Learning indoor movement habits for predictive control

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Abstract: Using Wi-Fi signals is an attractive and reasonably affordable option to deal with the currently unsolved problem of widespread tracking in an indoor environment. Our system, history aware-based indoor tracking system (HABITS) models human movement patterns and this knowledge is incorporated into a discrete Bayesian filter to predict the areas that will, or will not, be visited in the future. These probabilistic predictions may be used as an additional input into building automation systems for intelligent control of heating and lighting. This paper outlines current indoor tracking methods and the weaknesses associated with them. It describes in detail the operation of the HABITS algorithm and discusses the implementation of this algorithm in relation to indoor Wi-Fi tracking with a large wireless network. Testing of HABITS shows that it gives comparable levels of accuracy to those achieved by doubling the number of access points. It is twice as accurate as existing systems in dealing with signal black spots and it can predict the final destination of a person within the test environment almost 80% of the time.

Keywords: localisation; indoor environments; Bayesian filter; movement prediction; intelligent control; building automation systems; 802.11 Wi-Fi; history aware-based indoor tracking system; HABITS.

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1 Introduction

This paper presents research into improving the capabilities of indoor wireless tracking systems. Currently available technologies suffer from weaknesses in terms of accuracy, precision and latency in their location estimates. From the range of options available, those using 802.11 Wi-Fi are gaining increasing popularity due to their relatively low costs and high scalability levels. However, these suffer from a number of significant drawbacks which prohibit their use for many applications. It is these specific drawbacks that our system history aware-based indoor Wi-Fi tracking system (HABITS) targets (Furey et al., 2008).

HABITS is an intelligent software system, that overcomes these problems. This is achieved by automatically learning the movement patterns and habits of people in a structured environment. The habits are then fed back into the system allowing for real-time updates, overcoming signal black spots and predicting future movements in the short, medium and long term.

This paper is structured as follows. Section 2 gives the motivation for this research, a short overview of the reasons why wireless networks are set up and the problems associated with these when used for tracking. It outlines the barriers to high quality, affordable tracking associated with standard Wi-Fi network implementations. Next, the background research to our solution is discussed, followed by a description of the Ekahau real time locating system (RTLS) (www.ekahau.com, 2010), which is a test bed for our solution. In Section 5 the HABITS implementation is described in detail, along with the description of an operational scenario and testing in a real world environment. The results of tests, along with a potential application of HABITS to building automation control systems are then addressed. Finally a conclusion to the paper is provided.

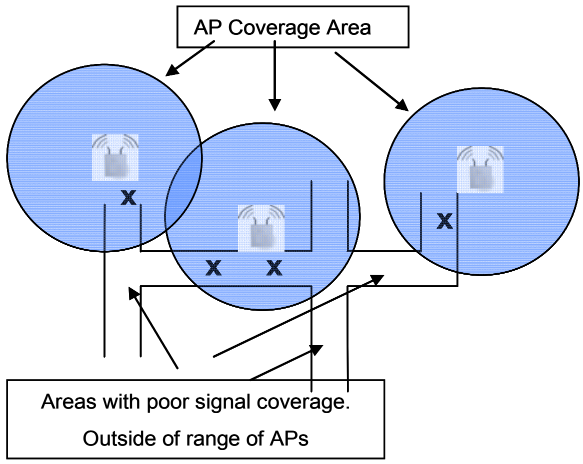
2 Wireless network installations

In many cases wireless networks (802.11 Wi-Fi) are an afterthought in large buildings. Where feasible, large organisations will connect most of their devices using a fixed wired network. Even when a Wi-Fi network is installed, it is usually just a number of wireless access points (APs) that are wired on to the main local area network (LAN). It is not a mesh network where the network is truly wireless. The purpose is to allow users to have temporary mobile access or to access the network in an area that is not covered by the wired segments.

When designing a WLAN indoors a number of factors are considered. The most important consideration is the ability to transmit data to mobile devices at as high a rate as possible, without losing quality of service (QoS) (Wang and Du, 2005). However, this is dependent on installing as little extra infrastructure as possible. Unfortunately, these goals are not those that the designer of indoor Wi-Fi tracking systems thinks of. The positioning of APs for these two tasks is different. In terms of throughput, as few APs as possible are used as long as they cover the whole area. This is done to minimise cost and installation overhead time. For a tracking system to be effective, a large number of reference points are usually required. This is in order to make the system more accurate and effective. In the case of a wireless local area network (WLAN), the reference points used for positioning are 802.11 wireless APs. The positioning of these is of the utmost importance, a zigzag pattern is recommended by Ekahau (2009) to ensure that the radio signal patterns in each area are suitably different from one another. For the majority of users, the cost of trebling the number of APs is prohibitive. The extra cost and time involved is usually not worth it. Also, many organisations (e.g., universities) have an existing WLAN in place that they would like to utilise. If it is a new installation in a high value and specialised site (mine, hospital or factory), then the layout can be designed with tracking as the main aim, but most users want to use their existing networks with minor or no tweaks.

Figure 1 demonstrates what happens when an insufficient number of APs are installed. Large areas are outside the range of the APs. With only three APs at one side a number of areas remain outside of the good coverage zones. In the other areas, standard positioning systems will lose their accuracy or will fail.

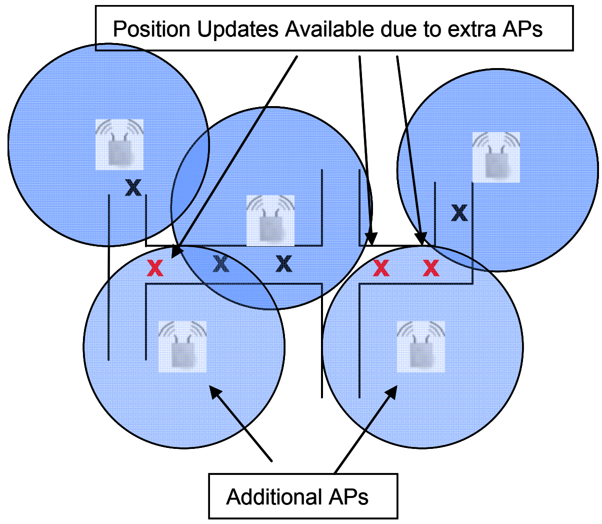
Figure 1 Too few APs (see online version for colours)



With the addition of extra infrastructure (two more APs on the other side of the corridor), the majority of the corridor space is now covered and position fixes are available as Figure 2 illustrates.

