Heuristics-based Indoor Positioning Systems: A Systematic Literature Review

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Context: Many heuristics-based indoor positioning approaches have been developed to enhance positioning estimation. However, there is no comprehensive survey of these heuristics information and methods.

Objective: The main objective of this study is to provide a holistic view and an in-depth analysis of what heuristics information and methods have been used, their general achievements and limitations. This study aims to provide a comprehensive summary to facilitate further research on indoor positioning heuristics.

Method: We conducted a systematic literature review (SLR) on indoor positioning heuristics.

Results: Ninety-three (93) primary studies were selected. We found two general types of heuristics information and four primary heuristics methods, which we summarized in this paper. We also found that many of these positioning heuristics are tested in experimental settings only. Some heuristics claim practical applications but are not tested for the challenging and typical indoor environments.

Conclusion: Most existing heuristics information and methods rely on the assumptions that may not be true in real life environment, hence limiting the usefulness of the positioning outcomes. Based on the analysis of this SLR, we propose two research directions to enhance positioning estimation.

Keywords: Positioning Systems, Systematic Literature Review, Heuristics Algorithms, Indoor Environments

1. Introduction

Indoor positioning research is concerned with developing techniques and algorithms to estimate the positions of tracked targets in indoor environments. Indoor positioning has attracted much research effort due to many potential applications it may offer (Muthukrishnan, Lijding, and Havinga (2005); Vossiek et al. (2003); Fouskas et al. (2002)). For example, consider an elderly care environment where elderly residents need to be tracked; a positioning system would allow for monitoring of patients' safety in terms of their general location in the facility and their specific position in rooms. Other applications include tracking customer's movement in shopping malls to provide promotional messages; or providing museum visitors audio or video description of artefacts. Applications like these would require precise knowledge of the tracked targets' position so as to determine an emergency situation (e.g, whether the elderly patient is sitting on a sofa, staying on the bed, or lying on the floor), and ensure the relevancy of the information provided.

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Various indoor positioning systems have been developed, utilising different technologies and algorithms (Mautz (2012); Gu, Lo, and Niemegeers (2009); Liu et al. (2007)). However, due to the complex nature of indoor environments, a positioning system could be inaccurate under various challenging conditions such as multipath reflection, non line-of-sight transmission, etc. To achieve higher accuracy and more sensible outcomes, general or contextual knowledge has been used to refine positioning results from positioning instruments. For example, the knowledge that the tracked target cannot jump over a big distance, and hence *the current position should be close to the last estimated position*, has been employed (Zhou and Sang (2012)). Accordingly, if the estimated position, computed using measurement results from positioning instruments, is too far from the last position, the final position is chosen such that it is close to the last position and to the same direction as the estimated one. The knowledge of the tracked target's motion has also been used in supporting positioning estimation. For example, a particle filter-based positioning system has been developed, in which it is assumed that *the tracked target's position is most likely to be the last estimated position* (Tsuji et al. (2010)). This knowledge, together with measurement results from positioning instruments, are then used in particle filter to provide the final estimation of the tracked target's position. Knowledge, such as *the current position should be close to the last estimated position* and *the tracked target's position is most likely to be the last estimated position*, is called heuristics information; and algorithms utilising heuristics information for positioning estimation, such as particle filter, are called heuristics methods. Heuristics methods and heuristics information are the main focus of this review.

A number of surveys of different indoor positioning systems and techniques have been conducted. A classification scheme together with an evaluation of 15 positioning solutions in the early stage of indoor positioning research has been presented (Hightower and Borriello (2001b)). A survey on wireless indoor positioning techniques and systems was conducted by Liu et al. (2007). In this work, 20 indoor positioning solutions were evaluated against a set of proposed performance metrics including accuracy, precision, complexity, scalability/ space dimension, robustness, and cost. A survey of mathematical methods for indoor positioning, especially those based on radio frequency signals, has been carried out (Seco et al. (2009)). In this work, the methods were classified into 4 categories: geometry-based methods, minimization of the cost function, fingerprinting, and Bayesian techniques. Mautz evaluated 13 positioning solutions against a set of criteria including accuracy, range, signal frequency, principle, market maturity and acquisition costs (Mautz (2009)). A comparison of different indoor positioning systems in terms of a number of criteria such as security and privacy, cost, performance, robustness, complexity, user preferences, commercial availability, and limitations has been conducted (Gu, Lo, and Niemegeers (2009)). An analysis of 13 indoor positioning technologies, and their measuring principles, has been presented by Mautz (2012).

Whilst the above-mentioned reviews focus on different technologies and methods for indoor positioning, or an evaluation on the performance of current positioning solutions against a set of performance metrics, this systematic literature review (SLR) has a special focus on the use of heuristics information and methods in indoor positioning estimation. Current positioning solutions have limitations (Liu et al. (2007); Mautz (2009, 2012)); and various heuristics-based approaches have been developed to enhance positioning estimation by employing additional information other than measurement results. A systematic review on heuristics-based indoor positioning is necessary to understand what heuristics information and methods have been used, and their efficiencies in enhancing positioning estimation, as well as to facilitate research on heuristics for indoor positioning estimation. As far as we know, there has been no SLR carried out for indoor positioning research. We chose to adopt the SLR method to systematically identify, evaluate, and interpret all available studies relevant to our research questions (Kitchenham and Charters (2007)).

This study presents the results of a SLR on heuristics-based indoor positioning research from January 2004 to December 2015. The main objectives of the study are: (1) providing a holistic view of heuristics-based indoor positioning research, including an in-depth analysis of what heuristics information and methods have been used; (2) exploring general achievements and limitations, whereby identifying potential research directions to further enhance positioning estimation.

The paper is structured as follows: We describe our research method in Section 2. We present the results about heuristics information and heuristics methods in, respectively, Sections 3 and 4. We analyse the achievements and limitations of current heuristics-based approaches in Section 5. We discuss possible directions for future work in Section 6. We conclude the paper in Section 7.

2. Research Method

In this section, we present the context of our research together with the research questions (Section 2.1), and the review protocol employed in this SLR (Section 2.2).

2.1. Context and Research Questions

2.1.1. Indoor Positioning Research

Various indoor positioning systems have been developed (Koyuncu and Yang (2010); Gu, Lo, and Niemegeers (2009); Liu et al. (2014)). These systems are characterized by different implementation decisions, such as *Sensory Technologies* or *Positioning Techniques*, as illustrated in Fig. 1. For example, a WLAN-based indoor positioning system has been developed (Outemzabet and Nerguizian (2008)). In this work, WLAN (IEEE 802.11) is chosen as the base technology, with received signal strength (RSS) chosen as the sensory data. The system works by measuring the RSSs from different WLAN access points (AP) in monitored areas. The measured RSSs are then compared against a pre-built database, consisting of RSS values at different positions, to infer an initial position. The initial position, together with the heuristics information that *the tracked target is most likely at the position, predicted using knowledge of the tracked target's velocity and the travelling time*, are then used in Kalman filter to provide the final estimation. In this case, the positioning technique is classified as *Scene Analysis*, and heuristics method used is Kalman filter. In the following, we discuss these different implementation decisions:

Sensory technologies: Various technologies have been used for indoor positioning such as WiFi (Laoudias, Michaelides, and Panayiotou (2012); Mirowski et al. (2012); Bai et al. (2014)), ultra-wideband (Cazzorla et al. (2013); Zhou et al. (2011); Suski, Banerjee, and Hoover (2013)) or RFID (Chen, Lin, and Lin (2011); Opoku, Homaifar, and Tunstel (2014); Hightower, Want, and Borriello (2000)), etc. Overall, a decision on positioning technology is based on user requirements, which need to be precisely described for each intended application (Mautz (2012)).

Sensory data: Depending on the sensory technologies, different sensory data

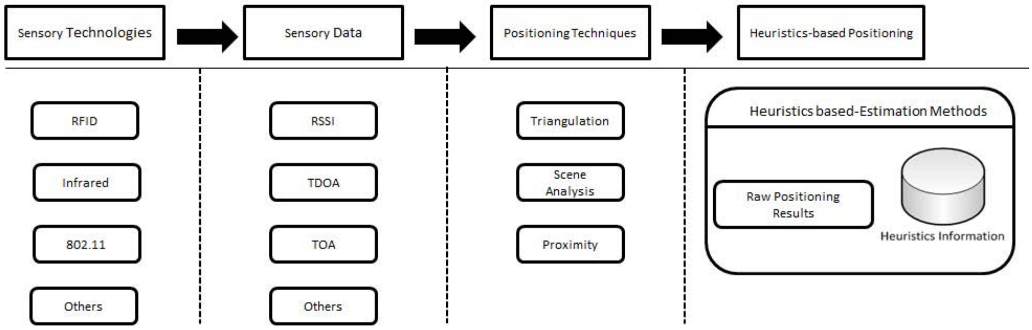

Figure 1.: Different implementation decisions in developing an indoor positioning system

can be collected for positioning estimation including received signal strength (RSS), time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), etc. These sensory data can be used directly, or indirectly by calculating intermediate information, to estimate position. For example, the RADAR system (Bahl and Padmanabhan (2000); Bahl, Padmanabhan, and Balachandran (2000)) utilises RSS for positioning estimation. The tracked target's position is computed by comparing the measured RSSs with a pre-computed database, where the database can be constructed either empirically or using a signal propagation model. An ultra-wideband (UWB)-based indoor positioning system has also been developed (Gigl et al. (2007)), utilising RSS to compute distances from the tracked target to different known base stations whereby weighted least square (WLS) is used to estimate the position.

Positioning techniques: Using the sensory data, various algorithms and techniques have been developed to estimate position. These algorithms and techniques can be classified into 3 categories: triangulation-based techniques, scene analysis-based techniques, and proximity-based techniques (Hightower and Borriello (2001a)). Triangulation-based techniques estimate position by dealing with angles (angulation-based techniques) or distances (lateration-based techniques). Scene analysis-based techniques estimate position by capturing and comparing features of a *scene* observed at a particular position. Proximity-based techniques estimate position by determining if the tracked target is within the proximity of a known location.

Heuristics-based positioning: Heuristics-based positioning seeks to employ heuristics information and heuristics methods to improve raw positioning results from positioning instruments. Heuristics information is *any general positioning information or contextual knowledge about the environments in which positioning measurement takes place, other than measurement results from positioning instruments, that provides implications on the tracked target' position.* Heuristics methods are *techniques or algorithms utilising heuristics information for improving positioning estimation of a positioning system to achieve an accurate and sensible outcome.* We only focus on heuristics that compute positioning estimations or trajectories with the positioning measurements as a given; the methods, algorithms and techniques that are mainly used to improve ranging or heading estimation, at a sensor level, are not in the scope of this work. Examples of heuristics for positioning estimation or trajectory include utilising knowledge of environmental map to avoid producing positions that cross walls or impassable obstacles, or exploiting knowledge of the tracked target's motion to predict their likely positions.

2.1.2. *Research Questions*

Despite that various heuristics approaches have been developed in indoor positioning research, there is no comprehensive understanding of what information can be used, how it is used, and the efficiencies of applying heuristics in enhancing positioning estimation. This SLR aims to provide insights into these issues by investigating the following questions:

Research Question 1: What heuristics information has been used for indoor positioning?

Rationale: Heuristics-based positioning techniques use general positioning information or contextual knowledge to aid positioning estimation. The answers to this question would tell us what information can be useful in heuristics-based positioning, allowing assessment of whether other information can be used for enhancing positioning estimation.

Research Question 2: What heuristics methods have been used for indoor positioning?

Rationale: The answers to this question would tell us what estimation methods have been used in heuristics-based positioning, and how they make use of heuristics information.

Research Question 3: What are the general achievements and limitations of current indoor positioning heuristics?

Rationale: We want to explore the achievements of current heuristics-based approaches, and their underlying constraints or assumptions. By doing this, we could gain insights of the performance and limitations of current heuristics-based approaches, providing analysis to identify potential research directions for further enhancements.

