Object Search for the Internet of Things Using Tag-based Location Signatures

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***Abstract*—In this paper, an object search solution for the Internet of Things (IoT) is proposed. This study first differentiates localization and searching. Localization is to calculate an object's current location. Searching is to return a set of locations where a target object could be. It is possible that the locations of the returned set are not contiguous. Searching accuracy can be improved if the number of the returned locations is small. Even though localization technique is applicable to searching applications, a simpler and easier solution will attract more enterprise users. In this paper, based on a concept called location signature, defined by a set of reference tags, an object searching method named Location Signature Search (LSS) is proposed. The study of LSS shows that the searching accuracy can be very high if a location signature is not shared by too many locations. Since location signatures are affected by the deployment of the reference tags, trade-off between searching accuracy and implementation cost is achievable. A real world experiment is conducted in this research. The results show that LSS indeed is a practical method for object searching applications.**

***Index Terms*—Internet of Things, location signature, object search, RFID, ubiquitous computing**

I. INTRODUCTION

The *Internet of Things* (*IoT*) envisions a world where each everyday object has a unique identity and is able to connect to a wireless data network [1][3]. Being a digital identity for an object, *Radio Frequency Identification* (*RFID*) technology has recently been adopted by a wide range of industries such as retail and pharmaceuticals. The successful utilization of RFID technology can also help realizing the IoT vision – a global infrastructure of networked physical objects [2]. In fact, with IoT, people can live in a smarter world [4].

Recent IoT applications to support enterprise operations can be seen on manufacturing [5][6][7][8] and supply chain [9][10][11]. The ability of bridging the virtual world of digital information and the real world of products and logistical units is the key reason why IoT becomes more and more promising in solving existing business problems [7][12]. On the other hand, IoT has also attracted great attention from indoor tracking and localization applications [13][15-20][22-26][28-35].

Indoor localization, especially accurately positioning, is crucial for many ubiquitous computing applications [21][27]. In fact, for many enterprise applications, searching and identifying where an important asset is, for example, a specific mold inside a factory, is very important [27]. Even though *Global Positioning System* (*GPS*) technology is widely used to track moving objects outdoors, it performs quite poorly when operating indoors.

Solutions using RFID technology for indoor localization or positioning have been proposed recently by many research teams. Examples include SpotON [20], and LANDMARC [23]. SpotON utilizes the RF signal strength to perform location calculation. LANDMARC uses reference tags, RF map and a large number of received signal strength data stored in a database to position an active tagged object's location. Triangulation is another popular technique for RFID-based localization and positioning. In recent years, many researches employ triangulation algorithm to help indoor localization in places like factor's assembly lines or conveyer belts [31][32][33]. To track so many tagged objects in an enterprise, many RFID readers must be deployed to help track these objects. Thus, integrating RFID technology with wireless sensor network to form a wireless RFID network [35] is another burgeoning trend in IoT-based localization.

Instead of tracking the tag attached on the object, another IoT indoor localization solution uses tags as known location references and it tracks the moving reader mounted on the object [15][18][19][22][26][34]. In order to know where a given object is, with mathematical analysis of the sampling set of the references tags sensed by its attached reader, an object's current location can be estimated. These types of solutions are especially useful for moving robot systems or tracking moving wafer boxes in semiconductor manufacturing or testing facilities [30].

In this paper, in stead of emphasizing localization, we are more interested in the issue of *searching* an object in

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a known area where locations in that area are well marked. The difference between localization and searching is that localization is to calculate an object's current coordinates while searching is to identify a set of limited locations an object could appear. If all the locations in an area are well marked, knowing a restrict set of positions regarding an object being searched in that area can greatly increase searching accuracy; but the same set of positions may not return a meaningful coordinate for that object since those positions may be totally irrelevant with respect to actual coordinates.

