Smartphone Indoor Positioning Using WiFi, PDR, Magetic Fingerprints and Particle Filtering

Stefan Knauth[0000−0001−6873−472X]

Faculty for Computer Sciences, Mathematics and Geomatics
HFT Stuttgart – University of Applied Sciences
Schellingstr. 21, Stuttgart, Germany

Abstract. The evolution of an existing offline algorithm for smartphone based indoor localization is outlined, discussed and evaluated. The existing algorithm performs dead reckoning using accelerometer-, compass- and gyroscope data as well as WiFi fingerprinting. Steps are detected using accelerometer data. Compass and gyroscope are used for heading estimation. Drift compensation and step length estimation is performed by a particle filter using map information as well as WiFi information. Floor detection is based on RSSI (Radio signal strength indicator) evaluation and on map information. The evolution comprises a PDR-enhanced radio map generation algorithm, the particle filter with motion parameter adjustment by WiFi data, and Magnetic fingerprinting. The modifications are described and discussed. The performance is evaluated against a publicly available database.

1 Introduction

Smartphone Indoor positioning, particularly in public environments, is a highly demanded technology. As of today, it is yet a topic of ongoing intense research in information- and communication technology fields. WiFi RSSI (received signal strength indicator) indoor positioning using smartphones is a commonly applied technology and dates back to 2001 ([2]). RSSI algorithms are typically based on fingerprinting. However, depending on circumstances like unavailability of a radio map or reduced accuracy requirements, other methods like proximity, centroid, multilateration, radio tomography, and more have been successfully deployed. Smartphone based localization may be performed 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. Unfortunately, in typical scenarios the obtainable accuracy of pure RSSI localization is limited to some meters [3, 8, 11], as for example observed in the EvAAL-ETRI 2015 competitions on indoor localization in large environments [16] or the Smartphone-based Off-Line Indoor Location Competition at IPIN 2016 [15].

Contemporary smart phone positioning algorithms typically combine RSSI information and further smartphone sensor data, mainly inertial measurement data from gyro- and acceleration sensors, compass data, as well as magnetic data. Using dynamic filtering, for example particle- and Kalman filter, the obtained accuracies can be increased significantly. [17, 4, 12].

In the paper the design of a WiFi fingerprinting- an dead reckoning algorithm with floor plan based particle filtering is outlined. The proposed algorithm is an evolution based on the authors algorithm applied in the last IPIN competitions (2016, 2017 and 2018). A new feature of the algorithm is the inclusion of magnetic fingerprinting.

2 Exisiting algorithm

The HFTS algorithm used in the 2018 competition is based on WiFi and pedestrian dead reckoning (PDR), and a particle filter (PF). It is an evolution of the algorithm deployed at the 2016 competition [7] and the 2017 Competition [6].

For dead reckoning, heading estimation is performed using compass and gyroscope data. The gyroscope is able to detect heading changes quite accurately on a short timescale, but will drift in the long-term. In contrast, compass heading is subject to strong local magnetic perturbations but shows no drift on a long-term scale. Therefore, gyroscope data is used for detection of immediate heading changes. The heading relaxes to the compass direction with a certain time constant of some seconds. Step detection is performed by peak detection of the accelerometer data.

WiFi positioning is performed using the scalar product correlation fingerprinting algorithm [8] which is based on k-nn and the cosine similarity. Prior to the estimation of the unknown competition track, a radio map is obtained by evaluating the reference data provided by the competition organizers. These data are enriched with true ground positions and RSS readings. Therefore obtained RSS vectors can be related to a position. As the true ground readings occur only rarely, the actual reference position between two reference points is interpolated by PDR.

The actual positioning process comprises 2 phases. In the first phase RSS positioning is performed employing the radio map. RSS readings are obtained at a rate of one reading every 4 seconds. For each reading a position is estimated. Also the floor is estimated by RSS. If the actor is moving, the position will change considerably in the 4 seconds between two subsequent RSS readings. Therefore, the position between the two readings is interpolated based on dead reckoning. The heading offset and the actual step length is not known at this stage. However, as for the start- and the endpoint of the 4 second track a RSS position estimation exists, the step length and heading offset are adjusted such that the track connects the two points.