2.2. *Review Protocol*

A systematic literature review (SLR) is a means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest (Kitchenham and Charters (2007)). A SLR aims at providing a thorough and fair synthesis of existing works through a well-defined methodology for performing the review. The methodology includes a well-defined search process that aims to detect as much relevant literature as possible, explicit inclusion and exclusion criteria to assess whether to select a potential primary study, and the information to be obtained from each primary study. In this SLR, we conducted an automatic search on IEEE Xplore database. IEEE Xplore database was chosen as a reference database due to its wide research publication spectrum, ranging from electrical and electronics engineering to measurements, instrumentation, communications, software research and computer science, and hence, covering many research aspects of indoor positioning. Furthermore, many publication venues for indoor positioning research are covered by IEEE Xplore. We conducted manual search on references of accepted study in an iterative manner, in phase 3 of the search process. This is to avoid missing heuristics methods and information used in heuristics-based positioning, which is the main focus of this SLR. The search period was set from January 2004 to December 2015. The search process included 3 phases which are depicted in Fig. 2. Overall, applying the search terms to the database resulted in eleven-thousands-five-hundreds-and-nine (11509) papers. After checking the title and excluding duplicate papers, there were three-thousands-and-twenty-eight (3028) papers left. We then checked the papers based on their abstract, and selected four-hundreds-twenty-six (426) papers. After the full-text of the remaining papers was checked, there were eighty-two (82) papers retained. Manual search was performed in a iterative manner whilst exploring the references of accepted papers, it resulted in twelve (12) more papers in the set with one (1) paper being a more up-to-date version of another paper in the set of eighty-two (82) papers. In the end, there were ninety-three (93) papers selected for further analysis. Data items extracted from primary studies for the analysis in this SLR include *Heuristics information*, *Heuristic method*, *Experimental environment*, and *Positioning outcome*. Specifically, *Heuristics information* is used to answer research question 1, while *Heuristics methods* directly contribute to the answer of research question 2. *Experimental environment* and *Positioning outcome* are used to answer research question 3. Details about the review protocol employed in this study are presented in Appendix A.

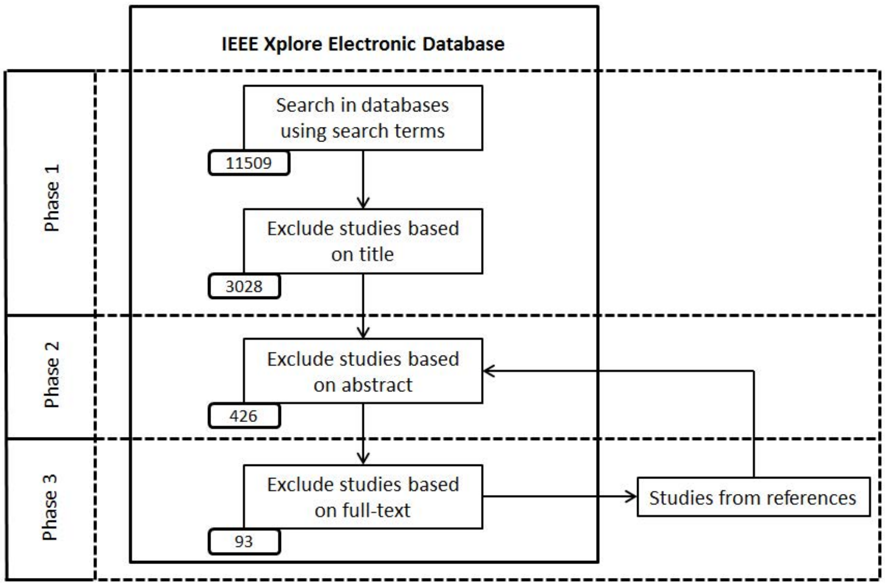

Figure 2.: The search process and selection results. The number in the rounded rectangles indicates the number of studies accepted

3. Results - RQ1: Heuristics Information

There were ninety-three (93) primary studies selected in this review. The selected studies are presented in Appendix B. Overall, the ninety-three (93) studies are distributed over fifty-eight (58) publication venues. The large number of publication venues suggests that heuristics-based indoor positioning has attracted interest from different research communities. Fig. 3 shows the distribution of primary studies over the review period. The figure shows that, overall, the number of heuristics-based positioning studies has been increasing with variations between years.

Following research question 1, we analyse primary studies to investigate what information has been used in heuristics-based positioning. We have found that there are 2 sources of information: (i) historical positioning results (Section 3.1) and (ii) environmental map (Section 3.2). Note that a primary study may use either or both of these 2 sources.

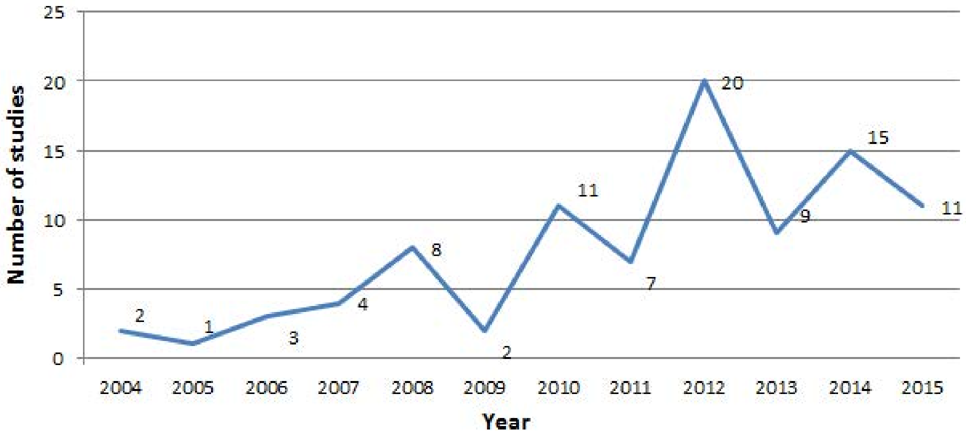

Figure 3.: Distribution of selected studies over searching time period

3.1. Information Based on Historical Positioning Results

Historical positioning results (HPR) are positioning results obtained prior to the current estimation. We have found that there is certain HPR-based information, predicting where the next position should be or computing the likelihood of next positions, that is used to refine raw positioning results from positioning instruments. Based on how the next position or the likelihood of the next position is inferred, we classify HPR-based information into motion-based and non-motion-based information. The summary of primary studies employing HPR-based information across these 2 categories is presented in Table 1. Note that a study may use either or both types of information.

3.1.1. Motion-based Information

Motion-based information is about the tracked targets' position based on their motions. Different motion-based information has been employed including: stationary, velocity-based, distance-based, and special motion-based information. Fig. 4 shows the frequency distribution of these types of information in primary studies.

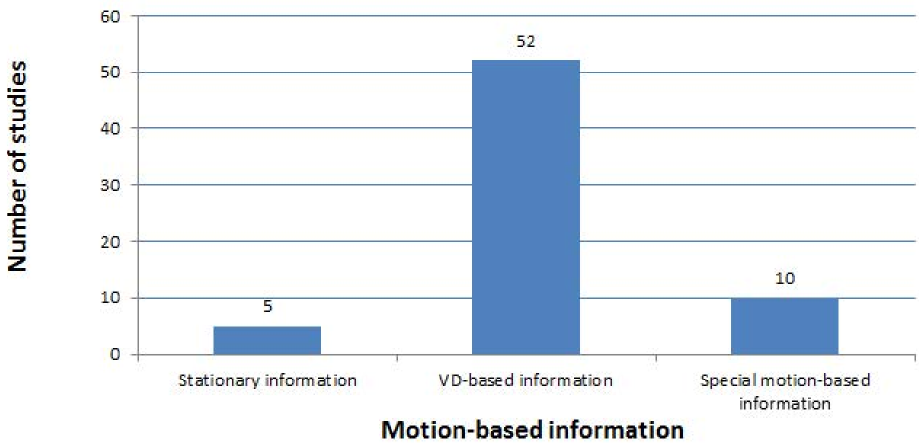

Figure 4.: Frequency distribution of different motion-based information employed in primary studies, where **VD-based information** stands for *Velocity-based and Distance-based information*

Stationary information: The information is based on the assumption that it is likely the tracked target has not made any motion since the last estimation, and hence gives the prediction that the tracked target's position is most likely the same as its last position.

Velocity-based and Distance-based information: The information is based on the law of physics, together with knowledge or assumptions on the tracked targets' motion parameters such as moving speed or distance, to deduce the next position. Note that velocity-based and distance-based are, in nature, the same; since given the time interval and the heading, velocity can be calculated given distance and vice versa.

Special motion-based information: The information relies on special assumptions about the motion of the tracked target. Specifically, in [S15], the tracked target's motion is assumed to be the combination of random walking - which is developed based on eleven parameters such as pursued activity, emotions, degree of disorientation, age, obstacles, etc. - and goal-oriented walking - whose destination points are chosen randomly. The combined model switches between these two models randomly after several time steps. In [S17], given the last position, the next position is assumed to be maximum two steps along each x and y direction, and one step along the z direction. This results in seventy-five (75) possible next positions given a current position. [S32, S44, S65, S72, S82, S84] assume that the motion of the tracked target from its previous position is a random walking process. In [S48], the transitional Probability Distribution Function (PDF) from one location to another is assumed to be normally distributed, in which the mean is the distance between the two points minus the travelling displacement, and the variance is assumed to depend on the variance of the speed and the squared travelling time. Meanwhile, the transitional PDF from one position to others, in [S60], is calculated using the computed distances, the expected speed of the user, and the inference whether or not user is moving or staying still which is based on the variances of collected signal strengths.

3.1.2. Non-motion-based Information

This type of information gives prediction of the next position through analytical or statistical methods that are independent from the motion of tracked targets. In [S13], the evolution in time of the positions is modelled as analytic function, in which the nth-order Taylor expansion is used to approximate its value. Meanwhile, [S34] computes the tracked target's position based on a forget factor (α), indicating how much likelihood the current position is computed based on the current estimation result, and the last position. In [S43], the transitional PDF from one position to another is assumed to be a constant for all pairs of previous and next positions. The transitional PDF from one location to another is calculated in [S52] by dividing the number of historical samples when the tracked target moves from the origin to the destination by the total number of samples originating from the origin (including to itself). In [S61], the state of the algorithm is a sequence of points, in which each point consists of a location, an orientation, and a collection of histograms for each base station. The next location of a state is predicted using the sequence of past location with appropriate weights, where the weights are the parameters of the optimum prediction filter (Proakis and Manolakis (1992)). Then the probability of a next state given a current state is assumed to be Gaussian distributed, which favours points that are closer to the predicted location.

Table 1.: Summary of studies using historical positioning results-based information

Historical Positioning Results-based Information:	Study
Motion-based Information:	
Stationary Information:	S4, S17, S42, S67, S90
Velocity-based and Distance-based Information:	S1, S2, S3, S5, S6, S7, S8, S9, S10, S11, S12, S14, S18, S19, S21, S22, S23, S24, S25, S26, S27, S28, S29, S30, S31, S34, S35, S36, S38, S39, S40, S41, S45, S46, S47, S49, S50, S51, S53, S54, S55, S56, S57, S58, S59, S66, S68, S69, S71, S74, S85, S88
Special motion-based Information:	S15, S17, S32, S44, S48, S60, S65, S72, S82, S84
Non-Motion-based Information:	S13, S34, S43, S52, S61

3.2. Information Based on Environmental Map

Environmental maps show the physical layout of the environment. Map-based information provides indications of the tracked target's position using knowledge of environmental layout. Based on how it supports positioning estimation, we classify map-based information into two categories: suggestive information and preventive information. Table 2 presents the summary of primary studies and the corresponding map-based information. Note that a study may use either or both types of information.

Suggestive information uses maps to give indications of where the true position is likely to reside in. For example, [S59] uses map and suggestive information **SI1** (Table 2) to suggest next possible positions. In this work, a map is partitioned into a set of points connected by edges. Particle filter is then used to estimate the tracked target' position, where particles, whose state represents a possible position, are only propagated along the edges of partitioned map.

Preventive information uses maps to avoid impossible positions. For example, works such as [S11, S35] use map and preventive information **PI1** (Table 2) to eliminate particles moving to inaccessible areas or crossing walls.

4. Results - RQ2: Heuristics Methods

Heuristics methods utilise heuristics information to refine raw positioning results from positioning instruments. In this section, we investigate what methods have been used (Section 4.1) and how they make use of heuristics information (Section 4.2).

4.1. Overview

Various methods such as Hidden Markov Model (HMM) and Bayesian filters (e.g., Kalman filter and particle filter) have been developed. Fig. 5 shows the frequency distribution of heuristics methods used.