In an indoor environment, radio signal attenuation (change in intensity as it travels through an object) and refraction (change in direction as it travels through a medium) are a major problem as reported by Kaemarungsi (2004). Radio frequency (RF) signals bounce all over the place. Factors such as furniture, people and/or temperature can all affect the way a signal travels around a building. Fox (2003) suggests that RTLS's designers attempt to overcome these issues by using a combination of received signal strength indicators (RSSI) and probabilistic mathematical techniques like Kalman and particle filters. RSSI gives a relative measurement of the received signal strength at the device and intelligent filters attempt to overcome the uncertainty in the measurement by use of probabilistic smoothing and prediction techniques. Much research has been carried out on these methods (Fox, 2003). Microsoft Research's RADAR project (Bahl and Padmanabhan, 2000) and Intel Research's PlaceLab Project (LaMarca et al., 2005), both created impressive early indoor Wi-Fi tracking systems. However, since these projects ended around 2005, the majority of the research into Wi-Fi RTLS has been carried out by private companies. As of 2010, a number of these are available. This paper details a method which builds on top of these commercial systems and tries to improve accuracy using a different approach to that taken by Microsoft and Intel. For an in-depth survey of currently available RTLS, see Gu et al. (2009).

Figure 2 Extra APs increase coverage (see online version for colours)



2.1 *Current fixes to indoor Wi-Fi localisation problems*

If a tracking system is set up on a WLAN that was just designed for basic data transfer and as an add-on to a fixed network then it is susceptible to failure. The Finnish company Ekahau, market leader in indoor RTLS has developed a number of intelligent methods to improve the capabilities of their RTLS. Their patented software 'rails', keeps the tracked object on a particular path. This lessens the jumping through walls effect, due to fluctuations in RSSI, in which a tracked object would suddenly appear on the other side of a wall which it was not possible for it to have moved through i.e., no door in that location. A location quality filter can also be adjusted in an attempt to eliminate wild results, for example, only position updates that have a probability of over 80% will be reported to the user. A third solution is the addition of a location beacon which is a small wireless device that acts as a radio marker and is permanently fixed in an area with poor signal strength for tracking purposes. These beacons are not used for communication and can only be used in conjunction with the existing WLAN. This can also be done with APs that are not part of the network, i.e., ad-hoc. These location beacons have their own drawbacks and are battery operated making them an interim solution.

Outlined in the next section is a novel approach to overcome some of these cost and signal issues. This approach is designed to operate in particularly large indoor environments.

3 Background and literature review

Using past movements to improve localisation is an under researched area, although a number of useful studies have been conducted. Mature technologies, such as GPS navigation, have used this approach to predict where and when a user will reemerge from a tunnel. Also, the approach is used in cellular systems to predict which cell a mobile user will enter next.

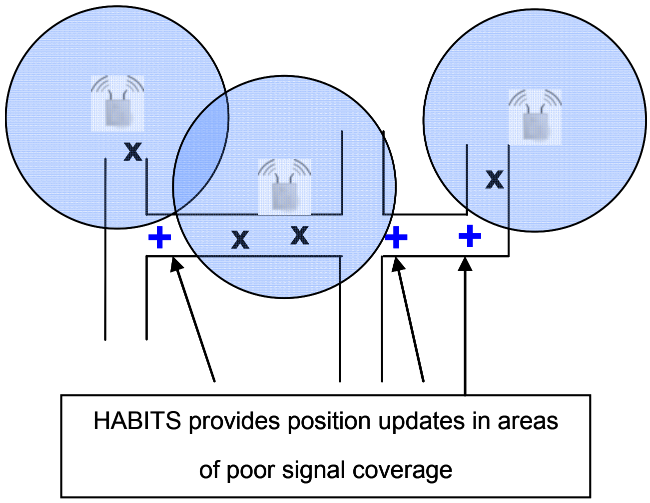
Petzold et al. (2006) used various machine learning techniques and mathematical methods to model indoor movement patterns. Using these models, predictions of the next location of a certain user have been made with 69% accuracy without pre-training and 96% accuracy with pre-training. Another study by Zhou (2006) has shown that by using knowledge of previous movements, overall accuracy could be improved by 14.3% and estimations of the wrong room and wrong floor could be improved by 69.7% and 50% respectively.

A recent study (Song, 2010) of past locations from mobile phone records, found that general human mobility patterns over a wide area were predictable 94% of the time. A related, relatively new field of reality mining (Eagle and Pentland, 2006) has been developed which records movements of people throughout the day with the intention of predicting future behaviour. These studies on learning human movements for prediction show that the research community is beginning to utilise movement information in a new way.

Using previous movements to help improve accuracy levels in Wi-Fi positioning has been attempted in a number of studies (Bahl and Padmanabhan, 2000; Lassabe, 2009), but the focus has been on trying to improve the RSS-based problems. HABITS does not try and improve on the RSS methods but instead uses the movement habits of users as a means of adding intelligence to the system. This knowledge is then used to overcome signal black spots and to predict where the user will travel to next as Figure 3 shows.

Recently we have implemented and tested a number of RTLS systems and the results of these can be found in the study on behalf of JANet UK – location awareness trails (Furey and Curran, 2008). Of these, the Ekahau RTLS utilises the existing Wi-Fi network and in our tests was the best overall indoor tracking system. For this reason it was the chosen platform for implementing HABITS. A number of stages are involved in implementing this system and these are outlined in the next section.

