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BASISMAP: sequence-based similarity search for geomagnetic positioning

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Abstract: Indoor localization has become a popular topic with the development of location-based services (LBS) and indoor navigation systems. Beside these circumstances indoor positioning has been the focus of attention for researchers as the most important component of these applications. Many signals are used as distinguishable features for indoor positioning. RF-based Wi-Fi and BLE systems are the most popular ones and these have been preferred because of their high distinguishable feature. The use of geomagnetism, a natural signal found all over the world, has also been of interest to many researchers. Geomagnetic signals being distorted in the indoor area due to the effect of the structure by using that information takes opportunity to determine the relevant location. In this study, a new method is proposed to convert these unknown signals into location data using a magnetic fingerprint database. The sequential data collected using a dynamic comparison buffer in motion is evaluated with the help of the similarity search method called matrix profile, and position is obtained. The study was compared with other methods in the literature and its prominent and weak points were shared. The performance of the study was evaluated using site-survey by collecting data in an office environment. It has been concluded that the cumulative error is below 2.2 m in the normal operating phase of the system on a 100-m-long path. Compared to the literature, a low complexity and efficient solution is proposed. Furthermore, matrix-profile-based path matching method was used for the first time in magnetic sequence-based localization.

Key words: Geomagnetic positioning, indoor localization, recursive filtering, sequence matching, similarity search

1. Introduction

Indoor localization has become a well-known topic that has received attention and work over the past decade and an area where many solutions are proposed. It has enabled the development of many applications called LBS such as indoor navigation and tracking, marketing, entertainment, location-based information retrieval (such as in-gallery tours, underground realtime information) and emergency or security applications. Although there are different requirements for each application, 1–10 m sensitivity can offer solutions in closed areas [1].

The rapid growth of smartphones in today's market has greatly increased the ubiquity of these devices. Embedded with GPS, microphones, cameras, accelerometers, gyroscope, ambient light, and magnetic field sensors, they provide a variety of tools to develop innovative solutions for this problem. The main difference that separates indoor localization from outdoor is that global navigation satellite systems (GNSS) are too weak to be used indoors, unlike outdoors. Although many methods have been developed for location determination in indoor areas, the solution has several difficulties. Distance-based or RF-signal-level-dependent solutions usually require signal emitter or collector infrastructures. For example, Wi-Fi access points (APs) or mobile networked

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systems require the presence of the receiving signal level and can provide an indoor localization service at which these signals can be measured. These types of approaches can work in many environments, but they can be useless in cases where the infrastructure is not available or cannot be used. These systems may not be active during a power outage, for example for routing in an emergency evacuation situation, or in an emergency in the mine, the infrastructure may not be established to determine the location of the worker. However, geomagnetic signals are found at every point in the earth and each interior has a fingerprint that carries the trace of it.

The indoor positioning process based on magnetic sensors has gained popularity as it does not require infrastructure. In fact, there is evidence that the geolocation system based on the magnitude of the magnetic field exists in nature. A number of animals, such as reptiles, homing pigeons, fish, and lobsters, have the ability to navigate using magnetic field data. In [2], the area where the lobsters are located was tested with orthogonal arranged magnetic coil system and spinning lobsters proved that they have a magnetic compass sense. In [3], an experimental study was conducted on the relationship between magnetic and olfactory systems of pigeons. It has been observed that the deterioration of the olfactory systems of pigeons affects the magnetoreceptors and can simultaneously impair the magnetic sense. Test results show that the navigation of spiny lobsters is based on a magnetic map perception. This shows us that some animals are able to derive position information by using local geomagnetic field changes or by tracking the geomagnetic data itself.

The use of ubiquitous magnetic field in indoor positioning applications is an emerging technology and there are many studies and developments in this topic. Many factors such as steel-reinforced concrete, metallic door frames, columns, furniture, electronic equipment, and tools cause irregularities in the magnetic field making it extremely difficult to track a person using the changing magnetic field data. Like radio maps in Wi-Fi fingerprint systems, which are based on collecting radio signal data at different locations and then storing this information for further positioning requirements. Magnetic field distortions caused by human-made sources in an indoor environment [4] have a uniqueness that enables magnetic fingerprints to be used [5].

According to Li et al., in [4], geomagnetic intensity at different locations are detectable and the variation of geomagnetic intensity over time in the same environment is quite small. The amplitude of the measurement varies with intensity, but the signal shape remains similar. Moreover, the measured intensity may vary from device to device, but still yields a data sequence similar to a previously captured signal [6].

In this work, we introduce a geomagnetic indoor positioning system using magnetic pattern matching using Smartphone sensors (accelerometer, gyroscope, magnetic field sensor). In order to track the user in an indoor area, we propose a system combined with a tracking filter to determine his/her location by searching for similarities in site-survey magnetic fingerprints and to track them afterwards. The main purpose of this study is to show the feasibility of the proposed study. Although using low-cost magnetic sensors for indoor positioning does not require an infrastructure like Wi-Fi APs, integrating it into existing solutions with minor changes can make this system more reliable.

2. Related work

When the positioning techniques with the magnetic field and its fingerprints are examined, the searching for similarity come to the fore. Although some studies focus on deep learning-based positioning techniques, many studies uses similarity search methods and alongside similarity search most of them include a tracking filter. The most commonly used method for similarity search is dynamic time warping (DTW), which is an elastic search method. In addition, methods such as particle filter (PF), Monte Carlo localization (MCL) methods, and hidden Markov model (HMM) have also been applied as a tracking filter. In Table , these methods are shared by referring to the methods and sensors used.

Some studies focusing on leader-follower method. FOLLOW ME in [7] uses a leader follower method for path mapping and utilizes the last known position calculations for this purpose. FOLLOW ME guides users using the walking patterns of previous pedestrians and also relies on GPS data to increase accuracy. Similarly in GROPING [8], the aim is to create a magnetic map database by collecting data from users. The system is based on received signal strength indicator (RSSI) of the Wi-Fi and geomagnetic field. Luo et al. [9] has presented a method of obtaining a floor plan that uses turns as landmarks. According to this study, the similarity with DTW is determined based on the turn information and magnetic data.

In the study of Magicol [10], local object variations in an underground car park, office floor, and supermarket were examined. The authors conducted experimental work to overcome the low detectability of the magnetic field by vectoring successive magnetic signals at each step. In Magicol, an indoor localization and monitoring system has been developed that measures the relative magnitude of distortions and changes of the geomagnetic field using the agumented particle filters (APF), DTW, and optional Wi-Fi radio maps. Magicol can also combine Wi-Fi signals to achieve much improved positioning accuracy for indoor environments by using Wi-Fi infrastructure. Similar to Magicol, MaLoc [11] utilizes a particle filter together with Inertial Navigation System (INS) to measure the user location. Candidate locations with the best magnetic field matching are selected, then the particle filter further reduces the weights of incorrect locations and performs localization.

