Probabilistic Cleaning over Trajectory Events of Mobile RFID Objects

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Abstract

Cleaning up the trajectory events of mobile RFID objects should take the uncertainty of location and unreliability of event detection into account at the same time. In the paper, we first discuss the rules to distinguish false detection events in RFID object trajectories. Then, as a unified cleaning framework, we establish a probabilistic region connection graph to represent region detection features, region connection relationships, and region transition probabilities between neighboring physical regions. Focusing on interpolating the missing events, we suggest two path-based probabilistic cleaning strategies, namely, the Most Likely Path (MLP) strategy and the Highest Weighting Probability Path (HWPP) strategy.

1 Introduction

With the rapid development of Radio Frequency Identification (RFID), sensor and wireless technologies, a large amount of trajectory data of moving objects is emerging [1∼3]. A trajectory is made up of a sequence of detection events about the location and time of a mobile object. Trajectory data mining, such as mining movement patterns and periodic patterns of the mobile objects, has many important and real-world applications including object behavior analysis, traffic control, location based services, etc [4∼6]. However, the data collected by sensors and RFID readers are usually noisy and incomplete. For instance, because of the instability, shielding, collision and other reasons, there are mainly two kinds of false detection in RFID applications: 1) missing detection, that is, the readers didn't detect the tagged objects inside their detection ranges; 2) cross detection, namely, the readers have detected the objects outside their detection ranges. It is necessary and meaningful to clean up the false detection events from the trajectory data for RFID-based applications.

Fig. 1 is an example of RFID-based object monitoring in a supermarket, where multiple RFID readers are deployed in various physical regions, including 2 entries (EN_1 and EN_2), 9 shopping areas ($S_1 \sim S_9$) and 2 exits (EX_1 and EX_2), to monitor the movement trajectories of customers. Assume that the reader in each area can also detect the objects passing by the aisle near the area, and the detection ranges of the readers deployed in different areas don't overlap.

Suppose that we have collected a trajectory of customer c, which consists of 6 ordered events $e_1 \sim e_6$: $\{e_1 =< c, EN_1, 10 : 00 : 00, 10 : 00 : 00 >, e_2 =< c, S_1, 10 : 01 : 00, 10 : 15 : 00 >, e_3 =< c, S_8, 10 : 36 : 00, 10 : 45 : 00 >, e_4 =< c, S_9, 10 : 46 : 00, 10 : 49 : 00 >, e_5 =< c, S_6, 10 : 49 : 05, 10 : 49 : 10 >, e_6 =< c, EX_2, 10 : 50 : 00, 10 : 50 : 00 >\}$. The first and the second elements of each event are the

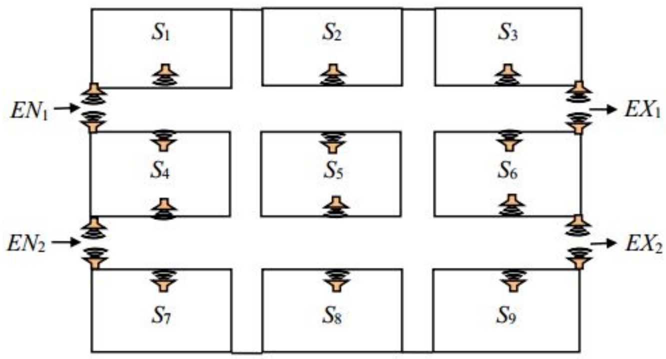

Figure 1: Example of RFID-based object monitoring in supermarkets

customer identification and the region identification, the third is the time that the customer enters the region, and the forth is the time to leave the region. The format of the time is HH/MM/SS. Also, we assume that the moving time from a region to its neighboring region without passing any other region. i.e., the direct moving time, is 60 seconds.