Figure 3 HABITS overcomes the need for extra APs (see online version for colours)



4 Ekahau RTLS – test bed system

The Ekahau (2010) website claims that the, "Ekahau real time location system (RTLS) is the only Wi-Fi-based location tracking solution that can operate over any brand or generation of Wi-Fi network while offering sub room, room, floor and building-level accuracy". The stages involved in the deployment of the RTLS using Ekahau site survey (ESS) include:

- perform a calibration survey by walking around the building with a laptop and record the radio fingerprints at each location
- setup zones (optional) around areas of interest to indicate if a user/tag enters or leaves it
- perform a test survey and analyse location accuracy which gives accuracy statistics showing which areas have poor accuracy.

This deployment indicated the areas that needed attention and where additional APs would be advised. These signal black spots are shown in Figure 4 for the Ekahau implementation at the University of Ulster.

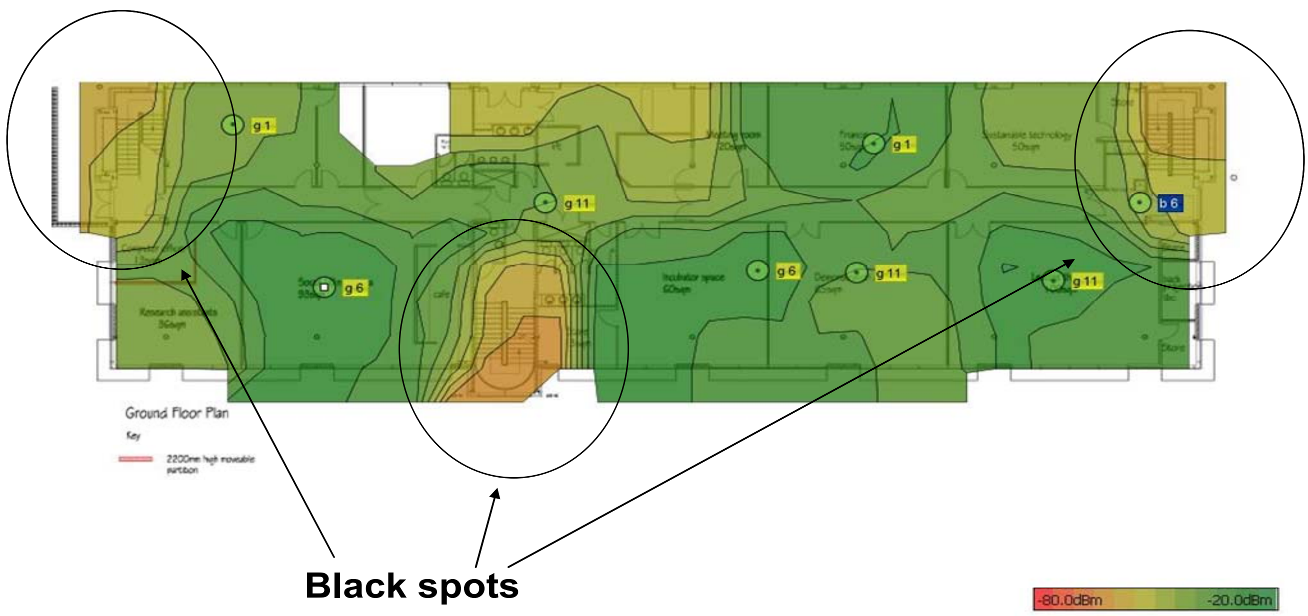
To improve the accuracy statistics, organisations with a large budget would install extra infrastructure to overcome these black spots even though this is one of the Wi-Fi RTLS main selling points – that no extra infrastructure is necessary! In our implementation, a redesign of the WLAN was not an option. After extensive testing and recalibration of the RTLS an alternative solution to the problem was sought.

It is these problems that HABITS system attempts to overcome, with the creation of a system that learns the probabilities of movement patterns of a user and uses this knowledge to intelligently predict where the user will go. This solution is explained in the next section.

5 The HABITS movement modelling framework

While HABITS uses the same radio signals and equipment as other systems, it allows for positioning and continuous real time tracking with accuracy levels, and in areas that were not previously possible. However, HABITS will only work in certain environments where people follow particular habitual movement patterns, for example, work environments, factories or hospitals. Figure 5 shows the context in which HABITS can be used. When a mobile device is tracked by Ekahau and the HABITS algorithm is applied it can still be tracked when it is no longer within line of sight (LOS) of three or more APs. This is normally the minimum required for accurate localisation.

Figure 4 Black spots identified in MS building (see online version for colours)



The highest frequency rate of position updates from Ekahau is 5s. These updates are often up to 15 s apart. Each update is sent to HABITS along with the learnt historical movement data and from this an intelligent prediction of the next likely location is given. Short term predictions effectively fill in the blanks in between updates from the Ekahau system.

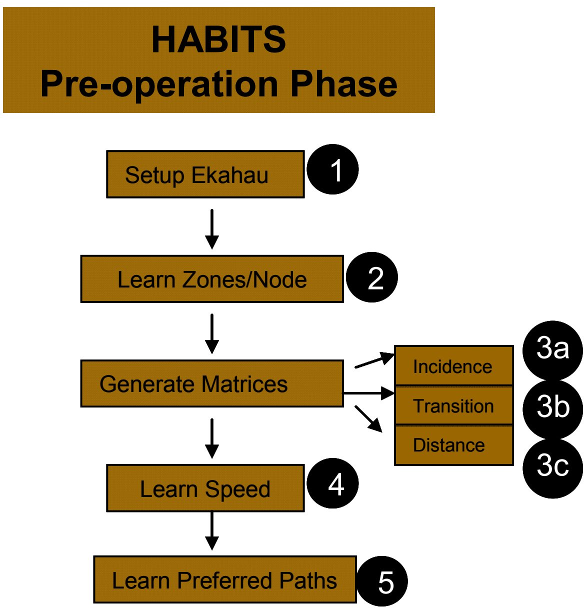
Figure 5 Context of HABITS (see online version for colours)

To make predictions of future movements, HABITS makes use of two machine learning techniques. The first is a Bayesian filter which conducts predictive data fusion using Bayes theorem. The second is fuzzy logic which enables HABITS to use an approximate reasoning process in addition to the Bayesian filter to more accurately model and predict human movement habits.