4.1.1. Bayesian filters

Bayesian filters are used to construct posterior probability density distribution (PDF) of a dynamic system's state from noisy sensory data. In the context of indoor positioning, the state could be position of the tracked target, together with some auxiliary components such as velocity or acceleration. The estimation goes through two phases: prediction and update. In the prediction phase, the next state

Table 2.: Summary of studies using map-based information

Map-based Information:		Study
Sugestive Information:		
ID	**Information**	
SI1	The tracked target's next position should be reachable from the current position	S16, S37, S48, S59, S60, S61, S63, S65, S75, S77, S84, S91
SI2	The tracked target's next position should be close to the current position	S14, S63, S65, S75, S77, S81
SI3	The tracked target's activities (such as climbing up/down stair) should be performed at areas where such activities are possible	S20, S33, S53, S62, S76, S80, S91, S92, S93
SI4	The tracked target tends to move to more free space areas	S17, S89
SI5	The use of velocity-based model to predict the tracked target's position is more accurate when it moves a long a straghtline	S47
Preventive Information:		
Number	**Information**	
PI1	The tracked target cannot move through obstacles, to inaccessible areas, or outside tracking areas	S11, S14, S15, S17, S35, S36, S45, S53, S54, S59, S64, S70, S73, S76, S78, S79, S80, S81, S83, S86, S87, S88, S89

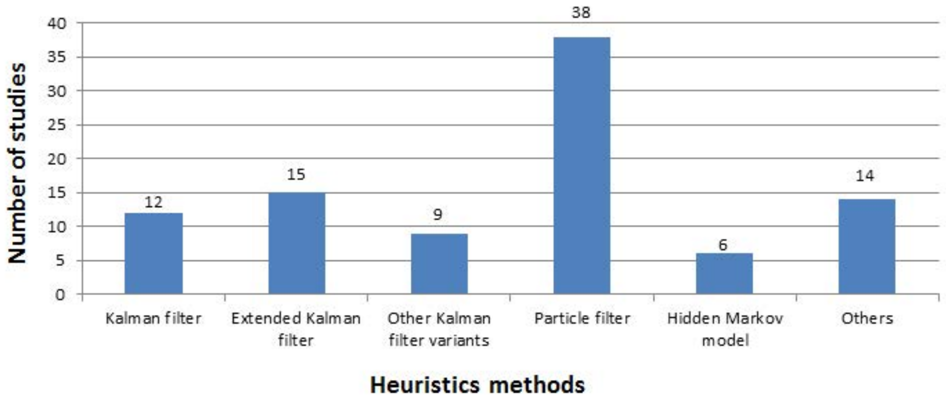

Figure 5.: Frequency distribution of different heuristics methods employed in primary studies

PDF is predicted using the *system dynamics*, which is usually the motion model in indoor positioning. In the update phase, the predicted state PDF is updated using the *perceptual model*, which describes the likelihood of observing the sensory data given the predicted state PDF. Kalman filter, extended Kalman filter, and particle filters are different implementation variants of Bayesian filter, employing different representations of state PDF, specifications of the system dynamics, and perceptual model.

Kalman filter (KF): KF assumes the posterior PDF is Gaussian, and the underlying system is linear. KF uses *velocity-based and distance-based information* (Section 3.1.1) to build up the system dynamics, which gives the prediction of the current position given the last position. The prediction outcome, together with the measurement outcomes from positioning instruments, are then used to provide the final estimation of the tracked target's position.

Extended Kalman filter (EKF): EKF extends KF to deal with non-linear systems, while the Gaussian assumption on the posterior PDF remains unchanged. EKF uses *stationary information* and *velocity-based and distance-based information* (Section 3.1.1) to develop the prediction model in the estimation.

Other Kalman filter variants: Other Kalman filter variants have also been used in heuristics-based positioning including: Unscented Kalman filter [S55], Robust EKF [S7], Adaptive Kalman filter [S19], Constrained Unscented Kalman filter [S22], and Sigma-point Kalman smoother [S45]. These filters are based on the Gaussian assumption of the posterior PDF, and mostly use Velocity-based and Distance-based information (Section 3.1.1) in their prediction model for positioning estimation.

Particle filter (PF): In PF, the posterior PDF is characterized by a set of particles. Each particle consists a set of states up to current time with associated weight, which is chosen based on the principle of importance sampling (Bergman (1999); Doucet, Godsill, and Andrieu (2000)). PF uses HPR-based information (Section 3.1) to develop the state transitional prior, which denotes the probability of a new state given the current state, and map-based information (Section 3.2) to constrain the distribution of particles.

4.1.2. Hidden Markov Model

Hidden Markov Model (HMM) (Rabiner and Juang (1986)) is a tool for representing probability distributions over sequences of observations (Ghahramani (2001)). In HMM, the state of the system is hidden to observer; however, the output dependent on the state is visible. There are a finite number of states in the model, which, in indoor positioning, represent locations or sequence of locations of tracked targets. HMM requires the state space be pre-computed and fixed, and the state satisfies the *Markov property*, meaning that the current state is only dependent on the last state, not any state before that. The mechanism of HMM is as follows: at each time step, a new state is inferred using the *state transition probability* (STP), which defines the probability of entering a new state given the current state. After the transition, the output is produced according to a *emission probability*, which is only dependent on the current state. Both the state transition probability and emission probability are *time-invariant*. HMM uses HPR-based information (Section 3.1) to build up the STP, and map-based information (Section 3.2) to constrain the transitional probability between 2 states. In indoor positioning, Viterbi algorithm (Rabiner (1989)) are often used to calculate the most probable states (locations or sequence of locations) given the sequences of outputs (measurement results from positioning instruments) in HMM.

4.1.3. Other Heuristics Methods

Apart from Bayesian filters and HMM, other specialized heuristics methods have also been developed:

[S14]: For each fingerprint - a set of measured signal strength values at a position - in a set of temporally consecutive signal fingerprints, a set of k most likely positions are estimated, a matrix is then formed where each column is the set of estimated positions at the corresponding time step. Using environmental map, the shortest path from the first column to the last column is calculated. Since paths may allow impossible moves that jump between floors, the algorithm chooses the floor that occurs most in the shortest path. To avoid lagging, the algorithm is enhanced in the case that the tracked targets are detected to be at the same position as previous time step. In this case, the next position is inferred using a number of historical estimated positions; this is done by inferring the velocity from the deviation between the starting position and the last position, and the elapsed time. If the tracked targets change movement direction during the considered number of previous positions, the velocity is calculated using the position at which the tracked targets change the direction, instead of the starting position.

[S16]: A positioning algorithm that uses the notion of separating ellipsoids (Xiao and Deng (2010)) is proposed to form fingerprints and distance measure such that maximally separated ellipsoids are computed from the training data for each location. Measurements inside an ellipsoid is mapped into the corresponding location, while measurements that fall outside of the ellipsoids are mapped into the closest ellipsoid. To reduce the computational complexity, the dimensionality of the problem is reduced by restricting the number of considered locations; this is achieved by using the A* algorithm (Hart, Nilsson, and Raphael (1968)) and the environmental map to find the set of possible locations.

[S31]: This work uses *velocity-based information* (Section 3.1.1) to predict the position of the tracked target. The predicted position, together with the measured received signal strength (RSS), are then used to provide the final estimation of the tracked target's position [S31, Algorithm 1].

[S34]: Infinite Impulse Response (IIR) has been employed to estimate the final position as follow:

$$\hat{\mathbf{u}}_m^{IIR} = \alpha \hat{\mathbf{u}}_{m-1}^{IIR} + (1 - \alpha)\hat{\mathbf{u}}_m \tag{1}$$

where $\mathbf{u}_m = [x_m, y_m]^T$ is position of tracked target; $\hat{\mathbf{u}}_m^{IIR}$ is estimation output from IIR at time step m; $\hat{\mathbf{u}}_m$ is estimation output from the maximum a posteriori (MAP) estimation method at time step m; and α is called forget factor, ranging from 0 to 1.

[S37]: In this work, the monitoring area is divided into sub-spaces, and possible paths between sub-spaces are pre-calculated. In the positioning stage, the algorithm will only search for the tracked target's position in sub-spaces that are connected to the current sub-space.

[S39]: This work assumes that the movement direction and speed are normally distributed, in which movement direction may be calculated using magnetometer or from historical positioning results. Based on this assumption, a probabilistic vector originating from the last known position and pointing toward the movement direction is calculated. This vector, together with the probability distribution based on the measured signal strengths, are then used to calculate the final probability of the current position.

[S75]: The environmental map is represented as a link-node network, and various rules have been developed to adjust positioning results from a WPS to possible positions in the map. For example, each positioning result from the WPS will be mapped into the closest link; if the current position is mapped into a different link than that of the previous position, the algorithm will update the mapping according to whether or not the links intersect, the distance between the links, the distance on the current link measured from the intersection, etc.

[S77]: In this work, the monitoring area is partitioned into sub-areas; the shortest distance between any two sub-areas is pre-computed using the floor plan and stored in a table. This information is then used to compute the achievable neighbour areas, which should be close and reachable from the current area, where the tracked target may locate. The system will then only need to compare the measured RSSs with the sub-database containing RSSs from reference points in the predicted areas.

[S78]: In this work, a positioning estimation is achieved by fusing data from Passive Infrared (PIR) sensor and wearable acceleration sensor. The distribution of furniture in the monitoring environment is used to limit the possible walking path to further enhance the estimation accuracy.

[S20, S33, S62, S80, S91, S92, S93]: These works developed map matching-based positioning techniques to estimate the tracked target's position. Specifically, the tracked target's activities, such as going up and down stairs, or travelling information, such as travelling distance or turnings, are used to compare with the environmental map to infer position. For example, in [S20], inertial sensors are used to estimate walking trajectory by calculating travelling distance, detecting turning or taking elevator activities. A map matching algorithm is then developed to infer the tracked target's position by comparing the estimated trajectory with the environmental map. In [S92], a positioning estimation method comprising three ideas (dead-reckoning, urban sensing, and WiFi-based partitioning) is proposed. In this work, sensor reading from mobile devices is used to identify and detect landmarks in the environment, which are locations that possess unique patterns of sensory data such as climbing up stairs. Positioning estimation is achieved using dead-reckoning schemes while detected landmarks are used to re-calibrate the estimated position.

4.2. The Use of Heuristics Information in Heuristics Methods

We investigate the relationships between heuristics methods and heuristics information; that is, which heuristics information is used in a heuristics method. Table 3 shows the relationship in terms of which primary studies using certain methods and information.

Table 3.: Classification of studies in terms of heuristics methods and heuristics information, where **VD-based** stands for *Velocity- and Distance-based*

Heuristics Method	Map-based Information		Historical Positioning Result-based Information			
			Motion-based			Non-motion-based
	Suggestive	Preventive	Stationary	VD-based	Special motion-based	
Kalman filter				S1, S6, S8, S10, S25, S27, S28, S30, S49, S51, S57, S58		
Extended Kalman filter	S47		S4	S2, S3, S7, S9, S21, S26, S29, S38, S41, S47, S55, S66, S69, S74		
Other Kalman filter variants	S48	S45		S7, S19, S22, S45, S55, S68, S71, S85	S48	
Particle filter	S53, S59, S61, S63, S65, S76, S84, S89	S11, S15, S17, S35, S36, S53, S54, S59, S64, S70, S73, S76, S79, S83, S86, S87, S88, S89	S17, S42, S67	S5, S11, S12, S18, S23, S24, S34, S35, S36, S46, S50, S53, S54, S56, S59, S88	S15, S32, S44, S65, S72, S82, S84	S13, S61
Hidden Markov Model	S17, S60, S81	S17, S81		S40	S17, S60	S43, S52
Others	S14, S16, S20, S33, S37, S62, S75, S77, S80, S91, S92, S93	S14, S78, S80	S90	S14, S31, S39		S34

Overall, map-based information has been mainly used in PF, contributing twenty-six (26) out of forty-nine (49) works. With regards to motion-based information, velocity-based and distance-based information has been widely adopted across different heuristics methods, except HMM. PF has also been used to employ stationary and special motion-based information more than other methods. In the case of non-motion-based information, PF and HMM contribute 2 works each while other heuristics methods contribute 1. In the following, we investigate how the heuristics information is used in each heuristics method. Map-based information and their corresponding ID has been presented in Table 2.

