Title: A LOCATION AND TRACKING SYSTEM

Abstract: A location and tracking system (1) comprises a site survey tool (2), a location engine (3), a self-calibration engine (4), and a fingerprint database (5). The system (1) operates for a wireless network of access points in a building and it generates from initialization data a model of the physical environment. The model may for example be in the form of data representing geometry of lines in plan and signal attenuation values for the lines. The system then uses this model to generate a fingerprint of projected signal strengths in the environment. The system may maintains a fingerprint for every environment model or there may be only one model at any one time, or there may be a number. Where the latter, the system may assign a weighting to each model to indicate its confidence value. Upon detection of a mobile node in the environment the system (1) estimates position of the node according to the current fingerprint, and in real-time performs self-calibration of the environment model, in turn giving rise to fresh updated fingerprints for future tracking. This continuous self-calibration ensures excellent tracking accuracy even with modification of the environment, such as changing of an access point configuration, moving a partition wall, or movement of a metal filing cabinet.
(88) Date of publication of the international search report:
       6 January 2011
### INTERNATIONAL SEARCH REPORT

**Inventor:** GOISS/02

**According to International Patent Classification (IPC) or to both national classification and IPC:**

**SEARCHED**

Minimum documentation searched (classification system followed by classification symbols)

**GOIS**

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched

Electronic data base consulted during the international search (name of data base and, where practical, search terms used)

**EPO-Internal**

### DOCUMENTS CONSIDERED TO BE RELEVANT

<table>
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<th>Category*</th>
<th>Citation of document, with indication, where appropriate, of the relevant passages</th>
<th>Relevant to claim No.</th>
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<tr>
<td><strong>X</strong></td>
<td>WO 2004/008796 A1 (EKAHAU OY [FI]; MISIKANGAS PAULI [FI]; LEKMAN LARE [FI]); 22 January 2004 (2004-01-22); pages 6-8; figures 1,2,5,7</td>
<td>1,15,22, 23</td>
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<td><strong>X</strong></td>
<td>US 2007/149216 A1 (MISIKANGAS PAULI [FI]); 28 June 2007 (2007-06-28); paragraphs [0023], [0 97], [119], [120]; figure 1</td>
<td>2-5, 11-14, 16-20</td>
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* Special categories of cited documents:

- **A** document defining the general state of the art which is not considered to be of particular relevance
- **E** earlier document but published on or after the international filing date
- **L** document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)
- **O** document referring to an oral disclosure, use, exhibition or other means
- **P** document published prior to the international filing date but later than the priority date claimed

**Further documents are listed in the continuation of Box C.**

**See patent family annex.**

**Date of the actual completion of the international search:**

15 November 2010

**Date of mailing of the international search report:**

22/11/2010

**Name and mailing address of the ISA/Authorized officer:**

European Patent Office, P.B. 5818 Patentlaan 2
NL - 2280 HV Rijswijk
Tel: (+31-70) 340-2040, Fax: (+31-70) 340-3016

Kern, Olivier
<table>
<thead>
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<tr>
<td>A</td>
<td>page 16, line 18 - page 18, line 7 page 20, line 17 - page 21, line 25</td>
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INTERNATIONAL SEARCH REPORT

Box No. II  Observations where certain claims were found unsearchable (Continuation of item 2 of first sheet)

This international search report has not been established in respect of certain claims under Article 17(2)(a) for the following reasons:

1. ☐ Claims Nos.: because they relate to subject matter not required to be searched by this Authority, namely:

2. ☐ Claims Nos.: because they relate to parts of the international application that do not comply with the prescribed requirements to such an extent that no meaningful international search can be carried out, specifically:

3. ☐ Claims Nos.: because they are dependent claims and are not drafted in accordance with the second and third sentences of Rule 6.4(a).

Box No. III  Observations where unity of invention is lacking (Continuation of item 3 of first sheet)

This International Searching Authority found multiple inventions in this international application, as follows:

see additional sheet

1. ☑ As all required additional search fees were timely paid by the applicant, this international search report covers all searchable claims.

2. ☐ As all searchable claims could be searched without effort justifying an additional fees, this Authority did not invite payment of additional fees.

3. ☐ As only some of the required additional search fees were timely paid by the applicant, this international search report covers only those claims for which fees were paid, specifically claims Nos.:

4. ☐ No required additional search fees were timely paid by the applicant. Consequently, this international search report is restricted to the invention first mentioned in the claims; it is covered by claims Nos.:

Remark on Protest

☐ The additional search fees were accompanied by the applicant's protest and, where applicable, the payment of a protest fee.

☐ The additional search fees were accompanied by the applicant's protest but the applicable protest fee was not paid within the time limit specified in the invitation.

☒ No protest accompanied the payment of additional search fees.
This International Searching Authority found multiple (groups of) inventions in this international application, as follows:

1. claims: 1-5, 11-20, 22, 23
   estimation of the position of a mobile node

2. claims: 6-10, 21
   modelling of obstacles for a fingerprint database
<table>
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<td>WO 2004008796 A1</td>
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<td>US 2005037776 A1</td>
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A location and tracking system (1) comprises a site survey tool (2), a location engine (3), a self-calibration engine (4), and a fingerprint database (5). The system (1) operates for a wireless network of access points in a building and it generates from initialization data a model of the physical environment. The model may for example be in the form of data representing geometry of lines in plan and signal attenuation values for the lines. The system then uses this model to generate a fingerprint of projected signal strengths in the environment. The system may maintains a fingerprint for every environment model or there may be only one model at any one time, or there may be a number. Where the latter, the system may assign a weighting to each model to indicate its confidence value. Upon detection of a mobile node in the environment the system (1) estimates position of the node according to the current fingerprint, and in real-time performs self-calibration of the environment model, in turn giving rise to fresh updated fingerprints for future tracking. This continuous self-calibration ensures excellent tracking accuracy even with modification of the environment, such as changing of an access point configuration, moving a partition wall, or movement of a metal filing cabinet.
Inputs: Main obstacles layout
System configuration
Initial position of mobile nodes

Setting of initial parameters of obstacles
Segmentation of walls and main obstacles
Pre-processing of possible mobile nodes trajectories
Initial channel parameters estimation
Gathering of channel parameters by mobile nodes
Mobile nodes speed estimation (optional)

$m$ from 1 to $M$ (number of mobile nodes)
Creation of subset of possible trajectories (hypothesis) for the $m^{th}$ mobile node
$h$ from 1 to $H_m$ (number of hypothesis)
Simulation of the $m^{th}$ mobile node motion along the $h^{th}$ trajectory (hypothesis) and creating the corresponding fitness function
Optimisation of parameters of obstacles in the $h^{th}$ hypothesis
Adjustment of the current parameters of obstacles toward the optimised
Prediction of channel parameters (Fingerprint update for the $h^{th}$ hypothesis)
Localisation error estimation by standard process of mobile node localisation
Ranking of the hypothesis

$h < H_m$
Selection of the $M$ most likely hypothesis

$m < M$
Cross evaluation of the mobile nodes hypothesis by multi-node localisation error estimation and combined parameters of obstacles
Selection of the $H_c$ most likely combined hypothesis

Fig. 3
Fig. 4

Adaptive Fingerprinting

Initial Wall Parameter
Light Wall 10.0
Heavy Wall 10.0
Window 10.0
Floor

Floorplan Segmentation
Width 100 meters
Radiation 50 dB

Transmit Power
Max +10 dB
Min -12 dB

Deviation 0 dB
Learning Factor: 1.00
Threshold 4 dB

Constant Power Transmit
Sequential Calibration

Fig. 5
Fig. 6
Wall segment

Fig. 7
- Edge  ○ Access Point
- Vertex △ Starting Point

Fig. 8
○ Access Point

Colour Scale (dBm)
- 30
- 37
- 44
- 51
- 58
- 65
- 72
- 79
- 86
- 93
- 100
Fig. 10

(a) Voronoi graph
(b) Vertices and edges of the graph

Fig. 11
Fig. 12

\[ \text{PK} = \text{Access Point} \]
\[ \hat{A} = \text{Target with a mobile device} \]

Fig. 13

\[ \text{\( \bigcirc \) = true location} \]
\[ \text{\( \Theta \) = estimated location} \]
\[ \text{\( e \) = error} \]
\[ \text{\( z_t \) = cloud of particles (output of particle filter location estimation)} \]
Example of possible proposed trajectories for one mobile node, which are evaluated and ranked one-by-one in the inner loop of the self-calibration system.

