Predictive Indoor Tracking by the Probabilistic Modelling of Human Movement Habits

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I. Research Aim

- The aim of this research is to create an algorithm that enhances Wi-Fi tracking capability in an indoor environment.
- The **HABITS** (History Aware Based wi-fi Indoor Tracking System) algorithm will allow for real-time continuous tracking in areas where this was not previously possible due to signal black spots. Historical movement patterns will be used to probabilistically facilitate this.

II. Positioning Systems

- Positioning is a process to obtain the spatial position of a target.
- In recent years the need has arisen for the development of Location Based Services (LBS) which work in an indoor environment. Large public buildings; universities, hospitals and shopping centres have become target areas.
- Due to the poor performance of Satellite and Cellular systems indoors, a separate system is required.
- 802.11 Wi-Fi networks as specified by the IEEE are available in many large buildings. The signals transmitted by the Access Points (APs) provide a readily available network of signals which may be used for positioning

III. Ekahau

- The Ekahau RTLS (Real Time Location System) is used to provide the position of a Wi-Fi device.
- It does not rely on proprietary infrastructure or readers in order to track devices.
- The existing 802.11 Wi-Fi network is used for all tracking with signal strengths of the Access Points (APs) being recorded as shown in fig 1.

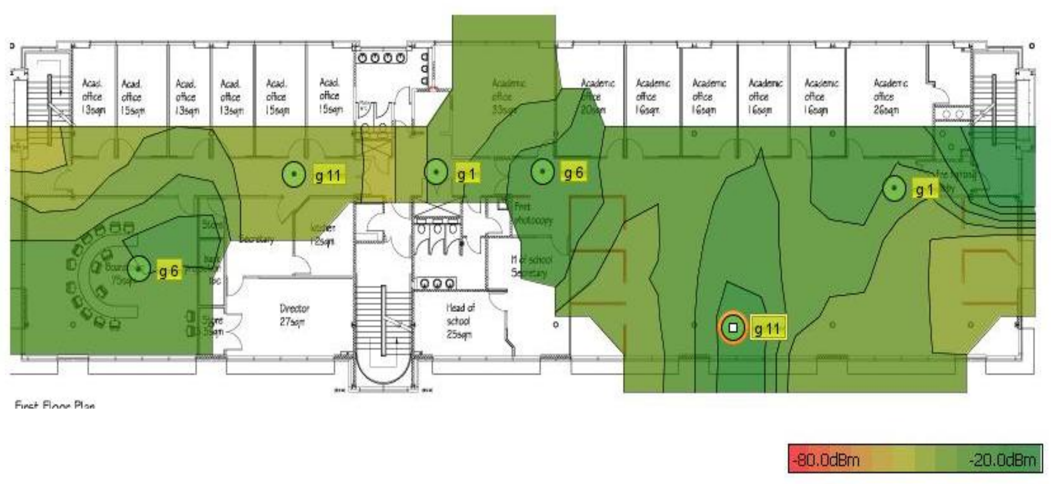

Fig 1: Heat Map showing areas of similar RSS values

- Ekahau Site Survey records RSSI data of the test area.
- This data is mapped to a model which shows the areas where a Wi-Fi enabled device may travel (Fig 2).

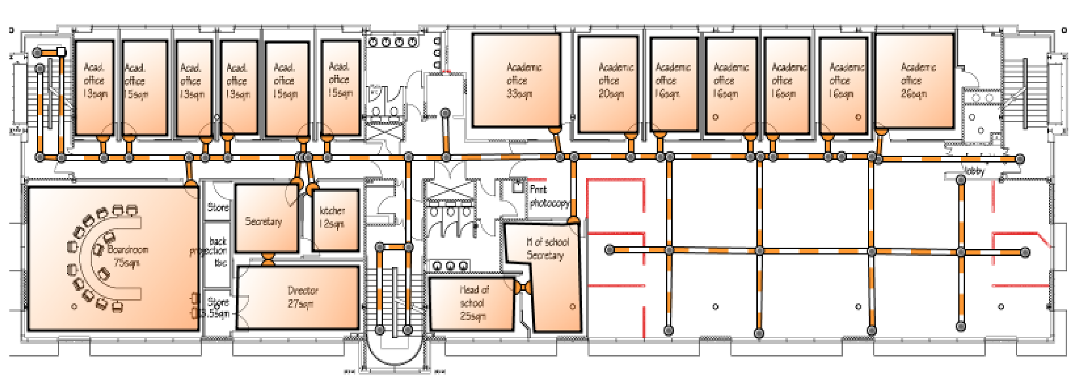

Fig 2: Map showing areas where a user may travel

- The observed Wi-Fi signal strength data is recorded at each location. A probability is then assigned to each location based on this data as Fig 3 shows.

