Incorporating Past Human Movement into Indoor Location Positioning Systems for Accurate Updates

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Abstract

Using Wi-Fi signals is an attractive and reasonably affordable solution to the currently unsolved problem of widespread tracking in an indoor environment. However, this approach is hampered due to the underlying characteristics of radio waves (i.e. multipath effects) and due to infrastructural requirements. HABITS (History Aware Based Indoor Tracking System) overcomes these difficulties by modeling the historical movement habits of people in a workplace environment. It then learns from these habits and intelligently predicts the next location using a discrete Bayesian filter. This knowledge not only improves on currently available systems in terms of accuracy, yield and latency but can also be used as an input to building automation (heating, lighting) systems as an energy saving feature.

Keywords: Localisation, Indoor, Bayesian filter, Prediction.

1 Introduction

This paper presents research carried out in the Intelligent Systems Research Centre in the University of Ulster at Magee into improving the capabilities of indoor wireless tracking systems. Currently available systems suffer from weaknesses in terms of accuracy, precision and latency in their location estimates. The HABITS (**H**istory **A**ware **B**ased **I**ndoor Wi-Fi **T**racking **S**ystem) framework/algorithm overcomes these weaknesses by using intelligent methods to learn the movement habits of users in a structured environment. The habits are then fed back into the algorithm allowing for real-time updates, overcoming signal black spots and predicting future movements in the short, medium and long term.

This paper is divided into a number of sections as follows. Section 2 gives a short overview of the reasons why wireless networks are setup and outlines the weaknesses of tracking systems associated with these due to the underlying wireless network layout. Next the background research to our solution is discussed. In section 4 the HABITS movement modeling framework is described in detail. Finally the results of testing HABITS are given along with conclusions in sections 5 and 6.

2 Wireless Network Installations

In many cases wireless networks (802.11 Wi-Fi) are an afterthought in large buildings. Where feasible, major organisations will connect most of their devices using a fixed wired network. Even when a Wi-Fi network is installed it is commonly just a number of wireless access points (AP) 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 often just to allow users to have temporary mobile access. Some of the other reasons why WLANS (Wireless Local Area Network) are set up are to allow mobile users to roam about while remaining connected, 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. Foremost is the ability to transmit data to mobile devices at as high a rate as possible without losing Quality of Service (QOS) [1]. This needs to be done while installing as little extra infrastructure as possible. Unfortunately these goals aren't the same ones that the designer of indoor Wi-Fi tracking system thinks of. The positioning of Access Points (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 costs and installation overhead time. Unfortunately this configuration is not what is required by the tracking system designer. For a tracking system to be effective a large number of reference points are usually required in order to make the system more accurate and effective. In the case of Wireless Local Area Network (WLAN) the reference points used for positioning are 802.11 wireless access points. The positioning of these is of the utmost importance, a zigzag pattern is usually recommended to ensure that the radio signal patterns in each area are suitably different from one another [2]. 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 most organisations have an existing WLAN in place that they would prefer to utilise (e.g. University). If it is a new installation in a high value, specialised site (mine, hospital, factory, etc) then the layout can be designed with tracking as the main aim but most users want to use their existing networks with minor or zero modifications.

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 [3]. Radio Frequency (RF) signals bounce all over the place and factors such as furniture, people and/or temperature can all affect the way a signal travels around a building [3]. Real Time Locating System's designers attempt to overcome all this by using a combination of Received Signal Strength Indicators (RSSI) and probabilistic mathematical techniques like Kalman and Particle filters [4]. 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 [4] and many commercial systems/applications are available which allow for indoor localisation. This paper details a method which builds on top of these commercial systems and tries to improve accuracy using a different approach.

3 Solution background

The University of Augsburg [5] have used various machine learning techniques and mathematical methods to model indoor movement patterns. Using these models, predictions of next location of a certain user have been made with 69% accuracy without pre-training and 96% accuracy with pre-training. Another study at the University of Freiberg [6] 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 of mobile phone records also found that human mobility patterns were predictable 94% of the time [7].

A similar approach has been used in mature technologies like GPS navigation to predict where and when a user will reemerge from a tunnel. Also in cellular systems to predict which cell a mobile user will enter next. Using previous movements to help improve accuracy levels has been attempted in a number of studies ([8], [9]), but the focus has been on trying to improve the RSS based problems. This study does not try and improve on the RSS methods but instead uses the movement habits of users as a means of giving the system artificial intelligence. This knowledge is then used to overcome signal black spots and to predict where the user will travel to next.

In the Magee campus of the University of Ulster we have implemented and tested a number of Real Time Locating Systems (RTLS) and the results of these can be found in a study by JANet UK (Location Awareness trails) [10]. Of these, the Ekahau RTLS [2] utilizes the existing Wi-Fi network and in our tests achieved the best overall results. For this reason we use Ekahau as our test bed system. It does, however, contain a number of weaknesses. Fig 1 shows signal black spots where existing systems lose their accuracy.