The M most likely trajectories left to the next iteration

Legend

- The most likely trajectory/hypothesis
- The other likely trajectory/hypothesis
- Terminated unlikely trajectory/hypothesis
- Switch between the most likely trajectories/hypothesis
- Initial starting point

The iterations in the intermediate loop of the self-calibration process

Note: Number indicates estimated likelihood
PDF of velocity with $v_{t-1} = 0 \text{ m/s}$.

Fig. 16

Standard deviation of target direction $\alpha_t$.

Fig. 17
PDF of the direction with $\alpha_{\alpha_1} = 0$.

Fig. 18

Evolution of particles with motion model.

Fig. 19

Gaussian distribution $p_{hit}$

Fig. 20
Penalty $\eta$ for missing or extra RSS value.

Fig. 21

Illustration for the calculation of the measurement model.

Fig. 22
(a) RSS fingerprint.

(b) Initial particle distribution.

(c) Measurement probability.

(d) Updated particle distribution

Update of the particles distribution with the likelihood observation function.

Fig. 23
LOCATION AND TRACKING SYSTEM

FIELD OF THE INVENTION

[0001] The invention relates to location and tracking systems such as those within a building. An example is a system for navigation in large office buildings, for tracking location of security personnel in an airport.

[0002] In a typical location and tracking system the position of a mobile node is inferred from location-specific physical parameters of the wireless communication channel which exists between fixed nodes and the mobile node such as RSS (Radio Signal Strength), TDOA (Time Difference of Arrival), impulse response characteristics, angle of arrival, and multi-path propagation characteristics.

[0003] However, the wireless channel parameters in a multi-path environment (such as indoor environment) are subject to the electromagnetic properties of the environment such as signal transition and reflection losses, signal phase shift, and signal depolarisation when interacting with the environment.

[0004] The invention is directed towards providing a location and tracking system with improved ability to track locations of mobile nodes. Another objective is to avoid need for considerable additional equipment in the environment.

SUMMARY OF THE INVENTION

[0005] According to the invention, there is provided a location and tracking system comprising wireless base stations, an input interface, and a processor, wherein the processor is adapted to:

[0006] (a) receive physical environment inputs and provide an initial physical environment model;

[0007] (b) generate an initial channel parameters fingerprint for the environment according to the initial environment model;

[0008] (c) monitor channel parameters of a mobile node in the environment and use said parameters and the fingerprint to locate the mobile node;

[0009] (d) modify the environment model according to said node locating step (c);

[0010] (e) update the fingerprint according to the modification of the environment model in step (d); and

[0011] (f) repeat steps (c) to (e) in subsequent iterations.

[0012] In another aspect, the invention provides a location and tracking method performed by a location and tracking system linked with wireless base stations, and having an input interface, and a processor, wherein the method comprises the steps of:

[0013] (a) receiving physical environment inputs and providing an initial physical environment model;

[0014] (b) generating an initial channel parameters fingerprint for the environment according to the initial environment model;

[0015] (c) monitoring channel parameters of a mobile node in the environment and using said parameters and the fingerprint to locate the mobile node;

[0016] (d) modifying the environment model according to said node locating step (c);

[0017] (e) updating the fingerprint according to the modification of the environment model in step (d); and

[0018] (f) repeating steps (c) to (e) in subsequent iterations.

[0019] The initial environmental model may be generated in step (a) by the system in response to the inputs or it may be received as a pre-generated file. The invention achieves by virtue of steps (b) to (5) self-calibration for location of mobile nodes in the environment. Any change made to the environment, such as modification of a base station, erection of a partition wall, or even movement of a piece of furniture will be automatically taken into account for further location of mobile nodes.

[0020] In one embodiment, the location engine is adapted to execute a filtering algorithm to estimate location in step (c).

[0021] In one embodiment, the processor is adapted to determine in step (c) possible mobile node trajectories, and to use said trajectories for environment model modification in step (d) and subsequent fingerprint updating in step (e).

[0022] In one embodiment, the processor is adapted to dynamically maintain a multi-hypothesis decision tree in step (c) in which it iteratively evolves branches representing the most likely mobile node trajectories.

[0023] In another embodiment, the processor is adapted to use mobile node speed estimation for steps (c) and (d).

[0024] In one embodiment, the processor is adapted to modify wall segment parameters of the environment model in step (d).

[0025] In one embodiment, in step (a) the inputs include:

[0026] layout of main obstacles including building floor plans and wall layout;

[0027] layout of base stations; and

[0028] starting position of a mobile node.

[0029] In a further embodiment, parameters of environment obstacles are initially set to a common default value.

[0030] In one embodiment, for the step (a) the processor is adapted to divide the obstacles into smaller segments and to optimise parameters of the smaller segments to more precisely represent each segment's mean local influence on signal attenuation.

[0031] In one embodiment, the processor is adapted to apply parameters to the segments so that they characterise the obstacles they are part of and also the influence of smaller obstacles including furniture in proximity to large obstacles.

[0032] In one embodiment, for step (c) the processor is adapted to use an empirical signal propagation model with a linear optimisation method for prediction of received signal strength.

[0033] In one embodiment, the processor is adapted to perform, for steps (c) and (d), simulation of an mth mobile node motion along a hth trajectory and creation of a corresponding fitness function.

[0034] In one embodiment, the fitness function describes how similar the channel parameters estimated along the hth trajectory by the prediction model, which uses current obstacles parameters, is to gathered channel parameters by a mobile node along its true trajectory.

[0035] In one embodiment, the fitness function takes the form of a set of linear equations for an optimisation method.

[0036] In one embodiment, the processor is adapted to execute a particle filter algorithm to locate a mobile node in step (c), in which particles are mapped to the physical environment as represented by the physical environment model.

[0037] In one embodiment, the processor is adapted to generate visual displays of the physical environment in which particles distribution is illustrated for user visualisation of likelihoods of locations of the mobile node.
In one embodiment, the processor is adapted to eliminate particles in successive iterations according to constraints imposed by the physical environment model and a motion model, in which remaining particles converge around the actual mobile node location.

In another embodiment, the processor is adapted to automatically recognize rooms in the physical environment model and to maintain a count of particles in each room to provide a per-room probability of presence of the mobile node.

In one embodiment, the processor is adapted to provide a random or uniform initial particle distribution mapped into the physical environment model, to filter the initial particle distribution with a likelihood observation function to generate a second particle distribution and to use said distribution for a next filtering iteration.

In one embodiment, the likelihood observation function is given by combining densities to obtain a likelihood observation function of measurement $p(z_t|x_t)$, and is given by:

$$p(z_t|x_t) = \prod_{i \in K} p_{\text{model}}(z_t^i|x_t^i) \cdot \prod_{i \in L} p_{\text{sensor}}(z_t^i|x_t^i) \cdot \prod_{i \in M} p_{\text{extr}}(z_t^i|x_t^i) \cdot \beta$$

where:

- $K$ is the set of measurement in $(z_t^i \cup z_t^r)$,
- $L$ is the set of measurement in $(z_t^r - z_t^i)$,
- $M$ is the set of measurement in $(z_t^r - z_t^i)$,

and the expressions of $|K|$, $|L|$, $|M|$ denotes the number of elements in $K$, $L$, $M$ respectively.

$\beta$ represents the weighting factor and $k$ denotes AP identification.

In one embodiment, the processor is adapted to perform step (d) by adjusting the current parameters of obstacles towards the optimised parameters of obstacles which influence the channel parameters along the $h^{th}$ trajectory, in which the adjustment is given by:

$$L_{w}^t = L_{w}^t + \Delta L_{w}^t$$

where:

- $L_{w}^t$ represents/wall segment loss at time (index of iteration) $t$,
- $L_{w}^t$ represents $t^\text{th}$ wall segment loss at iteration $t-1$, and
- $\Delta L_{w}^t$ denotes the delta of a wall segment loss at time $t$.