In Magil-MagFi [12], the similarity between the signal observations from the user and the observations on the survey paths was determined using Smith-Waterman algorithm, and the search was made on the previously defined map with high accuracy. Magil and MagFi (an extension that fuses Magil with Wi-Fi RSSI fingerprints) are much more computationally applicable, and when deployed on smartphones, they produce an efficient and robust solution to the random behavior of a user. Another method based on particle filter with step-wise pedestrian dead reckoning (PDR) motion model and resampled particles according to undirected weighted graph model and floor plan constraints is presented in LiMag [13]. LiMag also uses DTW for specifying the path according to magnetic and light intensity features of unknown location.

LocateMe [14] uses landmarks for detecting location and this method maps the target location to the landmarks according to the similar trends in signal change. It improves computational efficiency by reducing search space with landmark identification. In LocateMe, DTW is used for path-matching. Although there are some faster techniques for computing DTW including PrunedDTW, SparseDTW and FastDTW, they are still higher in complexity and requires much more processing power to compare vector distances. Another method also uses DTW is GIPSy [15]. GIPSy uses XY with Z direction vectors from gravity and magnetic sensors for similarity search. Only accelerometer and magnetic sensors are used with the DTW algorithm. GIPSy defines pedestrian tracking problem as a hidden Markov model (HMM).

mPILOT [16], DeepML [17], and accurate magnetic indoor localization (AMID) [18] use artificial neural networks or deep neural networks for localization. However, these studies often require large data to train models and need site survey in general. In DeepML, a deep network structure with long short-term memory (LSTM) architecture using the Magnetic and Light sensor data of the smartphone is used in the indoor localization system. This method needs to train LSTM network according to site survey. In mPILOT and AMID, the authors use landmarks and signal trend to identify user position. AMID extracts features, such as monotonic increase, monotonic decrease, convex, concave, by analyzing the geomagnetic signal and determines the location by classifying with convolutional neural network from deep neural networks. For mPILOT using neural network and landmarks are defined as binary grids. Searching on a binary grid map decreases processing cost. All these deep-learning-based methods need excessive data collection and site-survey.

Matrix profile was introduced in 2016 in [19]. Matrix profile is a new scalable algorithm for time series subsequence similarity search problem. This algorithm can produce high-quality approximate solutions for extremely large data sets in reasonable time. According to Ratanamahatana et al. [20], comparing DTW with time series data may lead to incorrect classification results. Moreover, the ubiquitous properties of the magnetic signal will lead to inaccuracies if the system is not evaluated for a specific location.

In this work, we present the methodology and evaluation of BASISMAP - sequence-BAsed SImilarity Search for geoMAgnetic Positioning. Matrix Profile [21] method was used for the first time in magnetic-sequence-based localization. By using matrix profile, the overall computational cost drops significantly compared to DTW. In addition, this study proposes a map generation method that helps align sequences to normalized way-point length. In summary, we make the following contributions.

- Matrix Profile based path matching method was used for the first time in magnetic sequence-based localization instead of using popular DTW-based methods.
- A similarity search process using dynamic buffering based on variance is presented, which provides an advantage in optimizing processing without compromising performance where magnetic fingerprint vary more than usual.
- Normalization based on step length was applied to improve the similarity search.

This paper is organized as follows. Sections 1 and 2 mainly summarize the motivation and purpose of the research and related work in the literature respectively. Section 3 gives a detailed introduction to both magnetic field indoor positioning and the proposed algorithm. The experimental set-up and results are shown in Section 4. Finally, the conclusions are presented in Section 5.

3. Materials and methods

In the proposed method, a solution for tracking a person by using the matrix profile with indoor magnetic distortions as a vector normalized to step length and location determined by using the probabilistic data association filter (PDAF) and unscented Kalman filter (UKF) is presented. According to Table , most of the geomagnetic positioning algorithms use DTW to test the similarities between the magnetic database and the collected data.

The sequential data assumption was made for a pedestrian walking through a corridor or path in one direction and all magnetic sensor data is sequentially sampled. Sequentially sampled magnetic data creates the path magnetic fingerprint. All instances are aligned with the position on the path. Step length estimation and distance normalization are used to align magnetic data. A block diagram representation of the proposed method is given in Figure 1. When the figure is examined, several steps for generating magnetic sequence data like motion/step detection, step length estimation, turn detection, magnetic data resampling and dynamic buffering, sequence matching, data association, and tracking filtering are presented in related sections.

3.1. Motion detection

The detection of the pedestrian in motion is critical to the performance of the system. The system is operated using acceleration sensor, magnetic sensor, and gyro data per step. Stationary and mobility is detected using

Table . Geomagnetic positioning systems.

Study	Signal	Map type	Methods
Magicol [10]	acc, mag, gyro, opt. wifi	Path-based, Site survey	DTW, APF
GIPSy [15]	acc, mag	Path-based, Site survey	DTW, HMM
FOLLOWME [7]	acc, mag, gyro, GPS, barometer	Path-based, Leader-follower	DTW, Step Detection, Turn Detection
Luo et al. [9]	acc, mag, gyro, barometer	Path-based, Floor plan Crowd-sourcing	DTW, clustering, Step-Length, Turn det.
GROPING [8]	acc, mag, gyro, opt. wifi	Path-based, Crowd-sourcing	DTW, MCL
LocateMe [14]	mag	Landmark-based, Path samples, Site survey	DTW
LiMag [13]	acc, mag, gyro, als	Path-based, Site survey	DTW, PF, UWGM
Magil [12]	mag, opt wifi	Path-based, Site survey	Smith-Waterman algorithm, graph search
MaLoc [11]	acc, mag, gyro	Path-based, Site survey	APF, Step length est., Heading est.
mPILOT [16]	acc, mag, gyro	Landmark-based, Path samples, Site survey	MLP, Binary Graph Search, Step-length estimation
AMID [18]	acc, mag	Landmark-based, Path samples, Site survey	CNN
DeepML [17]	mag, als	Point-based, Site survey	LSTM
BASISMAP (proposed)	acc, mag, gyro	Path-based, Site survey	MPdist/MASS, PDAF, UKF

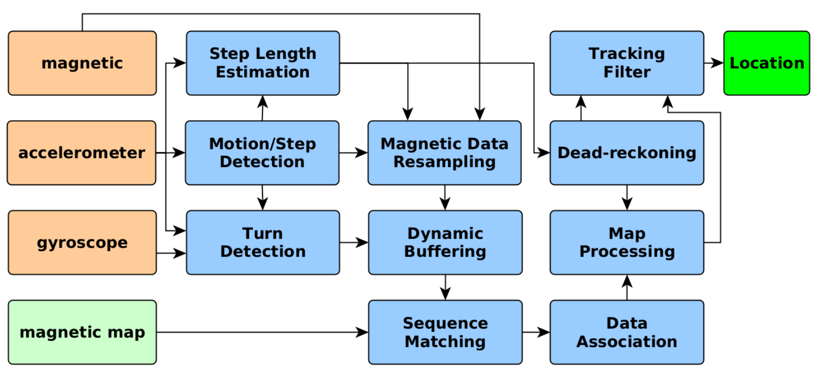

Figure 1. Block diagram of the overall system.

the acceleration sensor with detecting a step action. Step length and motion information (motion/step detector) are used to associate magnetic sensor data with the location. The magnetic sensor data in each step is used to query position information by collecting sequence information.