4.2.1. The Use of Map-based Information in Heuristics Methods

Map-based information has been mainly used in PF-based estimation, with eight (8) works using suggestive information - which indicates where the true position is likely to reside in - and eighteen (18) works using preventive information - which indicates where the true position should not be at. Of those using suggestive information, [S53, S76] use map and suggestive information **SI3** to determine which floor the tracked target is at in a multi-storey environment. Accordingly, the tracked target's transition over floors can only be done at transitable points such as stairs and elevators. Suggestive information **SI1** has been employed in PF-based estimation, in which particles are only propagated to new positions that are reachable from the current ones [S59, S63, S65, S84], or penalty will be applied to sequences of positions that contain unconnected locations [S61]. Suggestive information **SI4** has been employed in [S89] to give higher weight to particles that are in the middle part of a path. Suggestive information **SI2** has been used in [S63, S65] to only propagate particles to new positions that are close to the current ones. Of those using preventive approaches, preventive information **PI1** is used to remove particles that represent impossible paths such as moving through walls, to inaccessible areas, or outside of tracking areas [S11, S15, S17, S35, S36, S53, S54, S59, S64, S70, S73, S76, S79, S83, S86, S87, S88, S89].

Map-based information has also been used in HMM-based estimation. [S17] uses preventive information **PI1** and suggestive information **SI4** in estimating the tracked target's position. Accordingly, the transitional PDF will be zero if there is blocking obstacle between two positions, and transitions with more free space are emphasized while transitions with less free space are weakened. [S81] uses suggestive information **SI1** and preventive information **PI1** in the estimation, in which the transitional PDF between 2 positions will be set to zero if they are separated by walls or the distance between them exceeds a pre-defined value. [S60] uses suggestive information **SI1** in the estimation. In this work, based on the floor plan, possible tracks are drawn. Then a set of nodes, which presides on the tracks, are chosen 1m away from each other. Then Dijkstra algorithm is used to compute the shortest path from one node to others. The state of the HMM is the location of these nodes. A technique to infer the state transitional PDF between two states is developed, using the distances calculated, the expected speed of the user, and the inference whether or not user is moving or staying still based on the variances of collected signal strengths.

An EKF-based estimation has employed suggestive information (**SI5**) [S47]. In this work, map is used to adjust the weights of prediction outcome (from the system dynamics) and measurement outcome (from perceptual model). For example, based on their experiments, they concluded that when the tracked target moves along a straight line, the prediction outcome should be given more weights. Map-based information has also been used in other Kalman filter variants and other heuristics methods. Suggestive information **SI1** is used in [S48] in supporting positioning estimation, in which a map is represented in terms of location points connected to each other based on line of sight condition. Meanwhile, [S45] adopts preventive information **PI1** to develop a system dynamics model, in which the current position is computed using the last position together with the so-called *room model involving a potential field created throughout the indoor environment in order to repel estimated motion away from walls.*

Other methods have also utilised map-based information to support positioning estimation. [S14] estimates the tracked target's position by choosing the shortest path among possible travelling paths. Since a path may contain positions from different floors, and the tracked target cannot jump between floor (preventive information **PI1**), a floor that occurs most in the path is chosen, other floors are removed. Furthermore, in case that the estimated result is too far from the last estimation, the final result is chosen so that it is close to the last position (suggestive information **SI2**). In [S16], map is used together with the A* algorithm (Hart, Nilsson, and Raphael (1968)) to search for locations that are reachable from the current location (suggestive information **SI1**) to reduce the complexity of the positioning algorithm. In [S37], map is used to divide the monitoring area into sub-spaces, the current position is only searched in sub-spaces that are connected with the previous sub-space (suggestive information **SI1**). In [S75], a map is represented as a link-node network whose geometric attributes, such as distance between any two links or whether two certain links intersect, are used to adjust positioning results from a WiFi-based Positioning System (WPS). Specifically, changes of links between two consecutive positions are only allowed if the links intersect (suggestive information **SI1**) or the distance between them is less than a pre-defined threshold (suggestive information **SI2**). In [S77], the monitoring area is partitioned into sub-areas and a map is used to calculate the shortest distance between any two sub-areas. This information is then used to narrow down the search space for the tracked target's position, in which the current sub-area should be close and reachable from the previous one (suggestive information **SI1** and **SI2**). In [S78], environmental layout is used to avoid impossible locations from the positioning estimation (preventive information **PI1**). In [S20, S33, S62, S80, S91, S92, S93], positioning estimation is improved by utilising the mapping of the tracked target's detected activities, such as climbing stairs or taking elevators, to locations where such activities are allowed based on the environmental map (suggestive information **SI3**). Furthermore, in [S80], when the tracked target is at an open space, their movement is also constrained by walls (preventive information **PI1**).

4.2.2. The Use of Historical Positioning Results-based Information in Heuristics Methods

With regards to motion-based information, the number of studies utilising this type of information is dominating those using non-motion-based information, contributing sixty-eight (68) out of seventy-three (73) studies - 93.2%. In general, while Kalman filter variants use motion-based information to build up the system dynamics, which gives prediction of the next position given the current position, PF uses motion-based information to build up the state transitional prior, which denotes the probability of a new state given a current state.

Besides, HMM-based estimation also uses motion-based information to develop the state transition probability (STP) [S40]. In this work, the STP is computed using the distance displacement since the last time step, where the distance is calculated based on measurement results from accelerometer, or based on the assumption of constant moving speed. All positions within the distance from the last position are assigned higher probability than others. Furthermore, [S17] uses motion-based information to define the number of possible positions that the current position can transition to. In [S60], the STP is calculated using the travelling distance, the expected speed, and the motion status (moving or staying still) of the tracked target.

Other heuristics methods use Velocity- and Distance-based (VD-based) information in their estimation. In [S14], to avoid lagging, when the estimated position is the same as the last position, the positioning result is calculated based on the heading, the speed and time interval, which are inferred from the set of previous positions. Besides, while VD-based information is used to build up a motion model in [S31], stationary information is used for the motion model in [S90]. VD-based information has also been used to calculate a probabilistic vector originating from the last known position and pointing toward the movement direction [S39].

With regards to non-motion-based information, the information has been used to develop state transitional prior in particle filter [S13, S61], or STP in HMM [S43, S52]. Furthermore, [S34] uses a forget factor (α) to control how much probability that the current position is estimated from the current estimation result and the last position.

5. Results - RQ3: Positioning Heuristics: Achievements and Limitations

In this section, we discuss the general achievements and limitations of heuristics-based indoor positioning. We study the general achievements in terms of positioning accuracy obtained through experiments of primary studies. We first investigate the environmental conditions under which the experiments were conducted (Section 5.1), and analyse the positioning results (Section 5.2). We then study the limitations of heuristics methods (Section 5.3).

5.1. Experimental Environment

Indoor positioning faces various challenging conditions such as non line-of-sight (NLOS) transmission or multipath reflection. These conditions are caused by the complex nature of indoor environment. In this section, we report the experimental environment of primary studies in terms of a number of indoor environmental characteristics including: the size of the experimental area; whether the environment allows dynamic movement of surrounding objects; whether the system is tested tracking multiple targets simultaneously; whether the environment is a multi-room area; and surrounding objects and materials. This analysis allows us to understand to what extent the positioning systems have been tested under realistic scenarios.

The size of experimental area: The size of experiment area indicates how big the experimental area is. The experiments should be conducted in an area whose size is relatively similar to that of a typical environment, where the positioning system is intended to operate. Of one-hundred-and-eleven (111) experiments conducted in primary researches, thirty-eight (38) experiments do not specify the size of the experimental areas. Note that one research may conduct more than one experiment. Fig. 6 shows the histogram of the experimental areas. It can be seen that the majority of experiments were conducted in an area less than $4000m^2$ (93 percentile), where the highest range is from $20m^2$ to $200m^2$. Some of them were conducted in a large area such as [S33] ($10000m^2$). On the other hand, some of the experiments were conducted in a very small area such as [S56] ($1.05m^2$) or [S25] ($1.5m^2$).

Surrounding dynamic movement: Environments, where the positioning systems are deployed, may exhibit different movements other than those performed

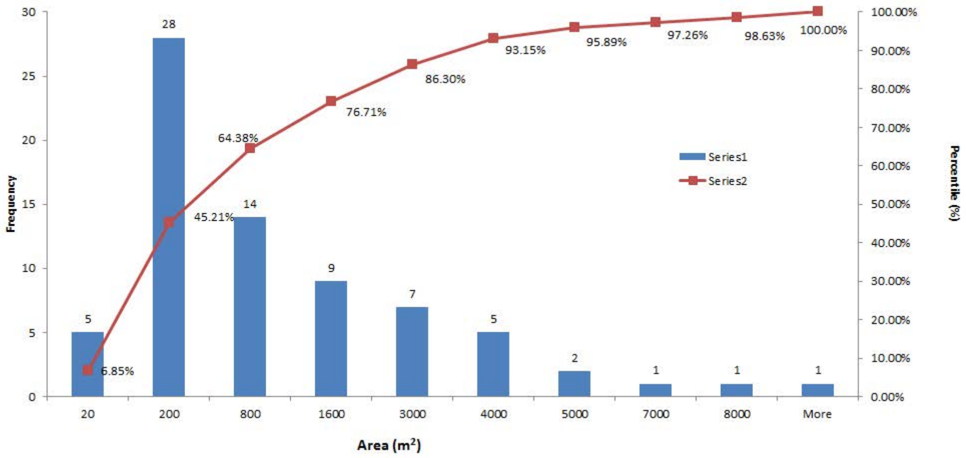

Figure 6.: Histogram of experimental areas

by the tracked targets. For example, a warehouse where assets are being tracked usually exhibit movements by workers, lifting trucks, etc. These movements may interfere with the positioning process by, e.g., intermittently blocking line-of-sight transmission, or creating unintended reflection. As such, positioning systems should also be able to account for these situations. Of all one-hundred-and-eleven (111) experiments, there are only four (4) ([S13, S34, S57, S89]) experiments that cater for dynamic movement of surrounding objects.

Multiple-target tracking: Positioning systems are usually developed to multiple targets at the same time. This requirement is more challenging than single-target tracking, since the tracking of one target may interfere the tracking of the others. Furthermore, tracking more targets introduces extra load to the system, and hence may have impacts on the accuracy achieved. Therefore, positioning systems should also be tested under multiple-target tracking condition, where there are two or more targets being tracked at the same time. In this review, we have found that there are three (3) studies ([S27, S34, S74]) experimenting with multiple tracked targets simultaneously. Specifically, there were 4, 5, and 2 targets being tracked in the experiments of, respectively, [S27, S34, S74].

Multi-room tracking: Real world environments may span over a number of smaller *rooms*, separated by walls, doors, etc. This separation may introduce, e.g., non line-of-sight, and intermittently shadowing condition to the positioning process. In this study, we consider *rooms* as separated or partly separated sessions of the whole area. For example, a squarely circular corridor can be considered as four (4) different *rooms*, where each *room* corresponds to an edge. Of all one-hundred-and-eleven (111) experiments, there are fifty-six (56) experiments that were conducted in a multi-room areas, where the experimental area contains at least 2 rooms.

Surrounding objects and materials: Surrounding objects - such as furniture or windows - also introduce challenges to positioning process, since they can introduce non-line-of-sight condition and, depending on the object materials - such as glass, wood, or concrete - and positioning techniques, unintended signal reflections. As such, open space tracking area may be less challenging than a dense environment occupied by furniture such as tables, chairs, kitchenwares, etc. Of all one-hundred-and-eleven (111) experiments, forty-one (41) of them describe or partly describe the surrounding objects and materials in the tracking environments.

Table 4 shows the frequency distribution over the above-mentioned environmental characteristics that occur in the experiments of primary studies. It can be seen that while the majority of experiments provide information about the size of experimental areas, surrounding objects and materials, and were conducted in a multi-room areas, few of them were conducted with multiple targets simultaneously and allowed surrounding dynamic movement.