In another aspect, the invention provides a computer readable medium comprising software code adapted to perform operations of a location and tracking system as defined above in any embodiment when executing on a digital processor.

**Detailed Description of the Drawings**

**Brief Description of the Drawings**

The invention will be more clearly understood from the following description of some embodiments thereof, given by way of example only with reference to the accompanying drawings in which:—

**Figure 1** is a block diagram illustrating the main components of a location and tracking system of the invention, and **Figure 2** is a perspective view of a typical indoor environment in which the system operates;

**Figure 3** is a flow diagram illustrating operation of the system to perform mobile node tracking and self-calibration;

**Figure 4** is an example of a floor plan with a particular wall layout and access points, within which the location of a mobile node is tracked;

**Figure 5** is a screen shot for initializing the system with environment parameters;

**Figure 6** is another example floor plan, with segmented walls;

**Figure 7** shows possible trajectories in this environment, represented as a Voronoi diagram in the floor-plan;

**Figure 8** is a display of fingerprints in this environment showing predicted channel parameters in an environment, in which the scale represents level of predicted channel parameter such as signal strength in a regular grid, and **Figure 9** shows another predicted fingerprint generated from a site-specific prediction model;

**Figure 10** shows a sample output screen for operation of a site survey module of the system, the screen showing signal strength as measured by a mobile node in the environment;

**Figure 11** is a set of diagrams illustrating proposed trajectories for a mobile node at a starting point $A$;

**Figure 12** is a diagram illustrating fitness function creation with a multi-wall model (MWM);

**Figure 13** is a plan view, showing a location error of the position estimated by a particle filter;

**Figure 14** is a diagram illustrating how the system dynamically maintains options and probabilities on possible trajectories;

**Figure 15** is a sample calibrated fingerprint generated by the system after several iterations of self-calibration, in which the fingerprint differs from the fingerprint shown in **Figure 8** in the optimised parameters of the environment model (such as, wall parameters), which were used in the fingerprint prediction mode; and

**Figures 16 to 23** are diagrams illustrating implementation of a particle filter algorithm.

**Description of the Embodiments**

**Figure 1** refers to **Figure 1** a location and tracking system 1 comprises a site survey tool 2, a location engine 3, a self-calibration engine 4, and a fingerprint database 5. The system operates for a wireless network of access points such as shown in **Figure 2**. In hardware terms it comprises a conventional PC computer and mobile WiFi enabled handheld devices such as smart phones linked to wireless access points of a conventional WiFi network.

**System 1** generates from initialization data a model of the physical environment. The model may for example be in the form of data representing geometry of lines in plan and signal attenuation values for the lines.

The system then uses this model to generate a fingerprint of projected signal strengths in the environment. The term “fingerprint” means a map of channel parameters (such as signal strength and Time of Arrival, TOA) at all of a set of points in the environment. These points may be in a regular grid pattern, with position of some points being offset to avoid being coincident with an obstruction such as a wall.

The system maintains a fingerprint for every environment model. There may be only one model at any one time, or there may be a number. Where the latter, the system may assign a weighting to each model to indicate its confidence value. For example if models are being maintained for
a person moving through a building, the system may maintain a set of possible trajectories for the person. There might be a model for each trajectory, but a confidence weighting assigned according to the degree of confidence in the associated trajectory. In another example, the system is configured to maintain only one model at any time. This may correspond to only the trajectory for a single mobile node, and with the highest confidence value. The choice of number of models to maintain is dependent on the processing resources in the system and the extent of complexity of the environment, and the frequency with which it is changed.

[0072] The hardware of the system is an existing wireless communication network, and so no additional hardware is required where there is a wireless communication network such as a WiFi network in place.

[0073] Upon detection of a mobile node in the environment the system estimates position of the node according to the current fingerprint, and in real-time performs self-calibration of the environment model, in turn giving rise to fresh updated fingerprints for future tracking. This continuous self-calibration ensures excellent tracking accuracy even with modification of the environment, such as changing of access point configuration, moving a partition wall, or movement of a metal filing cabinet.

[0074] The major steps, 101-122, implemented by the systems are shown in FIG. 3. The following describes these steps in detail.

Step 101

[0075] Input to the system 1 is:

[0076] layout of main obstacles such as building floor plans or wall layout,

[0077] layout of location and tracking system fixed nodes,

[0078] initial (starting) position of mobile nodes (at the entrance to the building, for example).

[0079] FIG. 4 shows the example of a floor-plan with access points (“APs”) and wall layout used as an input to the self-calibration system 1.

Step 102

[0080] Corresponding parameters of all environment obstacles and therefore all segments are initially set to the same default value. Default values are any reasonable mean values of obstacle parameters as characterised by the channel parameters prediction model used in the next point. The absolute values are not as important as their uniformity throughout the environment in the initial stage. A sample screen for inputting these parameters is shown in FIG. 5.

Step 103

[0081] The walls and main obstacles are then divided by the processor into smaller segments. The parameters of smaller segments can be better optimised to more precisely represent the segment’s mean local influence on the signal attenuation than long walls. The segment’s parameters therefore characterise not only the parameters of walls or main obstacles they are part of, but reflect also the influence of smaller surrounding obstacles such as furniture in the proximity of wall and variation of the longitudinal wall characteristic caused by pipes and ducting within the wall etc., which can have significant influence on the signal attenuation. The size of the segments depends on the type of environment and varies between 2 to 10 meters. We found that the segment size between 2 and 4 meters is suitable for indoor and between 5 and 10 meters for outdoor.

[0082] Algorithm 1 shows the algorithm for segmenting walls. The input of the algorithm is segment size (l), and output of the algorithm is a set consisting of segmented wall.

<table>
<thead>
<tr>
<th>Algorithm 1: SegmentWall(l, W)</th>
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<tbody>
<tr>
<td>1: for each wall in the floor plan</td>
</tr>
<tr>
<td>2: d = length of wall</td>
</tr>
<tr>
<td>3: walls = div (d, l)</td>
</tr>
<tr>
<td>4: if walls quotient &gt; 1</td>
</tr>
<tr>
<td>5: w = segment the wall</td>
</tr>
<tr>
<td>6: W = W + w</td>
</tr>
<tr>
<td>7: else</td>
</tr>
<tr>
<td>8: w = the wall</td>
</tr>
<tr>
<td>9: W = W + w</td>
</tr>
<tr>
<td>10: end if</td>
</tr>
<tr>
<td>11: end for</td>
</tr>
<tr>
<td>12: return W</td>
</tr>
</tbody>
</table>

Step 104

[0083] FIG. 6 shows example of an environment with segmented walls.

Step 104

[0084] The possible trajectories of mobile nodes in the described environment are pre-processed to accelerate the creation of a subset of possible trajectories in step 110. The trajectories are built as a Voronoi diagram of the floor-plan, the graph edge representing all the most likely routes for mobile node movement. The density of the Voronoi diagram varies depending on the predefined requirements on the location accuracy.

[0085] Algorithm 2 below shows the steps for creation of possible trajectories. The input of the algorithm is a vertex v in the Voronoi graph G and the distance travelled d by a mobile device. The output of the algorithm is a set of vertices V, which is basically a set of way-points inside the trajectory.

<table>
<thead>
<tr>
<th>Algorithm 2: Traverse(v, V, d)</th>
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<tbody>
<tr>
<td>1: V = V + [v]</td>
</tr>
<tr>
<td>2: D = total length of edges in V</td>
</tr>
<tr>
<td>3: if D &lt; d then</td>
</tr>
<tr>
<td>4: for each vertex w adjacent to v do</td>
</tr>
<tr>
<td>5: Traverse( w, V, d)</td>
</tr>
<tr>
<td>6: end for</td>
</tr>
<tr>
<td>7: else</td>
</tr>
<tr>
<td>8: save V [V is a candidate of trajectory]</td>
</tr>
<tr>
<td>9: end if</td>
</tr>
</tbody>
</table>

Step 105

[0086] FIG. 7 shows a screenshot of the possible subset of motion trajectories in a floor-plan.

Step 105

[0087] Estimation of the expected channel parameters fingerprint in the area of interest taking into account the default parameters of obstacles by appropriate empirical or physical channel parameters prediction models.