There are many studies in the literature where adaptive-threshold-based step detection with a sliding window is realized by using the acceleration sensor [22]. Step threshold is calculated from the average of the minimum and maximum values within the window by using the absolute acceleration data for step detection. In our study, we are using window-based adaptive thresholds method whose flow chart is given in Figure 2.

After step detection phase, step length should be estimated. The step length estimation method introduced in [23] is used in this study. According to method, when a step is detected, the maximum and minimum

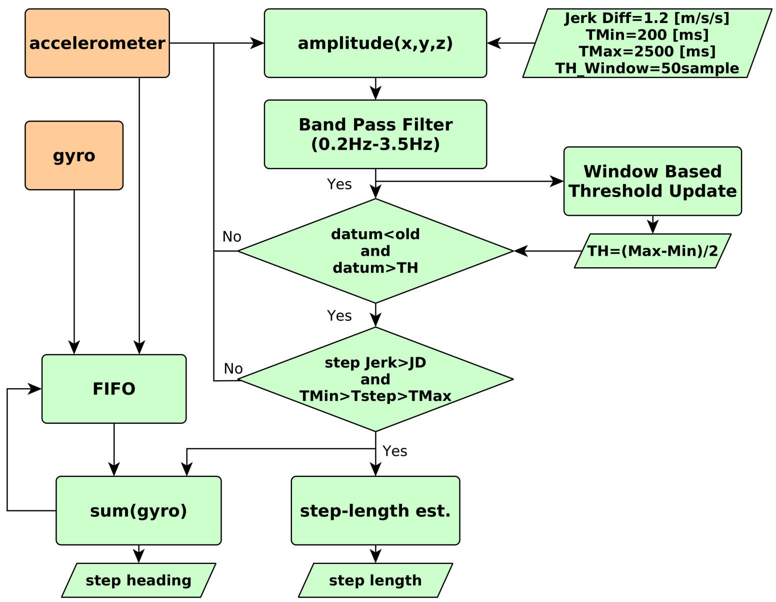

Figure 2. Step and heading estimation.

acceleration is associated with a coefficient. Step length varies depending on the height, gender, and physical characteristics of the person. With the coefficient specified in the method suggested in [23] study, it has been shown by experiments that there is a cumulative error below 5%. We choose the method given in [23] because it has only one parameter to tune and also this parameter has minor effect on performance according to other methods.

The expression (1) is used to estimate step length. ΔT_{step} stands for step duration, and acc_{max}, acc_{min} stand for minimum and maximum acceleration in a step event, respectively. The coefficient of K determined experimentally and was taken as 0.8. This parameter becomes important when creating map data. For this reason, the average value was calculated considering the corridor length and the number of steps while estimating this the parameter.

$$steplength = K \times \Delta T_{step} \times \sqrt[4]{acc_{max} - acc_{min}} \tag{1}$$

Turn detection method in [9] is used with the data obtained from the accelerometer and gyro during the step. In order to tag a turn as a landmark, the difference between the peak values of the signals has been utilized. This landmark defines begin and end position for the interested path. By using begin/end positions, we embed magnetic sequence information to our map database.

n and m are accelerometer and gyro sensor data vectors. The average acceleration values are calculated using the acceleration sensor data n in a certain range to calculate the pedestrian rotation angle for each step. m has been chosen large enough to cover a few steps as used in [9]. Average acceleration window must be longer than the turn detection window $n > m$. Average axial acceleration values are obtained by using the equations in (2). In this way, the average gravity vector (a_x, a_y, a_z) is derived.

$$a_x = \frac{1}{n}\sum_{k=1}^{n} a_x^k, a_y = \frac{1}{n}\sum_{k=1}^{n} a_y^k, a_z = \frac{1}{n}\sum_{k=1}^{n} a_z^k \tag{2}$$

The average gravity vector is normalized according to earth navigation frame used as a rotation vector and equation (3) extracts the rotations by using gyroscope data (ω_x, ω_y, ω_z). In this way, the $\Delta\theta$ angle represents a right or left turn as defined in (4).

$$\omega_{v_x}^k = \frac{\omega_x^k.a_x}{|a|}, \omega_{v_y}^k = \frac{\omega_y^k.a_y}{|a|}, \omega_{v_z}^k = \frac{\omega_z^k.a_z}{|a|} \tag{3}$$

$$\Delta\theta = \sum_{k=1}^{m} |\omega_v^k|\Delta t \tag{4}$$

In Figure 3, the heading angle is collected by integrating with time, while the turn detector is in motion, the angle is calculated by evaluating the turns in each step, and thus turns can be detected. By keeping the turn detection threshold low or adding more than one threshold, turns at different angles can also be detected and can be used as landmarks; our solution uses $-90, -180, 90, 180$ as 4 different thresholds for rotation detection.

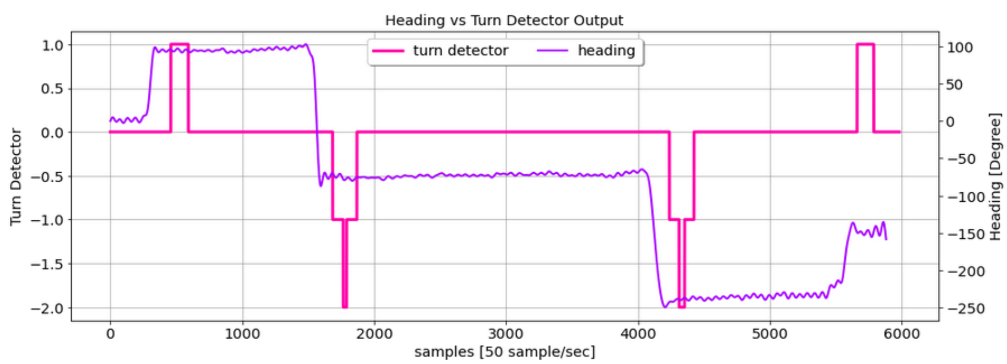

Figure 3. Turn detector output vs heading angle.