Table 4.: Frequency distribution over indoor environmental characteristics in the experiments of primary studies

Characteristics	Number of works
The Size of Experimental Area	73
Surrounding Dynamic Movement	4
Multiple-Target Tracking	3
Multi-Room Tracking	56
Surrounding Objects and Materials	41

5.2. Positioning Heuristics - Achievements

In this section, we report positioning accuracy of primary studies. We present positioning results of those studies whose experimental environment possesses at least three (3) out of the five (5) indoor environmental characteristics discussed in Section 5.1. A study is considered as satisfying *surrounding dynamic movement* if the experiment was conducted in an environment that contains movements other than those performed by the tracked targets. A study is considered as satisfying *the size of experimental area* if information about the size of the experimental area is provided regardless of its magnitude. The *surrounding objects and materials* condition is satisfied if information about the surrounding objects and their materials are provided. There are twenty-one (21) experiments that qualify and they are summarized in Tables 5 and 6.

It can be seen from the table that the majority of positioning results are of meter-scale. The best results, 6cm to 29cm, are obtained in [S5] where particle filter with velocity-based information is adopted. However, the experiment does not include dynamic movements from surrounding objects, and multiple-target tracking. Of those experiments that are under either or both of these 2 conditions, the results reported are from 1.85m to 2.86m using 50 percentile metrics ([S13]), 1.5m to 1.8m using root-mean-square (RMS) metrics ([S34]), 4.3m to 4.8m using 95 percentile metrics ([S89]), and 0.5m using mean error ([S74]). The best results achieved is from [S74]; however, the experiment in [S74] was conducted in an open space area with one run of two short travelling distances.

5.3. Positioning heuristics - Limitations

In this section, we investigate the limitations of heuristics methods and heuristics information for indoor positioning.

5.3.1. Limitation - Heuristics methods

We investigate the limitations of primary heuristics methods employed in heuristics-based positioning including: Kalman Filter (KF), Extended Kalman Filter (EKF), Particle Filter (PF), and Hidden Markov Model (HMM).

Kalman filter variants: KF assumes that the underlying processes are linear, and hence the system dynamics and perceptual model must be in linear forms.

Table 5.: Summary of experimental settings and results of heuristics approaches that satisfy at least three (3) out of five (5) environmental conditions, where **SEA** stands for *Size of Experimental Area*, **SDM** stands for *Surrounding Dynamic Movement*, **MTT** stands for *Multiple-Target Tracking*, **MRT** stands for *Multiple-Room Tracking*, and **SOM** stands for *Surrounding Objects and Materials.* A ✓ mark indicates that a given condition is satisfied or information about that condition is provided in the experiment, and a ✗ mark indicates otherwise.

Work	SEA	SDM	MTT	MRT	SOM	Accuracy metrics	Accuracy result
[S5]	$64m^2$	✗	✗	✓	✓	Mean error	From 6cm to 29cm
[S6]	$100m^2$	✗	✗	✓	✓	Mean error	From 1.64m to 2.92m
[S10]	$1750m^2$	✗	✗	✓	✓	Mean error	4.95m
[S12]	$1296m^2$	✗	✗	✓	✓	Mean error	1.12m and 1.07m
[S13]	$625m^2$	✓	✗	✓	✗	50 percentile	From 1.85m to 2.86m
[S15]	$400m^2$	✗	✗	✓	✓	CDF	90%: less than 4m
[S17]	$900m^2$	✗	✗	✓	✓	Mean error	less than 2m
[S30]	$400m^2$	✗	✗	✓	✓	Mean error	1.6m
[S33]	$10000m^2$	✗	✗	✓	✓	Mean error	1.6m
[S34]	$49.62m^2$	✓	✓	✗	✓	RMS	IIR-based approach: 1.5m. Partcle filter-based approach 1.8m
[S35]	$1300m^2$	✗	✗	✓	✓	Graph	Fig. 10 in (Kemppi et al. (2010))
[S35]	$5500m^2$	✗	✗	✓	✓	Graph	Fig. 11 in (Kemppi et al. (2010))
[S43]	$8000m^2$	✗	✗	✓	✓	Mean error	7m
[S43]	$2800m^2$	✗	✗	✓	✓	Mean error	3m
[S49]	$90m^2$	✗	✗	✓	✓	Smallest error	0.14m
[S58]	$960m^2$	✗	✗	✓	✓	RMSE	1.67m
[S62]	$1500m^2$	✗	✗	✓	✓	CDF	95%: 2.6m
[S74]	$66.9m^2$	✗	✓	✗	✓	Mean error	0.5m
[S79]	$4000m^2$	✗	✗	✓	✓	CDF	90%: 3.5m
[S86]	$144m^2$	✗	✗	✓	✓	CDF	90%: 2m
[S89]	$465m^2$	✓	✗	✓	✓	CDF	95%: from 4.3m to 4.8m

Furthermore, all noises in KF are assumed to be Gaussian distributed. These assumptions may not hold in real world scenarios, where most tracked targets have non-linear dynamics and noises are not necessarily Gaussian (Ansari, Riihijarvi, and Mahonen (2007)). EKF is a variant of Kalman that can linearize a nonlinear system, thus it allows the underlying models to be non-linear. However, the linearization process involves the calculation of Jacobian matrix, which is sometimes difficult (Bao et al. (2007)). Furthermore, since EKF only uses first order terms of Taylor series expansion, it may introduce large error in estimation results, and only reliable for systems that are almost linear in the time scale of the update intervals (Ko and Choi (2007)). The reliability of Kalman filter family also depends on the noise statistics of system process and measurement, which may not be known analytically. Hence, using the prior statistics of noises may degrade the system performance (Chai et al. (2012)).

Particle filter: The key advantage of PF is the ability to represent arbitrary probability densities, and thus allowing underlying models to be non-linear and non-Gaussian. The main disadvantage of PF is that the complexity grows exponentially with respect to the state dimension (Prieto et al. (2012); Fox et al. (2003); Daum and Huang (2003)). For resource-constrained devices, continuous executions of PF may result in high computational cost (Yang et al. (2012)).

Hidden Markov model: HMM works with discretised state space, and usually adopts Viterbi algorithm (Rabiner (1989)) to find the most probable path resulting in the sequence of observations. The complexity of the Viterbi algorithm is proportional to the number of states, which needs to be pre-computed and fixed.

Table 6.: Summary of positioning technologies, sensory data, and positioning methods of heuristics approaches that satisfy at least three (3) out of five (5) environmental conditions

Work	**Technology**	**Sensory Data**	**Positioning methods**
[S5]	UWB	TOA and TDOA	Triangulation and particle filter
[S6]	IEEE 802.15.4 and inertial sensor	RSS and inertial information	Triangulation and Kalman filter
[S10]	WLAN, high-sensitivity GPS, inertial sensors and digital compass	RSSI and Inertial information	Dead reckoning, fingerprinting, and Kalman filter
[S12]	Magnetometer and inertial sensors	Magnetic field and inertial information	Dead reckoning, fingerprinting and particle filter
[S13]	WLAN	RSS and TOA	Particle filter
[S15]	3GPP-LTE	TDOA	Particle filter
[S17]	WiFi	RSS	Fingerprinting, HMM, and particle filter
[S30]	WiFi and inertial sensors	RSS and inertial information	Dead reckoning, fingerprinting, and Kalman filter
[S33]	Inertial sensors	Inertial information	Map matching
[S34]	IEEE 802.15.4	RSSI	Maximum a posteriori (MAP), infinite impulse response (IIR), and particle filter
[S35]	An angle-based positioning system and inertial sensors	Angles and inertial information	Dead reckoning, triangulation and particle filter
[S43]	WiFi and inertial sensors	RSS and inertial information	Fingerprinting, dead reckoning, and HMM
[S49]	Multi Carrier - Wide Band (MC-WB) and inertial sensors	TDOA and inertial information	Triangulation, dead reckoning, and Kalman filter
[S58]	WLAN	RSS	Fingerprinting and Kalman filter
[S62]	Wifi and inertial sensors	RSSI and inertial information	EKF and map matching
[S74]	Kinect, acoustic device, and inertial sensors	Ranges, TOA, and inertial information	EKF
[S79]	Magnetometer and WiFi	Magnetic field and RSS	Fingerprinting and particle filter
[S86]	Magnetometer and inertial sensor	Magnetic field and inertial information	Fingerprinting, dead reckoning, and particle filter
[S89]	Inertial sensor	Inertial information	Dead reckoning and particle filter

Therefore, the granularity of the state space has some implications on the complexity. If the state spaces are too sparse, then the granularity of the accuracy is coarse. However, if it is too dense, then the computational complexity is high. To reduce the complexity, auxiliary optimization techniques have to be used in accompanying with the positioning estimation (Viol et al. (2012); Kelly, McLoone, and Dishongh (2008); Liu et al. (2010)).

Besides, KF filter variants and HMM only allow the next state to be predicted using the last state, and the state of these methods often does not include a sequence of previous positions. The only exception is [S61], where the state of the estimation includes a sequence of positions, and the next position in a state is computed using the sequence of past positions with appropriate weights. This is because designing the state of the system to be a sequence of positions will inevitably result in higher computational complexity as this corresponds to higher state dimensions and much larger state space. As such, this limits the applicability of these heuristics methods to only heuristics information that is based solely on the last estimated position.

5.3.2. Limitation - Heuristics information

Historical positioning results-based information (Section 3.1) often relies on certain assumptions. For example, assumptions about the tracked targets' motion, such as those shown in Table 7, are often made in motion-based information (Section 3.1.1). Non-motion-based information (Section 3.1.2) is also based on certain assumptions. For example, [S43] assumes that the transitional PDF from one position to another is constant for all pair of previous and next positions. The reliability of the heuristics information is hence dependent on how accurate these assumptions are. As human' movement is influenced by a number of factors such as surrounding environment and their pursued activity; assumptions made about their motion and positioning behaviour, without considering these factors, could lead to inaccurate prediction of their true position.

Map-based information (Section 3.2) has been widely used in indoor positioning. However, current map-based information is mainly based on physical constraints to eliminate impossible areas, or to suggest areas where the tracked target could be at; it cannot provide a fine-grained indication of the tracked target's position.

Besides, current heuristics information is usually based only on the tracked targets' last estimated position. Given that the estimation result at each time step could be erroneous, prediction of current position that is based solely on the last position could lead to unreliable result, and hence affecting positioning accuracy.

Table 7.: Common assumptions about the tracked target's motion in motion-based information

Assumption	Number of Studies
Velocity is assumed to be Gaussian distributed around the last velocity value	22
Acceleration is assumed to be Gaussian distributed around the last acceleration value	5
Heading is assumed to be Gaussian distributed around the last heading value	6
Angular rate is assumed to be Gaussian distributed around the last rate	3
The current position is assumed to be Gaussian distributed around the last position	5

6. Discussion and Future Work

Heuristics-based positioning has been widely developed. However, the accuracy results, obtained under challenging conditions of typical indoor environments, are still of limited usefulness. Of those studies conducting experiments that allow dynamic movement from surrounding objects, and/or tracking multiple targets simultaneously, the reported accuracies are of meter-scale (Section 5.2). While these accuracies may be sufficient for some applications, other applications may require more precise results. For example, determining whether a person is lying on a bed or on the floor is crucial in monitoring applications for elderly people, and demands sub-meter accuracy of the tracking system. In the following, we discuss the limitations of current heuristics information (**Limitation 1**), and identify other information (**Solutions 1.1** and **1.2**) that could be utilised for positioning estimation. In **Limitation 2**, we highlight the limitations of current heuristics methods and propose directions for developing new heuristics methods (**Solution 2**) that can utilise heuristics information identified in **Solutions 1.1** and **1.2**.

Limitation 1: Limitations in current heuristics information - Current heuristics information relies on certain assumptions that may not accurately reflect the motion or positioning behaviours of the tracked target, or cannot provide a precise indication of the tracked target's position. For instance, assumptions about the tracked targets' motion such as those described in Table 7 are often employed in motion-based information, upon which predictions of the tracked targets' position are made. However, as people's movements can vary under different environments and over different time periods, static assumptions about their motion can lead to inaccurate predictions of their positions. Meanwhile, current map-based information is only about the possibility of current position, and cannot provide precise indication of where the current position is. Based on the results of this review, we discuss possible ways to enhance heuristics-based positioning.

Solution 1.1: Using Contextual Information in Indoor Positioning - Many current research works exploit physical constraints extracted from environmental maps to eliminate impossible positions, or to suggest possible positions, thus providing results that are more sensible. However, current map-based information cannot give a precise indication of the current position.