[0088] In this implementation a simple empirical signal propagation model, called Multi-Wall-Model (MWM), is used for prediction of received signal strength (RSS) fingerprint. MWM is chosen because of its simplicity and efficient computation, but also for its suitability to the linear optimisation method used in this implementation. Both of these factors contribute to improving the speed of the overall self-calibration.
In the MWM, the path loss is given by the following equation:

\[ L = L_0 + 20\log(d) + \sum_{i=1}^{I} L_{w} + L_f \]  

(1)

Where:

- \( L_0 \) denotes the predicted signal loss,
- \( d \) is the free space loss at a distance of 1 meter from the transmitter,
- \( L_{w} \) denotes the contribution of \( i^{th} \) wall segment to the total signal loss,
- \( L_f \) is the contribution of floors to the total signal loss.

In this example, self-calibration is used for localisation on a single floor, where therefore signal-loss of floors \( L_f \) is not considered.

Algorithm 3 below shows the algorithm for signal level prediction with the multi-wall model. The input of the algorithm is position of an access point \( p \). The output is predicted signal level in the environment \( S \).

---

Algorithm 3: Prediction (\( p \))

1: \( P = -10 \, \text{dB} \)
2: \( S = 0 \)
3: for each grid \( g \) in the environment
4: \( d = \text{distance from } g \text{ to access point } p \)
5: \( L = \text{calculate with equation (1)} \)
6: \( s = P - L \)
7: \( S = S + s \)
8: end for
9: return \( S \)

Step 106

**[0109]** Start of the main loop of an iterative fingerprint self-calibration algorithm by the engine 4.

Step 107

**[0100]** Mobile nodes, subject to their pinpointing by the location engine 3, gather the observed channel parameters along their motion trajectory, and send them to the survey tool 3. This interval of gathering of parameters can vary from a few seconds to many minutes based on contextual or other information. A sample screen is shown in FIG. 10. The plots at the bottom of this screen are signal strength from different transceivers as seen by the mobile node.

Step 108

**[0101]** The gathered channel parameters could be optionally used by the location engine 3 to estimate motion behaviour of the mobile nodes such as speed and direction.

**[0102]** The motion behaviour estimation can be further improved by additional sensors, especially inertial sensors such as accelerometers, gyroscopes and magnetometers built-in the mobile node. The suitable methods used for estimating the mobile node speed and directions based on measurement of the inertial sensors are called "Dead Reckoning" methods.

Step 109

**[0103]** This is the start of a loop through all participating mobile nodes, \( M \), by the engine 4.

Step 110

**[0104]** Based on the length of the time interval of gathering of channel parameters (also an option on estimated mobile node motion behaviour) and the layout of obstacles in the environment, possible \( H_m \) motion trajectories (hypothesis) of the \( m^{th} \) mobile node are proposed.

**[0105]** FIG. 11 shows an example of proposed trajectories when a mobile node is at the Starting point A.

Step 111

**[0106]** This is start of an inner loop for evaluating the likelihood (ranking) of all proposed trajectories (hypothesis), \( H_m \).

Step 112

**[0107]** This includes simulation of the \( m^{th} \) mobile node motion along the \( h^{th} \) trajectory and creation of the corresponding fitness function. The fitness function describes how similar the channel parameters estimated along the \( h^{th} \) trajectory by the prediction model, which uses current obstacle parameters, is to the gathered channel parameters by a mobile node along its truth trajectory. The fitness function can take the form of a set of linear equations suited to the optimisation method used in the following step.

**[0108]** In this implementation the localisation is performed on a single floor. Therefore the fitness function for the optimisation of a wall segment parameter considering MWM (1) is written as follows:

\[ L = L_0 + 20 \log(d) + L_w = P^0 - z^0 = L_0 + 20 \log(d) + L_w \]

\[ \Delta L_m = P^0 - z^0 = L_1 - 20 \log(d) - L_w \]  

(2)

Where:

- \( L_w \) denotes the difference of wall segment loss,
- \( P^0 \) denotes the power transmitted from access point \( k \), (it is known or can be estimated as additional unknown similarly to by the described optimisation method as if it was an additional wall around the transmitter)
- \( z^0 \) represents the RSS measurement gathered by the mobile device from access point \( k \)
- \( t \) denotes time or index of process iteration
- \( L_w \) represents an/wall segment loss and
- \( \Delta L_w \) denotes the difference of an \( i^{th} \) wall segment loss.

[0116] Linear equations (2) are then created for every measurement point along the simulated \( h^{th} \) trajectory. A created set of the linear equations represents all wall segments which have influence on the signal strength along the trajectory.
Since the number of measurements is usually greater than the number of wall segments, the resulting set of linear equations form an over-determined system. This means that the number of equations is greater than the unknowns (i.e., $\Delta Lw$). A fast and robust algorithm to solve an over-determined linear system is the least-squares method.

Considering this over determined system where $m$ represents the number of linear equations and $n$ is the number of unknown coefficients with $m \geq n$. Recalling the fitness function in equation (2), $\beta$ is the $\Delta Lw$, and $y_i$ represents the right hand side of the equation.

[0117] The linear system is written:

$$\sum_{j=1}^{n} x_j \beta_j = y_i (i = 1, 2 \ldots m)$$

and the final fitness function in the matrix form suitable for example to the least-squares method:

$$X \beta = y$$

Where:

$$X = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \ldots & x_{nn} \end{bmatrix}, \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \beta = \begin{bmatrix} \Delta Lw_1^i \\ \Delta Lw_2^i \\ \vdots \\ \Delta Lw_n^i \end{bmatrix}$$

and

$$y = \begin{bmatrix} p_1 - c_i^1 - L_i - 20 \log d_i^{(1)} - Lw_i^1 \\ p_2 - c_i^2 - L_i - 20 \log d_i^{(2)} - Lw_i^2 \\ \vdots \\ p_n - c_i^n - L_i - 20 \log d_i^{(n)} - Lw_i^n \end{bmatrix}$$

Step 113

[0120] This step involves application of a formal optimisation method (such as the least square, agent-based, or stochastic search methods) to find optimal parameters of obstacles which maximise the similarity of the predicted channel parameters and gathered channel parameters along the $h^{th}$ trajectory.

[0121] In this implementation the least-squares method is used to solve the matrix (3), where the solution is given by:

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

Step 114

[0122] This is adjustment of the current parameters of obstacles towards the optimised parameters of obstacles which influence the channel parameters along the $h^{th}$ trajectory.

[0123] The adjustment is given by:

$$Lw_i^t = Lw_i^{t-1} + \Delta Lw_i^t$$

where:

[0124] $Lw_i^t$, ... represents $i^{th}$ wall segment loss at time (index of iteration) $t$.

[0125] $Lw_i^{t-1}$, ... represents $i^{th}$ wall segment loss at iteration $t-1$.

[0126] $\Delta Lw_i^t$, denotes the delta of a wall segment loss at time $t$.

Step 115

[0127] This step involves prediction (re-calculation) of the channel parameters fingerprint in the area of interest with a prediction model having adjusted parameters of obstacles.

Step 116

[0128] This step involves location error estimation, which takes into account the re-calculated fingerprint and gathered channel parameters and the $h^{th}$ trajectory as a ground truth.

[0129] FIG. 13 shows an illustration of the localization error.

[0130] In this implementation the Particle Filter algorithm (Algorithm 4) is used to estimate the location error, as follows.

```
Algorithm 4: Particle Filter ($\times_{t-1}$)

1: $\bar{X}_0 = X_0$
2: for $i = 1$ to $N$ do
3: sample $x_i' \sim p(x_i'|\times_{t-1})$
4: assign particle weight $w_i^t = p(z_i'|x_i')$
5: end for
6: calculate total weight $k = \sum_{i=1}^{N} w_i^t$
7: for $i = 1$ to $N$ do
8: normalise $w_i^t = k^{-1} w_i^t$
9: $\bar{X}_t = \bar{X}_t + \{x_i', w_i^t\}$
10: end for
11: $\times_t = \text{Resample} (\bar{X}_t)$
12: return $\times_t$
```

where:

[0131] $\times_{t-1}$ is the set of particles,

[0132] $N$ is the number of particles,

[0133] $x_i'$ is a particle state including particle location,

[0134] $w_i$ is a particle weight,

[0135] $p(x_i'|x_i')$ is transition distribution and

[0136] $p(z|x')$ is measurement distribution.