It can be found that the above trajectory is an unreasonable trajectory with two detection faults. The first fault occurred between e_2 and e_3, since there is no direct path from S_1 to S_8, which violates the *continuous motion constraint*, that is, an object can only move from a region to its neighboring region when its location changes. In this case, it can be considered that some events are missing between e_2 and e_3 as their time gap is quite large. The second fault came up between e_4 and e_5, since it is highly unlikely for a customer to move from S_9 to S_6 in such a short period of time (i.e., 5 seconds), violating the *direct moving time constraint* (i.e., 60 seconds). At this time, it is sure that one of e_4 and e_5 is a cross detection event.

Considering both constraints of continuous motion and direct moving time, we should remove the cross events and interpolate the missing events to get a more realistic trajectory. For example, a trajectory can be obtained by removing e_5 and interpolating two events occurring in S_2 and S_5 in turn between e_2 and e_3, i.e., $EN_1 \to S_1 \to \mathbf{S_2} \to \mathbf{S_5} \to S_8 \to \mathbf{S_9} \to EX_2$. However, since location movement of the mobile objects is uncertain, we may also get another potential reasonable trajectory by removing e_4 and interpolating two events occurring in S_4 and S_7, i.e., $EN_1 \to S_1 \to \mathbf{S_4} \to \mathbf{S_7} \to S_8 \to \mathbf{S_6} \to EX_2$. In fact, there are multiple potential reasonable paths between S_1 and S_8, so the problem to be solved is to determine a more reasonable trajectory among multiple candidate trajectories.

There are some data cleaning strategies for mobile RFID objects proposed. H. Fan et al. [7] proposed a behavior-based cleaning method for unreliable RFID data, which takes advantage of the kinematic characteristics to assist in RFID data cleaning under a movement behavior detection model. A recent work in [8] proposed a Bayesian inference based approach for cleansing the missing RFID data. It proposed an Adaptive Cleansing (AC) probabilistic model for object tracking in mobile environment. T. Tran et al. [9] proposed a probabilistic model to capture the mobility of the reader, object dynamics and noisy readings, and employ a sampling-based technique called particle filtering to infer locations of RFID objects. Considering the movement characteristic of RFID objects, R. Cocci et al. [10] and Y. Nie et al. [11] presented a data inference and compression method over RFID streams. H. Chen et al. [12] proposed a Bayesian inference framework to maximize the accuracy of RFID data collection. It suggested a Metropolis-Hasting sampler based on the posterior read rates to infer the hidden variables in the model. The work in [13] is the most related study to this research, which proposed a data imputation model by maintaining and analyzing the spatio-temporal correlations and constraints of the monitored objects, where optimized data structures and imputation strategies are developed. However, the method cannot be adapted to the environment where the objects have little correlation.

This chapter intends to study trajectory event cleaning strategies to remove the cross detection events and interpolate the missing detection events from the trajectories of mobile RFID objects. The rest of the paper is organized as follows. We describe the basic concepts and problem statement in Section 2. Section 3 presents a unified cleaning framework using probabilistic region connection graph. We suggest two path-based missing event interpolation strategies in Section 4, and conclude our work in the end.

2 Basic Concepts and Problem Statement

In the paper, a given physical range monitored by of a reader (or a group of readers) is called a physical region. For example, in supermarkets, a physical region can be an entry, a shopping area, or an exit,.

Definition 1 (Neighboring physical regions). Let r_i and r_j be two independent physical regions. If we can go to r_j from r_i directly, and vice versa, r_i and r_j are called a pair of neighboring physical regions.

Definition 2 (Direct moving time). Let r_i and r_j be a pair of neighboring physical regions, the direct moving time from r_i to r_j is the movement time from r_i to r_j without passing any other region, denoted as Γ_{ij}. Due to symmetry, $\Gamma_{ij} = \Gamma_{ji}$.

It is reasonable that Γ_{ij} obeys the normal distribution, i.e., $\Gamma_{ij} \sim N(\mu_{ij}, \sigma_{ij}^2)$, where μ_{ij} and σ_{ij} are the mean and standard deviation of Γ_{ij}, respectively. Comparing with the normal detection events, the cross detection events and missing detection events can be regarded as small probability events. Thus, we can divide the overall time domain of Γ_{ij} into three time subdomains.

