TASA: Tag-Free Activity Sensing Using RFID Tag Arrays

Daqiang Zhang, Jingyu Zhou, Minyi Guo, *Senior Member*, *IEEE*, Jiannong Cao, *Senior Member*, *IEEE*, and Tianbao Li

Abstract—Radio Frequency IDentification (RFID) has attracted considerable attention in recent years for its low cost, general availability, and location sensing functionality. Most existing schemes require the tracked persons to be labeled with RFID tags. This requirement may not be satisfied for some activity sensing applications due to privacy and security concerns and uncertainty of objects to be monitored, e.g., group behavior monitoring in warehouses with privacy limitations, and abnormal customers in banks. In this paper, we propose TASA—Tag-free Activity Sensing using RFID tag Arrays for location sensing and frequent route detection. TASA relaxes the monitored objects from attaching RFID tags, online recovers and checks frequent trajectories by capturing the Received Signal Strength Indicator (RSSI) series for passive RFID tag arrays where objects traverse. In order to improve the accuracy for estimated trajectories and accelerate location sensing, TASA introduces reference tags with known positions. With the readings from reference tags, TASA can locate objects more accurately. Extensive experiment shows that TASA is an effective approach for certain activity sensing applications.

Index Terms—RFID, activity sensing, tag-free localization, object tracking, frequent trajectories.

1 Introduction

Activity sensing aims at monitoring objects by location information, which is the fundamental information in pervasive computing environments [1], [2], [3]. The proliferation of wireless technologies in infrared [4], Bluetooth [5], [6], and ultrasonic [7], [8] has fostered a growing interest in location sensing. Based upon location data, location-aware systems identify the trajectories of moving objects, and thus provide customized services to users or applications. A current trend is to employ Radio Frequency IDentification (RFID), which is characterized by low cost, general availability, and automatic identification [9], [10], [11], [12]. So far, RFID has achieved widespread success in animal identification, asset tracking, object locating, surveillance systems, and security access.

However, RFID-based schemes impose a restriction on the tracked objects—they must be labeled with RFID tags. A typical method in RFID-based applications involves three steps. RFID tags are attached to targeted objects beforehand. Then, either RFID readers or targeted objects move in space. Once the objects are within the accessible range of RFID readers, the information stored in tags is emitted and received by readers. The overwhelming majority of existing RFID-based applications employ such a method to track legal objects that can be labeled in advance. Due to privacy and security constraints, it is impractical for objects to be labeled in some applications. Route tracking in industrial workshops, personal behavior investigation in metro stations, and interaction analysis between pedestrians and the vehicles are applications of this type. Moreover, objects may be reluctant to be attached in some cases, such as thieves in banks and strangers in warehouses. Consequently, tag-free or transceiver-free tracking for activity sensing applications like route tracking using RFID is highly desirable.

The above applications can be monitored by video surveillance [13] with certain limitations. First, video monitoring only covers predefined areas with limited display size and azimuth of the visual field, and omits large undefined areas [14], [15]. Once the monitoring areas change, the video surveillance systems may have to be redeployed. In fact, in most cases, the frequent areas may not be known and may frequently change over time. Second, many open issues in video surveillance prevent it from being used in automatic detection [16], [17], such as analyzing behavior, detecting irregular activities, fusing images from multiple cameras, handling occlusion, and the dependence of good illumination. The successes in video surveillance are mainly at the level of signal processing and much remains to be done [11], [18]. Third, the cost of video monitoring is expensive. "Technology has reached a stage where mounting cameras to capture video imagery is cheap, but finding available human resources to sit and watch that imagery for 24×7 hours is expensive" [16]. Finally, video monitoring requires much time for online detection, because a lot of computation is involved in image processing, object identification, and behavior analysis.

In this paper, we propose TASA—Tag-free Activity Sensing using RFID tag Arrays for location sensing and route tracking. TASA relaxes the monitored objects from

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attaching RFID tags and is capable of sensing concurrent activity in an online manner. TASA deploys passive RFID tags into an array, captures the Received Signal Strength Indicator (RSSI) series for all tags all the time, and recovers trajectories by exploring variation in RSSI series. We share the similar idea of locating a moving object via readings from RFID tag arrays [11], but relax the requirement of using active tags to mostly passive tags. Because noisy RSSI readings for passive tags have a significant influence on the tracking performance, TASA introduces some active tags at known positions as reference tags. These reference tags improve the estimated accuracy, as well as accelerate the process of recovering trajectories. The evaluation results of TASA show that our scheme is desirable in terms of accuracy and efficiency. To summarize, the main contributions of this paper are twofold.

- Providing an alternative to certain activity sensing scenarios (e.g., route tracking and group behavior analysis) in large areas using arrays of inexpensive passive RFID tags together with a few active tags as reference tags, which is cost effective and easily deployable. Our scheme removes the requirement of most existing RFID-based solutions that RFID tags are attached to the objects.
- Proposing a set of algorithms to remove noise in RFID readings and recover trajectories in an online manner. Particularly, TASA can recover routes of concurrent moving objects. Empirical studies show that our scheme achieves high accuracy and efficacy in detecting routes simultaneously traversed by multiple objects.

The rest of this paper is organized as follows: Section 2 introduces the background of RFID technology and identifies several challenging issues. Section 3 describes the TASA scheme in detail. Section 4 reports our empirical study. Section 5 briefly reviews the related work in location sensing and Section 6 concludes our work with future research directions.

2 Background

We have found several challenges in RFID readers and tags, which obstruct the application of RFID systems in location sensing. In this section, we first introduce RFID technology, and then identify the challenges. Finally, we propose our solutions to these challenges and describe the problem that this paper focuses on.

2.1 RFID-Based Activity Sensing

RFID refers to a technology that transmits and receives unique serial information using radio frequency waves, which has been applied to animal identification, assets tracking, supply chain management, and traffic control [9], [19]. The key elements of RFID systems consist of RFID readers, tags, and middleware software [20]. RFID readers are silicon-based radio transceivers, which interrogate and communicate with RFID tags by electromagnetic waves. RFID tags have a tiny on-board memory up to several kilobytes, storing their unique identification as well as some additional information.

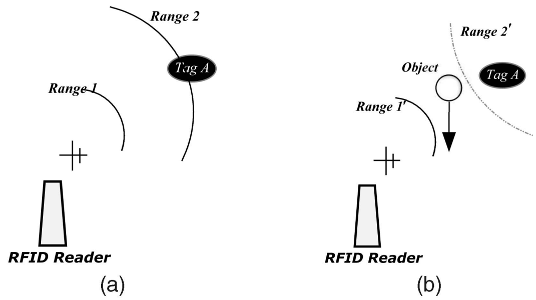

Fig. 1. The read range of a RFID reader changes when an object is passing by. (a) Original reader range, and (b) affected reader range.

In general, according to the way that the signal is induced, RFID tags can be classified as active tags and passive tags [21], [22]. Active tags use an internal power source to continuously power their RF communication circuitry, whereas passive tags, with no power supply, rely on external sources of power (e.g., RFID readers) to stimulate signal transmission. An active tag is substantially larger than a passive tag, because the tag contains two additional components—an on-board power supply and on-board electronics. The power supply of an active tag is a tiny battery, and the on-board electronics allows the tag to actively manipulate data and transmit data to readers [23]. Compared with passive tags, active tags have significant advantages in terms of sensitivity, communication range, data storage, and processing capacity. They support much larger communication range up to 100 m, transfer data at a higher bandwidth, and automatically determine the best communication path in crowded environments, but cost more than passive ones. We discuss the behavioral difference between active and passive tags in Section 2.2 and show how active tags are used in our approach for locating objects in Section 3.1.3. Note that with the advance in communication technology and integrated circuit, the gap between these two types of tags is conspicuously narrowed.