3.2. Magnetic map processing

A map requires small pieces of predefined items. These items consist of small to bigger areas like sectors, corridors, and floors. An indoor map includes areas such as floors, corridors, and sectors. Turning points within the floor are taken into account to identify a corridor, while the sectors are defined in sections with a length of 10-step. Since the corridors are projected on a graph based on the neighborhood relationship, instead of scanning all the data, searching on the corridors with neighbors reduces the processing load of the system during the transition between the corridors.

The turning points can indicate the beginning or the end of the corridor. If it is in the form of a loop, the entire floor can be regarded as a single corridor. While creating magnetic map database, the position information should be embedded in map database and this information should be gathered from it. Turn points are used as landmarks in the map and these landmarks should align according to the building plan.

The map database is organized as $100 sample\ per\ meter$ ($1 sample/cm$). Considering that the magnetic sensor data is collected on the $[sample/s]$ scale, data in $[sample/cm]$ scale is obtained by associating it with the step length to obtain position information from these data. The magnetic map is created by combining magnetic vectors normalized according to step-length. Spatial normalization of the data is provided during each pedestrian step.

In order to create or track a map by collecting magnetic fingerprint data in an unknown environment, outliers must be eliminated and map data should be generalized. These outliers may be local electromagnetic signals or magnetic fingerprints of a particular spot in the corridor. High magnetic noise and outliers in the environment can be eliminated by smoothing the magnetic fingerprint data. In our proposed study, the Savitzky-Golay [24] filter was used for this purpose. The Savitzky–Golay filter method fits successive subsets of adjacent data points with a low-degree polynomial by the method of linear least squares, which is also known as convolution [25]. Unlike other smoothing methods, this filter can be applied without group delay. This is a preferred feature in our case because it provides a good filtering with the lowest distortion depending on the window size and the polynomial degree. In our study, the window size is equal to a step sample size and polynomial order is 3.

Each corridor consists of sectors that take place consecutively. The similarity in these sectors is tracked by PDAF, which significantly increases the performance of the system. The unique nature of magnetic data also causes unpredictable data diversity. PDAF is proposed as a suitable solution to distinguish points with similar fingerprints in different regions.

In the initialization of the system, the floor of the user can be detected by using auxiliary location information like GPS-, beacon-, RF-ID–based systems. Similarity searches are made at all points within the floor and are first reduced to the relevant corridor and then to the relevant sector with the help of a data association filter. Using the unscented Kalman filter, estimation is made for the pedestrian tracking in the associated sector.

3.3. Map and sequence matching

In [19, 26], the authors introduce MASS Algorithm (Mueen's ultra-fast Algorithm for Similarity Search) or *Distance Profile*. According to matrix-profile distance, two time series are similar if they share many similar subsequences, regardless of the order of matching subsequences.

The similarity score is determined based on the minimum z-normalized Euclidean distance and the closest neighbor (distance index) is obtained as promising candidate match. The most similar path sections are found in the magnetic database by using the distance profile method between magnetic database and pedestrian magnetic data. This vector distance was used as the similarity metric for the given magnetic sequence.

Both the distance profile and the popular DTW methods allow to measure vector distance of two signals based on the assumption that one sequence contains another or gives a metric about how these were similar or not, but distance profile has the following advantages over DTW:

1- Distance profile is much more faster than DTW and has $O(n \log n)$ time complexity compared with $O(n^2)$ [21]. This is also advantageous for processing load and power consumption demands.

2- DTW-based similarity search methods require a warping window as a parameter but distance profile does not have any parameters. This warping parameter is also critical for unknown signals and should be evaluated for different use-cases. For our application when using DTW a bigger warping window may cause false classification of a different location point or if similarity search region is out of warping window, it could not detect similar sequences. This type of wrong assumptions or its results have been examined in [26].

We give some definitions below for certain terms used in our method. We are determining local matching in given path when we are estimating a pedestrian location.

Definition 1: A sequential magnetic data $\mathcal{M}$ is a sequence of real valued numbers given in uT unit. $m_i : \mathcal{M}_i = m_1, m_2, ..., m_n$ where n is the length of M.

Definition 2: A subsequence $\mathcal{S}_{i,j}$ of a $\mathcal{M}$ is a continuous subset of the values from $\mathcal{M}$ of length $i-j+1$ starting from position i. $\mathcal{S}_{i,j} = m_1, m_2, ..., m_{i+j-1}$, where $1 \leq i \leq i-j+1$.

Searching on magnetic database by using pedestrian magnetic fingerprint gives position information as normalized distance value. Figure 4 demonstrates the pedestrian passing through the corridor and similarity with the fingerprint of the corridor record in magnetic database. The vector given in red shows the data collected during the movement of the pedestrian, the green graph shows the map information, and the blue vector shows the similarity information obtained as a result of the matrix profile. As a result of the comparison, the closest distance gives the place where the similarity is highest. The point of highest similarity and the length of the buffer data gives the current position of the pedestrian.

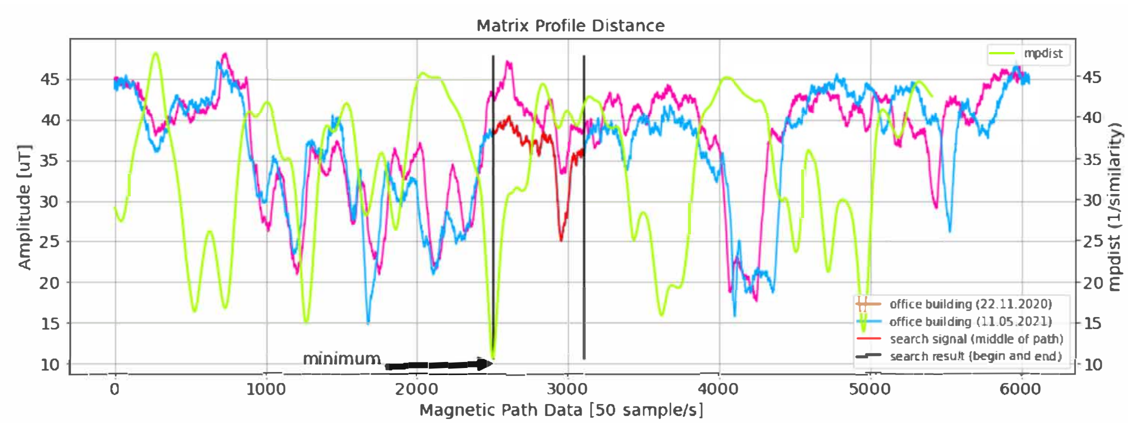

Figure 4. Two different pass similarity results for the same path.

For the similarity calculation, the fact that the two data are the same length and aligned to each other reduces the processing load. DTW or similar elastic search methods are preferred for working on variable length data. Presented method uses spatial normalization according to step length. While generating map data, aligning each sample to the specified length overcomes this problem.