- $[\mu_{ij} - 3\sigma_{ij}, \mu_{ij} + 3\sigma_{ij}]$: the time subdomain of normal detection;
- $[0, \mu_{ij} - 3\sigma_{ij})$: the time subdomain of cross detection, since it is not likely for the mobile objects to move between the neighboring physical regions in such a short period of time;
- $(\mu_{ij} + 3\sigma_{ij}, +\infty)$: the time subdomain of missing detection, since it doesn't need such a long time from r_i to its neighboring region r_j.

Definition 3 (Basic observation events). A basic observation event is the action that a reader observes a tagged object at a specific time, which can be represented as a triple $< o, r, t >$, where o is the unique identification of the object, r is the identification of the physical region that the reader monitors, and t is the observation timestamp.

Definition 4 (Detection events). A detection event is a tetrad $< o, r, t_{in}, t_{out} >$, where t_{in} is the time that o enters r, and t_{out} is the time to leave r.

Definition 5 (Arbitrary trajectories). An arbitrary trajectory of object o_i is made up of n ordered detection events about o_i, denoted as $TR_i = \left\{e_i^k\right\}, k = 1, 2, \ldots, n$, where e_i^k is the k-th detection event in the trajectory, and e_i^k and e_i^{k+1} are called as a pair of adjacent detection events.

For convenience, we also use an ordered physical region sequence to represent a trajectory, denoted as $TR_i = \{r_k\}, k = 1, 2, \ldots, n$, where r_k is the physical region of e_i^k.

Definition 6 (Location detection errors). In TR_i, if $e_i^k.r$ and $e_i^{k+1}.r$ are not neighboring physical regions, it is said that a location detection error occurs.

Definition 7 (Time detection errors). In TR_i, if $e_i^k.r$ and $e_i^{k+1}.r$ are neighboring regions, but $e_i^{k+1}.t_{in} - e_i^k.t_{out} \notin [\mu_{k,k+1} - 3\sigma_{k,k+1}, \mu_{k,k+1} + 3\sigma_{k,k+1}]$, it is said that a time detection error occurs.

Definition 8 (Reasonable and unreasonable trajectories). If there is neither location detection error nor time detection error between any adjacent detection event pairs $< e_i^k, e_i^{k+1} >$ in TR_i, it is said that TR_i is a reasonable trajectory. Otherwise, it is an unreasonable trajectory.

Since the probability of cross detection will be reduced with the increase of the distances between the readers and the objects, we assume the cross detection events only involve the time detection error between the neighboring physical regions.

Definition 9 (Cross event pairs). In TR_i, if $e_i^k.r$ and $e_i^{k+1}.r$ are neighboring physical regions, and $0 \leq e_i^{k+1}.t_{in} - e_i^k.t_{out} < \mu_{k,k+1} - 3\sigma_{k,k+1}$, $< e_i^k, e_i^{k+1} >$ is called a *cross event pair*, and one of them is a cross event.

Definition 10 (Missing event pairs). In TR_i, if $e_i^k.r$ and $e_i^{k+1}.r$ are not neighboring physical regions, or $e_i^k.r$ and $e_i^{k+1}.r$ are neighboring physical regions and $e_i^{k+1}.t_{in} - e_i^k.t_{out} > \mu_{k,k+1} + 3\sigma_{k,k+1}$, $< e_i^k, e_i^{k+1} >$ is called a *missing event pair*, and we infer that some events are missed between the pair.

Problem definition. Given an arbitrary trajectory $TR_i = \left\{e_i^k\right\}, k = 1, 2, \ldots, n$, for each pair of adjacent detection events $e_i^k, e_i^{k+1} \in TR_i$, if $< e_i^k, e_i^{k+1} >$ is a cross event pair, one of them is selected to be removed from the trajectory, or if $< e_i^k, e_i^{k+1} >$ is a missing event pair, a potential reasonable path between $e_i^k.r$ and $e_i^{k+1}.r$ is determined to interpolate into the trajectory, to generate a candidate trajectory $TR_i^{'}$, i.e., $TR_i^{'}$ has neither location detection errors nor time detection errors.

