order to have a reliable data source a publicly available database was used for the analysis. The database of the smartphone offline Track from the IPIN 2018 competition has been chosen. It contains more than 40 training- and validation data sets each covering 5..10 minutes of walking annotated with true ground information of 41 different ground truth points, distributed on 3 floors of the Atlantis shopping mall, Nantes, France. Also a large 20 minute evaluation data set with about 100 true ground references is available [13, 14].

2. Magnetic fingerprinting

The north-south direction of the Earth magnetic field has been used for the compass for centuries. The magnetic field is a vector, and a smartphone measures all 3 components of this field. The field at a certain location is constant or at least nearly constant if considering the migration of the magnetic poles. If one moves and changes his location on flat natural ground, the change in magnetic field is also only weak and hardly measurable in the range of a few kilometers. However, the field is strongly influenced by ferromagnetic materials such as iron. This leads to the fact that in modern buildings the field is by no means constant but rather has a characteristic location dependence, which is generated e.g. by reinforced concrete or iron girders, pipelines, machines etc..

If the magnetic field is measured along a defined path in a building, it generates a characteristic measurement curve. One possible principle of position determination based on the magnetic field works as follows: First, certain paths have to be defined in a building and the magnetic field has to be recorded along these paths and stored in a database. These recordings are the magnetic fingerprints. If an agent now wants to determine his position, he also measures the magnetic field along his path. For determination of the current position, the values for the last meters of walking, for example the last 5 meters are used. Now he searches the database for sections in the records (the fingerprints) that match his own recording. If such a section is found, it is likely that the agent is at the position that belongs to the end of the found section. The procedure is referred to as geomagnetic fingerprinting [15, 16, 17].

This method is very different from WiFi fingerprinting methods [1, 18], because with WiFi fingerprinting the position can be determined statically at a location based on the readings from different access points. As WiFi signals contain an identification of the transmitter, the comparison is spatially unambiguous, similar fingerprints only occur within neighbor positions. With magnetic Fingerprinting, there is only one access point, the earth. In order to obtain a meaningful fingerprint, a path comprising several meters needs to be recorded. If several paths share certain features, the matching between the magnetic fingerprints is not unambiguous, and further information like for example WiFi positioning or PDR history has to be used for selecting possible magnetic fingerprint candidates.

A matching procedure for magnetic fingerprints shall deliver a likelihood measure, e.g. a numerical value, and a displacement value e.g. a number expressing the temporal or spatial displacement between the magnetic trace from the evaluation path and a prerecorded reference path.

In the following sections, referring to the magnetic field or the magnetic signal means referring to the amplitude of the magnetic field vector. Of course, also other information like the z-component of the field or combinations could be employed for fingerprinting. There are two kinds of records used: In the positioning phase, the magnetic amplitude is recorded by the agents smartphone. This record, for which the true ground positions are to be determined, is named “evaluation trace”. The unknown path itself is referred to as the “evaluation path”. A magnetic reference measurement along a known path, recorded during the initial mapping phase, is referred to as reference fingerprint or “reference trace” (alias “training trace”).

3. Time to path mapping

The database comprises numerous “long reference records” which, each in different well-defined paths, pass a subset of 41 known true ground reference points, and the passage of the points is marked in the record. By employing a PDR positioning algorithm [19, 20] continuous position estimates are performed for these reference records. Magnetic data is thereby mapped from elapsed time to passed path length as well as ground position. For each 10 cm of passed path length, a data point is generated. From each “long record”, new records are split off each time a known true ground reference position is passed. These reference records each are cut such that they start 40 meters before passing the reference point and end 10 meters after the reference point. That is also the x scale on the figures presented later.

The database comprises also a “long evaluation trace”. Also for this evaluation trace the time when the agent passes the reference points is known. For this paper, a representative cut of the trace has been selected to serve as base for the analysis. The cut comprises a 20 meter sequence ending before the selected reference point. In a practical scenario, the true ground and passed positions may not be known for an evaluation path and a relative mapping from time to passed path length is not generally possible. Therefore in the paper, the mapping is performed by using only the step counter and a fixed step length. This compensates for stops in the walk, but not for different walking speeds.