The size of the magnetic sequence is chosen by looking at its variance. The vector content with higher variance gives more magnetic variation and a distinguishable feature content. Magnetic sequence data were collected and compared with the magnetic database record when pedestrian is moving.

The process flow diagram for the dynamic similarity search buffer is given in Figure 5. On paths where the variance of the collected data is low ($< 40uT$), the data size increases until the maximum data length is reached ($>$ 20 steps). When the variance reaches the desired levels, the old data in the memory starts to be deleted at the rate of 1 to 1.5. Maximum buffer length associate with step count and chosen long enough to making a similarity search. Figure 6 introduces this relation. The variance of the data collected from the pedestrian is examined and if there is more distinguishability by evaluating variance which stored in buffer than the specified threshold value. Buffer variance evaluation factor, regarded as a parameter, depends on the Earth's average magnetic field strength which is between $25uT$ and $65uT$.

In this way, the size of the data to be used decreases and energy efficiency increases. For detecting pedestrian position, first of all, the most suitable corridor is found by performing similarity searching method in all corridors in magnetic database. Subsequently, the most suitable sector within this corridor is verified using PDAF (Probabilistic Data Association Filter), and then the traveled distance and tracking is determined by using an unscented Kalman filter (UKF).

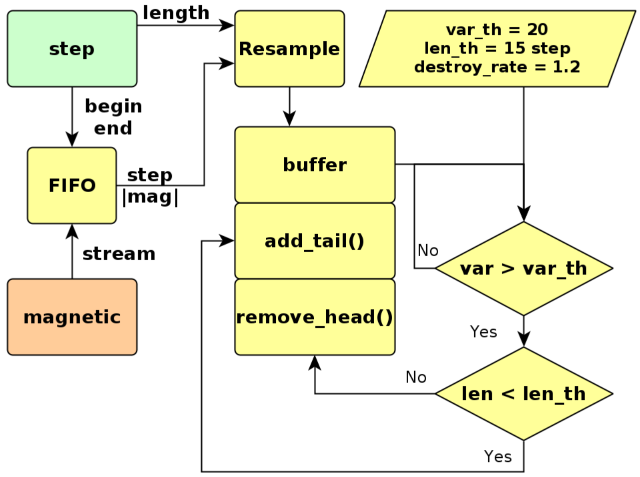

Figure 5. Variable length similarity search buffer.

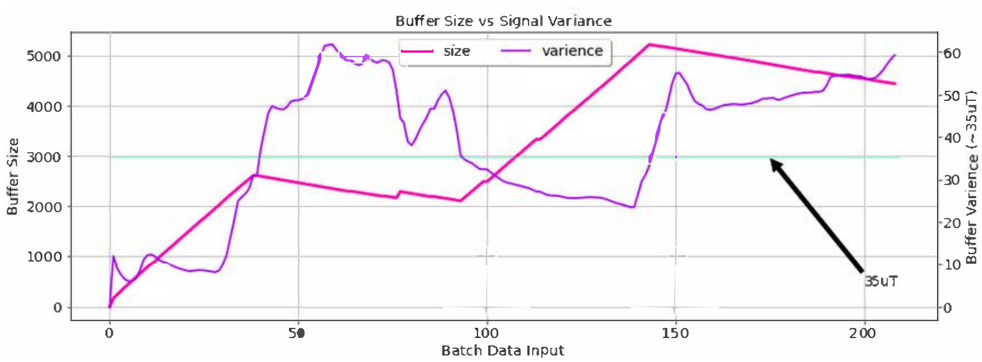

Figure 6. Buffer length vs buffer variance.

3.4. Probabilistic data association filter

Proposed method uses a grid-based approach for using Bayes filter. Grid-based filters tessellate the environment into small areas [27]. For our study, we define these small sectors 10 steps long. These small sectors contain the belief the person is currently in that area.

Comparing sequential data with the magnetic database, a distance profile with many local minimum points can be obtained. In this case, a data association filter is needed to obtain the most promising minimum point for estimating pedestrian sector. As shown in Figure 7, multiple similar positions were obtained by comparing similarity. Probabilistic Data Association Filter (PDAF) is used to determine which of these obtained positions is most promising.

Pedestrian position in an office building is given in Figure 7. When the given figure is examined, in the first graph, the green vector is matrix profile similarity result and there are three possible similar points. These local minimum points are marked as red dots. Within these points, the first one is the most promising one according to PDAF. Pedestrian sector is obtained using the PDAF output which is given as shaded bars in the first graph. The second graph in the same figure is given for the vector being compared and the previously stored map database.

The distance profile and the distance index are obtained by using similarity searching for the collected pedestrian data. However, a minimum distance point obtained can be misleading because the magnetic signal

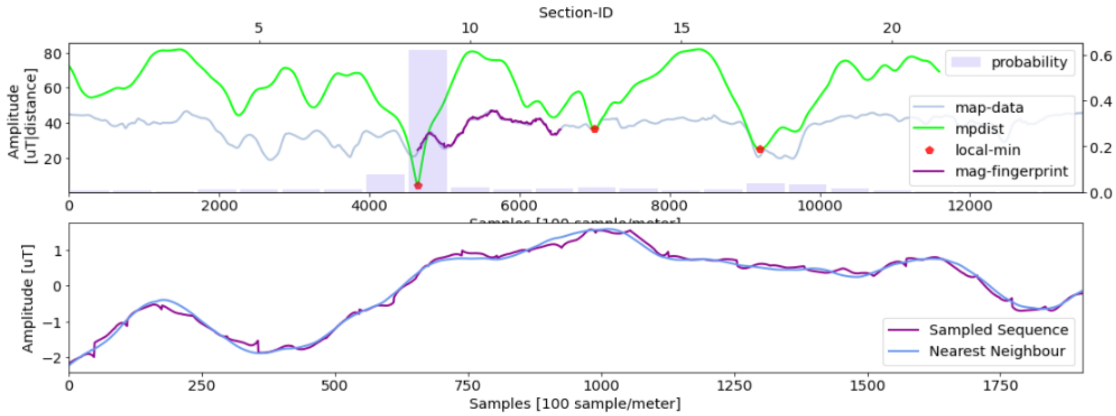

Figure 7. Similarty search and PDAF.

may change at that location or pedestrian data may have some measurement errors. Therefore, a solution is needed to predict which index of distance is the most promising. This problem is solved with the recursive Bayesian filter. A graphical model for system state and transition flow is given in Figure 8.