Among RFID-based solutions, most of them require objects to be labeled with tags beforehand. A tag-free RFID-based activity sensing is inspired from a phenomenon that the RSSI for a tag changes significantly when an object (e.g., a person) is passing by it. This phenomenon is illustrated in Fig. 1, where ranges 1 and 2 identify two original read ranges. When the object is traversing the tag A, the original range 2 decreases to the range $2'$. Object movement between the RFID reader and the tag A causes the shrinking of the reader's range. At this time, we have to increase the power level for the RFID reader so that it can reach the same range again. As a result, the value of RSSI for the tag A has a significant change. According to such RSSI changes, we are able to infer that the object is in the vicinity of the tag A. Further, by capturing RSSI series for all RFID tags, we can infer an object's location within a larger area without attaching tags to it.

In practice, RSSI readings can be very noisy. This can be caused by variations of RFID tags, RFID readers, or due to collisions [24], [25], [26]. We discuss these issues in the next section.

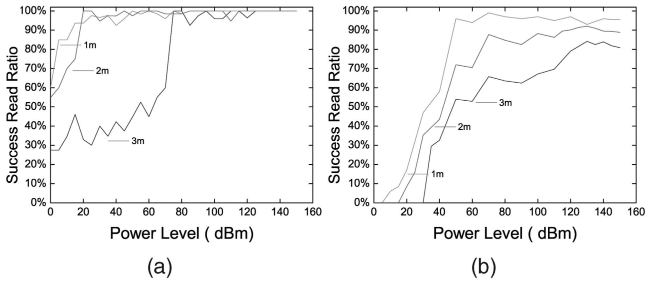

Fig. 2. RFID readers read an active or a passive tag 50 times with 1, 2, and 3 m distance, respectively. (a) Active tags. (b) Passive tags.

2.2 Challenges

RFID-based location sensing depends on the reliability of RSSI readings. In practice, we have found that there are a number of factors that adversely affect the reliability of RSSI readings. In the following, we discuss such factors.

2.2.1 Behavioral Variation in RFID Tags

The first issue arises from the behavioral variation in passive RFID tags. Passive tags jitter in their RSSI readings even in a perfect environment, i.e., both tags and readers are in a fixed position and there are no objects passing by and no environmental noise. Even worse, sometimes RSSI readings for passive tags are missing. Additionally, the same type, batch of passive tags working under the same condition may be different in RSSI.

The reason for these behavioral variations may come from manufacturing defects or differences within chips, integrated circuits, and noise. Sources of these noises consist of, but are not limited to, inaccurate measurement and noise from internal RFID components and external environment.

To reduce the effects of behavioral variations in RFID tags on location sensing, we use two methods in this paper to address this issue. One is to conduct preliminary experiments for every tag, and then to calculate statistical features for every tag, i.e., the mean value and standard deviation for RSSI. These features are used as the baseline in our experiment to calculate RSSI changes and to determine whether tags are affected by moving objects. Abnormal tags that have anomalous RSSI changes are excluded in preliminary experiments. The other method is to adopt active RFID tags for more accurate readings, which will be further discussed in Section 3.1.3.

2.2.2 Behavioral Variation in RFID Readers

Another issue is from the behavioral variation in RFID readers, which causes that RFID readers may not successfully query tags within their reading ranges [27]. In order to study how much the behavioral variation in readers may affect the reading rate, we conducted several experiments for RFID readers by changing RFID readers' power levels and distance to passive tags.

The operating frequencies of passive tags and active tags are 920 MHz and 430 MHz, respectively. Experiments were repeated 50 times for every power level and distance. Fig. 2 shows ratios of the successful read times to the total read times for an active tag and a passive tag with a distance of 1, 2, and 3 m away, respectively. The figure shows that both power level and distance have a significant impact on successful reads. When the power level increases, the successful rates for both tags become higher. On the other hand, successful rates decrease when the distance between the tag and the reader becomes larger. For the same power level, successful reads of active tags are much higher than those of passive ones. Thus, active tags can be sensed more quickly by readers with minor RSSI changes. In other words, active tags are more sensitive and reliable than passive tags.

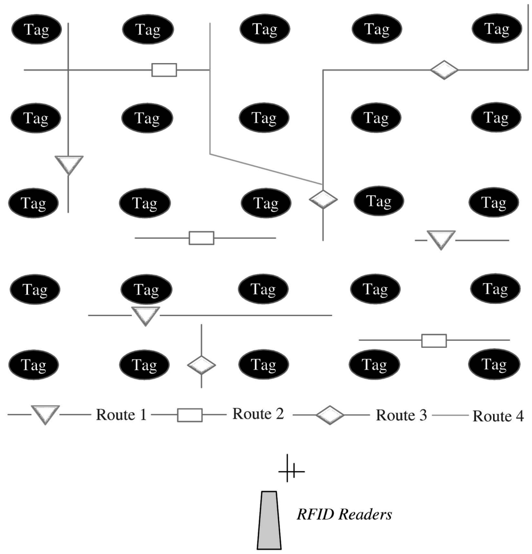

Fig. 3. Signal interference causes recovered trajectories to be incomplete and inaccurate.

2.2.3 Interference

A third issue is the signal interference caused by deploying multiple RFID tags and readers. In our study, we use the C1G2 type of passive tags. According to the EPCglobal C1G2 standards [28], these tags have a built-in collision avoidance mechanism. For a population of 10,000 tags, the collision rate is less than 0.1 percent [28]. In our experiment, we find that when multiple persons simultaneously move across a RFID tag array that is read by multiple RFID readers, signal interference becomes a minor factor affecting the accuracy of location sensing. It is worth to mention that there are two other types of collisions: reader-to-tag and reader-to-reader collisions. Literatures [24], [25], [26] have investigated these two collisions and proposed various sophisticated algorithms based on graph coloring. In our experiments, these collisions are not evident, and we have taken measures to minimize their effects (Section 3.1).

Fig. 3 illustrates such an experiment, where passive RFID tags are organized into an array with a 1-m distance between adjacent tags. These passive tags work at 920 MHz frequency. Four persons walk across the tag array simultaneously along four different trajectories with different speeds, ranging from 0.5 to 2 m/s. Based on the RSSI series, trajectories for these four persons are plotted in Fig. 3. We observe from the figure that these trajectories tend to be incomplete, sometimes inaccurate. One reason is that some of the readings for passive tags are missing due to behavioral variations in readers and tags. The other reason is that

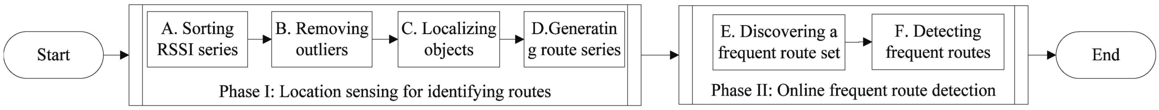

Fig. 4. An overview of the TASA scheme.

incorrect readings due to signal interference are captured by RFID readers.