5.1 HABITS pre-operation

For HABITS to operate, two separate phases must be performed: pre-operation and operation. Figure 6 shows a flow diagram of the pre-operation phase when HABITS is implemented in an indoor Wi-Fi environment.

Figure 6 Tasks to be completed before operating HABITS (see online version for colours)



The stages in Figure 6 are described as follows. In Figure 6(1) the underlying tracking system is implemented. This allows for past movements to be learned and provides a starting point from which predictions can be made when HABITS is in operation.

In order to collect historical movement data a topological map of the test area must be created. A topological map is one which consists of a number of nodes representing places of interest which are connected by edges representing paths where a user may travel. An example of this type of map is the London underground where each station is represented by a node and the edges indicate paths between them. These maps are not drawn to scale. The value of a topological map is that it is basically a graph and can be represented as a matrix which makes it suitable for mathematical manipulation and processing. From the Ekahau positioning data it was identified that a number of areas were of particular significance. These areas are covered by zones in Ekahau which allow for reporting of when a person carrying a mobile Wi-Fi device enters or leaves them, Figure 6(2). The zones shown in Figure 7 represent areas that are passed through frequently on the ground and first floors in the Intelligent Systems Research Centre (ISRC) MS Building at the University of Ulster. Each of these zones can be considered to be a node in a connected graph. The positioning of these zones is calculated using a number of data mining techniques.

The *edges* between *nodes* show paths that may be travelled and represent the movements of Wi-Fi tracked people in the building. The first item to identify was the areas where a user often stopped. We call these *wait nodes* and they have already been identified during the zone placement phase. These *wait nodes* are often targets when a person is moving and equate to likely destinations during any movement sequence. The sequence of nodes from one *wait node* to another are called *paths* and the most common of these are called *preferred paths*. The nodes in between are known as *transition nodes*. A graphical representation of two floors in the test area is shown in Figure 8 along with the particular node types. This diagram is a topological map of the zones shown in Figure 7.

The graph of the area is used along with the historical movement data of a person in order to calculate a number of different matrices which are necessary for HABITS to operate. An incidence matrix [Figure 6(3a)] shows whether it is possible to travel directly from one node to another and also indicates the possible routes that a user may travel. If a path exists then a 1 is placed at that location, otherwise a 0 is used. A distance matrix [Figure 6(3c)] may be combined with the incidence matrix to show the distance between nodes or the travel time from one node to the next. The 1's is the previous matrix are replaced with the distance/time metrics. To gather movement patterns of a user, a count of the number of times a user passes through a node is kept and a probability function for each node is calculated from this. This information is represented in a transition matrix [Figure 6(3b)] a section of which is shown in Table 1.

The transition matrix by itself gives only general predictions. A deeper analysis of the data is required to learn patterns of movement that would realistically equate to a user's movement habits.

Figure 7 Zones showing areas of interest (see online version for colours)

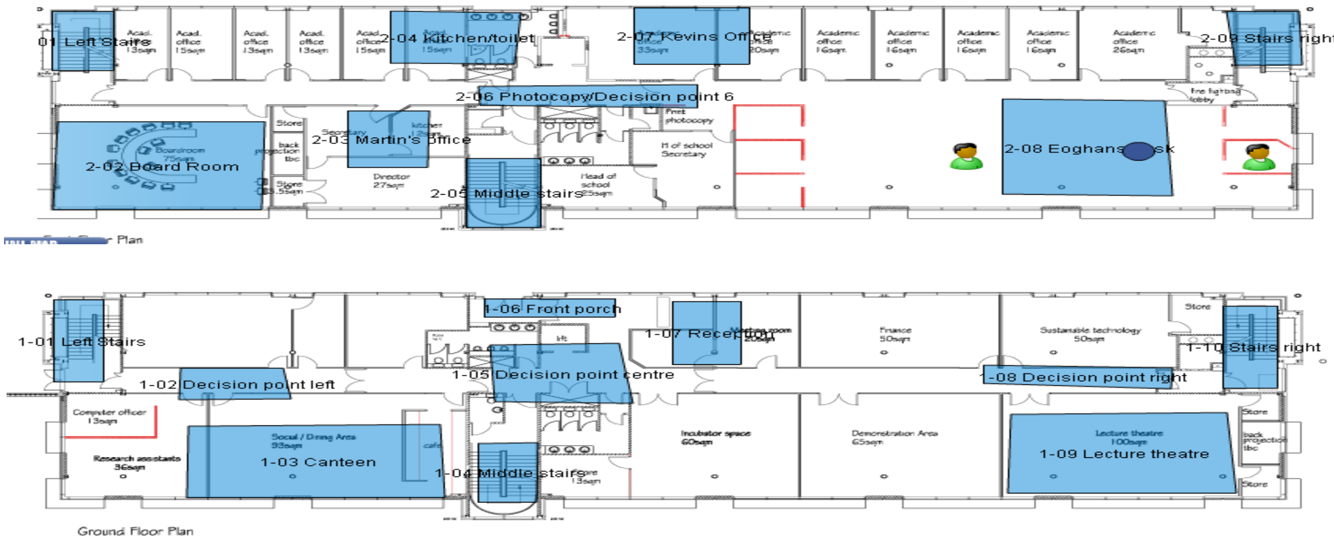


Figure 8 MS building represented as a graph (see online version for colours)

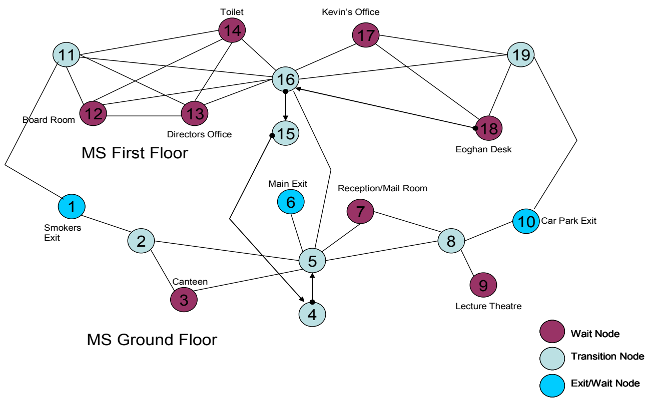


Table 1 A section of the transition matrix based on one month movements by a single user