3 Probabilistic Region Connection Graph

Generally, different physical regions have different detection features, depending on different device conditions and environment factors.

Definition 11 (Cross detection ratio). The cross detection ratio of region r_j is the probability that an object can be observed by the reader in r_j although the object doesn't locate in r_j, denoted as pc_j.

Definition 12 (Missing detection ratio). The missing detection ratio of r_j is the probability that an object cannot be observed by the reader in r_j although the object locates in r_j, denoted as pm_j.

Definition 13 (Normal detection ratio). The normal detection ratio of region r_j is the probability that an object can be observed by the reader in r_j if the object locates in r_j, denoted as pn_j, and $pn_j = 1 - pm_j$.

A physical region usually has multiple neighboring physical regions. We can compute the probabilities that an object moves from a physical region to its neighboring regions by analyzing historical trajectory data.

Definition 14 (Region transition probability). The region transition probability $p(r_j|r_i)$ is a conditional probability that an object moves from r_i to a neighboring region r_j.

Let $NE(i)$ be the set of neighboring regions of r_i. We have,

$$\sum_{j \in NE(i)} p(r_j|r_i) = 1. \tag{1}$$

Definition 15 (Region connection graph). All physical regions can be represented as a connection graph $G = (V, E, W, X)$, where

1) V is the set of $|V| = N$ vertices, i.e., the physical regions;

2) $E \in V \times V$ is the set of $|E| = M$ edges, i.e., the pairs of neighboring physical regions;

3) W is a 2-dimension attribute matrix associated with V, which describes the cross detection ratio and the missing detection ratio of each region;

4) X is an $N \times N$ adjacency matrix, where $x[i][j]$ records $p(r_j|r_i)$, μ_{ij} and σ_{ij}. In the matrix, $\mu_{ij} = \mu_{ji}$, $\sigma_{ij} = \sigma_{ji}$, but $p(r_j|r_i) \neq p(r_i|r_j)$.

Fig. 2 is the connection graph representation of the physical regions in Fig. 1. As an example, the node features and edge features related with S_1 are given. The pair (0.1, 0.25) (above the node S_1) represents that the cross detection ratio and the missing detection ratio of S_1 are 0.1 and 0.25, respectively. The triple (0.4, 60, 3) (above the edge between S_1 and S_2) means that the region transition probability from S_1 to S_2 is 0.4, the mean and standard deviation of the direct moving time from S_1 to S_2 are 60 and 3 seconds, respectively.

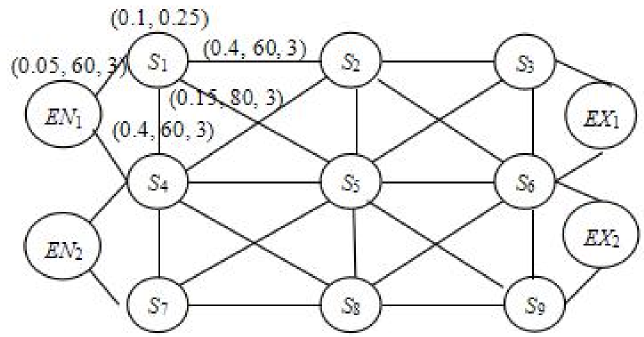

Figure 2: Probabilistic region connection graph

4 Probabilistic Cleaning Strategies

Since the cross detection events only occur between the neighboring physical regions, we can simply remove one of them randomly or select the one which region has higher cross detection rate to remove. However, interpolating the missing events is much more complicated, since there are a lot of potential reasonable paths in the region connection graph between the regions of the missing event pair. Thus, this section will focus on the issue of missing event interpolation.