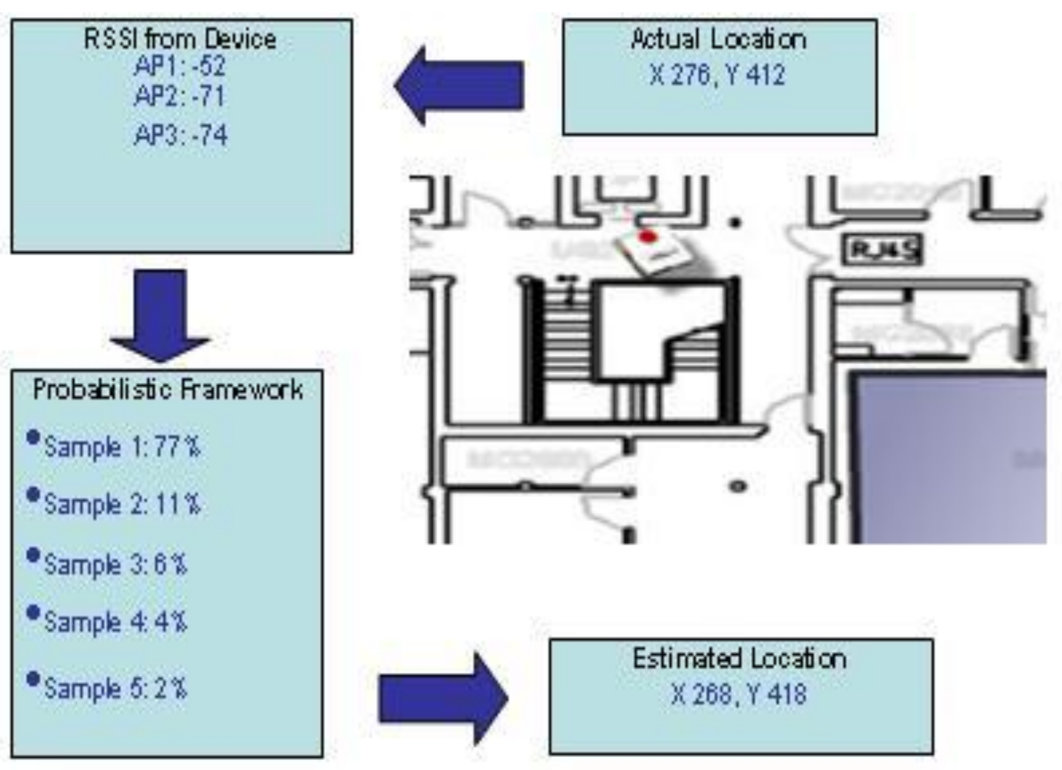

Fig 3: Probabilistic estimation in Ekahau

IV. Multisensor data Fusion

- Multi sensor data fusion can facilitate bringing together data from different sources.
- Using a combination of the live data from Ekahau, historical movement data and dead reckoning information, an enhanced live track may be produced which would be continuous (Ekahau has 5 sec updates at its fastest) and would continue to track when signals were poor - black spots.
- A number of filtering techniques may be used to produce a new estimate of the state of a system.

V. Bayesian Filtering

- Bayes filter is commonly used in robotics as a method to infer the position of a robot.
- This recursive algorithm enables a position estimate to be continuously updated by including the most recent sensor readings.
- A general form of the Bayes filter, which may be used for a discrete case like this, is outlined in pseudo code below.

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.