		From					
		1	*2*	*3*	*4*	*5*	*6*
To	1	0	0.167	0	0	0	0
	2	0.667	0	0.077	0	0.019	0
	3	0	0.667	0	0	0.167	0
	4	0	0	0	0	0.314	0

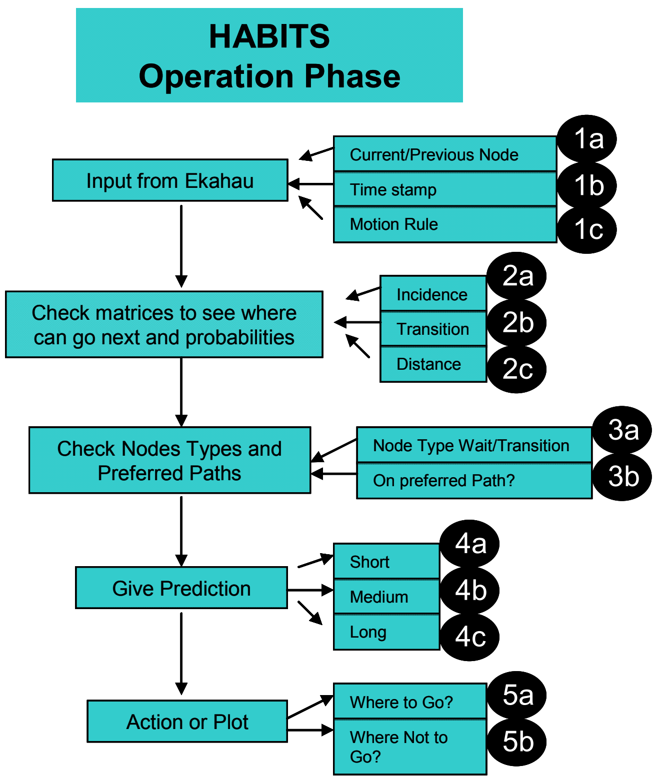
Users often travel *preferred paths* Figures 6(5)] at a particular time of day and the likelihood of particular destinations are increased or decreased at certain times of the day. For example, the probability of travelling to the canteen increases at lunchtime, between 12–1.30 pm. The average travel speed [Figures 6(4)] was also found to be different for different users, therefore, the distance matrices need to be individually tweaked. It was also noticed that the speed of users when travelling together was often reduced to that of the slowest user indicating that they may be in conversation. All of these patterns need to be considered.

When the pre-operation phase of HABITS is complete, it is ready to be used in real-time, as the next section describes.

5.2 HABITS operation

Figure 9 shows the main inputs and outputs of HABITS when in operation for one iteration. When new data becomes available this process is repeated. These contain all the information necessary to make predictions as to where a Wi-Fi tracked user will travel to next.

Figure 9 Operation of HABITS (see online version for colours)



An underlying tracking system is always required to give certain key information to HABITS. In Figure 9, boxes 1a–1c denote the information which is provided by the Ekahau RTLS. Knowledge of where the user is, whether they are in motion or not and the exact time are essential for HABITS to function. This is the only live information that HABITS processes.

Once the live user information is received, HABITS checks the matrices (Figures 9, 2a and 2c) to see what constraints on movement exist. Combining these constraints with the data from Ekahau allows an initial probability prediction to be made from the transition matrix (Figure 9, 2b). Information about node types and preferred paths is now added to HABITS to further improve the accuracy of the predictions as Figure 9, 3a and 3b depict. In Figure 9 predictions from HABITS depend on the time scale required and may be short term, 4a (a few seconds), medium term, 4b (a few minutes – end of current journey) or longer term, 4c (later that day or week).

The last stage of the operation of HABITS involves taking a particular action based on the predictions provided if the probability confidence is high enough or plotting these future locations on a map.

5.3 *HABITS intelligence*

The various inputs to HABITS listed in Figure 9 are combined using a number of artificial intelligence techniques. The first is an idea described by Fox (2003), which is extensively used in robotics – that of a *discrete Bayesian filter*. This filter works in conjunction with the graph matrices and gives out a probability estimate for the next location or a number of possible locations when at a particular node.

Pseudo code in Figure 10 shows the basic operation of a discrete Bayesian filter. It is basically a data fusion technique which uses Bayes theorem as a means of predicting the probability of moving from one node to the next. The various movement and sensor constraints are represented as mathematical models (u_t) which work along with the updates from Ekahau (z_t) and the transition matrix data, $p(x_t \mid x_{t-1})$ to give a prediction of next location. The n symbol in Figure 10 – line 4 is used to normalise the result to 1. However, this prediction alone is not sufficient to model a user's movement habits accurately.

Fuzzy logic is derived from fuzzy set theory and is a technique used when reasoning is approximate rather than precise. *Fuzzy rules* are similar to normal rules except that there are degrees of correctness. In this way we can represent ideas like 'John *often* goes to the canteen for lunch'.

The addition of the *fuzzy rule base* is to overcome one of the weaknesses of the Bayesian filter. This weakness is that it is tied to the *Markov assumption* which states that all the necessary information needed to predict the next step is located in the current step. This makes the discrete Bayesian filter into a Markov chain, which is any random process that is bound by the Markov assumption. As the Markov assumption does not hold true in our case, it has been overcome by the creation of a hybrid Bayesian-fuzzy filter/rule base. This gives us the best of both and allows for extra habits, such as being on preferred paths, to be included which do not fit into the discrete Bayesian filter. The novel combined use of a Bayesian filter along with fuzzy logic is represented diagrammatically as Figure 11 shows.