In the second phase, positioning is performed employing PDR and a particle filter. Step length estimation and heading error- and drift compensation are performed by the particle filter using the information of floor plans to detect the most likely path (see also [5, 17]). The particle filter contains a constant number of particles. Besides the position, a particle state also comprises individual step length and heading offset values. The filter is updated each time a step is detected: All particles are moved according to the estimated heading, individually modified by the particle specific offsets. Resampling is performed as follows: particles which collide with, for example, a wall, are replaced by a new ones. For collision detection the provided floor plans are used. New particles are seeded at the position of an existing particle, but with an own randomized step length and heading offset value. The global heading and step length are recalculated by averaging the heading values and step length of all particles. The reported PDR position is the averaged position of all particles.

Depending on the building layout, e.g open spaces, corridors, room sizes etc. the PF results alone may not be sufficient for absolute position determination. Therefore, the step length and heading are also adjusted by the obtained WiFi position from phase 1: After each step the longitudinal- and the lateral displacement between WiFi and PF position are evaluated and a configurable fraction of the displacement is added to the movement vector.

3 Magnetic fingerprinting

3.1 Principle

The geomagnetic field inside a modern building is disturbed for example by steel in the building structure or by furniture. This holds for both, the direction and the amplitude of the field vector. The magnetic disturbances typically are quite constant over time and have been used as reliable landmarks for positioning purposes [14, 10, 13]. The positioning procedure, while often referred to as "magnetic fingerprinting", differs considerably from WiFi fingerprinting methods [2, 9]. A WiFi fingerprint database comprises fingerprints from certain positions of the building. Positioning is performed by comparing a fingerprint from an unknown position with the fingerprints in the database. As WiFi signals contain an identification of the transmitter, the comparison is spatially unambiguously, similar fingerprints only occur within neighbor positions. Magnetic fingerprinting uses only one access point, the earth. So fingerprints can only obtained by recording the magnetic field along a path, and fingerprinting is performed by comparing a recorded path of a certain length with a database of several prerecorded path. It can be assumed that, if the fingerprints match, it is likely that the same path has been passed. If several path share certain features, the comparison is not unambiguously, and further information like for example WiFi positioning or PDR history has to be used for selecting which magnetic fingerprint is the most closest one to the estimated position. 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.

3.2 Correlation

In Fig. 1 the situation is shown for the datasets of the Atlantis shopping mall, Nantes, France, which have been created for the IPIN 2018 indoor localization

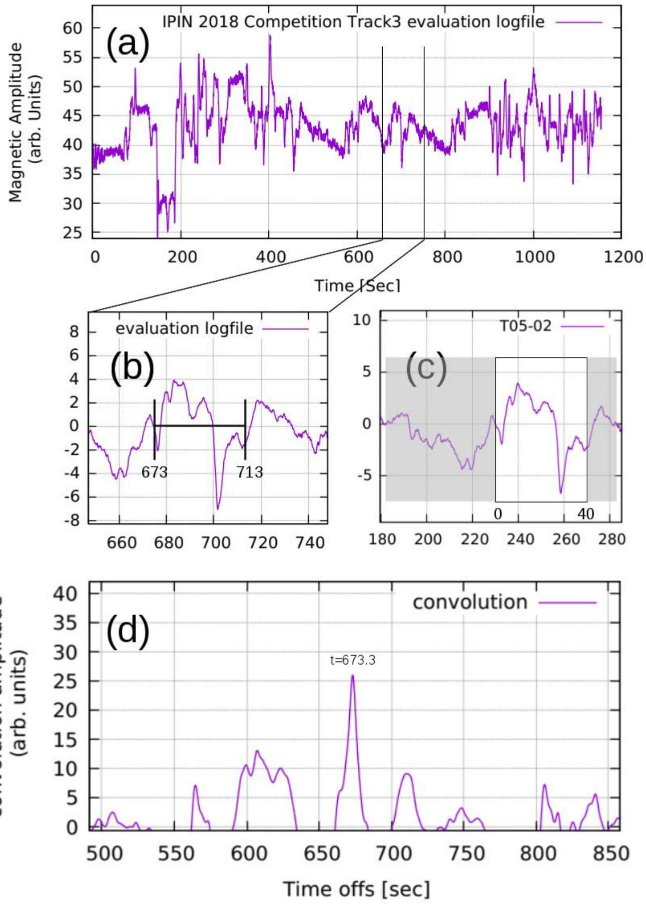

Fig. 1. (a) Magnetic amplitude trace recorded with a smartphone. (b) filtered subset of (a), (c) filtered reference record, (d) convolution of (a) with (b).

competition, Track 3 (smartphone off-site) [1]. Inset (a) is a magnetic trace of the evaluation dataset, plotted over walking time of the actor, who is recording data with a smartphone with a logging app. As it can be seen, the magnetic field exhibits quite some features and is far from being constant. The low value at 140–180 s is attributed to a ride in an elevator. Obviously, the field is shielded by the metal construction. The reasons for other features are not obvious, as it is common for magnetic fingerprinting. For inset (b) and (c), some low- and high pass filtering was applied. (b) presents a zoom of (a) at about 700 s of walking time. Inset (c) presents a path of a training file. The training files are enriched with true ground information, at a number of reference points. The marked 40 s long record is regarded as a fingerprint of the reference point fixed at t =270 s. Inset (d) shows the folding of the 40 s long fingerprint in (c) with with the magnetic trace (a).