2.3 Problem Statement

The problem that this paper focuses on is to check frequent trajectories being traversed by moving objects in an online manner. Frequent trajectories refer to the trajectories that are traversed frequently, i.e., the occurrence frequency is bigger than a certain threshold. They are routine or normal trajectories, while infrequent trajectories are often related to abnormal activities.

It relies on accurate location sensing for moving objects to solve this problem using RFID tag arrays. Then combined with timing information, we can recover trajectories traversed by objects and check them to be frequent or not. Due to the aforementioned challenges associated with RFID, RSSI series for passive tags are highly noisy and pose significant difficulty. In the rest of the paper, we describe our scheme.

3 TASA: Tag-Free Activity Sensing Using RFID Tag Arrays

In this section, we describe the details of our proposed TASA scheme for location sensing and frequent route detection. As shown in Fig. 4, TASA involves two phases. The first phase performs location sensing for moving objects in order to identify trajectories of these objects. This phase takes a number of RSSI series as an input and then produces a set of trajectories of moving objects. It consists of three steps of sorting input RSSI series, removing outliers, locating objects with the help of reference tags, and generating a set of routes.

The second phase takes the set of trajectories from the previous phase as an input and then performs online frequent trajectories detection for activity sensing. Within this phase, we first apply data mining algorithms to find frequent patterns of the route set, and then perform online classification of trajectories. The rest of this section details these steps, followed by discussions.

3.1 Phase I: Location Sensing

We model the entire tag array in a coordinate system with the tag located in the most lower, left corner as the origin of coordinate. The intervals between two neighboring x-axis and y-axis coordinates are the same distance as between two neighboring tags in real deployment. For example, the coordinate for the tag P_i marked in Fig. 5 is $(0, 2)$. Given that we use multiple RFID readers that are deployed on the ceiling, we simply assume that the communication between readers and tags suffers from a short delay [29]. We also assume that we have removed all abnormal passive tags in preliminary experiments as discussed in Section 2.2.1. Furthermore, we address the reader-to-tag and reader-to-reader collisions with region division and power control. We divide the entire experiment area into several subregions and adjust the power of each reader such that each reader merely covers subregions that are not overlapped with other readers. We do not use TDMA or other sophisticated algorithms to solve these collisions.

3.1.1 Sorting RSSI Series

As discussed in Section 2, passive RFID tags tend to generate incomplete, inconsistent, and noisy RSSI series due to the noise from internal RFID components, inaccurate measurement, and external environment interference. Such RSSI series conspicuously affects the estimated accuracy of recovered trajectories and increases the difficulty for the following steps, i.e., removing outliers and locating objects with reference tags. Consequently, we sort the RSSI series in chronological order.

Table 1 shows an example of a sorted RSSI series extracted from experiments, where each record is a quintuple of $Times$, $TagID$, $RSSI$, $ReaderID$, and $Coordinate$, representing the RFID reader labeled by $ReaderID$ returns the $RSSI$ at time period $time$ for the tag labeled by $TagID$ and located at $Coordinate$.

We use two policies to improve the efficiency of the sorting process. One policy is that when a tag's RSSI reading exceeds its normal RSSI variation range, the RSSI reading will be inserted into RSSI database (RDbase). In other words, only readings from affected RFID tags are kept in the database. The other policy is that we employ multiple readers and insert their readings in chronological order. Thus, we sort the RSSI readings during the data collection process, which dramatically reduces the size of RSSI database and helps to accelerate computations in the following steps. Note that we convert the original RSSI time series into a sorted series,

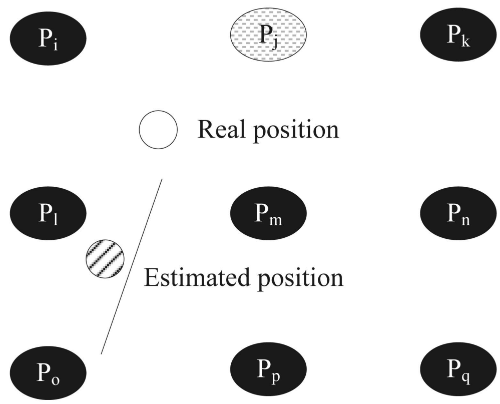

Fig. 5. An outlier affects the accuracy of location sensing.

TABLE 1
An Example of a Sorted RSSI Series

Time	TagID	RSSI	ReaderID	Coordinate
10:02:36	1	65	1	(0, 2)
10:02:36	2	55	1	(1, 2)
10:02:36	4	78	1	(0, 1)
10:02:36	5	71	1	(1, 1)
10:02:37	4	79	1	(0, 1)
10:02:37	5	73	1	(1, 1)
10:02:37	7	65	1	(0, 0)
10:02:37	8	65	1	(1, 0)
10:02:38	5	65	1	(1, 1)
10:02:38	8	65	1	(1, 0)
10:06:01	2	82	2	(1, 2)
10:06:05	3	63	1	(2, 2)

which still contains inconsistencies and noises due to challenges discussed in Section 2.2.

In this step, we use a parameter λ to be the threshold for RSSI variations of passive RFID tags. Tags are regarded as affected tags when their RSSI variations are larger than the value of λ. Parameter λ is determined empirically depending on the monitored objects and specific batches of RFID tags. Our experiment in Section 4.5.1 indicates that λ can affect the performance to some degree.

3.1.2 Removing Outliers

This step aims at removing outliers in RSSI readings from multiple readers. Due to the behavioral variations in RFID readers and tags, and the noise from RFID internal components and external environments, the collected RSSI series are inconsistent and noisy. Fig. 5 illustrates how an outlier can affect location sensing: the reading for the passive tag P_o is an outlier, which causes the estimated object location to deviate from its real position. Thus, we need to remove outliers in the data set to improve the accuracy of location sensing.

Fig. 6 illustrates the pseudocode of this step. The basic idea is that a tag is affected by a moving object when more than two of its neighbors are affected at the same time. Otherwise, the tag is unaffected and such a record in RDbase is an outlier and should be removed.

3.1.3 Locating Objects with Reference Tags

In this section, we explain how TASA makes use of reference tags to accurately locate a single object and multiple objects.

```
Input: RSSI series RD with outliers
Output: RD after removing outliers

// scan RD and remove the outliers
for each tag i in RD
    for each period t
        if the majority of its neighbors are not in RD
            remove record of tag i at time t
```

Fig. 6. The algorithm of removing outliers.

With respect to locating a single object, pure passive tag arrays and TASA achieve similar accuracy, although RSSI readings for passive tags are often inaccurate, noisy, and missing. Fig. 7a illustrates how pure passive tag array locates a single object. The object's location can be specified by four of its nearest neighbors that are passive tags P_i, P_j, P_l, and P_m whose RSSI readings are not highly reliable. For example, the RSSI reading for the tag P_j is missing, but the tag array can still locate the object with low errors. Fig. 7b shows that TASA locates a single object with the help of reference tags. We are able to infer that the moving object is near R_α, but away from R_β and R_γ. Combined with the fact that the object is also detected by passive tags P_j, P_l, and P_m, we can estimate the object's position to be the center of R_α, P_j, P_l, and P_m, much close to the real position.

However, it is a challenging job to locate multiple objects for passive RFID tags. Fig. 7c shows an example that passive tag array cannot accurately locate multiple objects. At this time, RSSI readings for passive tags P_j and P_i are missing or inaccurate. According to the affected tags, we can just get one location for objects. In general, a passive tag array falls short of detecting routes traversed by multiple objects at the same time due to the unreliable RSSI readings for passive tags. Consequently, we need some mechanisms to address these issues.