In order to develop a simpler and easier object searching solution, a concept called *location signature* is introduced. By first deploying reference tags on a target area, each location inside the area will have its own location signature defined by a subset of the deployed tags. Based on location signature, an indoor searching solution named *LSS* (*Location Signature Search*) is proposed. In order to study the characteristics of LSS, simulations and experiments are conducted. The results show that a good reference tag deployment scheme can dramatically reduce the number of reference tags used to build location signatures and still maintain the uniqueness property for each location. However, if some positions of an area allow lower accuracy resolution, i.e. their location signatures are shared by other locations, the number of reference tags used to build location signatures can be further reduced. In fact, if 95% searching accuracy is acceptable, the number of the reference tags used to build location signatures is less than 200 in a 100 ×100 logical grid area.

This paper is organized as follows. Section 2 describes the concept of location signature and object searching solution LSS. Section 3 studies the characteristics of LSS. Experiments and observations are given in Section 4. Section 5 is the concluding remarks.

II. LOCATION SIGNATURES AND OBJECT SEARCHING

In an enterprise, objects required to be searched, usually valuable assets, are either mounted with mobile readers or loaded on a recyclable pallet/trolley equipped with a mobile reader. Figure 1 shows an example of a RFID-equipped trolley from a semiconductor testing firm. A trolley is mounted with a RFID reader and two antennas: one for sensing the RFID tagged wafer boxes loaded on the trolley (antenna 1), and the other (antenna 2) for detecting the location tags placed beneath the floor. In this research, UHF RFID technology with frequency range 902-928 MHz is used to conduct the experiments. Instead of placing reference tags beneath the floor we deploy the tags on the ceiling, which is considered as a more cost effective approach for experiment environment.

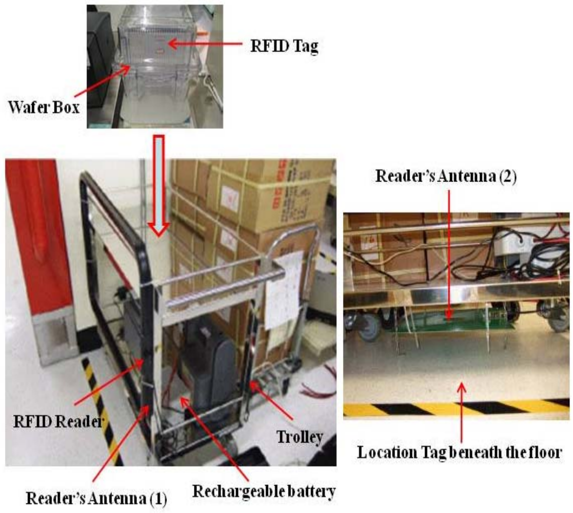

Figure 1. A trolley equipped with RFID reader to facilitate enterprise asset tracking

Even though localization solutions can be used to perform object searching, searching is not necessary as complicated as localization. Therefore, it is possible that there exists a simpler searching solution than those utilizing the addressed RFID positioning techniques.

In order to develop a simpler and easier object searching solution, location signature is introduced. By first deploying reference tags on an area carefully, each location inside the area has its own signature which is defined by a set of the deployed tags related to the location. If the location signature can be uniquely decided for each location in the area, indoor searching solution with expected accuracy becomes possible. Also, since the location signatures of a given area are fixed and can be pre-computed, the location of any given spot can be easily retrieved by using location signature as the corresponding index. Therefore, instead of tracking and calculating the location of a given object, an object can be easily searched by checking its current location signature.

Consider a target area A. Define the expected accuracy resolution of a given searching requirement as r. Accuracy resolution r means that an object locating inside a $r \times r$ square is considered as at the same position. If r is not a large value, for example let's say one meter, it means an object can be identified inside a one square-meter large area which is good enough for object searching. Also the boundary between any two square areas is assumed to be belonging to one specific square. That is, there is no ambiguous position. In order to simplify our future discussion, let A be an $N \times N$ square area where N is a multiple of r and therefore the area A becomes an $n \times n$ grid where each grid size is $r \times r$ and $n = N/r$.