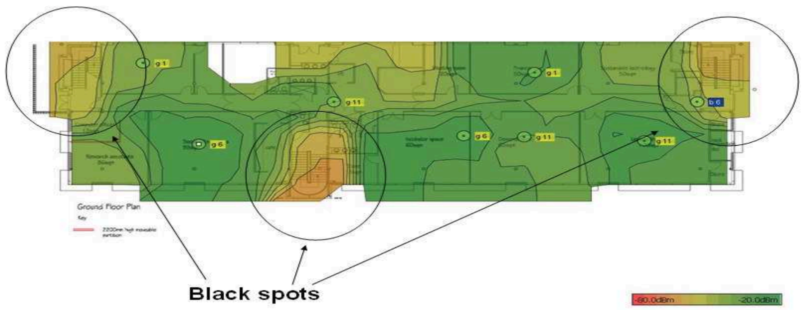

Figure 1: Black spots identified in building

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

4 The HABITS Movement Modeling Framework

While HABITS uses the same radio signals and equipment as other systems, it allows for positioning and continuous real time tracking with improved accuracy levels and in areas that were not previously accessible. HABITS will, however, only work in certain environments where people follow particular habitual movement patterns, for example work environments, factories, hospitals, etc. Figure 2 shows the context that HABITS can be used in. 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.

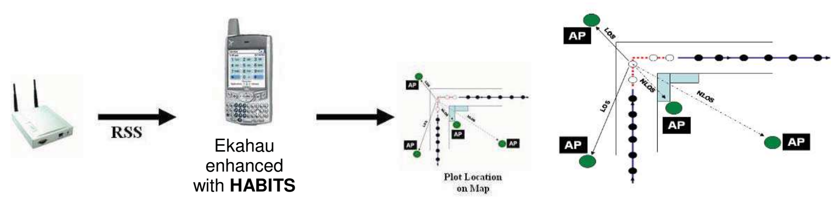

Figure 2: Context of HABITS

Figure 3 gives a simplified overview of the operation of HABITS. Every five seconds is the highest frequency rate of position updates from Ekahau. These updates are often up to fifteen seconds apart. Each update is sent to HABITS along with historical movement data and from this an intelligent prediction is given of the next location. Short term predictions effectively fill in the blanks in between updates from the Ekahau system.

To implement the HABITS algorithm, the following procedure must be carried out. The movement paths of people indoors must first be represented as a graph structure. A topological map (graph) can be learned from the past movement data. This graph of the area is used along with the historical movement data of a person in order to calculate incidence & transition matrices. A number of inductive learning methods are used to extract patterns and fuzzy rules from the historical movement data. A discrete Bayesian filter is then used to fuse the various bits of data together to give a prediction which is then further refined by the use of a set of Fuzzy logic rules. Figure 4 represents this process in a simplified format.

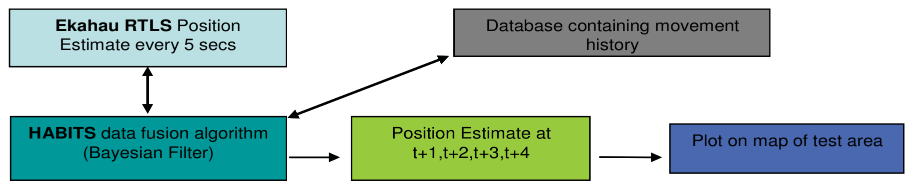

Figure 3: HABITS Architecture

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. The zones shown in Figure 4 represent areas that are passed through frequently on the ground and first floor in the MS building in the Universities of Ulster's Magee campus. 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 machine learning techniques, however the description of these is beyond the scope of this paper.

Figure 4: Zones showing areas of interest

The *edges* between *nodes* show paths that may be travelled and represent the movements of Wi-Fi tracked people in the building. The first thing to identify was the areas where a user often stopped, we called these *wait nodes* and they had 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 5 along with the particular node types.

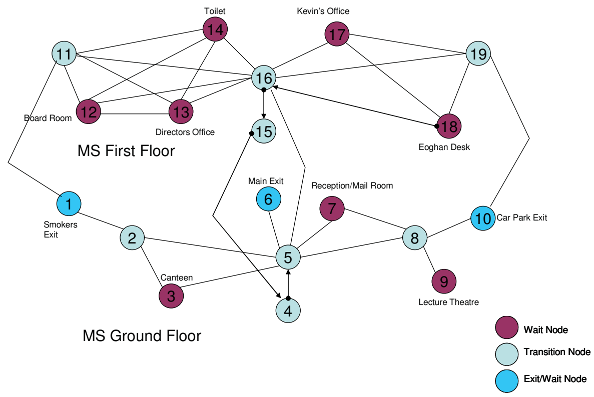

Figure 5: MS building represented as a graph

A number of different matrices are necessary for our study (see Figure 6). An incidence matrix 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 one is placed at that location, otherwise use a zero. A distance matrix may be combined with the incidence matrix to show the distance between nodes or the travel time from one node to the next. The ones in 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 Density Function (PDF) for each node is calculated from this. This information is represented in a transition matrix. A small section of the transition matrix can be seen in Figure 7.