A strong peak is clearly visible and can be identified with an accuracy of some tenth of seconds. The peak indicates the position where the 40 s fingerprint fits best into the trace (a). Assuming that the fingerprint was recorded along the same path and with the same walking speed, the position in (a) at the end of the folding interval (t =713.3 s) should be the same as in (c) at t =270 s. For the given case that is true as the same reference point was visited 0.2–0.3 secs before the end of the interval, in both cases. In the displayed case the difference in time between the visit of the reference point is below 0.2 secs, which relates to a spatial closeness well below 0.5 meters. Of course, generally it can not be assumed that the walking speed is constant and equal to the walking speed.

3.3 Proposed Magnetic Matching

A common way to compare map magnetic fingerprints is to use the "dynamic time warping" (DTW) algorithm, for adjusting the time values of the record to find the best match with a fingerprint [14]. It was found that for the carefully recorded data of the IPIN 2018 Track3 even without DTW a reasonable matching can be performed.

In the the proposed algorithm, anyways a different approach is used: As PDR already delivers a position estimate at each half step of the actor, the magnetic readings are remapped to "meters of passed track". This makes the magnetic information to some extent independent of stops in the actors movement or different walking and changing speeds. Of course, the accuracy of the PDR algorithm has to be considered.

The magnetic fingerprinting is most helpful if the fingerprints can accurately be mapped to a true ground reference point. The training- and valuation datasets of the IPIN 2018 Competition Track 3 use 41 accurately surveyed true ground reference positions. The reference points are visited in several combinations and directions. Each time a reference point is visited, the magnetic data for the last 40 meters is stored as a magnetic fingerprint. The record is annotated with the true ground position at the end and with the final heading of the actor.

In the positioning phase, the magnetic data is continuously recorded and mapped to the path length. after each detected half-step, e.g. every 30–40 cm, the latest 20 meters of data are compared to selected fingerprints in the database. The selection process selects those database fingerprints, which have a true ground endpoint within a certain distance of the current PDR/Wifi estimated position. A further selection step selects only those fingerprints, which match the estimated heading within a +/-45 degree window. The heading matching ensures for example, that symmetric fingerprints which are recorded in inverse direction, are not considered.

While for Figure 1 the comparison was performed by convolution, it turned out that even more accurate results will be obtained by using the root of the summed squared difference as measure for correlation. In Fig. 2 squared difference correlation results are shown between a measured trace and four different

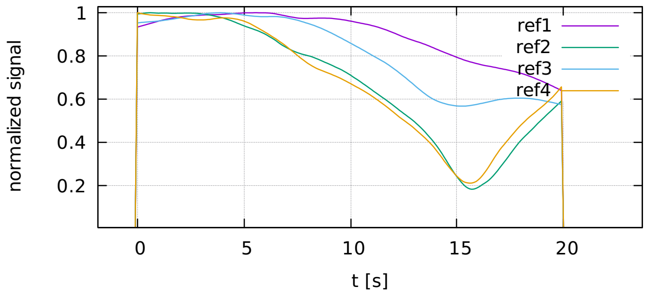

Fig. 2. Squared-difference correlation results between a measured trace and four different reference tracks which all end at the same point.

reference tracks. The reference tracks all end at the same true point point, at t=20 s. Refs. 2 and 4 have a nice down-peak indicating the best correlation with the measured track and indicate the same distance to the true ground point of about 4 seconds.

4 Results and Outlook

The inclusion of a magnetic fingerprint algorithm into an existing positioning algorithm has been proposed, explained and discussed. The algorithm feasibility has been tested using the dataset of the IPIN 2018 competition track 3: Magnetic fingerprints have been generated and applied in the positioning phase for selected phases of the evaluation track. 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. Next steps will be to fully implement the positioning phase and to evaluate its feasibility in a lab setup and with publicly available evaluation data.

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