Let $P = \{ p_{ij} \mid \text{where } 1 \leqq i \leqq n \text{ and } 1 \leqq j \leqq n\}$ be the set of all the physical locations inside area A. Assume the effective detecting radius of a mobile reader attached on an object is d. Let

$$S(p_{ij}) = \{tag_{uv} \mid \text{where } tag_{uv} \text{ is located inside the circle centering at position } p_{ij} \text{ with radius } d\}. \quad (2.1)$$

Then, $S(p_{ij})$ is recognized as the location signature of p_{ij}. Consider an arbitrary position named p_{st}. If $S(p_{st}) \neq S(p_{ij})$ for all $1 \leqq i \leqq n$ and $1 \leqq j \leqq n$, it is clear that the location p_{st} can be uniquely identified by $S(p_{st})$. In other words, when an object is on this location, it can be identified by the location signature $S(p_{st})$ with 100% accuracy. If the reference tag deployment is not good enough, it is possible that many neighboring locations are sharing the same signature. Assume there are another m locations sharing the same location signature $S(p_{st})$, then the searching accuracy for location p_{st} is:

$$(n \times n - m) / (n \times n) \times 100\%. \qquad (2.2)$$

In the real world, with the uncertainty of equipments and environment, tags detected by a reader may not always be the same even when at the same location. Therefore, there exist various situations required to be discussed. First, let S be the set of the reference tags sensed by the reader attached on some object x at the location p. Assume the location signature of p is T.

If $S = T$, the location(s) with the location signature T is (are) returned as the identified location(s) for searching object x.

If $S \neq T$, there exist two possible cases:

1. S also is a valid location signature,
2. S is not a valid location signature.

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For the first case, it is clear that wrong location(s) will be returned for searching and therefore the object x cannot be found at the returned location(s).

For the second case, less or more tags are detected at the location p. Since S is not a valid signature, no location(s) can be returned for searching. Let $\hat{S}$ denote a set of location signatures such that the members in $\hat{S}$ are either subsets or supersets of S. In other words, by adding or removing some tags, S becomes a valid location signature. Let m_i be the number of the locations sharing the same location signature S_i where $S_i \in \hat{S}$. Then, we say that the searching accuracy for object x at position p is:

$$\frac{n \times n - \sum_{\forall S_i \in \hat{S}} m_i}{n \times n} \times 100\% \qquad (2.3)$$

Based on the above definitions, LSS can be described in the following:

Step 1. Let A be the searching target area. Choose values for r and d. These two values decide the searching precision of the target area.

Step 2. Based on r and d, define a reference tag deployment scheme for the area A. Tag deployment scheme can be arbitrary or any preferred pattern. It is obvious that the location signatures are highly related to the chosen deployment scheme.

Step 3. Following the equation 2.1, build location signatures for all the locations on the area A. Each location and its location signature are paired together. It is possible that more than two locations are sharing the same signature.

Step 4. When searching an object x, LSS requests the corresponding mobile reader of x to return its current detected reference tags through wireless network. LSS uses the returned tags to represent x's current location S.

Step 5. If a location signature T is identified to be equal to S, the location(s) paired with T is (are) returned for searching. If object x cannot be found in the returned location(s), go back to Step 4.

Step 6. If no any location signature is identified to be equal to S, build set $\hat{S}$ and return all the location(s) paired with the location signatures in $\hat{S}$. Search object x within the returned location(s). If object x cannot be found in the returned location(s), go back to Step 4.

One of the major issues of using tag-based location signatures for LSS is how to guarantee that each location is paired with a unique location signature. This issue depends on how many reference tags are used and how they are deployed. In order to investigate the searching accuracy problem caused by the tag deployment, further studies with experiments are given in the next section.

III. Characteristics Of LSS

In order to study the characteristics of LSS, an LSS simulation is developed. It provides a user interface to show the deployed reference tags in green dots on the target area. Based on the mobile reader mounted on the object, the simulator calculates all the location signatures and shows a visualized accuracy map with the corresponding searching accuracy. The dot on the map with deep blue color represents its location signature is unique and therefore the searching accuracy on that location is 100%. The dot with lighter blue color means the location is sharing the location signature with other locations and following the searching accuracy equation 2.2, the computation is less than 100% for the location. When the blue color getting even lighter, it means the location is sharing the location signature with even more other locations and therefore the location's searching accuracy is far less than 100%.