VI. HABITS Overview and Context

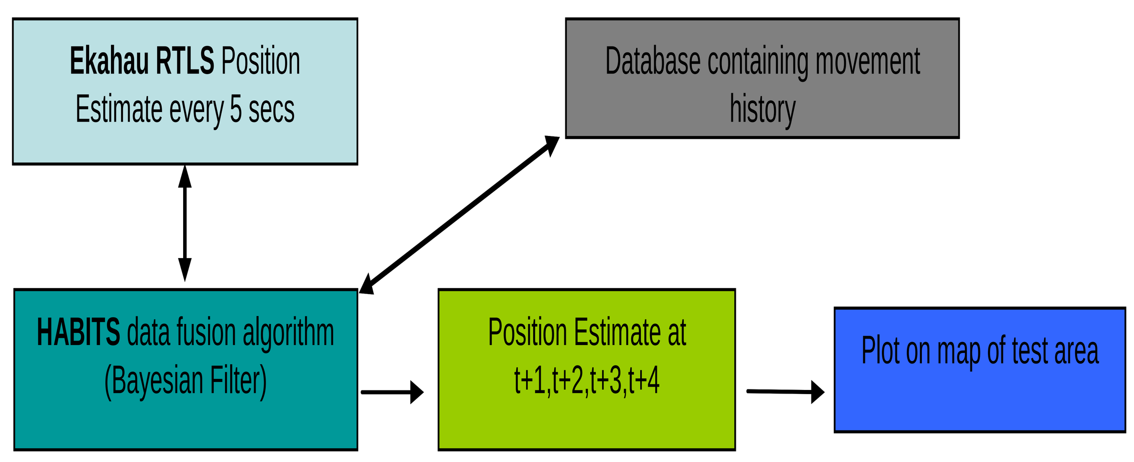

Fig 4: HABITS overview

Figure 4 gives the flow of data in HABITS.

- The Ekahau API enables a position estimate from the Ekahau system to be fed into the fusion algorithm.
- This information will then be compared to the data stored in the historical database.
- From this a prediction of the movement steps for the next 5 seconds will be calculated.
- These predicted positions will be plotted on the map. Figure 5 shows the context in which HABITS will be used.