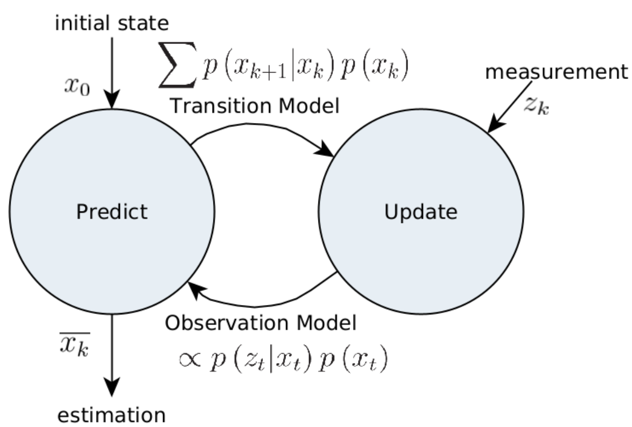

Figure 8. Recursive Bayesian estimation model.

Bayes filter represents the state by a random variable (x_k) for each time step k. The idea behind the Bayes filter is to estimate the system state or beliefs according to information coming from sensor measurements. We can represent our belief or state as $x_k = p(x_k|x_0, ..., x_{k-1}) = p(x_k|x_{k-1})$. This is a Markovian process and the current state is dependent on previous outcomes.

According to Bayesian Theorem given in estimation proportional likelihood and prior knowledge, we could assume $posterior \propto likelihood \times prior$ and make prediction with a maximum a-posterior (MAP) estimation to determine pedestrian location on map. $\hat{x}_k^{MAP} \equiv \underset{x_k}{argmax}\left[p(x_k|z_k)\right]$ gives us estimation results.

3.5. Tracking filter

In the previous sections, the search process and the estimation of the most suitable location on the map were provided. Tracking filter has an important place in both reducing the need for processing demand and increasing system consistency. One of the commonly used methods is the unscented Kalman filter (UKF) or sigma-point

Kalman filter. For UKF performance, sigma-points should be calculated appropriately. Our method uses the sigma point Kalman filter as tracking filter. Sigma points are initialized and calculated as introduced in [28]

PDR is used to collect data of unknown regions and to determine the area of interest from newly collected data. PDR can be performed using the turn and step detection performance of the moving person. In order to follow the person in the x, y coordinate plane, the step length and the rotation along the step are detected and the coordinate information is obtained according to the starting point. In addition to the coordinate information, magnetic sensor data is also collected during the step and then processed on the map. Considering the initial conditions, the heading angle of θ and the path taken in the plane x - y are set as 0 in the initial state.

Kalman filters use the state space model. Filter has two phases; one is for measurement or update phase and the other is state prediction. The pedestrian motion model given in (5) and (6) was used as the state space system model. Tracking filter inputs are x, y, l, θ. θ is the heading angle which is measured by turn detector. l is the last step length, and x, y is the last position in prediction phase and estimation position in measurement phase.

$$\underbrace{x_{t+1}}_{x_{prediction}} = \underbrace{\begin{bmatrix} l \times cos\theta & 0 & 0 & 0 \\ 0 & l \times sin\theta & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{F} \times \underbrace{\begin{bmatrix} x \\ y \\ l \\ \theta \end{bmatrix}}_{x_t} + \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{B} \times \underbrace{\begin{bmatrix} x_0 \\ y_0 \\ l_0 \\ \theta_0 \end{bmatrix}}_{u_t} \tag{5}$$

$$\underbrace{z_t}_{z_{measurement}} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{H} \times \underbrace{\begin{bmatrix} x \\ y \\ l \\ \theta \end{bmatrix}}_{x_t} \tag{6}$$

4. Experimental setup

The experiment was conducted on an office building which is shown in Figure 9. Android-based phones were preferred for data collection. The Android sensor stack provides data in raw via a standardized interface. IOS-based mobile devices do not offer this type of infrastructure. The senslogs[1] application running on the Android operating system records the data with time stamp for processing in csv (comma-separated values) file format. Data were collected for offline processing. Senslogs directly uses the android sensor stack. The Android sensor stack allows the use of calibrated and uncalibrated data. Autocalibrated data by android was used in our study.

Magnetic sensor, accelerometer, and gyro data were collected at a rate of 50 samples/s. Although data were collected with two different brands of mobile phones, the differences in these data were not shared within the scope of the proposed study. Since the proposed method uses sequence-based similarity metrics, signal shape is more important than the individual values in sequence [29]. In most scenarios phone was held by hand for monitoring navigation, but different cases were also evaluated. Data was collected both with carrying in a pocket and holding by hand. Although the system evaluates cases in different orientation, mixing these cases may lead to misleading turn detection.

[1]senslogs (2021). Sensor logger application [online]. Website https://github.com/tyrex-team/senslogs [accessed 01-2022].