The simulation parameters of LSS in this section are $N = 100$, $r = 1$, $n = N / r = 100$, and $d = 8$. It is clear that the $N \times N$ square area is divided into $n \times n$ =10,000 grid locations. Before continuing the discussions, an extreme case is introduced first. Assume each location in the target area is deployed by a reference tag. It is obvious that the sets of tags detected at all locations are all different and therefore it guarantees the uniqueness of every location in the area. However, this extreme case requires 10,000 reference tags and it is not realistic when considering the deployment cost. Therefore, in the following studies this case is treated as the benchmark for searching accuracy and deployment cost.

The first case we are interested in is a random case. Let 800 reference tags are deployed randomly in the target area. In this case, the deployment cost is only 8% of the benchmark case. There are around 70% locations in the whole area having unique location signatures and therefore the searching accuracies for these locations are 100%. In fact, the worst searching accuracy in this area is still larger than 99.8% and it represents that under this random tag deployment, the worst situation is that there exists a location signature shared by no more than 20 locations. In other words, instead of going through all 10,000 locations, any object inside the area can be identified within 20 locations. The tag deployment and searching accuracy for this case are given in Figure 2 (a) and (b), respectively. Figure 2 (c) shows the distribution of the searching accuracy for all the locations in the area.

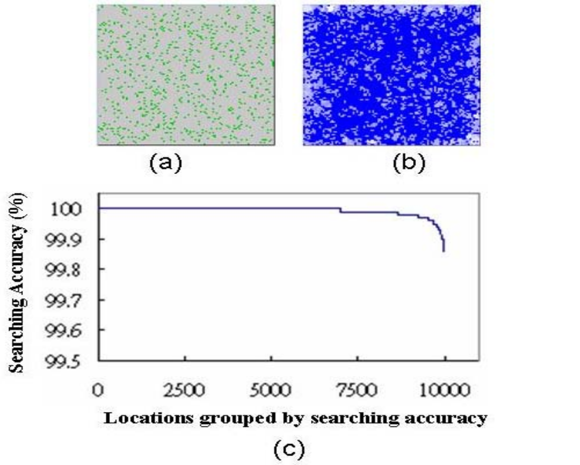

Figure 2. Case 1: (a) 800 reference tags randomly deployed in the area, (b) accuracy map of the area, (c) distribution of the searching accuracies for all locations.

With the results of the random case, a new question is raised: is it possible to design a better tag deployment such that it can increase the searching accuracy but further reducing the deployment cost? Figure 3 shows the results for this new case. This deployment uses 576 reference tags. They are deployed as a mesh in the area. The distance between any two vertical or horizontal tags is 4 grid locations. The deployment cost is less than the cost of the random case and its value is 5.76% of the benchmark case. There are 74.1% locations having unique location signatures and therefore the searching accuracies for those locations are 100%. The worst searching accuracy is larger than 99.9%. In other words, any object inside the area can be searched in less than 10 locations. It is obvious that either deployment cost or search accuracy, this case is better than the previous random case, i.e., a good deployment design really can improve the searching accuracy and reduce the deployment cost.

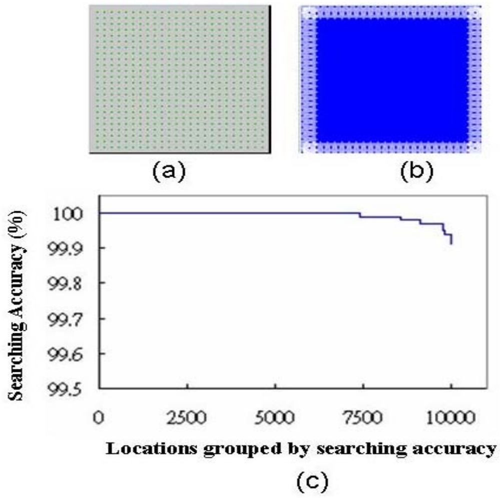

Figure 3. Case 2: (a) 576 reference tags deployed as a mesh in the area, (b) accuracy map of the area, (c) distribution of the searching accuracies for all locations.