As people's movements are influenced by their pursued activities and the environmental layouts; apart from physical constraints, information - such as the functionality of a room or the type of furniture - may be useful in supporting positioning estimation. For instance, people entering a lunch room may perform certain actions such as heating up meals, pouring a cup of coffee, etc. As such, the implications of environmental layout on the movements of the tracked targets can provide a basis to predict their position. Compared with current heuristics information, this contextual information provides indications of the tracked targets' positioning behaviour depending on their intents and surrounding environment, and hence could lead to more reliable and accurate prediction outcomes.

Solution 1.2: Exploiting Positioning Habit in Indoor Positioning - Many current heuristics information gives predictions of the tracked targets' position based on their last position. However, positioning estimation at each time step may contain deviation from the true position. As such, the prediction outcomes, based solely on the last position, may not be entirely reliable.

People have habits and tend to follow certain movement routines, i.e. sequences of positions, in their living and working environments. As positioning habits of a person give indications of his or her likely current position, they can be useful in supporting positioning estimation. Furthermore, as positioning habits give indications of current position based on the tracked target's sequences of past positions; compared with current heuristics information, the use of positioning habits could lead to more reliable outcomes. Whilst many methods utilise historical positions for indoor positioning purpose, the use of positioning habit - in terms of repeated sequences of positions of a person - has not been investigated.

Limitation 2: Limitations in current heuristics methods - Current heuristics methods are often based on certain assumptions and constraints that are unrealistic in real life environment, or limit the their applicability on sophisticated indoor positioning problems. For example, the underlying *system dynamics* and *perceptual model* in Kalman filter must be represented in linear forms, and all noises are assumed to be Gaussian distributed. Besides, if we broaden the use of heuristics information, new heuristics methods will also be needed.

Solution 2: Various methods have been developed to study the implications of historical locations of a person on his/her next location. For instance, a number of data mining methods have been used to extract location patterns from the tracked targets' past locations, upon which predictions of their next locations are made (Monreale et al. (2009); Yavaş et al. (2005); Ying et al. (2011)). For example, a data mining approach to predicting location of mobile users have been proposed

(Yavaş et al. (2005)). In this work, user mobility patterns are first mined from their historical trajectories. Based on these patterns, mobility rules are derived which are then used for predictions of their next location. A location prediction for mobile users in spatio-temporal context has been developed, in which the next location is predicted based not only on spatial historical trajectories, but also the temporal periodic patterns (Gao, Tang, and Liu (2012)). Apart from mobile users' geographic trajectories, their semantic trajectories, consisting of sequences of locations labelled with semantic tags, are also utilised for location prediction (Ying et al. (2011)). In this work, user clusters are formed based on similarities in semantic trajectories. Frequent geographic trajectories of users in the same cluster are then mined. Based on the mined semantic and geographic patterns, a cluster-based prediction technique to predict the mobile user's next location is developed.

A number of machine learning techniques have also been used to predict next location based on sequence of past positions (Petzold et al. (2005b,a, 2006)). For instance, the performance of different machine learning techniques - including dynamic Bayesian network, multi-layer perceptron, Elman net, Markov predictor, and state predictor - for location prediction has been analysed by Petzold et al. (Petzold et al. (2006)). The analysis results indicate that each technique possesses particular strengths and weaknesses, and the choice for a technique would depend on the application requirements and characteristics.

Our future work is to investigate for a suitable method to analysing the tracked targets' positioning behaviours in indoor environments, and develop a efficient mechanism to enhance positioning estimation by making use of the analysis results.

7. Conclusions

Indoor positioning is concerned with developing techniques and algorithms to estimate a tracked target's position inside indoor environments. As indoor positioning solutions, based on various positioning techniques and technologies, have limitations (Liu et al. (2007); Mautz (2012)), heuristics have been used to improve positioning estimation. In this study, we conducted a systematic literature review (SLR) on heuristics-based indoor positioning research to (i) provide a holistic view and an in-depth analysis of what heuristics information and methods have been used, and (ii) identify their limitations and potential research directions for further enhancements.

We followed the SLR guidelines (Kitchenham and Charters (2007)) for developing a review protocol. There were ninety-three (93) primary studies selected for the analysis. We have found that there were two types of heuristics information, that are historical positioning results (HPR)-based information and map-based information. HPR-based information can be further categorised into motion-based and non-motion-based information, while map-based information can be grouped into suggestive and preventive information. Besides, primary heuristics methods include particle filter, Kalman filter, extended Kalman filter, and hidden Markov model. With different heuristics information and methods that have been used, we found limitations in the positioning outcomes of proposed solutions obtained under challenging conditions of typical indoor environments.

We analysed heuristics information and methods, and found that they have certain shortcomings limiting the positioning performance. Based on the results of the analysis, we proposed two research directions for enhancing the positioning estimation. As people's movements are dependent on their intents and the layout of environment, e.g., the location of different furniture and equipment, the first direction is to study the implications of environmental layouts on people's movement in supporting positioning estimation. The second direction is to utilise people's positioning habits, in terms of their repeated sequences of positions, to enhance the estimation of their position. This SLR is beneficial to indoor positioning research as it provides a comprehensive understanding of current heuristics information and methods, their general achievements and limitations, thus providing a basis for improving research on indoor positioning heuristics.

Appendix A. Review Protocol

A systematic literature review (SLR) is a means of identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest Kitchenham and Charters (2007). A SLR aims at providing a thorough and fair synthesis of existing works through a well-defined methodology for performing the review. The methodology includes a well-defined search process that aims to detect as much relevant literature as possible, explicit inclusion and exclusion criteria to assess whether to select a potential primary study, and the information to be obtained from each primary study. In the following, we describe the review protocol employed in this review.

Appendix A.1. Search Process

We developed the search protocol based on the SLR guidelines Kitchenham and Charters (2007) and the protocol designed by Ding et al. Ding et al. (2014). The search process included the automatic search on an electronic database, and a manual search on the accepted studies from the automatic search as a supplementary source. The search process is as follows:

- Phase 1: The first author applied the searching keyword to the electronic database and retrieved potential primary studies. The first and second author then checked the titles of these primary studies against the inclusion and exclusion criteria. If a paper could not be decided if it should be included or not by title, it would be included for the second checking phase.
- Phase 2: Two authors checked the abstract of selected papers against inclusion and exclusion criteria. If it was difficult to decide whether to include or exclude a paper, the paper would be included for the next phase.
- Phase 3: Two authors checked the content of selected papers against inclusion and exclusion criteria. References of accepted studies were also manually checked to avoid missing relevant information. The manual search on references of a paper was conducted only if the paper was accepted.

The search process is illustrated in Fig. 2. Overall, applying the search terms to the database resulted in eleven-thousands-five-hundreds-and-nine (11509) papers. After checking the title and excluding duplicate papers, there were three-thousands-and-twenty-eight (3028) papers left. We then checked the papers based on their abstract, and selected four-hundreds-and-twenty-six (426) papers. After the full-text of the remaining papers was checked, there were eighty-two (82) papers retained. Manual search was performed in a iterative manner whilst exploring the references of accepted papers, it resulted in twelve (12) more papers in the set with one (1) paper being a more up-to-date version of another in the set of 82 papers. In the end, there were ninety-three (93) papers selected for further analysis.

Appendix A.1.1. Search Scope

Time period: We specified the time period for published papers from January 2004 to December 2015.

Electronic database: IEEE Xplore database was chosen as a reference database due to its wide research publication spectrum, ranging from electrical and electronics engineering to measurements, instrumentation, communications, software research and computer science, and hence, covering many research aspects of indoor positioning. Furthermore, many publication venues for indoor positioning research are covered by IEEE Xplore. We conducted manual search on references of accepted study, in phase 3 of the search process. This is to avoid missing heuristics methods and information used in heuristics-based positioning, which is the main focus of this SLR.

Appendix A.1.2. Search Terms

Based on the SLR guidelines Kitchenham and Charters (2007), we used population, intervention, comparison, and outcome criteria to define search terms for the automatic searching process.

- Population: The population was *Indoor Positioning*. We used different combinations of key words such as Indoor positioning system, Indoor localization technique, etc.
- Intervention: The intervention was *heuristics-based positioning*. However, since this SLR is the pivotal in studying heuristics-based indoor positioning, and heuristics have not been formally defined in literature; to avoid missing out relevant study, the intervention was intentionally left blank.
- Comparison: There was no compared approach.
- Outcome: We study heuristics-based positioning in terms positioning accuracy and precision. As such, we used both of them to construct the search keywords.
- Search keywords: The search keywords were:
    - Population: (Indoor **OR** Inside Building **OR** Local **OR** In Building) **AND** (Positioning **OR** localization **OR** Location Estimation **OR** Location) **AND** (Techniques **OR** Algorithms **OR** System **OR** Scheme **OR** Method **OR** Application)
    - Outcome: accuracy **OR** precision

Appendix A.1.3. Strategy

We followed the searching guidelines by Kitchenham and Charters Kitchenham and Charters (2007) and the strategy devised by Ding et al. Ding et al. (2014).

- An initial set of search terms was defined as in Section A.1.2.
- The search terms were refined after some trials search on the database. Boolean operators **AND** and **OR** are used to join terms: terms within *Population*, *Intervention*, *Comparison*, and *Outcome* were joined using the **OR** operator, while terms between them were joined using the **AND** operator.
- The search process was conducted by applying the search terms to the IEEE Xplore database. The search process then followed the protocol defined in Section A.1. The results were recorded in Excel Spreadsheet for further analysis.

Appendix A.2. Inclusion and Exclusion Criteria

We defined inclusion and exclusion criteria based on the SLR guidelines Kitchenham and Charters (2007). The inclusion criteria are:

- I1: Any study whose theme is developing techniques and algorithms that utilise heuristics information for indoor positioning purpose.

The exclusion criteria are:

- E1: Works in which positioning results are not obtained through experiments in real indoor environment, or positioning results for indoor scenarios cannot be extracted from the overall outcomes. Specifically, we employed the evidence level hierarchy proposed by Alves et al. Alves et al. (2010), and excluded works whose evidence level is less than 4. The evidence level is defined, from weakest to strongest, as follows:
    - Level 1: No evidence.
    - Level 2: Evidence obtained from demonstration or working out toy examples.
    - Level 3: Evidence obtained from expert opinions or observations.
    - Level 4: Evidence obtained from academic studies, e.g., controlled lab experiments.
    - Level 5: Evidence obtained from industrial studies, e.g., causal case studies.
    - Level 6: Evidence obtained from industrial practice.
- E2: Works that are a duplicate of others. In this case, the less mature ones are excluded.
- E3: Works in domains that are not explicitly specified as indoor environment. This is because indoor environments possess different characteristics from outdoor environments, and hence posing different challenges and requirements on positioning systems.
- E4: Works in which the tracked targets are stationary. This is because we only focus on positioning techniques or algorithms that can cope with moveable targets, where the targets' movements may introduce more challenges than stationary case.
- E5: Works in which the focuses are at physical/communication layer, such as low-level signal processing (e.g., UWB pulse or RFID signal) or sensor data estimation (such as angle or distance estimation). Furthermore, we only focus on positioning estimation of tracked targets in normal indoor environments, hence works that are designed for tracking targets in environments that are unstructured or of unknown structure are excluded.
- E6: Works in which detail implementations of proposed techniques or algorithms are not explained clearly.
- E7: Works that rely on knowledge, exchanged or propagated between tracked targets, for positioning estimation. This is because we only focus on passive tracked targets that are independent from each other.

Appendix A.3. Data Extraction and Synthesis

Table A1 shows the extracted items used for the analysis in this SLR. Specifically, *Heuristics information* is used to answer research question 1, while *Heuristics methods* directly contribute to the answer of research question 2. *Experimental environment* and *Positioning outcome* are used to answer research question 3. To ensure that the data extraction is not biased, the data were extracted and cross-checked by two authors. Any disagreement was resolved through discussion until consensus is reached.

Relevant RQ	Data Extracted	Research Question
RQ1	Heuristics Information	What heuristics information was used?
RQ2	Heuristics methods	What heuristics methods were used?
RQ3	Experimental environment	Under what environmental conditions the experiment was conducted?
RQ3	Positioning outcome	What accuracy were achieved?