4.1 Candidate paths and candidate trajectories

A reasonable candidate path between $e_i^k.r$ and $e_i^{k+1}.r$ is the path which direct moving time, i.e., $e_i^{k+1}.t_{in} - e_i^k.t_{out}$, should be between the lower bound and the upper bound of the sum of the time subdomains of normal detection of all neighboring region pairs in the path.

Definition 16 (Candidate path). Let $PA =< r_1, r_2, \ldots, r_m >$ be a path from $e_i^k.r(= r_1)$ to $e_i^{k+1}.r(= r_m)$. If the following condition holds,

$$\sum_{j=1}^{m-1}(\mu_{j,j+1} - 3\sigma_{j,j+1}) \leq e_i^{k+1}.t_{in} - e_i^k.t_{out} \leq \sum_{j=1}^{m-1}(\mu_{j,j+1} + 3\sigma_{j,j+1}), \tag{2}$$

it is said that PA is a candidate path between $e_i^k.r$ and $e_i^{k+1}.r$.

Definition 17 (Candidate trajectory). Let TR_i be an unreasonable trajectory without cross detection events. One of its candidate trajectory $TR_i^{'}$ is a trajectory after interpolating a candidate path into each missing event pair of TR_i.

Theoretically, if there are z missing event pairs in TR_i, we can get:

$$N = \prod_{j=1}^{z} n_j, \tag{3}$$

candidate trajectories, where n_j is the number of the candidate paths of j-th missing event pair.

4.2 The most likely path interpolating strategy

The idea of the Most Likely Path (MLP) interpolation strategy is to compare the joint probability of all candidate paths between a missing event pair, and use the one with the maximum probability for interpolating. A factor graph is an undirected bipartite graph consisting of a set of *random variable nodes* and a set of *factor function nodes* [14]. Each function node represents a function that depends only on the subset of the variable nodes.

It provides a natural way of representing global functions or probability distributions that can be factored into simpler local functions.

A candidate path $PA =< r_1, r_2, \ldots, r_m >$ is a directed graph (Fig. 3(a)), where the vertices represent the physical regions in the path, and the directed edge represents the location movement from the former region to the next one. Its joint probability is related with two factors:

1) The normal detection ratio of each region, and

2) The region transition probability of each directed edge.

Therefore, we convert the directed graph into a factor graph with node potentials $\{\Psi(r_i) : r_i \in G, i = 1, \ldots, m\}$ and edge potentials $\{\varphi(r_i, r_{i+1}) : (r_i, r_{i+1}) \in G\}$ as Fig.3 (b):

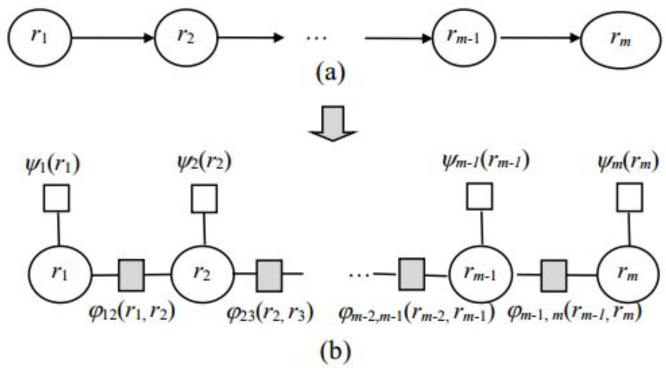

Figure 3: Candidate path and factor graph representation

- $\Psi(r_i)$ is the normal detection rate of region r_i, i.e.,

$$\Psi(r_i) = 1 - pm_i. \tag{4}$$

- $\varphi(r_{i+1}, r_i)$ is the region transition probability from r_i to r_j, i.e.,

$$\varphi_{i,i+1}(r_i, r_{i+1}) = p(r_{i+1}|r_i). \tag{5}$$

Therefore, the joint probability of PA can be computed by a product of all node potentials and all edge potentials as below:

$$p(r_1, r_2, \ldots, r_m) = \frac{1}{Z} \prod_{i=1}^{m} (1 - pm_i) \bullet \prod_{i=1}^{m-1} p(r_{i+1}|r_i), \tag{6}$$

where Z is a normalization constant, i.e.,

$$Z = \sum_{\forall r_i} \prod_{i=1}^{m} (1 - pm_i) \bullet \prod_{i=1}^{m-1} p(r_{i+1}|r_i). \tag{7}$$

The MLP strategy uses Eq. (6) to compute the joint probability of all candidate paths, and select the path with maximum probability for missing event interpolation.

