Manage the Data from Indoor Spaces: Models, Indexes & Query Processing

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Overview

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5. Appendix

About This Work...

Probabilistic Threshold k Nearest Neighbor Queries over Moving Objects in Symbolic Indoor Space. [3]
B. Yang, H. Lu, and C. S. Jensen.

- Published in year 2010 at the *EDBT* conference.
- **Minimal Indoor Walking Distance**(MIWD) along with algorithms and data structures are proposed for distance computing and storage.
- Effective object indexing structures, also capture the uncertainty of object locations.
- On this foundation, Probabilistic threshold kNN (PTkNN) query is studied.

Motivation

- Indoor positioning makes it possible to support interesting queries over large populations of moving objects.[4]
  - shopping mall, airports, office buildings
  - kNN queries over indoor moving objects enables the detection of approaching potential threats at sensitive locations in a subway system
- Existing kNN techniques in spatial and spatiotemporal databases are inapplicable in indoor spaces.
  - complex entities and topologies
  - indoor positioning techniques differ fundamentally from outdoor GPS, low sampling frequency and accuracy

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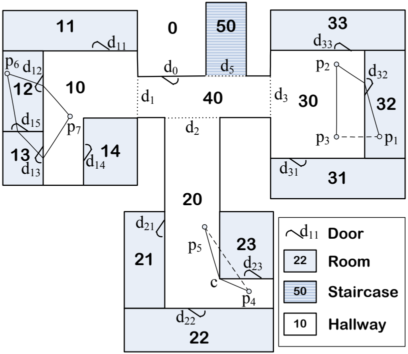
The mapping $Doors$ maps a room to the doors that connect the room to an adjacent room:

$$Doors : \Sigma_{rooms} \to 2^{\Sigma_{doors}} \tag{2}$$

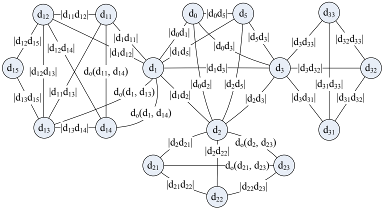
Minimal Indoor Walking Distance



- intra-room obstructed distance, termed as d_o. E.g., $d_o(p_2, p_3) = |p_2 p_3|$ and $d_o(p_4, p_5) = |p_4 c| + |c p_5|$.
- if in different rooms, it should take into account the doors connecting the rooms. E.g., $d_{MIN}(p_1, p_2) = |p_1 d_{32}| + |d_{17} p_9|$.
- if there exist several paths, the correct path should be the shortest one. E.g., $d_{MIN}(p_6, p_7) = |p_6 d_{12}| + |d_{12} p_7| \neq |p_6 d_{15}| + |d_{15} d_{13}| + |d_{13} p_7|$.

Minimal Indoor Walking Distance

Doors Graph is capable of retrieving the connecting doors between two rooms, which is convenient for computing MIWD.



Doors Graph

- $G_d = \{D, E, l_{weight}\}$
- $D = \Sigma_{doors}$ is the set of the vertices
- E: An edge $\{d_i, d_j\}$ exists if a room rm exists in Σ_{rooms} such that $\{d_i, d_j\} \subseteq Doors(rm)$
- $l_{weight} : E \rightarrow R$ assigns to an edge the obstructed distance between the two doors as $d_o(d_i, d_j)$

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$$d_{MIN}(d_p, d_q) = d_o(p, d_p) + \mathrm{D2D}(d_p, d_q) + d_o(d_q, q) \tag{4}$$

where $d_p(d_q)$ ranges over all doors of room $p(q)$.

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Algorithm 1 d_{MIW}(Position p, Position q)

if $Rooms(p)$=$Rooms(q)$ **then**
  $minDist \leftarrow d_o(p, q)$;
else
  $minDist \leftarrow +\infty$
for each door d_p in $Doors(Rooms(p))$ **do**
  for each door $d_q \neq d_p$ in $Doors(Rooms(q))$ **do**
    $l \leftarrow d_o(p, d_p) + d_o(d_q, q)$+ $D2D(d_p, d_q)$
    if $l < minDist$ **then**
      $minDist \leftarrow l$;
return $minDist$;

it is possible to adapt this notion of distance to accommodate other semantics. For example, a person might prefer a longer indoor path that passes as few doors as possible.