Figure 10 Discrete Bayesian filter (see online version for colours)

General Algorithm for Bayes Filtering

1 Algorithm_filter(bel(x_{t-1}), u_t, z_t):

2 for all xt do

3 $\overline{bel}(x_t) = \sum p(x_t \mid u_t, x_{t-1})\, bel(x_{t-1})$ **(PREDICTION STEP)**

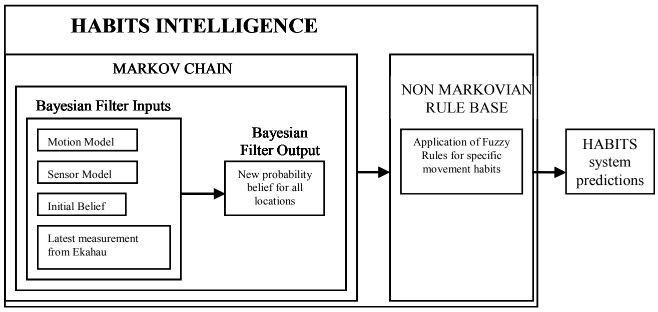
4 $bel(x_t) = \eta\, p(z_t \mid x_t)\, \overline{bel}(x_t)$ **(UPDATE STEP)**

5 end for

6 return bel (x_t)

Inputs belief bel(x_{t-1}) at t-1; most recent control u_t + measurement z_t.
Output is the belief bel (x_t) at time t.

Figure 11 Bayesian-fuzzy hybrid approach



5.4 *Operational scenario*

The scenario below describes HABITS' operation in a real-world scenario. The user is travelling from his desk to leave the building for lunch. The code and accompanying diagrams [Figures 9(a)–9(c)] show what the probabilities are of going to a particular node. This shows how the knowledge of a user's movement habits can be used to give predictions to a useful degree of accuracy. A possible use of these predictions is explained in the last section.

1 If tag = Eoghan

2 *node = 5 and previous node = 4*

3 node 5 NOT = wait node

4 Action = calc next node

5 *Next node = Either 2, 3, 6, 7, 8 (All have non-zero Probability) – Figure 12*

6 Check time period = Lunch

7 *If time = Lunch THEN next node is 6 or 3 (Probability > 80%) – Figure 13 lunch temporal rule*

8 Check other users in area

9 *If with John THEN next node = 6 (John doesn't go to the canteen!) – Figure 14 other user rule*

10 *If with Mary THEN next node = 3 (Mary usually goes to the canteen!)*

11 If alone then next node = 6 (40%) OR 3 (40%) – wait for more info!

12 Use speed and distance to calculate position at time t

13 *Calc and show positions at t + 1, t + 2 … t + n.*

Figure 12 Probability from Bayesian filter (see online version for colours)

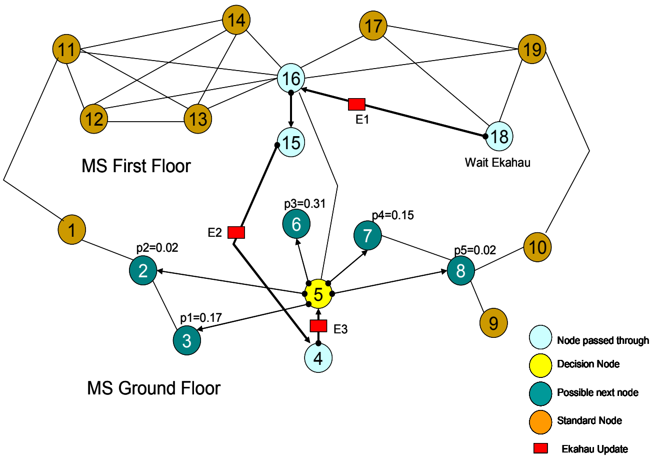


Figure 13 Probability from temporal fuzzy rule (see online version for colours)

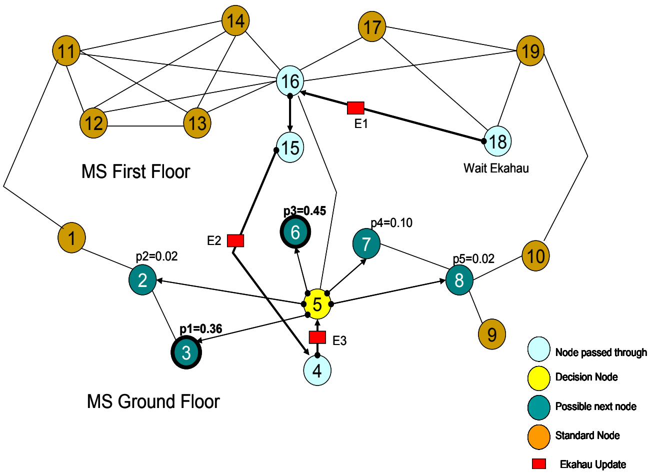
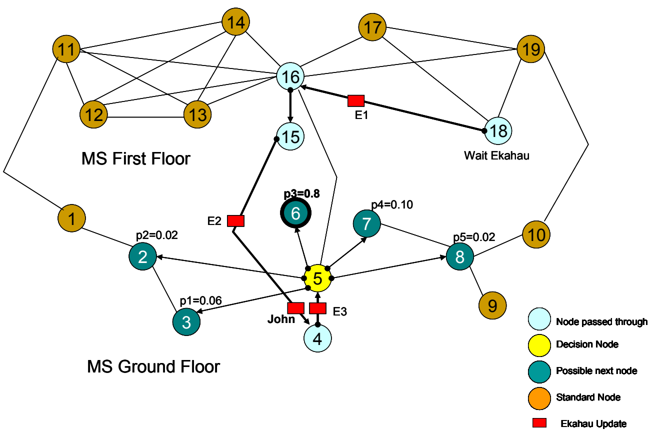


Figure 14 Probability from other user fuzzy rule (see online version for colours)



6 Testing and results

In order to test HABITS, a number of stages were required. Stage one involved testing the accuracy of the Ekahau RTLS. This was conducted as follows. The ESS application allows for surveys to be conducted determining the accuracy of the site specific implementation of the Ekahau RTLS. This involved manually clicking on the current real position on a map, whilst walking through the test area, which Ekahau then compared to the estimated position.