		FROM					
		1	2	3	4	5	6
	1	0	0.167	0	0	0	0
TO	2	0.667	0	0.077	0	0.019	0
	3	0	0.667	0	0	0.157	0
	4	0	0	0	0	0.314	0

Figure 6: A section of the transition matrix based on one months travel by a single user

The transition matrix by itself gives only general predictions. A deeper analysis of the data was required to learn patterns of movement that would realistically equate to a users movement habits. Users often travel *preferred paths* 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 heading to the canteen increases between 12-1.30pm. The average travel speed 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 at these times. All of these patterns have to be considered.

Listed below are the main inputs into HABITS. These contain all the information necessary to make predictions as to where a Wi-Fi tracked user will travel to next.

- *Standard Inputs – Some fixed some variable – will be updated as new data arrives*
    - Incidence/Distance Matrix
    - Transition Matrix showing initial transition probabilities
    - Look-up table showing node types and common paths
    - Average user speed
- *Factors that will affect weighting of probabilities represented as Fuzzy Rules*
    - Time of day (Morning/Lunch/Evening)
    - Day of week
    - Other users in same zone
- *From Ekahau RTLS*
    - X,Y position estimate at timestamp *t*
    - Confidence of estimate represented as a percentage
    - Whether a device is in motion or stationary (tags are equipped with accelerometers)

The various inputs to the HABITS system listed here are combined using a number of artificial intelligence techniques. The first is an idea which is extensively used in robotics – that of a *Discrete Bayesian filter* [4]. 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 decision point/node. Pseudo code in Fig 7 shows the basic operation of a discrete Bayesian filter. This 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 which work along with the updates from Ekahau to give a prediction of next location. However, this prediction alone isn't 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".

<u>General Algorithm for Bayes Filtering</u>

Algorithm_filter($bel(x_{t-1}), u_t, z_t$):
for all xt do
$\overline{bel}(x_t) = \sum p(x_t \mid u_t, x_{t-1})\, bel(x_{t-1})$ **(PREDICTION STEP)**
$bel(x_t) = \eta\, p(z_t \mid x_t)\, \overline{bel}(x_t)$ **(UPDATE STEP)**
end for
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 7: Pseudo Code for Discrete Bayesian Filter

The addition of the fuzzy rule base is to overcome one of the constraints of the Bayesian filter, namely 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 doesn't hold true in our case so we've overcome it by the creation of a hybrid Bayesian-fuzzy filter/rule base which gives us the best of both and allows for extra habits to be included which don't fit into the discrete Bayesian filter as the diagram in Figure 8 shows.

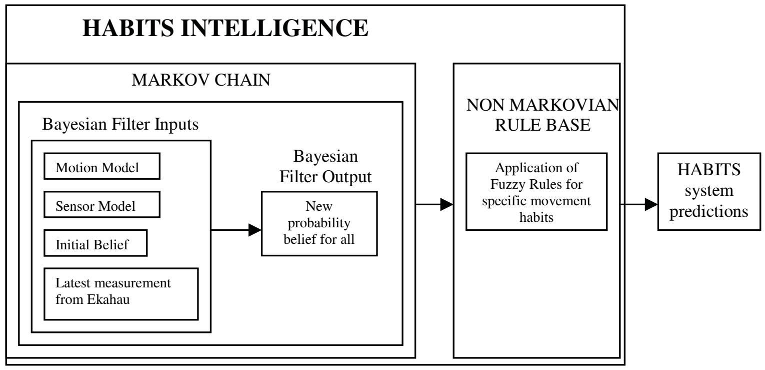

Figure 8: Hybrid Bayesian-Fuzzy System

An interesting and useful area of application for the HABITS framework could be in building automation control systems, specifically those that are dependent on the movement of people. Reportedly, Lighting and Heating, Ventilation and Air Conditioning (HVAC) account for approx 60% of a buildings energy costs [11]. HABITS gives short (<15 sec), medium (15 sec to 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.

5 Results

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 1.

Table 1: Results of testing HABITS

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

- 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 always gives a positioning estimate, even though it may have a probability of less than one associated.
- Savings over existing indoor tracking systems in terms of extra infrastructure required.

6 Conclusion

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. Either they suffer from high levels of inaccuracy due to the distortion of radio signals as they hit solid objects in an indoor environment or 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 overcome 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. 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 would be required before HABITS would be effective but again this could be acceptable.

While HABITS would initially be trailed in an indoor work environment, the theory and approach could be applied in other locations, even outdoors. While the knowledge of areas that a person habitually travels could be of use in many applications, a potentially more valuable outcome in terms of energy conservation, are the results relating to areas that are not commonly travelled. In the future is intended to test HABITS with a large group of people to see if the accuracy levels are affected.

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