[0137] Implementation of step 116 is described in more detail in a separate section below.

Step 117

[0138] The actual ranking (the likelihood estimation) of the $h^{th}$ trajectory is calculated taking primarily into account the localisation error and also other contextual information such as the motion behaviour pattern of the mobile nodes in the area of interest.

[0139] In the presented implementation the $h^{th}$ trajectory likelihood is calculated as a probability govern by Gaussian distribution with the mean localisation error of 0 meters and standard deviation of 3 m by the following expression:

$$e^h = \frac{1}{\sqrt{2\pi}} \exp \left( \frac{-c_i^2}{2\sigma^2} \right)$$

where:

[0140] $\omega^h$ denotes trajectory likelihood,

[0141] $\sigma$ represents the standard deviation of the Gaussian distribution.

[0142] $c_i$ represents the localisation error and
Localisation error in (5) is calculated as the mean Euclidian distance between the mobile node locations estimated by a formal localisation algorithm such as the particle filter and the ground truth positions along the hth trajectory

\[ e = \frac{1}{N} \sum_{i=1}^{N} ||x_{GT} - x_i|| \]  

where:
- N. . . is the number of the measurement along the hth trajectory,
- \( x_{GT} \) . . . are the ground truth positions and
- \( x_i \) . . . are the positions estimated by a formal localisation algorithm.

Step 118

The end of the trajectories (hypothesis) likelihood evaluation loop.

Step 119

Selection of a limited number of the most likely trajectories (hypothesis) for the hth mobile node. The other trajectories are terminated.

FIG. 14 shows an example of the evolution of the self-calibration process as a hypothesis tree for a mobile node where individual branches represent its possible trajectories, which are maintained or terminated depending on their estimated likelihood. The most likely trajectory is the trunk of the tree.

The system configuration in this implementation sets the threshold for the trajectories termination to 0.05. The threshold value impacts the number of maintained hypotheses, therefore, the computational requirements of the self-calibration system.

Step 120

This is the end of the mobile node multi-hypothesis trajectory evaluation. At the end of this loop every participating mobile node has an associated set of most likely hypotheses of trajectories.

Step 121

The process of ranking combined hypothesis follows the same steps as the ranking of the individual node trajectories from points 9 to 16, however, the optimisation of parameters of obstacles can be simplified by averaging, for example.

Step 122

This is selection of a limited number of the most likely combined-trajectories, \( H^- \). The other trajectories (hypotheses) are discontinued.

FIG. 15 shows a final predicted fingerprint based on the calibrated wall segment parameters. The scale represents level of predicted channel parameter such as signal strength in regular grid.

Particle Filter Algorithm: Step 116

The particle filter is a non-parametric implementation of the Bayes' filter. It approximates the posterior probability by a finite number of discrete samples with associated weights, called particles. The approximation of the posterior density is non-parametric. Therefore, it can represent a wider distribution than the parametric one, such as Gaussian. The particles are mapped to the physical environment model, and so the processor can generate visualisation user displays of the environment with the particle distribution illustrated.

The particle filter directly estimates the posterior probability of the state expressed in the following equation:

\[ p(x_t|z_t) = \sum_{i=1}^{N} w_i p(x_t \mid x_{t-1}^i) \]  

where:
- \( x_t \) . . . is the tth sampling point or particle of the posterior probability with \( 1 \leq i \leq N \),
- \( w_i \) . . . is the weight of the particle and
- \( N . . . \) represents the number of particles in the particle set, denoted by \( X_t \).

Each particle is a concrete instantiation of the state at time t, or put differently, each particle is a hypothesis of what the true state might be, with a probability given by its weight.

The property of equation (exp. 7) holds for \( N \uparrow \infty \). In the case of finite \( N \), the particles are sampled from a slightly different distribution. However, the difference is negligible as long as the number of particles is not too small.

```
Algorithm 3.2 Particle_Filter(X_n-1, z_n)
1: \( \bar{X}_n = X_n = 0 \)
2: for i = 1 to N do
3:   sample \( x_{t,i} \sim p(x_t|X_{t-1,i}) \)
4:   assign particle weight \( w_{t,i} = p(z_t|x_{t,i}) \)
5: end for
6: calculate total weight \( k = \sum_{i=1}^{N} w_{t,i} \)
7: for i = 1 to N do
8:   normalise \( w_{t,i} = k^{-1} w_{t,i} \)
9:   \( \bar{X}_n = \bar{X}_n + (x_{t,i} \cdot w_{t,i}) \)
10: end for
11: \( \bar{X}_n \) \( \Rightarrow \) Resample \( (X_t) \)
12: return \( X_n \)
```

The algorithm 3.2 above describes a generic particle filter algorithm. The input of the algorithm is the previous set of the particle \( X_{n-1} \), and the current measurement \( z_n \), whereas the output is the recent particle set \( X_n \). The algorithm will process every particle \( x_{n,i} \) from the input particle set \( X_{n-1} \) as follows.

Line 3 shows the prediction stage of the filter. The particle \( x_{t,i} \) is sampled from the transition distribution \( p(x_t|X_{t-1}) \). The set of particles resulting from this step has a distribution according to (denoted by \( \sim \)) the prior probability \( p(x_t|z_{n-1}) \). Line 4 describes incorporation of the measurement \( z_n \) into the particle. It calculates for each particle \( x_t \) the importance factor or weight \( w_{t,i} \). The weight is the probability of particle \( x_t \) received measurement \( z_n \) or \( p(z_n|x_t) \). Lines 7 to 10 are steps required to normalise the weight of the particles. The result is the set of particles \( X_n \) which is an approximation of posterior distribution \( p(x_t|z_n) \). Line 11 describes the step which is known as re-sampling or importance re-sampling. After the re-sampling step, the particle set, which was previously dis-
distributed in a manner equivalent to prior distribution \( p(x|z_{t-1}) \) will now be changed to particle set \( X_t \) which is distributed in proportion to \( p(x|z_t) \).

Re-Sampling

The early implementation of particle filter is called sequential important sampling (SIS). Implementation of SIS is similar to algorithm 3.2 above, but without the resample step (algorithm 3.2 line 11). The SIS approach suffers an effect which is called the degeneracy problem. This occurs when, after some sequence time \( t \), all but one particle has nearly zero weight. The problem happen since generally impossible to sample directly from posterior distribution, particles are sampled from related distribution, termed importance sampling. The choice of importance sampling made the degeneracy problem is unavoidable. The degeneracy problem will increase the weight variance over time and has a harmful effect on accuracy.

Re-sampling is an important step to overcome the degeneracy problem. It will force the particle to distribute according to the posterior density \( p(x|z_t) \).

Algorithm 3.3 Resample (\( X_t \))

1: \( X_t^* = 0 \)
2: for \( j = 1 \) to \( N \) do
3: \( r = \) random number uniformly distributed on \([0,1]\)
4: \( s = 0.0 \)
5: for \( i = 1 \) to \( N \) do
6: \( s = s + w_i^j \)
7: if \( s \geq r \) then
8: \( x_i^* = x_i^j \)
9: \( w_i^* = 1/N \)
10: \( X_t^* = X_t^* + [x_i^*, w_i^*] \)
11: end if
12: end for
13: end for
14: replacement \( X_t = X_t^* \)
15: return \( X_t \)

Algorithm 3.3 above describes a re-sampling step of particles. The modification lies in the iteration to draw newly sampled particles. The input of the algorithm is a set of particles and the output is the new resampled particles.

Line 3 shows the generation of random number \( r \). Lines 5 to 8 show the re-sampling steps. Line 8 shows when a particle is re-sampled only if its weight contribution causes the summation in line 6 to exceed or equal to the random sample \( r \). The probability of drawing a particle is in proportion to its importance factor. Particles with lower weight will have a lower chance and some will not be resampled. Since the re-sampling process is performed every time step, the new particles do not need to know the old weight and their weight will be set equally, as shown in line 9. Line 14 shows when members of particle set \( t \) is replaced by new resampled particles.