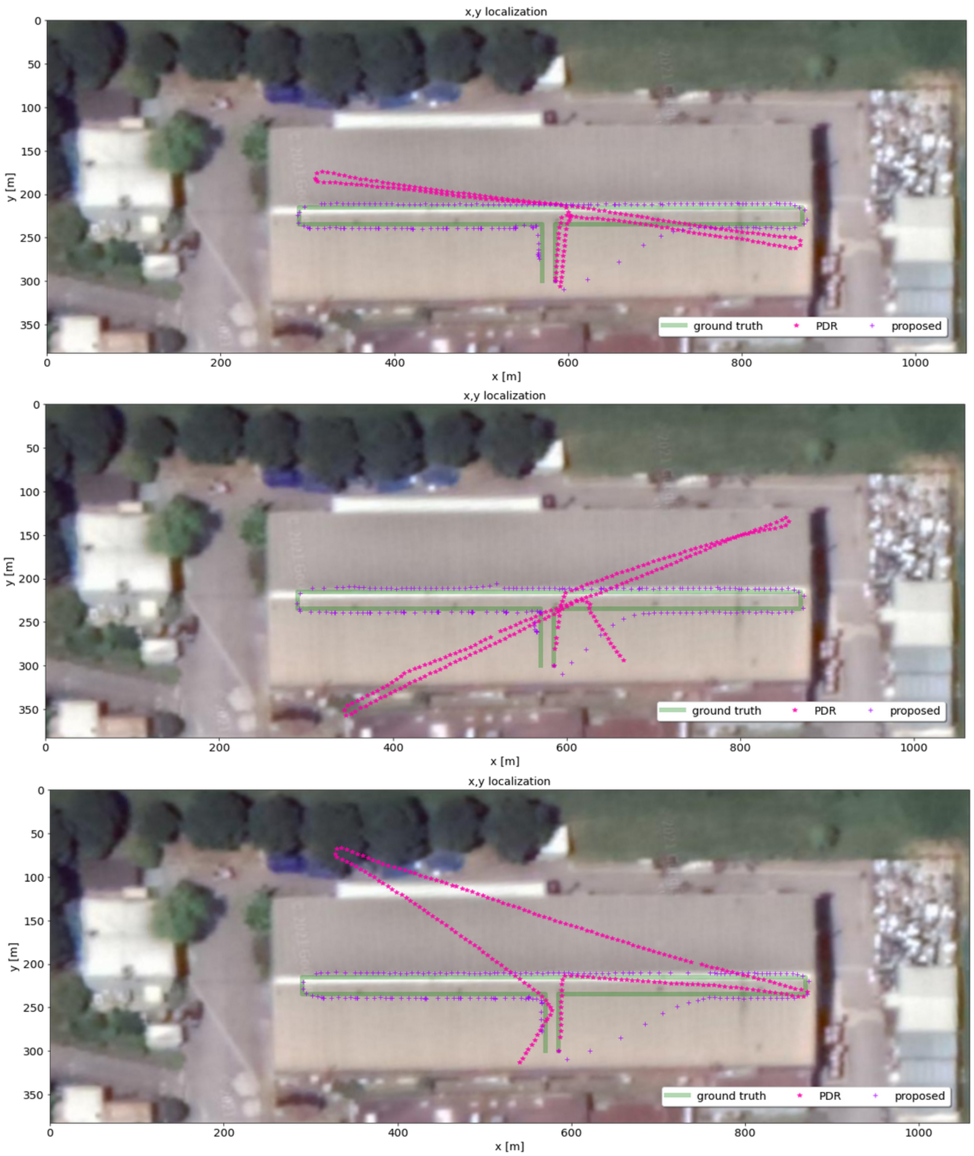

Figure 9. Office building real surveyed path and PDR vs the proposed method.

The proposed system components have real-time data processing capability but data were collected and processed offline. The data were divided into parts and applied to the system with mini-batches, and the outputs were collected and the results were visualized.

The magnetic database created with data collected in the office building. Using the same office building to evaluate our algorithm, 3 different passes are used for the same surveyed path to simulate pedestrian movement. These are given in Figure 9 respectively. Purple markers show proposed algorithm output and pink markers show without using magnetic sequence matching which is using only PDR algorithm.

5. Results

In order to analyze the performance of our proposed method, outputs were produced by comparing with PDR. When Figure 9 is examined, the fact that the PDR system is open to false detection in turns and drifts in turns shows that it is not possible to use PDR systems without using landmarks. Along with the method we recommend; position of a pedestrian in motion can be determined with a very low error compared to the PDR system after an initialization phase.

The position information obtained from the pedestrian motion model and the estimated sector information were combined using UKF. This method eliminates the errors accumulated and provides the ability to determine the position of the pedestrian who started to move at any point in the region to be localized. Position information obtained using magnetic sequence was supported by turning points. The magnetic sequence is divided into parts and the last known position information is used to reduce the search space, thus reducing the processing load. Using the building's features instead of head angle detection, detecting the pedestrian's change of direction or exiting the corridor has also provided a more consistent result by using the floor plan.

When Figure 9 is examined, we can infer that the sampling rate must be quite high to eliminate digital integration errors, and the ideal acceleration sensor and gyro must be used in order for the PDR system to work successfully. This is not possible in practice. Correct calculation of the motion direction angle will greatly reduce the error. However, it is not possible to obtain a consistent directional angle due to the indoor distortions of the magnetic field inside the building.

PDR system causes a maximum position error of around 45 m when the average position error is taken into account. However, the proposed method decreases this error to a maximum of 16 m. This is presented in Figure 10. CDF calculated according to Figure 9a which has minimum error on PDR and maximum error for the proposed method.

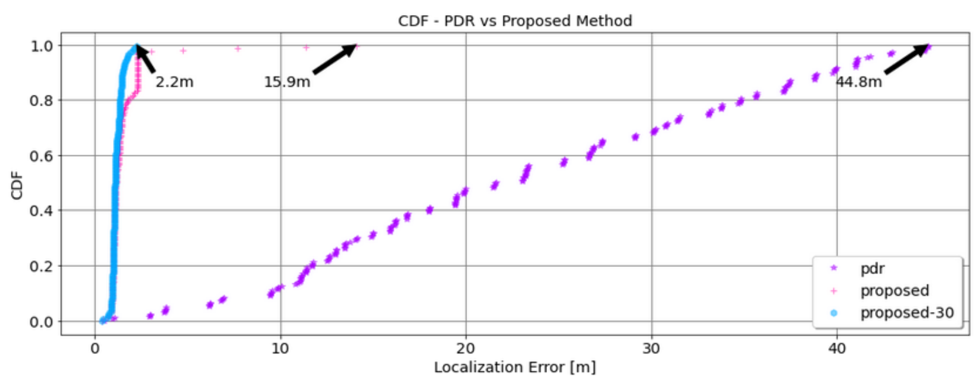

Figure 10. Cumulative distribution function for PDR and the proposed method localization error for minimum PDR error data (Figure 9(a))

Finding the position of the system requires taking about 20–30 steps, which significantly reduces the positioning error. It is also seen in the cumulative density function given in Figure 10 that the error decreases rapidly after initialization phase. System output is calculated by PDR algorithm output and after 20–30 steps, the proposed method finds a location, this time positioning error is at most 2.2 m for our experiment setup.

6. Conclusion

In this paper, we present a geomagnetism-based indoor localization system named BASISMAP. A dynamically buffered pattern search system, which aims to adapt environmental magnetic map changes without performance compromise, is proposed. The processing load of the similarity search was reduced by using the dynamic buffer. The longer the buffer length, the larger the size of the data to be compared for similarity, it reduces error; however, it has processing overheat and this issue is eliminated by using dynamic buffering.

Step-based spatial normalization on magnetic signal and comparing this sequence with a distance referenced map also reduces search space and processing load. Matrix profile-based path matching method, which is especially suitable for large data sets, is used in magnetic sequence-based localization. In this way, the overall computational cost is significantly reduced compared to DTW. When Table is examined, it is seen that most of the popular methods use DTW. DTW is an elastic search method which finds given sequence in a database by interpolating or extrapolating input sequence. This is a disadvantage for large areas or mobile devices which has limited processing power.

These features make our proposed solution ideal for using on edge devices like mobile phones or tablets.

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Author contributions

Conceptualization, formal analysis, methodology, validation, resources, data curation, visualization, writing original draft preparation, writing review and editing and funding acquisition: T.K. and B.E.; software: T.K.; project administration, supervision: B.E.. All the authors have read and agreed to the published version of the manuscript.