In the above two cases, there still exist some locations sharing their signatures with other locations. Therefore, another question is raised: is it possible to design a tag deployment such that the searching accuracy in the whole area is 100% but using fewer tags? Figure 4 is the results for Case 3. By observing the accuracy map of the previous case, it is obvious that the location signatures in the boundary area are not unique. Therefore, we redesign the tag deployment of the previous case by refining the boundary. The distance between any two vertical or horizontal tags in the boundary is changed to 2 grid locations. In this case, 1,161 reference tags are deployed on the area and the deployment cost is 11.61% of the benchmark case which is higher than the values of the previous two cases. However, in this case every location has its own unique location signature and therefore the searching accuracy is 100% for all locations in the area. In other word, any object appeared in the area can be identified exactly in its location without any other consideration.

Based on the above discussions, it is clear that with enough tags well deployed in the target area, 100% searching accuracy can be achieved. A curious question is again raised: if only few tags can be deployed as reference tags, then how bad LSS will perform. Figure 5 is the results for an example using less than 100 tags. In this case, only 98 tags are deployed in the area. The deployment design is in diamond pattern. It is obvious that the deployment cost is very low. In this case, there are only 2.16% locations having unique location signatures. It means if an object appeared in this area, it looks like the object is very difficult to be identified in an exact location. However, the whole area's searching accuracy is still higher than 99.5%, that is, the worst situation to search an object is going through no more than 50 different locations. Since LSS can return the exact positions of the locations, the above issue, searching over 50 locations, it should not cause too much trouble for general enterprise applications.

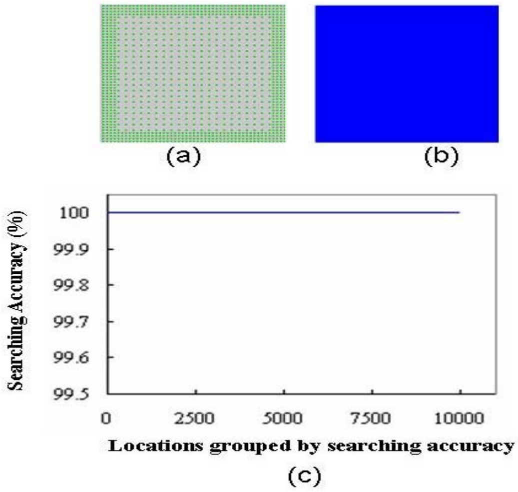

Figure 4. Case 3: (a) 1,161 reference tags deployed as a mesh with fine grained boundary, (b) accuracy map of the area, (c) distribution of the searching accuracies for all locations.

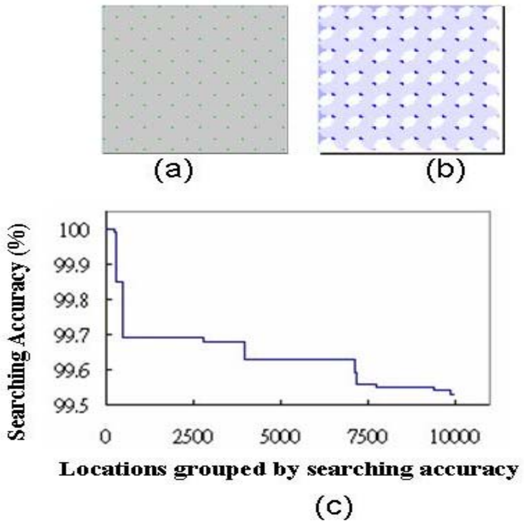

Figure 5. Case 4: (a) 98 reference tags deployed in the area with diamond pattern, (b) accuracy map of the area, (c) distribution of the searching accuracies for all locations.

The studies of the previous four cases have shown some fundamental characteristics of LSS. Next, we want to explore the usages of LSS with some real world constraints.

First, we consider the constraint such that some locations in the target area require higher searching accuracy while other locations do not. As an example, Figure 6 shows a rectangle hotspot in the area requiring 100% search accuracy. The tag deployment design for this case includes two different schemes. In the hotspot area, tags are deployed equally with 4 location distances. For the remaining area, tags are deployed equally with 8 location distances. With this hybrid deployment, totally 248 tags are used. The worst searching accuracy in the remaining area is 99.7%.