The particle filter, which is a non-parametric implementation of Bayes' filter, is well suited for state estimation in opportunistic system for a number of reasons. It is suitable for state estimation for a system that has large process noise in state dynamics, and it provides a good processor performance.

To implement a particle filter for opportunistic indoor localisation, motion and measurement probabilistic models have been devised, described below.

Motion Model

This implements a particle filter for and opportunistic system. It is a representation of the target's kinematics behaviour. It is used to construct the transition probability \( p(x|z_{t-1}) \) which has an important role for the prediction step in the particle filter. The first-order of person kinematics is less conservative than Brownian movement, in a way that the motion is not totally random as in Brownian movement. Therefore it is often more accurate. It assumes that the target direction is the same as the last observing movement. However, this assumption does not hold when people turn direction in a corner, enter a room, or avoid obstacles. This kind of action therefore is difficult to represent. Our approach for the motion model in indoor localisation is taken from both Brownian movement and a first-order motion model. The motion model assumes that the kinematics of a target has random values in it. However, this randomness is constrained by the previous state. This approach accurately reflects the target's kinematics behaviour (i.e.: a person) in opportunistic system. Especially, in a system that only uses RSS measurement, without additional motion sensor.

Velocity

To accommodate simple human locomotion patterns (such as remaining stationary, walking and running) and its limitations, the target velocity is constrained to take place only between limited ranges of speed. The succeeding velocity also takes into account the preceding one, since it is assumed that people tend not to change their kinematics abruptly in a normal condition. Based on observation of peoples' movement in the standard environment, the target velocity is given by the following rule:

\[
\begin{align*}
& v_i = \mathcal{N}(v_{i-1}, \sigma_v) \quad \text{and} \\
& v_i = \begin{cases} 
  v_i, & 0 \leq v_i \leq \text{Max}_v \\
  |v_i|, & v_i < 0 \\
  2\text{Max}_v - v_i, & \text{Max}_v < v_i
\end{cases}
\end{align*}
\]

with

\[
\alpha_v = \min(\text{Max}_v, \sqrt{\Delta t})
\]

where:

\( \text{Max}_v \ldots \) represents a Gaussian random number generator,

\( \text{Max}_v \ldots \) represents the maximum speed,

\( \min(\ldots) \) is a function which returns the smallest component,

\( \Delta t \ldots \) represents elapsed time,

\( \text{Max}_v \ldots \) represents the maximum threshold of the \( \Delta t \).

The value of \( \text{Max}_v \) is set to the fastest recorded human speed (~10 m/s) and \( \text{Max}_v \ldots 3 \) s. Fig. 16 shows an example of the velocity probability distribution function (PDF) when \( v_{i-1} = 0 \) m/s with various \( \Delta t \).

Direction

The succeeding direction also considers that preceding it. A velocity parameter is also included in the direction calculation. The motivation is to limit heading variation based on preceding speed, since people tend to slow down when they want to change their direction of movement. The target direction is given by the following rule:

[References]
\[ a_t = \mathcal{N}(\omega_{t-1}, \sigma_b) \quad \text{and} \quad a_t = \begin{cases} a_t & \omega_{t-1} \leq a_t \leq \pi \\ a_t + 2\pi & a_t < -\pi \\ a_t - 2\pi & a_t > \pi \end{cases} \]

where \( \sigma_b \) represents direction at time \( t \), \( \sigma_h \) the direction standard deviation.

\[ \sigma_h = 0.4\pi - \arcsin\left(\frac{\sqrt{\alpha_t}}{2}\right) \]

where \( \alpha_t \) represents direction at time \( t \), \( \sigma_h \) represents the direction standard deviation.

**FIG. 17** shows the \( \sigma_h \) for different velocities. FIG. 18 presents PDF of the direction based on different velocities with \( \omega_{t-1} = \). It can be seen that the heading variation is narrower when the velocity is increased.

**Particle Motion Model**

**[0180]** Each particle, which is a hypothesis of the target state in the real world, will have a kinematic characteristic according to the motion model during the prediction stage. The particle state can be modelled with:

\[ x'_t = \begin{bmatrix} x'_t \\ y'_t \\ v'_x \\ v'_y \\ \theta'_t \end{bmatrix} = \begin{bmatrix} \frac{1}{2}v_x \cos(\theta) \Delta t + n_x \\ \frac{1}{2}v_y \sin(\theta) \Delta t + n_y \\ v_x + \Delta t \Delta v_x \\ v_y + \Delta t \Delta v_y \end{bmatrix} \]

where:

**[0181]** \( \nu_x, \nu_y \ldots \) denotes velocity.

**[0182]** \( \omega_x, \omega_y \ldots \) describes particle direction at the time \( t \).

**[0183]** \( n_x, n_y \ldots \) is a noise with Gaussian distribution.

**[0184]** The particles’ velocity is governed by equation (9), whereas particles’ direction is given by equation (11). The noise \( n_t \) is added to achieve a better direction distribution by preventing particles from collapsing into a single point. A noise value of 0.5 m is used for this work.

**[0185]** FIG. 19 illustrates the evolution of particle distribution determined only by the motion model. The particle distribution is started from a known state in 2D space. The initial velocity \( v_n = 3 \) m/s and number of particles are 2000. Since there is no RSS measurement update performed, the distribution spreads wider over time.

**[0186]** The aforementioned particle distribution, which was constructed with the motion model, is a representation of transition probability. This density needs to be updated with the measurement probability \( p(z_t | x_t) \) to obtain the posterior distribution. The construction of measurement probability with the measurement model in an opportunistic system is explained in the next section.

**Measurement Model**

**[0187]** The measurement model describes a construction process by which the sensor measurement is generated. This model is utilised to obtain the measurement probability of \( p(z_t | x_t) \), often referred to as the likelihood observation function. In the particle filter, this function is used to incorporate a measurement update into the particle weight \( w'_t \).

**[0188]** There is a measurement model which considers the physical characteristics of signal propagation in indoor environments based on the fingerprinting method.

**[0189]** A fingerprint is a database of stored RSS measurements throughout the coverage area of all discrete possible states. These discrete states are often referred to as a grid. The fingerprint acts as the “true” RSS values obtained by the sensor, denoted by \( z^*_t \), at the state \( x_t \). Theoretically, smaller grid size gives better localization accuracy since the measurement model will be more distinct between grids. However, it is technology dependent. Based on the observations, WLAN RSS values are discernible when they are measured in a grid \( \pm 1 \) m, for example.

**[0190]** To obtain the likelihood observation function, statistical inference is performed between a true value stored in the fingerprint and recent RSS measurement (termed as signature).

**[0191]** The mobile device is able to simultaneously retrieve RSS measurements from different APs, therefore \( z_t \) is a set of measurements which is described as:

\[ z_t = [z_1, z_2, \ldots, z^*_t] \]

where:

**[0192]** \( z_1, \ldots \) denotes RSS value \( z_t \) at time \( t \) from AP with identification \( k \) (MAC address is used for WLAN AP).

**[0193]** The probability \( p(z_t | x_t) \) is obtained as the product of the individual likelihood observation function.

\[ p(z_t | x_t) = \prod_{k \in G} p(z_{x_k} | x_t) \]

**Algorithm for the Measurement Model**

**[0194]** The measurement model comprises three types of probability densities, each of which corresponds to a type of dissimilarity:

**[0195]** 1. Measurement with noise. Assuming that the sensor can capture the true RSS measurement, the returned value is still subject to error caused by shadowing (or slow fading) and multipath fading. This fading, which appears as a time-varying process, makes the RSS value fluctuate even when it is measured at the same position.

**[0196]** Since the sensor (i.e., WLAN interface) has an internal mechanism to suppress multipath fading, the received error is largely caused by shadowing which has a Gaussian distribution. Therefore, the noisy measurement may be modelled within a Gaussian distribution with mean value of \( z^*_t \) and standard deviation of \( \sigma^* \). The Gaussian is denoted by \( p_{\text{Gauss}} \) as described in FIG. 20.