Table A1.: Extracted data from each primary study

Appendix B. Primary studies in the review

[S1] S. Outemzabet and C. Nerguizian, Accuracy Enhancement of an Indoor ANN-Based Fingerprinting Location System Using Kalman Filtering.

[S2] A. Colombo et al., Flexible Indoor Localization and Tracking Based on a Wearable Platform and Sensor Data Fusion.

[S3] W.-Y. Hu et al., Wibest: A Hybrid Personal Indoor Positioning System.

[S4] J. Lategahn et al., TDOA and RSS Based Extended Kalman Filter for Indoor Person Localization.

[S5] W. Suski et al., Using a Map of Measurement Noise to Improve UWB Indoor Position Tracking.

[S6] P. Tarro et al., Fusion of RSS and Inertial Measurements for Calibration-Free Indoor Pedestrian Tracking.

[S7] R. Zhang et al., TDOA-Based Localization Using Interacting Multiple Model Estimator and Ultrasonic Transmitter/Receiver.

[S8] Y. Tian et al., Adaptive-Frame-Rate Monocular Vision and IMU Fusion for Robust Indoor Positioning.

[S9] V. Malyavej et al., Indoor Robot Localization by RSSI/IMU Sensor Fusion.

[S10] M. Bhuiyan et al., Utilizing Building Layout for Performance Optimization of a Multi-Sensor Fusion Model in Indoor Navigation.

[S11] M. Kessel and M. Werner, Automated WLAN Calibration with a Backtracking Particle Filter.

[S12] S.-E. Kim et al., Indoor Positioning System Using Geomagnetic Anomalies for Smartphones.

[S13] J. Prieto et al., Adaptive Data Fusion for Wireless Localization in Harsh Environments.

[S14] R. Zhou and N. Sang, Enhanced Wi-Fi Fingerprinting with Building Structure and User Orientation.

[S15] C. Gentner et al., Particle Filter Based Positioning with 3GPP-LTE in Indoor Environments.

[S16] G. Soldi and A. Jakobsson, Wireless Positioning Using Ellipsoidal Constraints.

[S17] N. Viol et al., Hidden Markov Model-Based 3D Path-Matching Using Raytracing-Generated Wi-Fi Models.

[S18] M. Fallon et al., Efficient Scene Simulation for Robust Monte Carlo Localization Using an RGB-D Camera.

[S19] W. Chai et al., INS/Wi-Fi Based Indoor Navigation Using Adaptive Kalman Filtering and Vehicle Constraints.

[S20] H. Ookura et al., Development and Evaluation of Walking Path Estimation System Using Sensors of Android Device and Vector Map Matching.

[S21] J. Jung et al., Fuzzy-Logic-Assisted Interacting Multiple Model (FLAIMM) for Mobile Robot Slip Compensation.

[S22] T. Nick et al., Camera-Assisted Localization of Passive RFID Labels.

[S23] S. Bartoletti et al., UWB Sensor Radar Networks for Indoor Passive Navigation.

[S24] L. Yang et al., A Hybrid Method for Achieving High Accuracy and Efficiency in Object Tracking Using Passive RFID.

[S25] B. Bischoff et al., Fusing Vision and Odometry for Accurate Indoor Robot Localization.

[S26] M. Rodrigues et al., Mobile Robot Localization in Indoor Environments Using Multiple Wireless Technologies.

[S27] H. Kuusniemi et al., L. Pei, Y. Chen, and R. Chen, Multi-Sensor Multi-Network Seamless Positioning with Visual Aiding.

[S28] D. Liu et al., Exploit Kalman Filter to Improve Fingerprint-Based Indoor Localization.

[S29] A. Colombo et al., A Wearable Embedded Inertial Platform with Wireless Connectivity for Indoor Position Tracking.

[S30] W. Xiao et al., Integrated Wi-Fi Fingerprinting and Inertial Sensing for Indoor Positioning.

[S31] L. Chen et al., Motion Restricted Information Filter for Indoor Bluetooth Positioning.

[S32] J. Jung and H. Myung, Range-Based Indoor User Localization Using Reflected Signal Path Model.

[S33] J. Link et al., Footpath: Accurate Map-Based Indoor Navigation Using Smartphones.

[S34] D. Anzai and S. Hara, An Area Layout-Based Map Estimation for Indoor Target Tracking.

[S35] P. Kemppi et al., Hybrid Positioning System Combining Angle-Based Localization, Pedestrian Dead Reckoning and Map Filtering.

[S36] A. Redondi et al., LAURA - Localization and Ubiquitous Monitoring of Patients for Health Care Support.

[S37] Y. Zhao and M. Li, An Indoor Positioning Algorithm Based on Path Tracking Assistance.

[S38] A. Jimenez et al., Indoor Pedestrian Navigation Using an INS/EKF Framework for Yaw Drift Reduction and a Foot-Mounted IMU.

[S39] R. Schulcz et al., Indoor Location Services and Context-Sensitive Applications in Wireless Networks.

[S40] J. Liu et al., Accelerometer Assisted Robust Wireless Signal Positioning Based on a Hidden Markov Model.

[S41] L. Zamora-Cadenas et al., Improving the Performance of an FMCW Indoor Localization System by Optimizing the Ranging Estimator.

[S42] J. Tsuji et al., Zigbee Based Indoor Localization with Particle Filter Estimation.

[S43] J. Seitz et al., A Hidden Markov Model for Pedestrian Navigation.
[S44] J. Jung and H. Myung, Indoor User Localization Using Particle Filter and NLOS Ranging Model.
[S45] A. S. Paul and E. Wan, RSSI-Based Indoor Localization and Tracking Using Sigma-Point Kalman Smoothers.
[S46] C. Yi et al., Bayesian Robot Localization Using Spatial Object Contexts.
[S47] J. Yim et al., Utilizing Map Information for WLAN-Based Kalman Filter Indoor Tracking.
[S48] H. Wang et al., Simultaneous Multi-Information Fusion and Parameter Estimation for Robust 3-D Indoor Positioning Systems.
[S49] V. Amendolare et al., WPI Precision Personnel Locator System: Inertial Navigation Supplementation.
[S50] S. Outemzabet and C. Nerguizian, Accuracy Enhancement of an Indoor ANN-Based Fingerprinting Location System Using Particle Filtering and a Low-Cost Sensor.
[S51] S. Moafipoor et al., Multi-Sensor Personal Navigator Supported by Adaptive Knowledge Based System: Performance Assessment.
[S52] D. Kelly et al., A Bluetooth-Based Minimum Infrastructure Home Localisation System.
[S53] O. Woodman and R. Harle, Pedestrian Localisation for Indoor Environments.
[S54] Widyawan et al., A Bayesian Approach for RF-Based Indoor Localisation.
[S55] W. Bao et al., Self-Localization of Mobile Robot Based on Binocular Camera and Unscented Kalman Filter.
[S56] J. Ansari et al., Combining Particle Filtering with Cricket System for Indoor Localization and Tracking Services.
[S57] J. Michel et al., Multisensor Based Indoor Vehicle Localization System for Production and Logistic.
[S58] A. Kushki et al., Location Tracking in Wireless Local Area Networks with Adaptive Radio Maps.
[S59] F. Evennou et al., Map-Aided Indoor Mobile Positioning System Using Particle Filter.
[S60] J. Krumm and E. Horvitz, LOCADIO: Inferring Motion and Location from Wi-Fi Signal Strengths.
[S61] C. Gentile and L. Klein-Berndt, Robust Location Using System Dynamics and Motion Constraints.
[S62] S. Jeon et al., Indoor WPS/PDR Performance Enhancement Using Map Matching Algorithm with Mobile Phone.
[S63] Y. Yang et al., Recursive Bayesian Estimation Using a Topological Map for Indoor Position Tracking.
[S64] G. Berkovich, Accurate and Reliable Real-Time Indoor Positioning on Commercial Smartphones.
[S65] K.Weekly et al., Indoor Occupant Positioning System Using Active RFID Deployment and Particle Filters.
[S66] A. Correa et al., Distance-Based Tuning of the EKF for Indoor Positioning in WSNW.
[S67] P. Yang and W. Wu, Efficient Particle Filter Localization Algorithm in Dense Passive RFID Tag Environment.
[S68] V. Malyavej and P. Udomthanatheera, RSSI/IMU Sensor Fusion-Based Localization Using Unscented Kalman Filter.
[S69] A. Correa et al., Indoor Pedestrian Tracking System Exploiting Multiple Receivers on the Body.
[S70] T. Fetzer et al., Statistical Indoor Localization Using Fusion of Depth-Images and Step Detection.
[S71] Y. Zhang et al., An Indoor Positioning Algorithm for Mobile Objects Based on Track Smoothing.
[S72] X. He et al., WiFi iLocate: WiFi Based Indoor Localization for Smartphone.
[S73] X. Chen et al., Indoor Positioning Fusion Algorithm for Smartphones.
[S74] C. Jiang et al., Robot-Assisted Human Indoor Localization Using the Kinect Sensor and Smartphones.
[S75] P. Wilk and J. Karciarz, Optimization of Map Matching Algorithms for Indoor Navigation in Shopping Malls.
[S76] X. Li et al., Sensor Fusion-Based Infrastructure Independent and Agile Real-Time Indoor Positioning Technology for Disabled and Elderly People.
[S77] H. X. Liu et al., Map-Aware Indoor Area Estimation with Shortest Path Based on RSS Fingerprinting.
[S78] Y. Li et al., Indoor Human Tracking and State Estimation by Fusing Environmental Sensors and Wearable Sensors.
[S79] Y. Shu et al., Magicol: Indoor Localization Using Pervasive Magnetic Field and Opportunistic Wifi Sensing.
[S80] K. Zhang et al., An Area State-Aided Indoor Localization Algorithm and Its Implementation.
[S81] S. Lamy-Perbal et al., A HMM Map-Matching Approach Enhancing Indoor Positioning Performances of an Inertial Measurement System.
[S82] F. Karlsson et al., Sensor Fused Indoor Positioning Using Dual Band WiFi Signal Measurements.
[S83] R. Ban et al., Indoor Positioning Method Integrating Pedestrian Dead Reckoning with Magnetic Field and WiFi Fingerprints.
[S84] F. Ebner et al., Multi Sensor 3D Indoor Localisation.
[S85] L. Chen et al., Constraint Kalman Filter for Indoor Bluetooth Localization.
[S86] R. Putta et al., Smartphone based indoor tracking using magnetic and indoor maps.
[S87] F. Evennou and F. Marx, Advanced Integration of WiFi and Inertial Navigation Systems for Indoor Mobile Positioning.
[S88] L. Köping et al., Indoor Localization Using Step and Turn Detection Together with Floor Map

Information.
[S89] F. Li et al., A Reliable and Accurate Indoor Localization Method Using Phone Inertial Sensors.
[S90] L. Chen et al., Bayesian Fusion for Indoor Positioning Using Bluetooth Fingerprints.
[S91] I. SPASSO, Algorithms for Map-Aided Autonomous Indoor Pedestrian Positioning and Navigation. PhD thesis, EPFL, 2007.
[S92] H. Wang et al., No Need to War-Drive: Unsupervised Indoor Localization.
[S93] Y. Nam et al., Map-Based Indoor People Localization Using an Inertial Measurement Unit.

References

Alves, Vander, Nan Niu, Carina Alves, and George Valena. 2010. "Requirements engineering for software product lines: A systematic literature review." *Information and Software Technology* 52 (8): 806 – 820. http://www.sciencedirect.com/science/article/pii/S0950584910000625.

Ansari, J., J. Riihijarvi, and P. Mahonen. 2007. "Combining Particle Filtering with Cricket System for Indoor Localization and Tracking Services." In *IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications, 2007. PIMRC 2007.*, 1–5. Sept.

Bahl, P., and V.N. Padmanabhan. 2000. "RADAR: an in-building RF-based user location and tracking system." In *Proceedings of the IEEE INFOCOM,* Vol. 2775–784. March.

Bahl, Paramvir, Venkata N Padmanabhan, and Anand Balachandran. 2000. *Enhancements to the RADAR user location and tracking system.* Tech. rep.. Microsoft Research.

Bai, Yuntian Brian, Suqin Wu, Guenther Retscher, Allison Kealy, Lucas Holden, Martin Tomko, Aekarin Borriak, Bin Hu, Hong Ren Wu, and Kefei Zhang. 2014. "A new method for improving Wi-Fi-based indoor positioning accuracy." *Journal of Location Based Services* 8 (3).