Test survey results corresponded to the signal strength maps in the ESS and showed that areas of low signal strength also had poor location accuracy and therefore were target areas for this research. Test surveys carried out in stairwells showed very low accuracy, up to 10 m from true. This was directly as a result of AP placement being designed for data communication.

The second stage of testing established the accuracy, yield and latency of HABITS. For a period of one month, three occupants of the Intelligent Systems Research Centre carried an Ekahau tag with them at all times. Each of these test subjects had a different role within the centre. User 1 being an academic, User 2 being a research associate (RA) and User 3 being a 2nd year PhD student. The different types of user were chosen to evaluate whether the system worked better with one type than another. It was assumed before the test that the RA would have the most predictable habits, as the other two tend to work to their own schedule whereas the RA is paid to work at a particular location for a set duration each day.

The zones chosen as nodes on the topological map were only those which had been proven to give good accuracy and precision readings. Each had their own work area designated as a zone (base zone). Whenever they left this zone and for each zone that they entered a record was kept. This was achieved by setting up zone enter/exit rules which was done through the software development kit (SDK) connected to the Ekahau positioning engine. The sequence of nodes entered along with the timestamp was recorded for all movements for four weeks. The first three weeks worth of movement data was separated from the last week worth. This allowed for movement habits to be learned from the first three weeks (learning set) and the last week (test set) to be used for testing purposes.

From the learning set, user specific data, such as average travel speed was calculated. The transition matrices for each user, along with a set of fuzzy logic rules were also extracted from this learning dataset. For each user these were different.

In order to test HABITS, each journey in the last week (test set), was run through a number of test scripts. These scripts calculated the HABITS predicted next node and then verified this against the actual visited next node. The results for the three test subject were averaged to give overall results for HABITS.

In the test environment, HABITS improved on the standard Ekahau RTLS (market leading commercial system) in a number of key areas as listed in Table 2.

Table 2 Results of testing HABITS

	Accuracy (average) m	*Yield (in test area) %*	*Latency s*	*Cost*
Ekahau (APs configured for data communication)	4.5	80	5–15	Ekahau RTLS
Ekahau plus Bayesian filter only	6 (includes wrong guesses)	97	1	Ekahau RTLS
Ekahau plus Bayesian filter and fuzzy rules	2	97	1	Ekahau RTLS
Ekahau with 5 extra APs per floor	2	100	5–15	Ekahau RTLS plus €100 per AP

The test metrics are described below:

- accuracy (closeness of position fix to the true (but unknown)
- yield (the ability to get position fixes in all environments in test area)
- latency (time delay between each position fix), HABITS should always give something even though it will have a probability associated
- savings over existing indoor tracking systems in terms of extra infrastructure required.

These results show that when implementing a system such as Ekahau without redesigning the AP layout, the average accuracy achieved of 4.5 m is well below the level of 1m which is claimed by Ekahau. Adding substantially more APs (5 per floor) did improve the average accuracy to approximately 2 m in our test area. However, this improvement came with a significant extra cost in terms of installation and calibration time, also in financial terms as APs for our deployment cost around €100 each. Application of HABITS showed a marked improvement compared to just using the Ekahau system by itself. Results show why the fuzzy rules are necessary to bring accuracy levels to an acceptable standard.

6.1 *Overcoming signal black spots*

Figure 15 shows the effect that a signal black spot has on the tracking performance of a commercially available indoor Wi-Fi-based RTLS.

At timestamp t = 1 (t_1), Ekahau can give a reasonably accurate estimate of the location of the user. The signal coverage in this area is sufficient, as it is in the location indicated by t_2. At t_2, the HABITS algorithm has kicked in as is indicated by the '+' sign. The problem occurs when the signal black spot area is reached, as happens at t_3. Due to weak signal coverage, the RTLS cannot get a good position estimate and will usually report the last good position fix it had. HABITS (indicated by a + sign), however, can still give a position estimate of the true location at time t_3 even through no updated position fix is available from the RTLS.

Table 3 shows the improvements due to HABITS at particular black spots. The three black spots tested below are those indicated in Figure 4 and are the three stairwells in the research centre. When using Ekahau alone the accuracy of a position estimates is very low in these areas. However, on journeys through the building, HABITS was able to more than half the error in estimate of location within these black spots. While a user is travelling through a black spot, HABITS estimates were within the figures listed 95% of the time. It was concluded that the 5% of the time the estimate were above the stated accuracy were due to stopping and turning around or just stopping midway through the journey.

Figure 15 Signal black spots (see online version for colours)

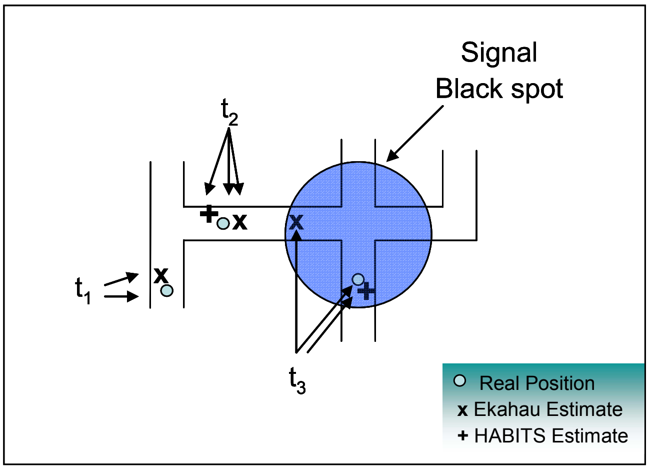


Table 3 Accuracy of HABITS in signal black spots

	Accuracy (95%)	
	Ekahau	*HABITS*
Black spot 1 (Left stairwell)	8 m	3 m
Black spot 2 (Centre stairwell)	10 m	4 m
Black spot 3 (Right stairwell)	7 m	3 m

6.2 *Prediction with HABITS*

In addition to using HABITS to overcome areas of weak signal strength, it may also be used for prediction. Table 4 shows the success of medium term predictions where the end node of a particular journey is predicted. The users-based node (desk) is the key to making predictions with HABITS. Of the total number of journeys made during the test period, 43% had the base node as the destination and 52% had the base node as the starting point. This means that 95% of all journeys undertaken by our test subjects involved travel to or from their base node. All of the test subjects showed very high (>90%) predictability when travelling to their own work station. When travelling from the base station, the final destination was more difficult to predict. However, HABITS still predicted the correct destination over 60% of the time for all users. User 2, the RA, was still predictable in over 85% of their journeys from their base station. Other journeys in the building had a much lower predictability. Some small patterns were apparent such as going to the toilet after the canteen, but overall these journeys proved to be beyond the predictability of HABITS. The average predictability of final destination of any of the test subjects was almost 80%. This means, in our test week, for four out of every five journeys taken, HABITS correctly predicted the final destination. It must be noted that these results are for journeys of greater than two nodes.