Theorem 1. Let $SP_s =< r_1, r_2, \ldots, r_s >$, $SP_t =< r_1, r_2, \ldots, r_t >$ be two candidate subpaths from regions X to Y, and $SP_s \subset SP_t (s < t)$, if $p(r_{s+1}|r_s) < p(Y|r_s)$, then $p(X, SP_s, Y) > p(X, SP_t, Y)$.

Theorem 1 is used to prune the candidate paths. Its proof is discussed in detail in [15].

Theorem 2. (The most likely candidate trajectory). A reasonable trajectory obtained by interpolating the missing events using the MLP strategy is the most likely candidate trajectory.

Theorem 2 is obvious, since the probability of a trajectory is the product of all node potentials and all edge potentials. That is, interpolating the missing paths with maximal local probabilities can guarantee the trajectory with maximal global probability.

4.3 The highest weighting probability path interpolating strategy

The MLP strategy takes the normal detection ratios and region transition probabilities into consideration. But in the real world such as supermarkets, people usually tend to select short paths for shopping. The highest weighting probability path (HWPP) interpolating strategy combines the factors both of path probabilities and path lengths, and selects the candidate paths with the highest weighting probabilities to interpolate.

We use $\frac{\beta^m |Paths^m_{X,Y}|}{\sum_L \beta^L |Paths^L_{X,Y}|}$ as the weights of the probability for the candidate paths with length m, which has two features:

1) The shorter the length of a candidate path is, the higher the weight of its probability is;

2) The paths with the same length have the same weight.

Definition 18 (Path weighting probability). Let $PA =< r_1, r_2, \ldots, rm >$ be a candidate path between $e_i^k.r(= r_1)$ and $e_i^{k+1}.r(r_m)$, the weighting probability of PA, denoted as $p_w(PA)$, is computed as:

$$\begin{aligned} p_w(PA) &= \frac{\beta^m |Paths^m_{r_1,r_m}|}{\sum_L \beta^L |Paths^L_{r_1,r_m}|} \times p(r_1, r_2, \ldots, r_m) \\ &= \frac{\beta^m |Paths^m_{r_1,r_m}|}{Z * \sum_L \beta^L |Paths^L_{r_1,r_m}|} \times \prod_{i=1}^{m} (1 - pm_i) \bullet \prod_{i=1}^{m-1} P(r_{i+1}|r_i), \end{aligned} \tag{8}$$

where $|Paths^L_{r_1,r_m}|$ is the set of all paths with length L from $e_i^k.r$ to $e_i^{k+1}.r$.

Theorem 3. Let $SP_s =< r_1, r_2, \ldots, r_s >$, $SP_t =< r_1, r_2, \ldots, r_t >$ be two subpaths from regions X to Y, and $SP_s \subset SP_t (s < t)$. If $p(r_{s+1}|r_s) < p(Y|r_s)$ and $Paths^t_{X,Y} < Paths^s_{X,Y}$, then $p_w(X, SP_s, Y) > p_w(X, SP_t, Y)$.

Theorem 3 is used for HWPP strategy to prune the candidate paths. its proof is also discussed in [15].

5 Conclusions

To address the challenges of the uncertainty of location movement and the unreliability of event detection of mobile RFID objects, this paper first analyzes the constraints both of location motion and direct moving time between the neighboring physical regions. Then, a probabilistic region connection graph model is established as a unified cleaning framework. Using the factor graph model, two path-based missing event interpolating strategies and their pruning rules are discussed. The experimental results in [15] show that the proposed strategies are effective and efficient.

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