References

[1] Basiri A, Lohan ES, Moore T, Winstanley A, Peltola P et al. Indoor location based services challenges, requirements and usability of current solutions. Computer Science Review 2017; 24: 1-12. doi: 10.1016/j.cosrev.2017.03.00215

[2] Boles LC, Lohmann KJ. True navigation and magnetic maps in spiny lobsters. Nature 2003; 421: 60–63. doi: 10.1038/nature01226

[3] Mora CV, Davison M, Martin Wild J, Walker MM. Magnetoreception and its trigeminal mediation in the homing pigeon. Nature 2004; 432: 508–511. doi: 10.1038/nature03077

[4] Li B, Gallagher T, Dempster AG, Rizos C. How feasible is the use of magnetic field alone for indoor positioning?. In: IEEE 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN); New South Wales, Sydney, Australia; pp. 1-9. doi: 10.1109/ipin.2012.6418880

[5] Haverinen J, Kemppainen A. A global self-localization technique utilizing local anomalies of the ambient magnetic field. In: IEEE 2009 International Conference on Robotics and Automation; Kobe, Japan; pp. 3142-3147. doi: 10.1109/robot.2009.5152885

[6] Yeh SC, Hsu WH, Lin WY, Wu YF. Study on an indoor positioning system using Earth's magnetic field. IEEE Transactions on Instrumentation and Measurement 2019; 69 (3): 865-872. doi: 10.1109/tim.2019.2905750.

[7] Shu Y, Shin KG, He T. Last-mile navigation using smartphones. In: ACM 2015 Proceedings of the 21st Annual International Conference on Mobile Computing and Networking; Paris, France; pp. 512-524. doi: 10.1145/2789168.2790099

[8] Zhang C, Subbu KP, Luo J, Wu J. GROPING: Geomagnetism and crowdsensing powered indoor navigation. IEEE Transactions on Mobile Computing 2014; 14 (2): 387-400. doi: 10.1109/tmc.2014.2319824

[9] Luo H, Zhao F, Jiang M, Ma H, Zhang Y. Constructing an indoor floor plan using crowdsourcing based on magnetic fingerprinting. Sensors 2017; 17 (11): 2678. doi: 10.3390/s17112678

[10] Shu Y, Bo C, Shen G, Zhao C, Li L et al. Magicol: Indoor localization using pervasive magnetic field and opportunistic WiFi sensing. IEEE Journal on Selected Areas in Communications 2015; 33 (7): 1443-57. doi: 10.1109/jsac.2015.2430274

[11] Xie H, Gu T, Tao X, Ye H, Lv J. MaLoc: A practical magnetic fingerprinting approach to indoor localization using smartphones. In: ACM 2014 International Joint Conference on Pervasive and Ubiquitous Computing; Seattle Washington, USA; pp. 243-253. doi: 10.1145/2632048.2632057

[12] Wu H, Mo Z, Tan J, He S, Chan SH. Efficient indoor localization based on geomagnetism. ACM Transactions on Sensor Networks (TOSN) 2019; 15(4): 1-25. doi: 10.1145/3342517

[13] Wang Q, Luo H, Men A, Zhao F, Huang Y. An infrastructure-free indoor localization algorithm for smartphones. Sensors 2018; 18 (10): 3317. doi: 10.3390/s18103317

[14] Subbu KP, Gozick B, Dantu R. LocateMe: Magnetic-fields-based indoor localization using smartphones. ACM Transactions on Intelligent Systems and Technology (TIST) 2013; 4 (4): 1-27. doi: 10.1145/2508037.2508054

[15] Shahidi S, Valaee S. GIPSy: Geomagnetic indoor positioning system for smartphones. In: IEEE 2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN); Banff, Alberta, Canada; pp. 1-7. doi: 10.1109/ipin.2015.7346761

[16] Ashraf I, Hur S, Park Y. mPILOT-magnetic field strength based pedestrian indoor localization. Sensors 2018; 18 (7): 2283. doi: 10.3390/s18072283

[17] Wang X, Yu Z, Mao S. DeepML: Deep LSTM for indoor localization with smartphone magnetic and light sensors. In: IEEE 2018 international conference on communications (ICC); Kansas City, MO, USA; pp. 1-6. doi: 10.1109/icc.2018.8422562

[18] Lee N, Ahn S, Han D. AMID: Accurate magnetic indoor localization using deep learning. Sensors 2018; 18 (5): 1598. doi: 10.3390/s18051598

[19] Yeh CC, Zhu Y, Ulanova L, Begum N, Ding Y et al. Matrix profile I: all pairs similarity joins for time series: a unifying view that includes motifs, discords and shapelets. In: IEEE 2016 16th international conference on data mining (ICDM); Barcelona, Spain; pp. 1317-1322. doi: 10.1109/icdm.2016.0179

[20] Ratanamahatana CA, Keogh E. Everything you know about dynamic time warping is wrong. In: 2004 Third workshop on mining temporal and sequential data (TDM-04); Seattle, USA; pp. 53-69.

[21] Gharghabi S, Imani S, Bagnall A, Darvishzadeh A, Keogh E. An ultra-fast time series distance measure to allow data mining in more complex real-world deployments. Data Mining and Knowledge Discovery 2020; 34 (4): 1104-35. doi: 10.1007/s10618-020-00695-8

[22] Lee HH, Choi S, Lee MJ. Step detection robust against the dynamics of smartphones. Sensors 2015; 15(10): 27230-27250. doi: 10.3390/s151027230

[23] Mikov A, Moschevikin A, Fedorov A, Sikora A. A localization system using inertial measurement units from wireless commercial hand-held devices. In: IEEE 2013 International Conference on Indoor Positioning and Indoor Navigation; Montbeliard-Belfort, France; pp. 1-7. doi: 10.1109/ipin.2013.6817924

[24] Press WH, Teukolsky SA. Savitzky-Golay smoothing filters. Computers in Physics 1990; 4(6): 669-672. doi: 10.1063/1.4822961

[25] Shao W, Zhao F, Wang C, Luo H, Muhammad Zahid T et al. Location fingerprint extraction for magnetic field magnitude based indoor positioning. Journal of Sensors 2016; 2016: 1-16. doi: 10.1155/2016/1945695

[26] Rakthanmanon T, Campana B, Mueen A, Batista G, Westover B et al. Searching and mining trillions of time series subsequences under dynamic time warping. In: ACM 2018 Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining; Beijing, China pp. 262-270. doi: 10.1145/2339530.2339576

[27] Fox D, Hightower J, Kauz H, Liao L, Patterson D. Bayesian techniques for location estimation. In: Proceedings of the 2003 workshop on location-aware computing; Seattle, USA; pp. 16-18.

[28] Wan EA, Van Der Merwe R. The unscented Kalman filter for nonlinear estimation. In: Proceedings of the IEEE 2000 Adaptive Systems for Signal Processing, Communications, and Control Symposium; Lake Louise, AB, Canada; pp. 153-158. doi: 10.1109/asspcc.2000.882463

[29] He S, Shin KG. Geomagnetism for smartphone-based indoor localization: Challenges, advances, and comparisons. ACM Computing Surveys (CSUR) 2017; 50 (6): 1-37. doi: 10.1145/3139222