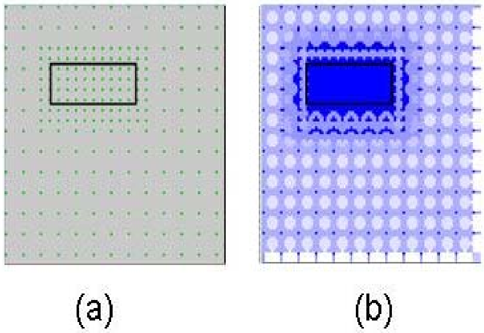

Figure 6. Case 5: (a) 248 tags deployed in the area, (b) accuracy map of the area.

Finally, we consider another situation such that the target area is not a completely open space, i.e., there exists non-free locations for putting objects on them. Figure 7 gives an example of this kind. In this case, 504 reference tags are deployed equally with 4 location distances. It is trivial that no reference tags are deployed on those non-free locations. However, the searching accuracy in this area still can be maintained better than 99.8%.

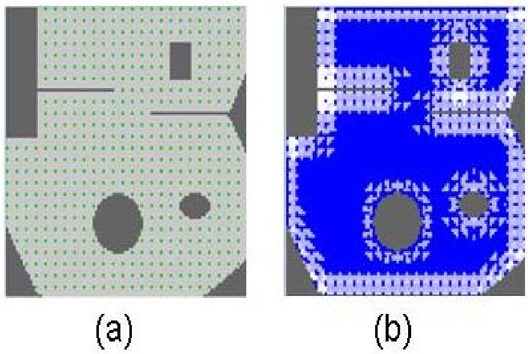

Figure 7. Case 6: (a) 504 tags deployed in the open area, (b) accuracy map of the open area.

By observing the above six simulations, it shows that LSS indeed can be developed as a practical object searching solution for IoT applications. In order to further verify LSS behavior in the real world, an experiment is introduced in the next section.

IV. EXPERIMENTS

The schematic view of an LSS solution is depicted in Figure 8. The Location Signature Deployment (LSD) process begins with devising and simulating various reference tag deployment schemes. Then, a tag deployment scheme is adopted and saved in the location signature database. Upon receiving a query from a user who is inquiring where an enterprise asset is, LSS is performed to return a set of possible locations for searching.

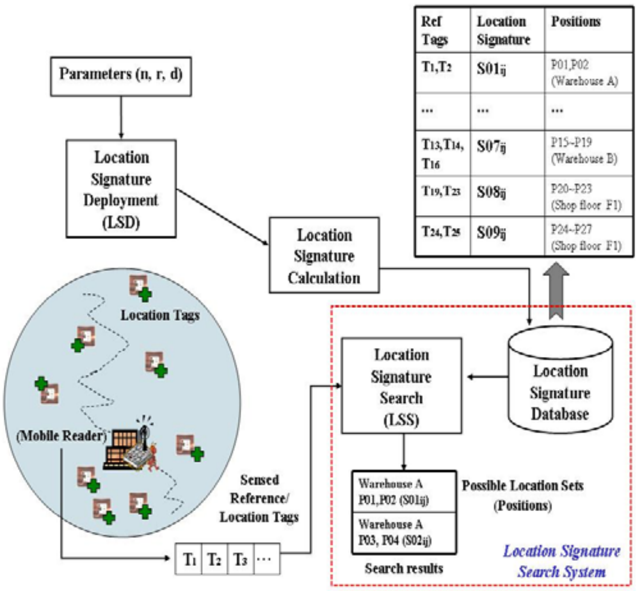

Figure 8. A schematic view of LSS system.