**[0197]** The value of \( z^*_t \) is given by the RSS measurement stored in the corresponding grid of the fingerprint. The measurement probability is governed by

\[ p_o(x_t | x_k) = \mathcal{N}(z^*_t; \sigma^*_t; \sigma_x) \]

where \( \sigma_x \) is the RSS value stored in the fingerprint and \( \sigma^*_t \) is the recent signature such that \( \{k \in G \cap \sigma^*_t\} \) or, to put it differently, the RSS value from an AP which appears in both signature and fingerprint. Notation \( \sigma^* \) is the intrinsic noise parameter for the measurement model.

**[0198]** 2. Missing RSS. Considering that it may be the case that not all of the RSS values that appear in the fingerprint grid and signature coming from the same APs, a question arises as to how to account for such data. This condition can happen when the signature is taken at a different location or
there is an extra/missing AP. In the case of no extra/missing AP, a different set of RSS values in the fingerprint grid and signature means that they are taken at different locations. Incorporating this information into the measurement model will eventually lead to better localisation accuracy.

[0199] In the case of RSS measurements from an AP which is missing in the signature but which is present in the fingerprint, the measurement probability is modelled by a Gaussian denoted by \( p_{\text{miss}} \). The measurement probability is governed by:

\[
p_{\text{miss}}(z^* | x) = N(\mu; 0, \sigma, \nu)
= \frac{1}{\sigma \sqrt{2\pi}} \exp\left( -\frac{(z^* - \mu)^2}{2\sigma^2} \right) \tag{18}, \tag{19}
\]

where \( \eta \) is the penalty parameter given for the missing RSS. The density \( p_{\text{miss}} \) is calculated for missing \( z^* \), such that \( \{ z^* < x \} \).

[0200] 3. Extra RSS. In the case where there is an extra RSS value of an AP which exists in the signature but which is absent in the fingerprint, the measurement probability is also modelled by a Gaussian denoted by \( p_{\text{extra}} \) and governed by:

\[
p_{\text{extra}}(z^* | x) = N(\mu; 0, \sigma, \nu)
= \frac{1}{\sigma \sqrt{2\pi}} \exp\left( -\frac{(z^* - \mu)^2}{2\sigma^2} \right) \tag{20}, \tag{21}
\]

where \( \eta \) is the penalty parameter given for the extra RSS. The density \( p_{\text{extra}} \) is calculated for extra \( z^* \), such that \( \{ z^* > x \} \).

[0201] These three densities are combined to obtain the likelihood observation function of RSS measurement \( p(z | x) \). The likelihood observation function is given by:

\[
p(z | x) = \frac{1}{\prod_{i=1}^{[K]} p_{\text{miss}}(z^*_i | x_i) \prod_{i=1}^{[L]} p_{\text{miss}}(z^*_i | x_i) \prod_{i=1}^{[M]} p_{\text{extra}}(z^*_i | x_i)}
\]

where:

- \( K \) is the set of measurement in \( (z^*_k < x) \),
- \( L \) is the set of measurement in \( (z^*_l = x) \),
- \( M \) is the set of measurement in \( (z^*_m > x) \),
- \( \beta \) represents the weighting factor and
- \( \beta \) is the set of AP identification.

[0202] Algorithm 3.4 describes the steps necessary to obtain the likelihood observation function. The input of the algorithm is the measurement \( z \) and the state \( x \). The output is the likelihood observation function of \( p(z | x) \).

---

**Algorithm 3.4 Measurement Model \( p(z | x) \)**

1. \( p = 1 \)
2. \( q = 1 \)
3. \( y = 1 \)
4. \( S = 0 \)
5. get \( z^*_p \) from the fingerprint
6. for \( k = 1 \) to \( m \)
7. \( p = p \cdot p_{\text{miss}}(z^*_i | x) \)
8. end for
9. \( p = p^{1/20} \)
10. for \( k = 1 \) to \( l \)
11. \( q = q \cdot p_{\text{miss}}(z^*_i | x) \)
12. end for
13. for \( k = 1 \) to \( m \)
14. \( q = q \cdot p_{\text{extra}}(z^*_i | x) \)
15. end for
16. \( S = |K| + |L| + |M| \)
17. \( y = p_q S \)
18. return \( y \)

[0209] The intrinsic noise parameter for the measurement model \( \eta \) is set to 4 dBm which was observed as a appropriate value for common indoor environments.

[0210] The value of the penalty \( \eta \) in equation (19) of \( p_{\text{miss}} \) and (21) of \( p_{\text{extra}} \) is governed by the following expression

\[
\eta = \begin{cases} 
(5/30)(z_e + 100), & z_e \leq -70 \\
(15/25)(z_e + 70) + 5, & -70 < z_e < -45 \\
20, & z_e > -45 
\end{cases}
\tag{23}
\]

[0211] The aforementioned equation is formulated to mimic the tail part of a Gaussian distribution. The RSS range is taken from maximum and minimum RSS values measurable from a WLAN interface (-100 dBm and -45 dBm). Maximum penalty is given by the maximum signal loss caused by people shadowing (20 dBm). Linear interpolation is used to obtain penalty \( \eta \) values.

[0212] The result is that the value of \( \eta \) is in proportion to the RSS value missing in the fingerprint \( z^*_p \), or extra in \( z_e \). Greater missing/extra RSS values, will have a proportionately higher penalty \( \eta \) (FIG. 21).

[0213] The value of intrinsic parameters of standard deviation \( \sigma \) and penalty \( \eta \) can be applied to environment similar with office setting (characterised by many walls, corridors and rooms), such as hospital, campus or apartment.

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**Examples**

[0214] FIG. 22 is used to illustrate how to obtain the likelihood observation function of a particle \( p(z | x) \). It shows a fingerprint from 3 APs, a target and a particle.

[0215] Supposing that the target measured RSS value \( z = \{ AP1 = 70 \text{ dBm}, AP2 = 70 \text{ dBm}, AP3 = 75 \text{ dBm} \} \). The corresponding fingerprint grid where the particle \( x \) is located, has value of \( z^*_p = \{ AP3 = 65 \text{ dBm} \} \). If the value of both \( \sigma \) and \( \eta \) are set to 4 dBm, the \( p(z | x) \) can be calculated as follows:

\[
p(z | x) = \frac{1}{\prod_{i=1}^{[K]} p_{\text{miss}}(z^*_i | x_i) \prod_{i=1}^{[L]} p_{\text{miss}}(z^*_i | x_i) \prod_{i=1}^{[M]} p_{\text{extra}}(z^*_i | x_i)}
\]

[0216] Calculating \( p_{\text{miss}} \) from AP3 with equation (19):
-continued

\[
\frac{1}{\sqrt{2\pi}} \exp \left(-\frac{(7.5 - (-6.5))^2}{2.2^2}\right) = 0.0044
\]

[0217] Calculating \( P_{\text{extra}} \) from AP1 and AP2 with equation (21): \[ P_{\text{extra}}(c_0 | n_1^e) \cdot P_{\text{extra}}(c_0^e | n_1^e) = \left( \frac{1}{\sqrt{2\pi}} \exp \left(-\frac{y^2}{2\sigma^2}\right) \right)^2 \] \[ = \left( \frac{1}{4\sqrt{2\pi}} \exp \left(-\frac{1.4^2}{2.2^2}\right) \right)^2 \] \[ = 0.0037 \]

[0218] Calculating \( p(x_t | X_t^e) \) with equation (22): \[ p(x_t | X_t^e) = \frac{0.0044 - 0.0037}{1 + 2} = 0.000054 \]

Measurement Model & Particles Distribution

[0219] The likelihood observation function update to the particle distribution is illustrated in FIG. 23. FIG. 23(a) shows three access points and its RSS measurement throughout the coverage area which is used as the fingerprint. In the initial time, the particles will be uniformly distributed as shown in FIG. 23(b). Once measurement \( z_t \) is obtained, the likelihood observation function or measurement probability is calculated based on equation (22). The result is illustrated in FIG. 23(c). Higher likelihoods are shown with bigger blue circles. Furthermore, the particles' weight is updated with the likelihood observation function and subsequently is resampled. The new particle distribution and estimated target location are shown in FIG. 23(d).

Estimation of Target State

[0220] Once the posterior probability is obtained, the state is estimated using a particle set \( X_n \) which is distributed in proportion to \( p(x_t | z_t) \), \( X_t \) is a return value of algorithm 3.2 of particle filter. Algorithm 3.5 below describes steps to estimate this state.