Bao, Wei, Chongwei Zhang, Benxian Xiao, and Rongbao Chen. 2007. "Self-localization of Mobile Robot Based on Binocular Camera and Unscented Kalman Filter." In *2007 IEEE International Conference on Automation and Logistics,* 277–281. Aug.

Bergman, Niclas. 1999. "Recursive Bayesian Estimation." *Department of Electrical Engineering, Linköping University, Linköping Studies in Science and Technology. Doctoral dissertation* 579.

Cazzorla, A., G. De Angelis, A. Moschitta, M. Dionigi, F. Alimenti, and P. Carbone. 2013. "A 5.6-GHz UWB Position Measurement System." *IEEE Transactions on Instrumentation and Measurement* 62 (3): 675–683.

Chai, Wennan, Cheng Chen, E. Edwan, Jieying Zhang, and O. Loffeld. 2012. "INS/Wi-Fi based indoor navigation using adaptive Kalman filtering and vehicle constraints." In *2012 9th Workshop on Positioning Navigation and Communication (WPNC),* 36–41. March.

Chen, Rung-Ching, Yu-Cheng Lin, and Yu-Shuang Lin. 2011. "Indoor position location based on cascade correlation networks." In *2011 IEEE International Conference on Systems, Man, and Cybernetics (SMC),* 2295–2300. Oct.

Daum, Fred, and Jim Huang. 2003. "Curse of dimensionality and particle filters." In *Aerospace Conference, 2003. Proceedings. 2003 IEEE,* Vol. 4 4_1979–4_1993. IEEE.

Ding, Wei, Peng Liang, Antony Tang, and Hans van Vliet. 2014. "Knowledge-based approaches in software documentation: A systematic literature review." *Information and Software Technology* 56 (6): 545 – 567. http://www.sciencedirect.com/science/article/pii/S0950584914000196.

Doucet, Arnaud, Simon Godsill, and Christophe Andrieu. 2000. "On sequential Monte Carlo sampling methods for Bayesian filtering." *Statistics and Computing* 10 (3): 197–208.

Fouskas, Kostas, George Giaglis, Panos Kourouthanassis, Adamantia Pateli, and Argiris Tsamakos. 2002. "On the potential use of mobile positioning technologies in indoor environments." *BLED 2002 Proceedings* 33.

Fox, Dieter, Jeffrey Hightower, Lin Liao, Dirk Schulz, and Gaetano Borriello. 2003. "Bayesian filtering for location estimation." *IEEE pervasive computing* 2 (3): 24–33.

Gao, Huiji, Jiliang Tang, and Huan Liu. 2012. "Mobile location prediction in spatio-temporal context." In *Nokia mobile data challenge workshop,* Vol. 4144.

Ghahramani, Zoubin. 2001. "An introduction to hidden Markov models and Bayesian networks." *International Journal of Pattern Recognition and Artificial Intelligence* 15 (01): 9–42.

Gigl, T., G.J.M. Janssen, V. Dizdarevic, K. Witrisal, and Z. Irahhauten. 2007. "Analysis of a UWB Indoor Positioning System Based on Received Signal Strength." In *4th Workshop on Positioning, Navigation and Communication, 2007. WPNC '07,* 97–101. March.

Gu, Yanying, A. Lo, and I. Niemegeers. 2009. "A survey of indoor positioning systems for wireless personal networks." *IEEE Communications Surveys Tutorials* 11 (1): 13–32.

Hart, P. E., N. J. Nilsson, and B. Raphael. 1968. "A Formal Basis for the Heuristic Determination of Minimum Cost Paths." *IEEE Transactions on Systems Science and Cybernetics* 4 (2): 100–107.

Hightower, Jeffrey, and Gaetano Borriello. 2001a. "Location sensing techniques." *IEEE Computer* 34 (8): 57–66.

Hightower, Jeffrey, and G. Borriello. 2001b. "Location systems for ubiquitous computing." *Computer* 34 (8): 57–66.

Hightower, Jeffrey, Roy Want, and Gaetano Borriello. 2000. *SpotON: An indoor 3D location sensing technology based on RF signal strength.* Tech. rep.. UW CSE 00-02-02, University of Washington, Department of Computer Science and Engineering, Seattle, WA.

Kelly, Damian, S. McLoone, and T. Dishongh. 2008. "A Bluetooth-based minimum infrastructure home localisation system." In *IEEE International Symposium on Wireless Communication Systems. 2008. ISWCS '08.*, 638–642. Oct.

Kemppi, P., T. Rautiainen, V. Ranki, F. Belloni, and J. Pajunen. 2010. "Hybrid positioning system combining angle-based localization, pedestrian dead reckoning and map filtering." In *2010 International Conference on Indoor Positioning and Indoor Navigation (IPIN),* 1–7. Sept.

Kitchenham, Barbara A, and Stuart Charters. 2007. "Guidelines for performing systematic literature reviews in software engineering." .

Ko, Sang-Il, and Jong-Suk Choi. 2007. "Indoor mobile localization system using UKF and pre-filtering." In *Intelligent Robots and Systems, 2007. IROS 2007. IEEE/RSJ International Conference on,* 2865–2870. Oct.

Koyuncu, Hakan, and Shuang Hua Yang. 2010. "A survey of indoor positioning and object locating systems." *IJCSNS International Journal of Computer Science and Network Security* 10 (5): 121–128.

Laoudias, Christos, Michalis P. Michaelides, and Christos G. Panayiotou. 2012. "Fault detection and mitigation in WLAN RSS fingerprint-based positioning." *Journal of Location Based Services* 6 (2): 101–116. http://dx.doi.org/10.1080/17489725.2012.692618. http://dx.doi.org/10.1080/17489725.2012.692618.

Liu, Dawei, Bin Sheng, Fen Hou, Weixiong Rao, and Hongli Liu. 2014. "From Wireless Positioning to Mobile Positioning: An Overview of Recent Advances." *IEEE Systems Journal* 8 (4): 1249–1259.

Liu, Hui, H. Darabi, P. Banerjee, and Jing Liu. 2007. "Survey of Wireless Indoor Positioning Techniques and Systems." *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews* 37 (6): 1067–1080.

Liu, Jingbin, Ruizhi Chen, Ling Pei, Wei Chen, T. Tenhunen, H. Kuusniemi, T. Kroger, and Yuwei Chen. 2010. "Accelerometer assisted robust wireless signal positioning based on a hidden Markov model." In *2010 IEEE/ION Position Location and Navigation Symposium (PLANS),* 488–497. May.

Mautz, R. 2009. "The challenges of indoor environments and specification on some alternative positioning systems." In *6th Workshop on Positioning, Navigation and Communication, 2009. WPNC 2009.*, 29–36. March.

Mautz, Rainer. 2012. "Indoor positioning technologies." Ph.D. thesis. Habilitationsschrift ETH Zürich, 2012.

Mirowski, Piotr, Philip Whiting, Harald Steck, Ravishankar Palaniappan, Michael MacDonald, Detlef Hartmann, and Tin Kam Ho. 2012. "Probability kernel regression for WiFi localisation." *Journal of Location Based Services* 6 (2): 81–100. http://dx.doi.org/10.1080/17489725.2012.694723. http://dx.doi.org/10.1080/17489725.2012.694723.

Monreale, Anna, Fabio Pinelli, Roberto Trasarti, and Fosca Giannotti. 2009. "Wherenext: a location predictor on trajectory pattern mining." In *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining,* 637–646. ACM.

Muthukrishnan, Kavitha, Maria Lijding, and Paul Havinga. 2005. *Towards smart surroundings: Enabling techniques and technologies for localization.* Springer.

Opoku, D., A. Homaifar, and E. Tunstel. 2014. "RFID-augmentation for improving long-term pose accuracy of an indoor navigating robot." In *2014 IEEE International Conference on Systems, Man and Cybernetics (SMC),* 796–801. Oct.

Outemzabet, S., and C. Nerguizian. 2008. "Accuracy enhancement of an indoor ANN-based fingerprinting location system using Kalman filtering." In *IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications, 2008. PIMRC 2008.*, 1–5. Sept.

Petzold, Jan, Faruk Bagci, Wolfgang Trumler, and Theo Ungerer. 2005a. "Next location prediction within a smart office building." *Cognitive Science Research Paper-University of Sussex CSRP* 577: 69.

Petzold, Jan, Faruk Bagci, Wolfgang Trumler, and Theo Ungerer. 2006. "Comparison of different methods for next location prediction." In *Euro-Par 2006 Parallel Processing,* 909–918. Springer.

Petzold, Jan, Andreas Pietzowski, Faruk Bagci, Wolfgang Trumler, and Theo Ungerer. 2005b. "Prediction of indoor movements using bayesian networks." In *Location-and Context-Awareness,* 211–222. Springer.

Prieto, J., S. Mazuelas, A. Bahillo, P. Fernandez, R.M. Lorenzo, and E.J. Abril. 2012. "Adaptive Data Fusion for Wireless Localization in Harsh Environments." *IEEE Transactions on Signal Processing* 60 (4): 1585–1596.

Proakis, John G., and Dimitris G. Manolakis. 1992. *Digital Signal Processing (2Nd Ed.): Principles, Algorithms, and Applications.* Indianapolis, IN, USA: Macmillan Publishing Co., Inc.

Rabiner, Lawrence R. 1989. "A tutorial on hidden Markov models and selected applications in speech recognition." *Proceedings of the IEEE* 77 (2): 257–286.

Rabiner, Lawrence R, and Biing-Hwang Juang. 1986. "An introduction to hidden Markov models." *ASSP Magazine, IEEE* 3 (1): 4–16.

Seco, Fernando, A Jimenez, Carlos Prieto, Javier Roa, and Katerina Koutsou. 2009. "A survey of mathematical methods for indoor localization." *Intelligent Signal Processing* 9–14.

Suski, W., S. Banerjee, and A. Hoover. 2013. "Using a Map of Measurement Noise to Improve UWB Indoor Position Tracking." *IEEE Transactions on Instrumentation and Measurement* 62 (8): 2228–2236.

Tsuji, J., H. Kawamura, K. Suzuki, T. Ikeda, A. Sashima, and K. Kurumatani. 2010. "ZigBee based indoor localization with particle filter estimation." In *2010 IEEE International Conference on Systems Man and Cybernetics (SMC),* 1115–1120. Oct.

Viol, N., J.A.B. Link, H. Wirtz, D. Rothe, and K. Wehrle. 2012. "Hidden Markov model-based 3D path-matching using raytracing-generated Wi-Fi models." In *2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN),* 1–10. Nov.

Vossiek, M., L. Wiebking, P. Gulden, J. Wieghardt, C. Hoffmann, and P. Heide. 2003. "Wireless local positioning." *IEEE Microwave Magazine* 4 (4): 77–86.

Xiao, L., and L. Deng. 2010. "A Geometric Perspective of Large-Margin Training of Gaussian Models [Lecture Notes]." *IEEE Signal Processing Magazine* 27 (6): 118–123.

Yang, Lei, Jiannong Cao, Weiping Zhu, and Shaojie Tang. 2012. "A hybrid method for achieving high accuracy and efficiency in object tracking using passive RFID." In *2012 IEEE International Conference on Pervasive Computing and Communications (Per-*

Com), 109–115. March.
Yavaş, Gökhan, Dimitrios Katsaros, Özgür Ulusoy, and Yannis Manolopoulos. 2005. "A data mining approach for location prediction in mobile environments." *Data & Knowledge Engineering* 54 (2): 121–146.
Ying, Josh Jia-Ching, Wang-Chien Lee, Tz-Chiao Weng, and Vincent S Tseng. 2011. "Semantic trajectory mining for location prediction." In *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems,* 34–43. ACM.
Zhou, Rui, and Nan Sang. 2012. "Enhanced Wi-Fi Fingerprinting with Building Structure and User Orientation." In *2012 Eighth International Conference on Mobile Ad-hoc and Sensor Networks (MSN),* 219–225. Dec.
Zhou, Yuan, C.L. Law, Yong Liang Guan, and F. Chin. 2011. "Indoor Elliptical Localization Based on Asynchronous UWB Range Measurement." *IEEE Transactions on Instrumentation and Measurement* 60 (1): 248–257.