In the TASA scheme, we choose to use a few active RFID tags placed at crucial locations to address the inaccurate and incomplete passive RFID readings. As shown in Fig. 2, active tags are more reliable than passive tags. Meanwhile, active tags are also more sensitive to moving objects than passive ones. Fig. 8 shows the RSSI readings for an active tag and a passive tag when an object passes by them from time 5 to 8. Compared with the passive tag, the active tag undergoes a rapid and significant change in its RSSI readings. Thus, TASA introduces a few active tags with known positions as reference tags to improve location sensing.

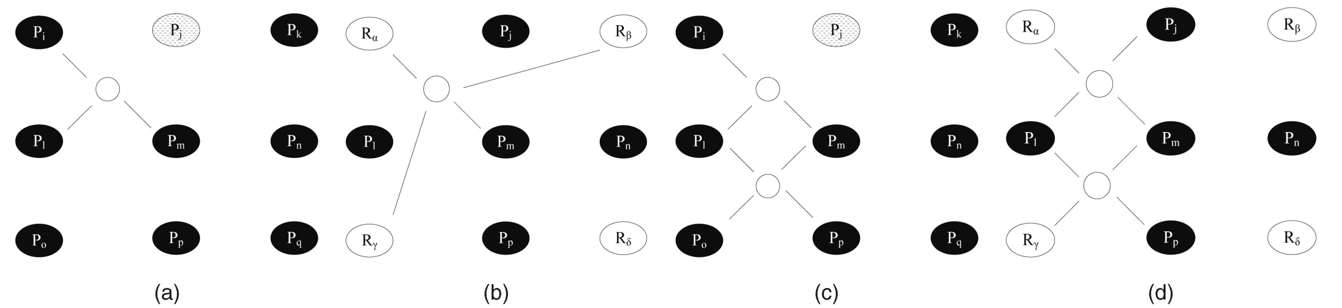

Fig. 7. Reference tags assist the TASA scheme to locate a single object and multiple objects. (a) Passive tag array locates a single object, (b) TASA scheme locates a single object, (c) passive tag array locates multiple objects, and (d) TASA scheme locates multiple objects.

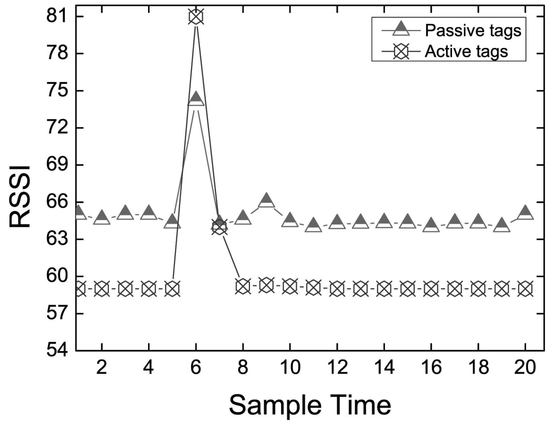

Fig. 8. Comparison of RSSI readings for both active and passive RFID tags when objects pass by.

Fig. 7d shows that TASA locates multiple objects with the help of reference tags. We are able to infer that moving objects are near the reference tags R_a and R_y from RSSI readings, because these reference tags are reliable. Consider that at least one passive tag detects the objects; we can accurately estimate the objects' positions, which are close to the real positions.

For each time period t, we detect that a reference tag, represented as L_0, is affected by the object movement, and its adjacent neighbors are also affected, denoted as $L_1, L_2, \ldots, L_k$. The center of these locations is used as the estimation for the moving object, which is defined as (1). Note that when multiple objects traverse the tag array simultaneously, several reference tags will be affected at the same time for each time period. For each reference tag, TASA checks its affected one-hop neighbors and then calculates a location so that TASA gets many estimated locations. Thus, TASA is capable of estimating locations for multiple objects:

$$\frac{\sum_{i=0}^{k} L_i}{k}. \tag{1}$$

The previous step of removing outliers filters records for unaffected tags and generates a sorted RSSI series as an array in chronological order. While this step calculates centers according to the neighborhood of reference tags, and locates objects with an approximate location for every time period. TASA explores a neighborhood relationship and route directions to locate objects. Recall that the entire tag array is modeled as a coordinate system with the tag located in the most left corner as the origin of coordinate. The neighborhood of a tag denotes its direct neighbors. For instance, tags P_j, P_l, P_p, and P_n in Fig. 7 are associated with the neighborhood relationship with the tag P_m.

Fig. 9 gives the pseudocode for locating objects with the help of reference tags. For each time period, the algorithm first finds affected active tags, then checks if its neighboring passive tags were affected, and calculates the center of all affected tags as the current locations of moving objects. Note that there may be more than one object being detected by the algorithm and TASA only checks two nearest tags for two reasons. One is that the nearest neighbors of a tag are significantly affected when an object is passing by the tag.

```
Input: RD, i.e., RDbase, an array of affected tags,
 RefReaderID, the set of ID of reference readers
Output: Location database LD

var row = RD.getRow();
var ts = null;
var tag = null;
var cNbor = null;
var cAffectedTag = null;
var cnTroid = null;

for (var i = 1; i <= row; i++)
{
    ts = RD[i].getTime();
    tag = RD[i].getReaderID();
    // records for reference tags
    if (tag in RefReaderID ){
        //finding neighboring affected passive tags
        cNbor =tag.getNeiborhood();
        for (var k = 1; k<=cNbor.count(); k++){
            var RSSI = cNbor[k].getRSSI();
            var Mean = cNbor[k].getMean();
            if {abs(RSSI - Mean) >= λ}{
                pcNbor =cNbor[k].getNeiborhood();
                while(count(pcNbor.affected())>=2){
                  cAffectTag.append(cNbor[k]);
                }
            }
        }
        //calculate the center of affected tags
        cnTroid = Calculate(cAffectTag, tg);
        //add centers to LD
        LD.append(ts, cnTroid.getCoordinate());
        //mark the affected reference tags as visited
        RD.mark(ts, tag, "visited");
    }
}
```

Fig. 9. The pseudocode for the LOR algorithm.

Other tags are slightly affected or not affected. The other is due to multiroute tracking, where some routes may be adjacent. If choosing more than two tags as parameters, TASA would make wrong detection.

So far, TASA has transformed the collected RSSI series to a set of route sequences in chronological order. Most of fragments of route sequences are calculated with the help of reference tags. However, TASA must take a case into consideration that reference tags fail sometimes or suffer from a bit longer delay, although it is a small probability event. In this case, TASA employs a policy that when more than two of all neighboring passive tags at a specific time are affected, TASA calculates a center of these passive tags and adds the center as the location of the object.

3.2 Phase 2: Activity Sensing

In this phase, TASA aims at detecting frequent routes in an online manner through two steps—discovering a frequent route set by incorporating minimum support and online detection of frequent trajectories.

3.2.1 Discovering a Frequent Route Set

Intuitively, one may apply frequent patterns discovering algorithms directly to find patterns in a set of trajectories. However, most of these algorithms rely on the exact sequence match, which is not the case in TASA, because RSSI readings for passive tags are inaccurate and incomplete. As a result, most existing work on pattern discovery doesn't work well.