4. Evaluating of methods for comparing magnetic traces

Figure 1 (a) shows 3 magnetic reference traces and one evaluation trace. All traces are high-pass filtered to remove the constant field contribution and low-pass filtered to reduce signal noise. The x-axis shows the route distance to a certain reference point of the database. Only those traces aligned to the walking direction are shown. The evaluation trace has been also adjusted

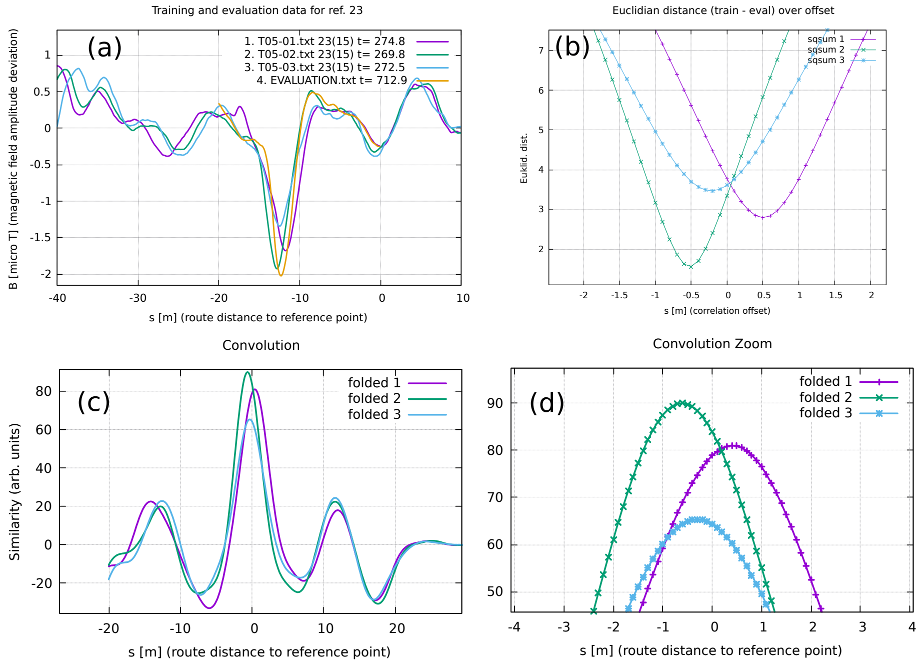

Figure 1: (a) Magnetic amplitude traces recorded with a smartphone. (b) Euclidean distance between 3 reference traces and the evaluation trace, over displacement. (c) convolution instead of Euclidean (d) zoom into convolution.

as the passing time of the reference point was known. In general, the path distance between reference and evaluation is not known but is the number to be determined. If, for example, the path distance between evaluation and a certain reference was -3 meters (3 meters before passing the reference point), the current position of the agent would be the position which is annotated for -3 m in the reference track. So, by determination of the route distance between reference and evaluation path, the unknown position can be determined.

Deviation from true position	Ref. 1	Ref. 2	Ref. 3	avg
Euclidian dist. min value	2.8	1.6	3.5	
Euclidian dist. min. path [m]	0.5	-0.5	-0.2	-0.07
Convolution max. val.	81.5	89.8	65.2	
Convolution max. path [m]	0.4	-0.6	-0.3	-0.17
DTW min value	1.23	0.36	2.35	
DTW min path [m]	0.0	-1.4	-0.8	-0.73
Modif. DTW min value	2.46	1.16	3.24	
Modif DTW min path [m]	0.6	-0.4	-0.5	-0.1

Table 1

Results: the “min./max. path [m]” is the magnetic positioning error.

The distance will be determined by correlation. In 1 (b) the Euclidean distance between a reference fingerprint and the evaluation fingerprint is shown over the fingerprint correlation