Table 4 Final destination prediction

	To base node (43.9% of journeys)	*From base node (52.4% of journeys)*	*Other (3.7% of journeys)*	*Average (all journeys)*
User 1 academic	0.91%	0.72%	0.18%	78.4%
User 2 research associate	0.94%	0.86%	0.35%	87.6%
User 3 PhD student	0.90%	0.61%	0.21%	72.3%
Overall average				79.4%

The testing of HABITS revealed a number of interesting facts. HABITS is suitable in environments were people follow particular movement patterns. The RA (User 2) proved to have much more predictable habits than the other two test subjects. It was concluded that this was indeed because they were paid to sit in the same spot each day and had set times for breaks. User 1 (academic) and User 3 (PhD students) did follow repeating movement patterns but these did not follow a rigid timetable. The conclusion from this was that the Academic had a changeable meeting schedule, whereas the student made particular journeys when he/she felt like it.

7 Building automation – lighting and HVAC control

A potential interesting and useful area of application for HABITS could be in control systems, specifically those that are dependent on the movement of people. Bolick (2010) reports that lighting and heating, ventilation and air conditioning (HVAC) account for approx 60% of building energy costs. HABITS gives short (<15 s), medium (15s–a few mins) and long (a few hours) term predictions on the general movement habits of people in a work environment. If we use this knowledge of where people will travel within a building and when, then we also know where they are not likely to go! This knowledge could be used as input to an intelligent control system for heating and lighting in a large building.

- *Lighting:* In the short term, if a system knew what room or area a person would travel to next, then the lights could already be on or in some standby mode to allow quick power up. This way they would not have to stay on standby continuously. Areas which were infrequently travelled could be put into low energy mode or switched off completely thereby saving energy consumption and money.
- *Heating:* With heating systems a similar but longer term approach could be applied. If we knew that at a certain time of day e.g. lunch, many people stood in the canteen or corridor then the heat could be adjusted up or down depending on the outside temperature and number of people. Conversely, if we know areas were people rarely travel then the heating could be turned off and would not be wasted while the area was not in use. While various sensors can currently control this, they only work when activated, i.e., when someone walks past them. HABITS could control the system in advance and could learn when the movement patterns changed. Existing sensors (motion) on doors could either be used in conjunction with HABITS or could be replaced by HABITS.

If a long term study was carried out or was simulated then the number of kilowatt hours saved could be calculated and this should prove to be substantial. The system could also be linked into controlling air conditioning systems in areas with hot climates. One reason that makes HABITS suitable for this type of application is that the predictions that HABITS gives are of varying degrees of accuracy and would not be suitable for life critical applications as there is a large element of probability involved. However, in building automation control systems a certain degree of inaccuracy would be acceptable if the overall energy savings were significant.

8 Conclusions

This research is concerned with the development of a more accurate algorithm for Wi-Fi positioning in an indoor environment. Indoor positioning systems suffer from one of two problems:

1 either they suffer from high levels of inaccuracy due to the distortion of radio signals as they hit solid objects in an indoor environment

2 they require a lot of extra infrastructure to be installed.

We have developed a novel way to overcome these difficulties by developing a system, called HABITS, that employs artificial intelligence methods to provide higher levels of tracking accuracy. Our algorithm uses the history of movement of users through a building as a means of predicting the most likely paths that they will travel in the future. HABITS also overcomes RF signal black spots where currently available systems fail. While HABITS will use the same radio signals and equipment as other systems, it will allow for positioning and continuous real time tracking with accuracy levels and areas that were not previously possible. Movement history has not been previously studied as a means of enhancing real-time indoor Wi-Fi tracking. HABITS can be applied in either infrastructural wireless networks or ad-hoc wireless networks.

Three main test areas were examined. First, the addition of HABITS to an existing RTLS gives comparable accuracy to that which would be gained by added extra infrastructure. Second, it can significantly improve upon how existing RTLS deal with signal black spots. HABITS doubles on the currently available accuracy in these areas. Third, in tests conducted on three occupants of the research centre, when on a journey of more than a few seconds, HABITS can correctly predict their final destination almost 80% of the time.

An approach such as HABITS has many potential application areas. Interesting future work on this project could involve applying HABITS to one of these areas. A particularly interesting application would be in intelligent building control. The buildings of the future will learn from their human occupants and HABITS can facilitate this.

A number of drawbacks do exist with the use of HABITS. The need to track the location of all personnel within a building may be unpopular but in certain environments the benefits may be worth it. Also, a certain learning time is required before HABITS is effective but again this could be acceptable. Lastly, it must be noted that HABITS will not work equally well in all environments with all people. As our tests demonstrated, it works better with people who have constraints on their movements. The less constraints, the less accuracy. However, the results of our tests show that HABITS could be very useful when applied in a suitable location.

HABITS has been initially trailed in an indoor work environment using Wi-Fi signals as the test system, however, the theory and approach could be applied to other tracking technologies, in other locations, even outdoors. While the knowledge of areas that a person habitually travels could be of use in many applications, potentially more valuable in terms of energy saving, are the areas that are not commonly travelled. In the future is intended to test HABITS with a large group of people to see whether the accuracy levels are affected.

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