In TASA, we extend previous pattern discovering algorithms with inexact match. Specifically, we select

```
Input: P, T: two route sequences
       m, n: the lengths of P and T
       k: the mismatch number
Output:s: the table that stores k information

// initialize score table: s
for i = 1 to N s[1, i] = 0;
for i = 1 to M s[i, 1] = i - 1;

// objective: finding approximate sequence
for i = 2 to n
    for j = 2 to m
        if (P_{j-1} == T_{i-1}) p = 0;
        else p = 1;

        s[j,i] = min(s[j-1,i-1]+p, s[j,i-1]+1, s[j-1,i]+1)

        if s[j,i] ≤ k
            report s[j,i]
```

Fig. 10. The algorithm for approximate sequence matching.

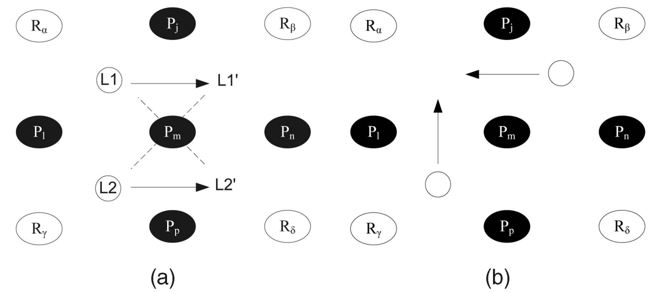

Fig. 11. Reference tags assist the TASA scheme to improve the accuracy of location sensing for traverse by multiple objects. (a) Multiple objects traverse a tag array with reference tags along two neighboring trajectories, and (b) multiple objects traverse a tag array with reference tags along partially overlapped trajectories.

Apriori [30] and FPGrowth [31], the two most influential frequent patterns discovering algorithms, as our algorithm core, and incorporate an inexact match algorithm with k differences. We call these two modified algorithms as iApriori and iFPGrowth, which efficiently search frequent patterns and are much robust to noisy RSSI sequences. Section 4 reports the performance of these two algorithms and the results show that iApriori performs better than iFPGrowth.

The inexact match algorithm with k differences is solved with dynamic programming. Let $P = p_1 p_2 \cdot \cdot p_m$ be a new route, and $T = t_1 t_2 \cdot \cdot t_n$ be a frequent route. Fig. 10 illustrates the approximate sequence matching algorithm, whose time complexity is $O(nm)$. The algorithm calculates the difference between P and T. When the difference between two sequences is less than k, they are regarded as the same route. Otherwise, they are different trajectories.

In TASA, we use a parameter δ to be the minimum support for frequent routes. In other words, a frequent route must be those which appear more than δ times in the set of routes. Section 4.5 studies how the parameter δ affects the performance of TASA.

3.2.2 Online Detection of Trajectories

This step determines the trajectories being traversed to be frequent or not in an online manner, based on the frequent route set generated in the previous step. In order to efficiently detect trajectories, we apply similar policies as discussed in Section 3.1.1, i.e., ignoring readings of unaffected tags and inserting records in chronological order. Then, TASA estimates possible location for objects, generates route sequences, and checks whether the discovered route is frequent or not with inexact match.

3.3 Discussions

3.3.1 Theoretical Analysis for Locating a Single Object

We assume that conspicuously abnormal tags are removed in preliminary experiments and active tags are always reliable. We also assume that persons neither suddenly change route directions when they traverse the tag array, nor keep still during the experiment. Let Δ be the square area delimited by four neighboring labels, e.g., tags R_α, P_j, P_l, and P_m in Fig. 7b. Let the failure probability for passive tags be ϱ, and the maximum error that TASA locates a single object be ε and its probability be τ. Theorem 3.1 shows that TASA can locate a single object with a low error rate.

Theorem 3.1. $P(\varepsilon \geq \Delta) \leq \varrho^3$

Proof. As shown in Fig. 7b, every square region has an active tag that can detect a moving object. The probability of three other passive tags which fail simultaneously is ϱ^3. When at least one passive tag senses the object, the estimated location computed by (1) falls into the Δ region. Then, TASA may locate object out of Δ range when all three passive tags of the same square fail at the same time, i.e., τ is ϱ^3. Thus, $P(\varepsilon \geq \Delta) \leq \varrho^3$. □

The failure rate of passive tags in our experiment is less than 0.1, which guarantees the performance of the proposed scheme. Additionally, when two or more nodes in a square are active tags, TASA can locate objects more accurately.

3.3.2 Locating Multiple Objects

TASA locates multiple objects with low errors with the help of reference tags under an assumption that objects neither suddenly change directions nor stand still in the experiment. Two primary cases for multiple objects are shown in Fig. 11a and Fig. 11b. Other cases can be reduced as one of these two cases.

Regarding the first case, two objects move along two neighboring trajectories during two consecutive periods t_1 and t_2. At t_1 period, we calculate two centers, L_1 and L_2. Note that RFID readers scan all tags every 50 ms, which indicates that the interval between time period t_1 and t_2 is about 0.02 s. Consider the world record for men's one hundred meter is about 10 m/s; humans can move about 0.2 m ($10 \times 0.02 = 0.2$ m) within such a short interval. Thus, TASA can capture most object movement. By exploring the continuity of trajectories traversed by persons and neighboring relationships of tags, we infer that the trajectories sequence can only be $L_1 -> L_1'$ and $L_2 -> L_2'$, not $L_1 -> L_2'$ and $L_2 -> L_1'$. Therefore, the error that TASA locates multiple objects is no bigger than the Δ range.

Similarly, by exploring the continuity of trajectories, TASA can locate objects in the second case as shown in Fig. 11b, where trajectories may intersect. Note that the fundamental reason TASA accurately locates multiple objects is the sensitivity and reliability of active tags.

3.3.3 Vulnerabilities and Countermeasures

TASA may be vulnerable to some attacks. For instance, if an intruder knows that RFID technology has been deployed in the monitored area, he/she may intentionally hide his/her path by interfering and disturbing the RSSI readings of RFID tag arrays.

To address this problem, our strategy is to hide RFID devices so that intruders may not be conscious of RFID tags or readers. Given that RFID is not sensitive to objects without excellent conductivity (e.g., metal) and the size of RFID tags is very small (e.g., 2 cm*3 cm*0.1 cm for passive tags in our study), we are able to mount readers and antennas on the ceiling, and deploy tags under the carpet or embed tags into the floor. In order to further conceal RFID devices, we may turn lights off for certain areas. Thus, intruders may be unaware of the RFID-based surveillance system. Moreover, we have conducted experiments to check the performance of our strategy. Experimental results in Section 4.3.1 show that hiding RFID devices do not affect the validity of our approach.

4 Evaluation

In order to evaluate the effectiveness of TASA in terms of accuracy and efficiency, we conduct a series of experiments. In particular, we try to answer the following questions:

1. What is the overall performance of TASA? Specifically, does it work well when RFID devices are hidden?
2. How do the reference tags influence the estimated accuracy and the running time of TASA? How does the density of tag arrays affect the estimated accuracy?
3. How do the parameters affect the accuracy of the proposed scheme?
4. How does our frequent pattern discovering algorithm affect the estimated accuracy and the running time of TASA?

For the above questions, we carried out experiments of four different activity types.