<table>
<thead>
<tr>
<th>Algorithm 3.5 State estimation(Xn)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: ( \hat{x}_i = 0 )</td>
</tr>
<tr>
<td>2: for i = 1 to (</td>
</tr>
<tr>
<td>3: ( \hat{x}_i = \hat{x}_i + x_i \cdot w_i )</td>
</tr>
<tr>
<td>4: end for</td>
</tr>
<tr>
<td>5: return ( \hat{x}_i )</td>
</tr>
</tbody>
</table>

[0221] It will be appreciated that the invention enables an automatic generation and update of the channel parameters fingerprint, merely initially requiring knowledge of layout of dominant obstacles and system infrastructure in the environment (the floor plan and system fixed node positions, for example). This is not onerous. It will also be appreciated that the invention avoids need for dedicated hardware, as it can use the hardware of an existing wireless network such as a WiFi network.

[0222] The invention is not limited to the embodiments described but may be varied in construction and detail. For example, it may be applied to outdoor location and tracking systems in particular areas. Also, the initial physical environmental model may be received in the initial inputs rather than being generated by the system.

1-23. (canceled)

24. A location and tracking system comprising wireless base stations, an input interface, and a processor, wherein the processor is adapted to
(a) receive physical environment inputs and providing an initial physical environment model;
(b) generate an initial channel parameters fingerprint for the environment according to the initial environment model wherein the fingerprint is generated by estimation in area of interest of the environment model using a physical channel parameters prediction model;
(c) monitor channel parameters of a mobile node in the environment and use said parameters and the fingerprint to locate the mobile node;
(d) modify the environment model according to said node locating step (c);
(e) update the fingerprint according to the modification of the environment model in step (d); and
(f) repeat steps (c) to (e) in subsequent iterations, wherein the processor is adapted to determine in step (e) possible mobile node trajectories, and to use said trajectories for environment model modification in step (d) and subsequent fingerprint updating in step (e), and wherein the processor is adapted to dynamically maintain a multi-hypothesis decision tree in step (c) in which it iteratively evolves branches representing the most likely mobile node trajectories.

25. The location and tracking system as claimed in claim 24, wherein the location engine is adapted to execute a filtering algorithm to estimate location in step (c).

26. The location and tracking system as claimed in claim 24, wherein the processor is adapted to use mobile node speed estimation for steps (c) and (d).

27. The location and tracking system as claimed in claim 24, wherein the processor is adapted to modify wall segment parameters of the environment model in step (d).

28. The location and tracking system as claimed in claim 24, wherein in step (a) the inputs include:
layout of main obstacles including building floor plans and wall layout;
layout of base stations; and
starting position of a mobile node.

29. The location and tracking system as claimed in claim 24, wherein parameters of environment obstacles are initially set to a common default value.

30. The location and tracking system as claimed in claim 24, wherein parameters of environment obstacles are initially set to a common default value, and wherein for the step (a) the processor is adapted to divide the obstacles into smaller segments and to optimise parameters of the smaller segments to more precisely represent each segment’s mean local influence on signal attenuation.

31. The location and tracking system as claimed in claim 24, wherein parameters of environment obstacles are initially set to a common default value, and wherein for the step (a) the processor is adapted to divide the obstacles into smaller seg-
ments and to optimise parameters of the smaller segments to more precisely represent each segment's mean local influence on signal attenuation, and wherein the processor is adapted to apply parameters to the segments so that they characterise the obstacles they are part of and also the influence of smaller obstacles including furniture in proximity to large obstacles.

32. The location and tracking system as claimed in claim 24, wherein for step (c) the processor is adapted to use an empirical signal propagation model with a linear optimisation method for prediction of received signal strength.

33. The location and tracking system as claimed in claim 24, wherein the processor is adapted to perform, for steps (c) and (d), simulation of an m<sup>th</sup> mobile node motion along a h<sup>th</sup> trajectory and creation of a corresponding fitness function.

34. The location and tracking system as claimed in claim 24, wherein the processor is adapted to perform, for steps (c) and (d), simulation of an m<sup>th</sup> mobile node motion along a h<sup>th</sup> trajectory and creation of a corresponding fitness function; and wherein the fitness function describes how similar the channel parameters estimated along the h<sup>th</sup> trajectory by the prediction model, which uses current obstacles parameters, is to gathered channel parameters by a mobile node along its truth trajectory.

35. The location and tracking system as claimed in claim 24, wherein the processor is adapted to perform, for steps (c) and (d), simulation of an m<sup>th</sup> mobile node motion along a h<sup>th</sup> trajectory and creation of a corresponding fitness function; and wherein the fitness function describes how similar the channel parameters estimated along the h<sup>th</sup> trajectory by the prediction model, which uses current obstacles parameters, is to gathered channel parameters by a mobile node along its truth trajectory; and wherein the fitness function takes the form of a set of linear equations for an optimisation method.

36. The location and tracking system as claimed in claim 24, wherein the processor is adapted to execute a particle filter algorithm to locate a mobile node in step (c), in which particles are mapped to the physical environment as represented by the physical environment model.

37. The location and tracking system as claimed in claim 24, wherein the processor is adapted to execute a particle filter algorithm to locate a mobile node in step (c), in which particles are mapped to the physical environment as represented by the physical environment model; and wherein the processor is adapted to generate visual displays of the physical environment in which particles distribution is illustrated for user visualisation of likelihoods of locations of the mobile node.

38. The location and tracking system as claimed in claim 24, wherein the processor is adapted to execute a particle filter algorithm to locate a mobile node in step (c), in which particles are mapped to the physical environment as represented by the physical environment model; and wherein the processor is adapted to eliminate particles in successive iterations according to constraints imposed by the physical environment model and a motion model, in which remaining particles converge around the actual mobile node location.

39. The location and tracking system as claimed in claim 24, wherein the processor is adapted to execute a particle filter algorithm to locate a mobile node in step (c), in which particles are mapped to the physical environment as represented by the physical environment model; and wherein the processor is adapted to automatically recognise rooms in the physical environment model and to maintain a count of particles in each room to provide a per-room probability of presence of the mobile node.

40. The location and tracking system as claimed in claim 24, wherein the processor is adapted to execute a particle filter algorithm to locate a mobile node in step (c), in which particles are mapped to the physical environment as represented by the physical environment model; and wherein the processor is adapted to provide a random or uniform initial particle distribution mapped into the physical environment model, to filter the initial particle distribution with a likelihood observation function to generate a second particle distribution and to use said distribution for a next filtering iteration.

41. The location and tracking system as claimed in claim 24, wherein the processor is adapted to perform step (d) by adjusting the current parameters of obstacles towards the optimum parameters of obstacles which influence the channel parameters along the h<sup>th</sup> trajectory, in which the adjustment is given by:

\[ \Delta w_i = \frac{L_w}{L_{w,1}} \Delta w_{1,i} \]

where:

- \( L_w \) represents i<sup>th</sup> wall segment loss at time (index of iteration) t,
- \( L_{w,1} \) represents i<sup>th</sup> wall segment loss at iteration t−1, and
- \( \Delta w_{1,i} \) denotes the delta of a wall segment loss at time t.

42. A location and tracking method performed by a location and tracking system linked with wireless base stations, and having an input interface, and a processor, wherein the method comprises the steps of:

(a) receiving physical environment inputs and providing an initial physical environment model;
(b) generating an initial channel parameters fingerprint for the environment according to the initial environment model wherein the fingerprint is generated by estimation in area of interest of the environment model using a physical channel parameters prediction model;
(c) monitoring channel parameters of a mobile node in the environment and using said parameters and the fingerprint to locate the mobile node;
(d) modifying the environment model according to said node locating step (c);
(e) updating the fingerprint according to the modification of the environment model in step (d); and
(f) repeating steps (c) to (e) in subsequent iterations, and wherein in step (c) possible mobile node trajectories are determined and the trajectories are used for environment model modification in step (d) and subsequent fingerprint updating in step (e), and wherein the processor dynamically maintains a multi-hypothesis decision tree in step (c) in which it iteratively evolves branches representing the most likely mobile node trajectories.

43. The computer readable medium comprising software code adapted to perform operations of a location and tracking method of claim 42 when executing on a digital processor.