Symbolic Indoor Positioning

each device detects and reports the observed objects at a relatively high sampling rate.

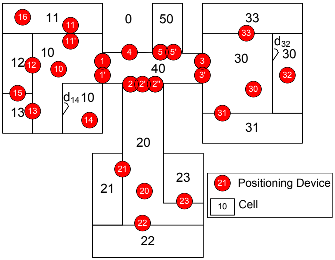
A reading $(deviceID, objectID, t)$ states that object $objectID$ is detected by device $objectID$ at time t.

Only its first and last appearances in a device's range are of interest.

- $flag = ENTER$ indicates that the object is entering the device's activation range
- $flag = LEAVE$ indicates that the object is leaving the device's activation range

Positioning Devices Deployment Graph [2]

- Two types of positioning devices
  - Partitioning Device – *undirected* (**UP**), e.g., d_{21} – *directed* (**DP**), e.g., d_{11} and $d_{11'}$
  - Presence Device – (**PR**)
- Note an indoor space is partitioned into *activation ranges* and *cells*



Deployment Graph

- $G = \{C, E, \Sigma_{devices}, l_E\}$
- C: the set of cells
- E: the set of edges, $\{c_i, c_j\}$ where $c_i, c_j \in C$
- $\Sigma_{devices}$: a mapping from $deviceID$ to activation range and type
- l_E maps an edge to a set of positioning devices, i.e., $E \rightarrow 2^{\Sigma_{devices}}$

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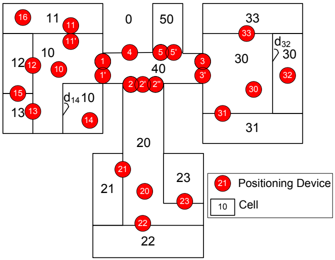

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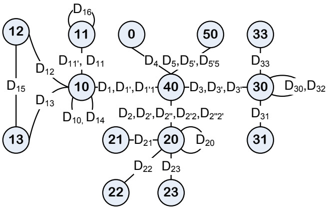
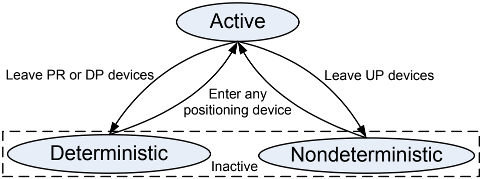


States of Indoor Moving Objects [2]



- An object is in an **active state** when it is inside the activation range of a positioning device.
- Otherwise the object is in an **inactive state**
- When an object is in the inactive state it is
  - **nondeterministic** if it can be in more than one cell
  - **deterministic** if it is in one specific cell

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$$OHT[objectID] = (STATE, t, IDSet);\ objectID \in O_{indoor}$$

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RFID Deployment Graph Construction [2]

Algorithm 1 **updateHashTables**(Pre-processing output O, DeploymentGraph G)

IDSet $sSet \leftarrow \emptyset$;
if $O.flag$ = $ENTER$ **then**
    $sSet \leftarrow OHT[O.objectID].IDSet$;
    if $OHT[O.objectID].STATE$ = $Active$ **then**
        for the single element c in $sSet$ **do**
            Delete $O.objectID$ from $DHT[c]$;
    else if $OHT[O.objectID].STATE$ = $Deterministic$ **then**
        for the single element c in $sSet$ **do**
            Delete $O.objectID$ from $CDHT[c]$;
    else
        for each element c in $sSet$ **do**
            Delete $O.objectID$ from $CNHT[c]$;
    Add $O.objectID$ to $DHT[O.deviceID]$;
    $OHT[O.objectID] \leftarrow (Active, O.t, \{O.deviceID\})$;
else
    Delete $O.objectID$ from $DHT[O.deviceID]$;
    $sSet \leftarrow G.\ell_E^{-1}(O.deviceID)$;
    if $Devices(O.deviceID).TYPE$ = UP **then**
        $OHT[O.objectID] \leftarrow (Nondeterministic, O.t, sSet)$;
        for each element c in $sSet$ **do**
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5. Lines 18–25: if the device is undirected, set O in OHT and add O to CNHT for the cells in sSet, else apply the same to CDHT

Deriving Uncertain Regions for Indoor Moving Objects

For outdoor moving objects [5], **Uncertainty Region**, denoted by $UR(o,t)$, is a region such that o must be in this region at time t.