- Type 1: one person goes by the tag array along one route bidirectionally.
- Type 2: two persons pass through the tag array successively.
- Type 3: four persons traverse bidirectionally along four completely diverse trajectories simultaneously.
- Type 4: four persons go through the tag array randomly at the same time. They frequently and suddenly change route directions when they traverse the RFID tag array.

In all the experiments, the speed at which persons traverse ranges from 0.5 to 2 m/s and all the experiments are repeated for about 80-100 times.

4.1 Experimental Settings

In our experiment, we use 4 Alien 9,800 readers and 65 passive Alien tags operating in 920 MHz frequency. We also use a GT&T GWL-8 $\times$ 00 reader and 16 GT&T active tags with 430 MHz operation frequency. These tags are placed in a 9×9 array and one reference tag for every nine tags, as illustrated in Fig. 13. We divide the monitored space into a 2×2 grid, select centers of cells, and deploy RFID readers to the corresponding positions of these centers. The layout is shown in Fig. 13. Readers are connected to a router that communicates with hosts by a wireless LAN. Thus, the readers can send readings to specified addresses. The distance between readers' antennas and tags is less than 3 m in our experiment. The distance between the nearest neighbors in a row or column is a fixed value, i.e., 0.5, 1, and 2 m in the experiment. We sample all tags in preliminary experiments to exclude those with significant behavioral variations. Our program runs on a Windows XP (SP3) machine with 3.0 GHz Pentium IV CPU and 1 GB RAM.

4.2 Metrics and Methodology

In order to figure out the overall performance, TASA is evaluated in terms of estimated accuracy and scalability, which are measured by error rate and program's running time, respectively. In this section, we carry out experiments, repeat every experiment three times, and select averaged over three times as final results.

Error rate is the degree of errors encountered in route recovery, which is an elementary metric of the performance for TASA. It is defined as

$$err = \frac{|N - \tilde{N}|}{N}, \tag{2}$$

where N is the number of frequent trajectories that objects traverse, and $\tilde{N}$ is the estimated value of frequent trajectories. The less the error rate is, the better performance that TASA achieves. Due to the noisy RSSI readings, we increase the fault-tolerant functionality by allowing the estimated route to be correct if it has over 90 percent similarity with the real route. We partition the data set T as test sets, T100, T200, T300, T400, T500, and T600, which are generated by randomly selecting 16.67 percent, 33.33 percent, 50 percent, 66.67 percent, 83.33 percent, and 100 percent of the data set, respectively. Every experiment will be run across all the test sets.

Scalability is another important concern, which affects the performance of TASA considerably. We conduct experiments to evaluate scalability by varying the test set from T100 to T600 and select program's running time as a metric. We also run experiments three times and calculate averaged values as final.

4.3 Overall Performance

We carry out experiments for all the test sets to evaluate the overall performance of the proposed scheme. The LOR algorithm is used to locate objects and the iApriori algorithm is employed to discover frequent trajectories. In these experiments, parameters λ and δ are set as 7 and 10, respectively. The distance between adjacent tags is half a meter.

4.3.1 Estimated Accuracy

In order to evaluate TASA in terms of estimated accuracy, we conduct experiments by varying the size of the test set for all types of activities. We name the algorithm presented in [11] as PA and select it as the baseline. Additionally, we conduct experiments by hiding RFID devices: RFID readers and antennas are mounted inside the ceiling, and RFID tags

TABLE 2
Error Rates⊖ of all Experiments

Error rates⊖

Test Set	Method	Type 1	Type 2	Type 3	Type 4
T100	TASA	5.21%	14.51%	13.44%	43.54%
	TASA-O	5.38%	17.32%	19.05%	52.68%
	PA	4.89%	18.67%	29.17%	57.66%
T200	TASA	4.36%	12.55%	12.73%	35.64%
	TASA-O	4.39%	14.82%	16.75%	41.27%
	PA	4.13%	17.86%	28.32%	54.19%
T300	TASA	3.64%	11.03%	11.68%	29.82%
	TASA-O	3.95%	12.08%	15.47%	35.73%
	PA	3.27%	15.39%	27.56%	52.48%
T400	TASA	2.40%	9.84%	10.52%	25.44%
	TASA-O	2.67%	11.26%	13.19%	30.79%
	PA	2.35%	14.51%	25.85%	50.87%
T500	TASA	1.28%	9.07%	9.89%	24.36%
	TASA-O	1.55%	10.92%	11.58%	30.12%
	PA	1.30%	12.33%	25.01%	51.09%
T600	TASA	0.96%	8.11%	8.43%	24.51%
	TASA-O	1.09%	9.84%	10.52%	28.44%
	PA	0.98%	12.19%	24.77%	50.48%

⊖ Lower error rate means better performance.

are under the carpet. Thus, the TASA system is invisible to users because their visuals are blocked by ceilings and carpets. We call such an experimental setting as TASA-O.

Table 2 illustrates the error rates for all experiments with the test set varying from T100 to T600. The overall error rates for all experiments decrease with the increase of the size of the test set and their values are small. The results indicate that TASA and TASA-O achieve higher levels of accuracy than PA in recovering routes traversed by multiple persons at the same time. This is because the PA algorithm does not consider the route recovery for multiple objects, which becomes more evident when the number of persons who traverse the tag array increases. For instance, the PA's error rates for *Type 3* and *Type 4* are much higher than those for *Type 2*. By contrast, TASA is capable of accurately checking trajectories traversed by multiple persons in an online manner. For *Type 1* activity, these three algorithms achieve similar accuracy, denoting that they are qualified for tracking a single object. Note that TASA-O achieves low-level error rate for online detecting objects, because RSSI readings are slightly affected by carpets and ceilings that are objects with weak conductivity.

The values of TASA's error rates for *Type 1* and *Type 2* activities are very small (i.e., up to 0.96 percent and 8.11 percent, respectively). This implies that the proposed scheme accurately keeps track of a single person and multiple persons who traverse the RFID tag array successively. With respect to *Type 3*, four persons simultaneously go through the RFID tag array along the totally different trajectories, which may cause many errors due to route overlap, direction change, and persons' stop. Thus, the value of TASA' error rate becomes larger than those of *Type 1* and a little bit less than those of *Type 2*. The value of TASA's error rate for experiment *Type 4* is the largest among all the experiments, ranging from 43.54 percent to 24.51 percent.

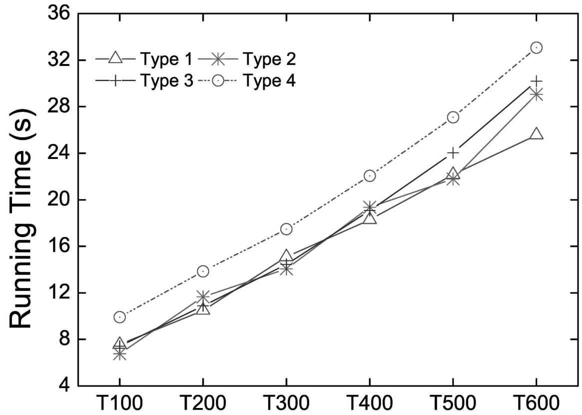

Fig. 12. Running time for all experiments with respect to different test sets.

This is because persons frequently and suddenly change route directions and overlap routes when they traverse the tag array. It is also caused by the behavioral variations in RFID readers and tags.

4.3.2 Scalability

TASA is supposed to be scalable owing to detecting trajectories in an online manner, which requires that it should check trajectories fast. During the detection, TASA collects RSSI readings of a large amount of tags from several readers, and processes these readings. In order to study the scalability of TASA, we conduct experiments by varying the test size from T100 to T600 and choose running time as the metric. The less the running time, the better the performance TASA can achieve.