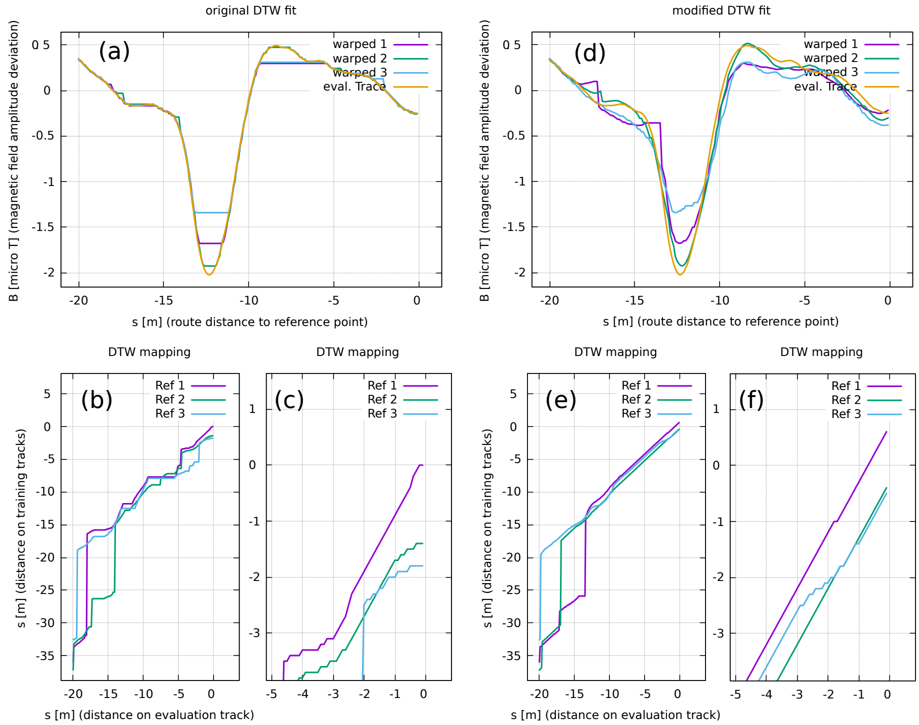

Figure 2: (a) plain DTW matching of the reference trace with the evaluation trace. (b) plain DTW point mapping. (c) zoom into (b). The line ends indicate the matching position. (d,e,f) show the same data as (a,b,c), but with a modified DTW algorithm.

offset. The minimum x value indicates the path offset in meters for the best match. In the ideal case this would be zero, as the measurements are aligned with the real time when each of the traces passes the reference point. Practically a small misalignment may be caused by measurement noise. Another source is the mapping of time to path length, which depends on the accuracy of the step detection. Nevertheless, the maximum obtained displacement is 0.5 m only, which is a reasonable accuracy.

Figure 1 (c) and (d) (zoomed) brings the result of a convolution. As expected, the results are quite comparable to the ones obtained by the Euclidean distance.

Figure 2 displays the result of dynamic time warping (DTW) (see for example [15, 21]). Figures (a) and (d) shows the warped reference curves. For (a), the standard warping algorithm is used. Here a problem of DTW can be seen: A difference in amplitudes between the signals will lead to a spreading of the warp in time, which can be seen as horizontal "jumps" for example at the minimum. To avoid this strict amplitude criterion, in (d) the warping algorithm has been modified by adding penalties to non-diagonal mappings. This forces a more natural mapping, as it can be seen also in the mapping diagrams (b) and (c) for the non-modified case, and (e) as well as (f) for the modified case. As it can be seen at the mapping end positions near coordinates (0,0), the unmodified case leads to errors of nearly 2 m, in the worst case. The modified warping stays within the 0,5 m result obtained already for Euclidean and convolution. However, the warping should principally have the advantage of being able to well adopt to variations in the step length (not shown here).

5. Results and Outlook

Magnetic fingerprinting has been investigated on the IPIN2018 track 3 smartphone offline database. By mapping magnetic readings to positions respectively passed path length, magnetic fingerprints have been constructed. It has been shown that positions may be mapped to reference points with an accuracy of better than 0.5 meters, for an exemplary case (Table 1). Three different approaches have been compared. It was found that Euclidean distance and convolution as well as DTW deliver results with comparable accuracy. For DTW, a modification has been proposed that favors diagonal mapping by introduction of penalties. However, DTW seems to be not as stable as the others.

The next step will be to continue the integration of the magnetic fingerprint algorithm into an existing positioning algorithm. From the preliminary results we deduct that, at regions where feature-carrying magnetic data is available and is close to true-ground references, an unknown path may be matched with a spatial accuracy in the range of 1 meter or better. The positioning phase will be fully implemented to demonstrate and evaluate its feasibility in a lab setup and with publicly available evaluation data.

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