In general terms, an object o_i's location can be modeled as a random variable with a probability density function $f_{o_i}(x,y,t)$ that has non-zero values only in o_i's uncertainty region $UR(o_i,t)$.

$$\int_{UR(o_i,t)} f_{o_i}(x,y,t)dxdy = 1 \quad (5)$$

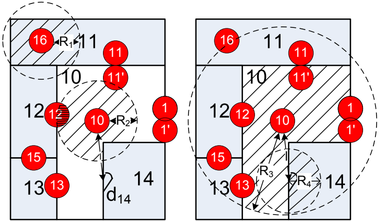
Deriving Uncertain Regions for Indoor Moving Objects

Assume that an *indoor object* has the same probability to be located anywhere inside its uncertainty region:

$$f_{o_i}(x, y, t) = \frac{1}{Area(UR(o_i, t))}, \quad (x, y) \in UR(o_i, t) \qquad (6)$$

- **Active object**: the activation range of the corresponding device.
- **Deterministic object**: the intersection between the object's cell and its *maximum-speed constrained circle*.
- **Nondeterministic object**: the union of the intersection between each cell and the circle.

Maximum-speed Constrained Circle



- assume o left $device_{16}$ at time t, intersection of maximum-speed constrained circle $C_{MSC}(o, device_{16}, t)$ and cell c_{11}.
- suppose o left $device_{10}$ at time t, UR is the intersection between room 10 and $C_{MSC}(o, device_{10}, t)$.

- as time t passes by, UR therefore contains two parts...
- uncertainty region of an active object can be refined as the intersection of the activation range of device and C_{MSC}. suppose o left $device_{10}$ and then is detected by $device_{12}$, its uncertainty region is the intersection of $C_{MSC}(o, device_{10}, t)$ and activation range of $device_{12}$.

PTkNN Query Processing

Definition (Indoor Probabilistic Threshold kNN Query)

Given a set of indoor moving objects $O = \{o_1, o_2, ..., o_n\}$ and a threshold value $T \in (0, 1]$, a PTkNN query issued at time t with query location q returns a result set $\mathbb{R} = \{A|A \subseteq O \wedge |A| = k \wedge prob(A) > T\}$, where $prob(A)$ is the probability that A contains the k nearest neighbors of the query location q at time t.

when the number of moving objects increases, the number of k-subsets (A in Definition 1) in the result set $\mathbb{R}$ increase exponentially. Specifically, there are $\binom{n}{k}$ possible k-subsets for a PTkNN query over n objects.

PTkNN Query Processing

Three techniques are proposed to speed up PTkNN query processing:

1. minimum indoor walking distances between the query location and the (uncertainty regions of) objects are used to prune the objects too far away to be in any possible k-subset, results in a subset $O' \subseteq O$.
2. for all k-subsets of O', cost-efficient probability estimates are used to prune the k-subsets whose probabilities definitely are lower than the threshold T.
3. for each remaining k-subset A, add A to $\mathbb{R}$ only if $prob(A) > T$.

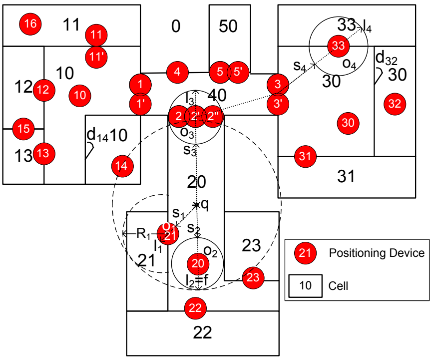
PTkNN Query Processing

Let $s_i(l_i)$ be the minimum(maximum) MIWD from q to the uncertainty region of o_i:

PTkNN Query Processing

Let $s_i(l_i)$ be the minimum(maximum) MIWD from q to the uncertainty region of o_i:

$$s_i = \min_{p \in UR(o_i,t)} d_{MIW}(q,p); \quad l_i = \max_{p \in UR(o_i,t)} d_{MIW}(q,p) \qquad (7)$$



- o_1 is being observed by $device_{12}$
- o_2, o_3, o_4 recently left $device_{20}, device_{2'}, device_{33}$ respectively
- o_4's MIWD computation should take into account the door connectivity

PTkNN Query Processing

Definition (k-bound)

Let f be the kth minimal one of all objects' l_is. If s_i of object o_i is greater than f, object o_i has no chance to be in any k-subset of the result set $\mathbb{R}$. This f value is called the k-bound. [6]

- k-bound can be calculated and updated dynamically during the distance based pruning as soon as k objects have been seen from O.
- by taking advantage of indoor space distance definition, the computation cost can be further reduced. E.g., the objects in the same cell can be pruned if one is pruned by the k-bound.

Distance Pruning

Algorithm 4 DistancePruning(Position q, int k)

ObjectSet $O' \leftarrow \emptyset$;
Double $f \leftarrow +\infty$;
CellSet $seeds \leftarrow \emptyset$;
Initialize a min-heap $H\langle\langle d, v\rangle\rangle$;
if q is in the activation range of a device dev **then**
    $O' \leftarrow DHT[dev]$; $seeds \leftarrow G.\ell_E^{-1}(dev)$;
    for each cell c in $seeds$ **do**
        $O' \leftarrow O' \cup CDHT[c] \cup CNHT[c]$; $EnheapDoors(H, c)$;
else
    Room $r \leftarrow Rooms(q)$;
    Cell $c \leftarrow Cells^{-1}(r)$;
    $O' \leftarrow CDHT[c] \cup CNHT[c]$;
    Add c into $seeds$; $EnheapDoors(H, c)$;
if $|O'| \geq k$ **then**
    $f \leftarrow Bound(O')$;
while H is not empty **do**
    $e \leftarrow deheap(H)$;
    if $e.v > f$ **then**
        break;
    Set $e.d$ as visited;
    $dev \leftarrow PA2D^{-1}(e.d)$; $O' \leftarrow O' \cup DHT[dev]$;
    for each cell c in $G.\ell_E^{-1}(dev)$ **do**
        if $c \notin seeds$ **then**
            $O' \leftarrow O' \cup CDHT[c] \cup CNHT[c]$;
            for each dev in $G.\ell_E(\{c, c\})$ **do**
                if $(PR2D(dev, d) + e.v) \leq f$ **then**
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$$P_{o_i}(r) = Pr(d_{MIW}(q, o_i) \leq r) \tag{8}$$

Let A be a k-subset of O'. The probability $Prob(A)$ that A contains the k nearest neighbors of q satisfies:

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$$Prob(A) \leq \prod_{o_i \in A} P_{o_i}(f) \leq P_{o_i}(f) \leq T \tag{10}$$

Therefore, if $P_{o_i}(f) \leq T$, o_i can be safely pruned from the candidate.

Probability Evaluation

After probability threshold pruning, each k-subset A in $\mathbb{R}$ may have their $Prob(A)$ greater than T.

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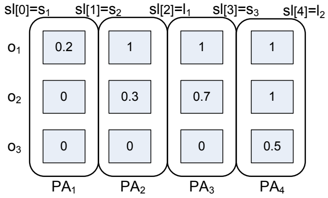

- o_z is the k-th nearest neighbor of q.
- to evaluate the probabilities efficiently, a partition based approximate evaluation method is used.
- let an array sl records all the minimum distances s_i in O' and the maximum distances l_i that satisfy $l_i \leq f$.
- sl should have $g = |O'| + k$ elements, sort it in ascending order.

Research Directions

- Analyzing historical trajectory data may discover associations among object movements, which can be used to design more efficient group pruning in processing a PTkNN query
- Regarding the uncertainty model of indoor moving objects, it is also interesting to conduct probabilistic analysis on other kinds of object distribution.

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The End. Thanks :)