Fig. 12 illustrates the scalability results for all the test sets, indicating that the running time increases linearly with the test sets. It takes much time for TASA to handle *Type 4* trajectories than other types. This is because iApriori requires more time to calculate the frequent patterns.

4.4 Effectiveness of Reference Tags

The reference tags have profound influence upon TASA, which accelerates localization and improves estimated accuracy. We check the performance of the LOR algorithm by comparing it with LO—LOR without reference tags. In this section, we carry out experiments for all types of activities to evaluate the performance of these algorithms. We also examine the influence of the density of the tag array. The distance between adjacent tags is half a meter and every experiment is run by the LO and LOR algorithms.

Figs. 3 and 13 illustrate the performance results of the LO and LOR algorithms, respectively. The former algorithm is merely valid in identifying frequent trajectories traversed by a single person, while the latter algorithm achieves high accuracy in recovering trajectories of single and multiple persons (e.g., *Types 2* and *4*). This indicates that the LOR algorithm significantly improves the estimated accuracy of trajectories recovery. This is because the RSSI readings of reference tags are much more reliable and more effective in removing noise than passive tags, and thus can localize objects more accurately. However, the LOR algorithm does not achieve very high accuracy for a

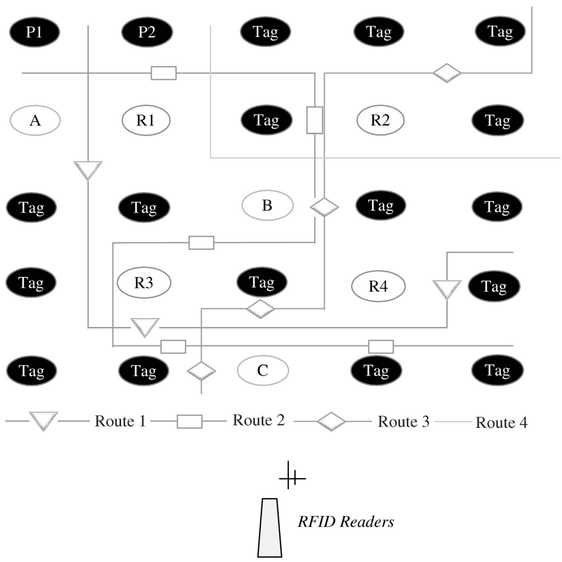

Fig. 13. Complex trajectories recognized using the LOR algorithm with reference tags.

complex activity of multiple objects, implying that LOR could be further improved.

Table 3 illustrates the running time for the LO and LOR algorithms. The LOR algorithm, rather than LO, has a relatively low overhead up to 16.3 percent for a simple activity, e.g., *Types 1* and *2*, as well as the heavy overhead up to 46.46 percent for a complex activity like *Type 4*. This is because the LOR algorithm spends much time in calculating the similarity for different trajectories, especially for complex activity. Such overhead could be reduced by improving computer configurations and is acceptable for the targeted applications that can tolerate several seconds delay.

TABLE 3
Running Time* for the LO and LOR Algorithms

Types	Type 1	Type 2	Type 3	Type 4
LOR	28.77	30.34	35.11	48.45
LO	25.56	28.06	30.19	33.08
Overhead	12.56%	8.13%	16.30%	46.46%

* All time is by the second.

4.4.1 Study on the Density of Tag Arrays

The density of the tag array plays an important role in TASA, which determines its efficiency. In this section, we conduct experiments for all types of activities to evaluate the performance of the density of the tag array by varying the distance between adjacent tags to 0.5, 1, and 2 m.

Fig. 14 illustrates the results of the density of the tag array, which denotes that error rate goes up rapidly with the increase of the distance between adjacent tags. When the density of the tag array decreases, especially for tag arrays larger than 1.5 m, TASA cannot accurately capture the RSSI readings and thus leads to higher error rates. In our experiment, we selected half a meter as the default distance between adjacent tags.

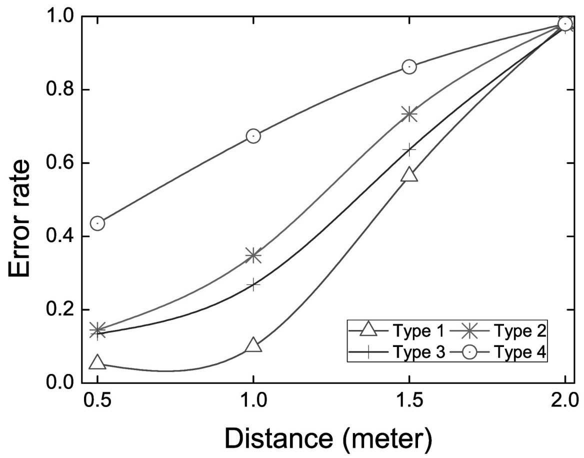

Fig. 14. Study on the density of the tag array.

4.5 Sensitivity of Parameters

In this section, we carry out several experiments to study the sensitivity of different parameters of our algorithm, as these parameters have significant impact on the performance of our system. Specifically, we study the sensitivity of the threshold λ and minimum support δ.

4.5.1 Sensitivity of the RSSI Threshold λ

The RSSI threshold λ controls how many RSSI series can be saved and later be explored by the proposed algorithm of frequent pattern discovering. Note that the parameter λ is decided empirically depending on the monitored objects and specific batches of RFID tags.

Fig. 15 illustrates the influence of the threshold λ for different types of activities. The better values of error rate for these experiments are achieved when λ is around 7. The

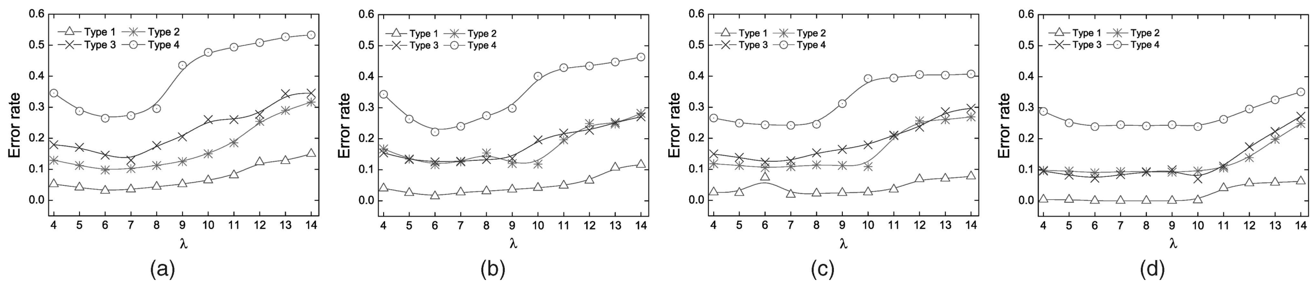

Fig. 15. Sensitivity of λ for different test sizes. (a) Error rate of different λ at T100, (b) error rate of different λ at T300, (c) error rate of different λ at T400, and (d) error rate of different λ at T600.