In this section, the above addressed system is implemented for conducting a real experiment. First, we use our lab as the target area. The size of the lab is a 24 × 12 m^2 rectangle area. The RFID reader mounted on the object in this experiment is an UHF AWID MPR-2010BN reader with frequency range 902-928 MHz and reader range 5 meters. The reference tags deployed in the area are UPM Raflatac UHF tags with frequency range 860-960 MHz. The location resolution chosen for the experiment is 0.6 meters. It means there are 800 different locations can be identified for searching in the area. The tag deployment is designed as a mesh and the reference tags are attached on the ceiling as shown in Figure 9. Distance between each pair of tags is 2.4 meters, i.e., the location distance between any two tags is four. This deployment has been first evaluated. It shows that 66 tags are required to use, 45.5% locations possess unique location signatures, and the worst searching accuracy in the area is 99.25%.

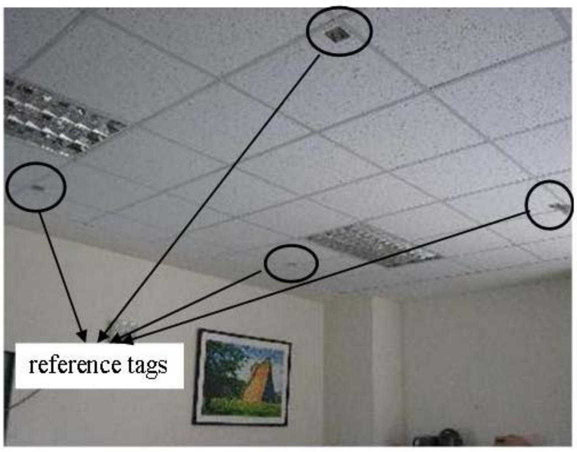

Figure 9. Experiment environment: a 24×12 m^2 rectangle area with reference tags deployed on the ceiling.

When performing an experiment, first the target object with mounted reader is randomly put on any available location in the area. Since the uncertainty caused by the experiment environment and equipment, the number of the location signature may be none, only one or larger than one. Therefore, based on LSS Step 6 given in Section 2, the returned locations may be quite large. It should be noticed that it is possible the object is not on any of the returned locations.

In this section, twenty experiments are conducted and Table 1 contains the experiment results. The second column of the table represents the number of the location signatures returned by LSS. The third column is the number of the locations identified by the signatures. The forth column is the searching accuracy. If the target object cannot be found in the returned locations, the value should be 0%. If the target object can be found in the returned locations, the searching accuracy is computed based on equations 2.2 or 2.3.

TABLE I.
RESULTS OF TWENTY EXPERIMENTS

Experiment	Number of Possible Signatures	Number of Locations Returned	Search Accuracy
1	29	54	93.4%
2	13	28	96.6%
3	29	64	92.1%
4	15	40	95.1%
5	12	34	95.9%
6	12	34	95.9%
7	12	34	95.9%
8	15	42	94.9%
9	14	26	96.9%
10	14	26	96.9%
11	3	7	99.3%
12	3	7	99.3%
13	3	3	99.8%
14	12	12	98.6%
15	1	1	100.0%
16	1	1	100.0%
17	1	1	100.0%
18	1	1	100.0%
19	4	7	99.3%
20	4	7	99.3%

The first observation of these experiments is that there is no any experiment its searching accuracy is 0%. In other words, the target object can be 100% searched in all these experiments.

The Second observation is that in some of these cases the exact location signature indeed cannot be identified. However, even under this kind of situations, the searching accuracies are still maintained better than 92.1%.

The third observation is that the number of the locations returned by the worst case is 64. Since the size of each location is 0.6 × 0.6 square meter area, searching a target object in such a location is really not a time-consuming job. In fact, searching through these 64 locations may take around ten minutes only.

Finally, the average searching accuracy of these twenty experiments is 97.4%. The average locations returned for searching is 21.45. From these real world experiments, LSS shows its potential usage for object searching applications.

V. CONCLUSION

In this paper, object localization and searching are first differentiated. For some IoT searching applications, knowing where the possible locations the target object could be is good enough. To satisfy the above requirement, an object searching solution named LSS is proposed. Idea behind LSS is based on a concept called location signature. Not like those known positioning and localization techniques, LSS is an easier and applicable object searching solution. The simulations and experiments conducted in this research show that the searching accuracy and the implementation cost of LSS are highly related to the tag deployment design. Therefore, the study of the above issue will be our future work.

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