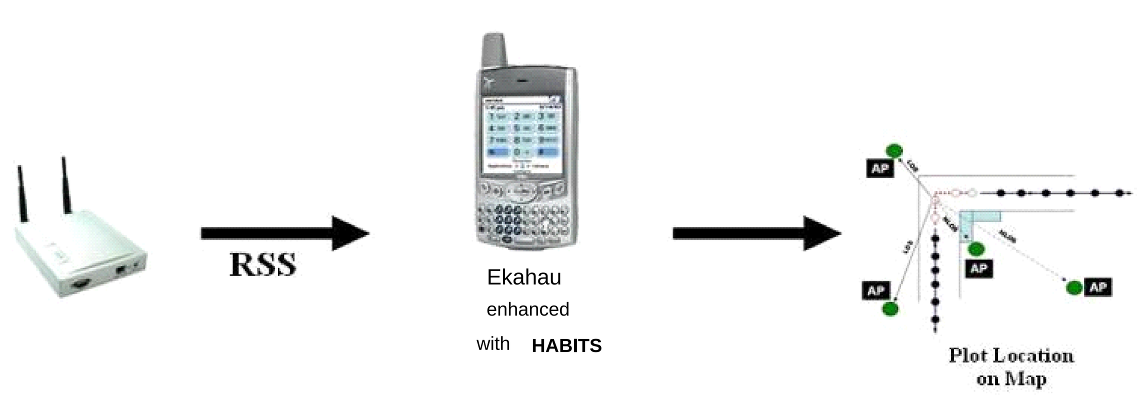

Fig 5: Context of HABITS

VII. Implementation Graphing/ Mapping

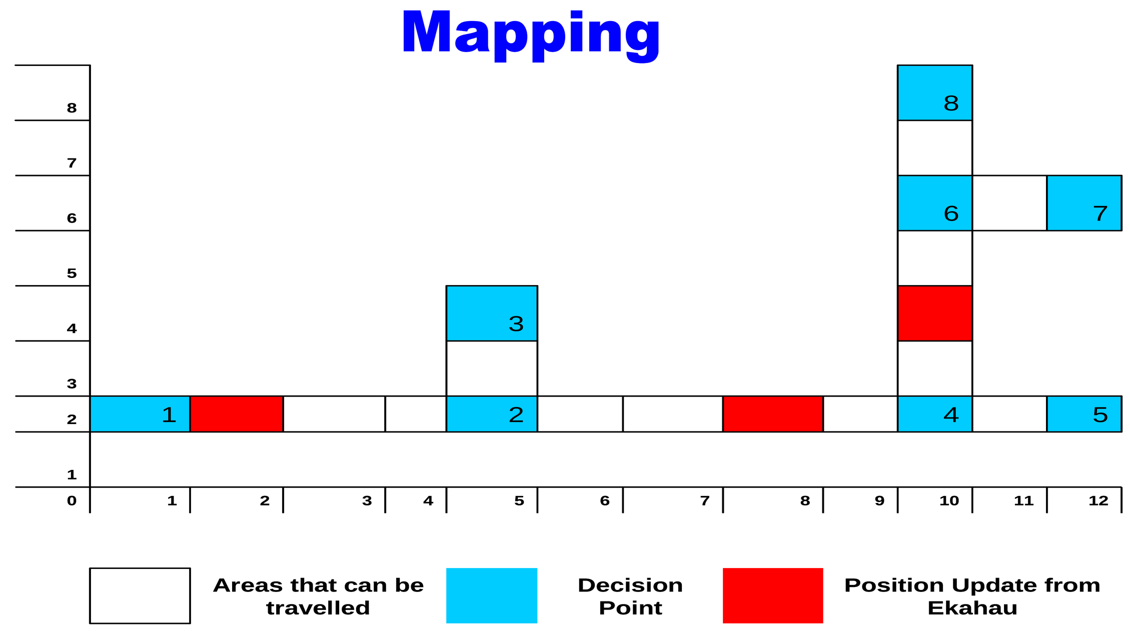

Fig 6: Indoor map represented as a graph

- The test area would need to be mapped in a similar way to Ekahau. These maps would contain all the possible routes that a person may travel.
- A graph may be used as a means of representing the movement of people indoors (Fig 6).
- This graph of the area will be used along with the historical movement data of a person (Fig 7) in order to calculate the transition matrix

Movement History of User 1

	Morning	Afternoon	Evening
Day 1	12467	5645,5467	76421
Day 2	12467	768,867	76421
Day 3	12467	768,867	76421
Day 4	12467	7645	5421

Fig 7: Historical movement sequences through the nodes.

VIII. Probablistic Matrices

- The more HABITS is used the more accurate it should become.
- When a critical set of historical movement data has been gathered it can be analysed for patterns.
- Probabilistic functions can be calculated for the decision points. Fig 8 shows the initial probability of moving from one state to a neighbouring one.
- This data will then be used to update the various weights/inputs to the HABITS algorithm .
- Movement patterns of a particular user or type of user can facilitate profiling which can be used for a number of ambient intelligent applications.

Prior State

New State	1	2	3	4	5	6	7	8
1	0.5	0.5	0	0	0	0	0	0
2	0.2	0.5	0.1	0.2	0	0	0	0
3	0	0.5	0.5	0	0	0	0	0
4	0	0.2	0	0.5	0.1	0.2	0	0
5	0	0	0	0.5	0.5	0	0	0
6	0	0	0	0.2	0	0.5	0.15	0.15
7	0	0	0	0	0	0.5	0.5	0
8	0	0	0	0	0	0.5	0	0.5

Fig 8: Transition Matrix

- HABITS can be tested by comparing its tracking capability with the standard Ekahau system in terms of Accuracy, Precision, Yield and Latency.

IX. Publications

- Curran, K., Furey, E., (2007). "Pinpointing Users with Location Estimation Techniques and Wi-Fi Hotspot Technology". Int Journal of Network Management
- Furey, E., Curran, K., Mc Kevitt, P., (2008) "HABITS: A History Aware Based Wi-Fi Indoor Tracking System". PGNET 2008 The 9th Annual Postgraduate Symposium: The Convergence of Telecommunications, Networking and Broadcasting 2008. Liverpool, John Moores University, UK
- Petzold, J., Bagci, F., Trumler, W. And Ungerer, T., 2006. "Comparison of Different Methods for Next Location Prediction". Lecture Notes In Computer Science, pp. 909