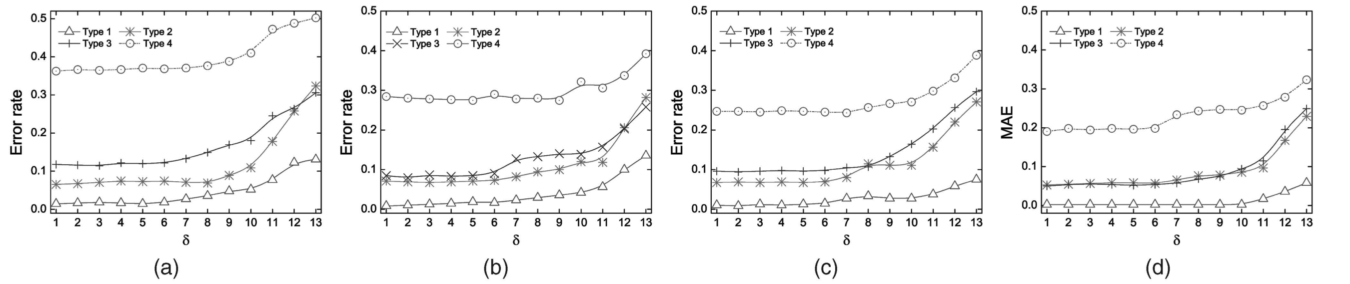

Fig. 16. Sensitivity of δ for different test sizes. (a) Error rate of different δ at T100, (b) error rate of different δ at T300, (c) error rate of different δ at T400, and (d) error rate of different δ at T600.

values of error rate are higher when λ is less than 7, because the smaller λ causes much noisy data to be included. When λ is higher than 8, the error rate also increases. This is because a higher λ filters out much useful data, leading to the decline in the estimated accuracy. Thus, we choose 7 as the value of the threshold λ in our experiment.

4.5.2 Sensitivity of the Minimum Support δ

In order to study how the minimum support δ affects our scheme, we do experiments with different support values.

The results in Fig. 16 show that the parameter δ has a significant impact on the performance of TASA. When δ is greater than 11, error rate tends to rise quickly. This is because using a larger δ value causes the LOR algorithm to aggressively filter out data. As a result, many useful RSSI readings that should be kept are removed. When threshold δ is less than 10, we observe that the error rate changes little, which indicates that the value of δ between 8 and 10 is an appropriate range.

4.6 Performance of Discovering Algorithms

We have implemented the iApriori and iFPGrowth algorithms for detecting frequent trajectories with noise. This experiment evaluates the performance of these two algorithms. Given that both algorithms achieve similar estimation accuracy, we focus on the comparison of running times.

Fig. 17 shows the results of all experiments, which indicates that the iApriori algorithm runs faster than iFPGrowth in all cases. As the size of the test set increases, they both experience fast rise, close to linear increment of time. The reason is that the iFPGrowth algorithm spends much time in maintaining the FP-Tree for short patterns, whereas iApriori spends less time to update the supports of candidate sets in every transaction. Because of high efficiency of the iApriori algorithm, we select it as the frequent patter discovering algorithm in our experiment.

5 Related Work

Activity sensing has drawn many attentions in recent years and has yielded lots of research results in vision-based, Bluetooth, infrared, ultrasonic, RFID, and sensors domains. This section briefly discusses these approaches.

Vision-based schemes capture scenarios as videos to locate objects by the vision recognition technique [13], [32]. With the improvement in adaptive streaming, content analysis, object identification, reusability, and scene modeling [33], [34], [35], vision-based schemes have achieved widespread use in academia and industry. In general, vision-based schemes collect much richer information, but they suffer from the line-of-sight problem [18], [36], [37], as lights can be easily blocked by objects. In comparison, we have shown that TASA can still work when RFID devices are hidden behind ceilings and under carpets. Additionally, the computation overhead of TASA is significantly lower than vision, allowing for online activity sensing. Hybrid surveillance schemes by combining sensor and vision technologies have also been proposed [38], [39]. These systems are limited by the short lifetime of batteries in sensors.

Surveillance technologies, such as Bluetooth, infrared, ultrasonic, sensors, and other wireless technology, have also been studied in the literature. Bluetooth is designed for indoor location sensing, but limited by energy consumption and short coverage [5], [6]. Diffuse infrared is used in Active Badge [4]. It is less effective in location schemes due to two fundamental problems—the line-of-sight requirement and short-range signal transmission. Ultrasonic-based schemes like Cricket [7] take the advantage of the ultrasound time-of-flight measurement technique to locate objects and thus achieve good accuracy. They involve a great deal of infrastructure to be highly accurate, leading to heavy cost. Global Positioning System (GPS) is another

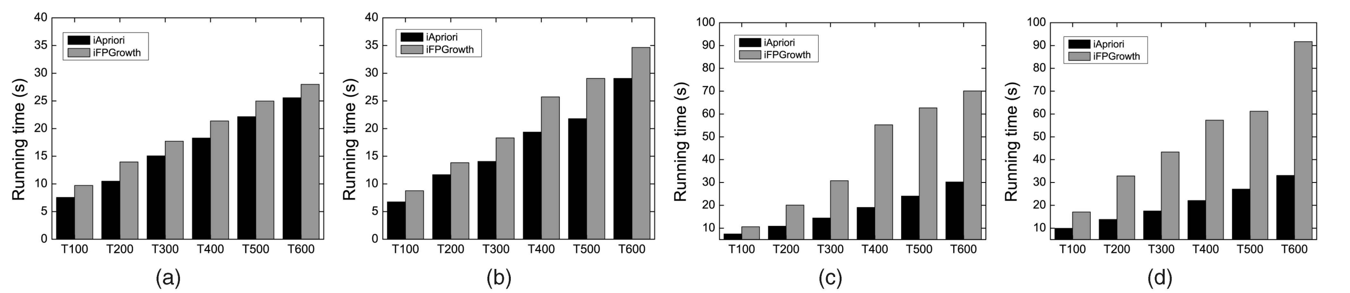

Fig. 17. Running time of both iApriori and iFPGrowth algorithms for all experiments. (a) Type 1, (b) Type 2, (c) Type 3, and (d) Type 4.

well-known location technique, but infeasible for indoor location sensing [40]. Wearable [41] and body sensors [42] require objects to carry transceivers beforehand, which is not needed in TASA.

RFID-based activity sensing has been proposed before [11], which shares the similar idea of exploiting the phenomenon that RSSI changes significantly when an object is passing by. TASA differs from the previous scheme [11] in two aspects. First, TASA uses passive tag arrays together with a few active reference tags, while the previous scheme [11] merely utilizes active tags. Thus, TASA is a more cost-effective approach. Second, TASA proposes several algorithms to reduce noise in the readings of passive RFID tags and achieve better accuracy. In particular, TASA is much effective for locating multiple moving objects.

6 Conclusion

In this paper, we have proposed TASA—Tag-Free Activity Sensing using RFID tag Arrays for location sensing and route tracking. The proposed scheme is an alternative to activity sensing applications with specific requirements, such as route tracking and group behavior monitoring. TASA performs well in terms of estimated accuracy and scalability, which is achieved by passive RFID tag arrays with a few reference tags. TASA is a cost-effective and tag-free approach for monitoring moving objects.

Currently, the proposed scheme still has some limitations. In our future work, we will investigate how to improve the localization accuracy for complex activities. We will also study how to improve the signal measurement by exploring relationships between RSSI and Low Quality Indicator (LQI).

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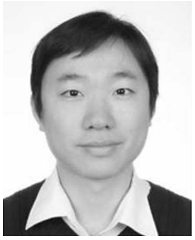

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