Object Level Mapping of an Indoor Environment using RFID

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Abstract—**Many of the indoor applications like navigation, indoor localization, object tracking require an indoor map. Indoor environments are dynamic in nature because of the objects present in it. To capture the essence of the indoor environment, it is essential to perform an object level mapping of an indoor space. This is because an object has the potential to alter the map of an indoor environment. Mapping a huge indoor environment could prove to be costly in terms of time with high infrastructure dependency. This compels us to find a simple solution in terms of cost, time and reliability to build an indoor map. The proposed solution should have minimal infrastructure dependence, so that it can be used in situations like disaster and rapid response scenarios, where the available infrastructure is minimal and time is of essence. We propose a Radio Frequency Identification(RFID) based approach which performs an object level mapping of the indoor environment using a portable RFID reader, RFID Ultra High Frequency(UHF) passive tags and inertial navigation sensors(INS). This approach identifies each object in the indoor environment using one or more passive tags. A novel algorithm has been developed which accurately maps the objects present in the indoor space. It is easily scalable to map huge indoor environments and can be applied without any intensive manual labor or expensive equipments. Our experiments show that this approach generates object level indoor maps with high accuracy.**

Keywords—***Indoor mapping, Object tracking, Indoor localization, RFID, Power levels, UHF Passive tags.***

I. Introduction

A map is an essential component of many indoor applications like asset tracking, navigation, etc. There exists many automatic mapping techniques like Simultaneous Localization and Mapping (SLAM), which use Radio Frequency Identification (RFID) and Wi-Fi to identify the navigable spaces in an indoor environment and map it. These strategies do not consider the object as an integral part of the indoor environment, but rather view the objects as obstacles.

An object is an important part of an indoor environment. After generating a map, objects present inside an indoor environment can be subject to changes in their positioning. This makes the original map inconsistent. So, it is essential to consider each object in the indoor space as a separate entity and account for their individual positions. So this consideration brings in the necessity for a robust map building approach, which can easily account for these changes. This type of modeling is required for mapping temporary installments, providing help during military operations or in situations like disasters [1][2][3][4]. Existing localization and mapping techniques like camera based approaches and sensor based methods are constrained by infrastructural and computational limitations. Camera based techniques are computationally expensive and require huge data sets to calibrate the system[5][6]. Configuring sensors for the existing sensor based techniques is cumbersome and hence are not suitable for mapping temporary and huge indoor installments.

We therefore require a method for uniquely identifying the objects present in an indoor environment. The tag based architecture of RFID, where each object can be tagged with one or more RFID passive tags is better suited for this. Existing RFID based techniques employ reference tags for effective localization and mapping of objects [7][8]. It is mandatory for these techniques to be aware of the precise location of reference tags for optimal results. A lot of human effort and time is required to configure this setup. Fixed RFID readers' infrastructure is not scalable and cost effective for huge indoor environments.

In this paper we address the problem of quickly and efficiently mapping indoor spaces (along with major objects) that are not highly dynamic, especially during the map generation process. We introduce a novel approach to provide an accurate map of an indoor environment by automatically mapping objects, overcoming the challenges mentioned above. We employ the usage of portable handheld RFID readers to detect and localize the tags in combination with Inertial Navigation Sensors (INS) which help locate the users carrying the readers. Inertial navigation sensors which are ubiquitous in current mobile devices can also be used. Hence the infrastructure required is minimal. This also allows for a crowd-sourced approach for such a mapping process. When using portable handheld readers with single antennas, traditional RFID metrics like Received Signal Strength Indicator(RSSI) cannot be used to localize and effectively map the objects. RSSI based techniques require more than one RFID reader/antenna for localization. Hence our approach employs the usage of power level variation in portable RFID readers to accomplish the same. After the detection of all the tags, a set of rules pertaining to the indoor geometric constraints are applied to improve the accuracy of the mapping. A robust algorithm which divides the indoor space into mutually exclusive components, to enhance the scalability and efficiency of our approach has been devised. To further reduce the cost of tagging, an object model that approximates complex objects or groups of objects (e.g chairs in a row in an auditorium) using bounding boxes is employed.

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The rest of the paper is organized as follows. Section III talks about the integration of the INS (Inertial Navigation System) with the RFID module. Section IV describes the system architecture and the prerequisites of the system. Section V details about the mapping algorithm. The different possible scenarios of the indoor environment where the reliability of the system has been tested are discussed in section VI.

II. Background and Related work

In many indoor applications, map is an integral part, hence it is essential that the complexity of building a map be optimal. The traditional techniques such as manual measurement and mapping are cumbersome and time consuming. Introducing sensors to accomplish indoor map building, reduces the complexity and generation time of the indoor map. Existing methodologies make use of camera, Wi-Fi, RFID, infrared and sonar to generate the map of an environment.

Camera based approaches are recently becoming popular for mapping the indoor space. One such approach uses a Kinect based mobile unit attached to the user to capture the outline of the path taken by the user thereby generating a 3-D map [5]. 3-D depth cameras are used for modeling dense 3-D indoor environments using the RGB-D framework [6]. While these approaches manage to deliver realistic 3-D maps of indoor spaces, they require expensive equipment like high resolution cameras and high computing power to accomplish the process of generating a map. They also require an ideal environment with proper lighting, and without occlusions. Moreover, huge data sets are required to train the system.

RF signal based approaches generally have lesser complexity than video based approaches. They use Radio Signal Strength Index (RSSI) along with the data from the inertial sensors to identify the obstacles and free spaces in indoor space. Positional sensors and Wi-Fi are used to predict the trajectory of multiple users [9]. The aggregate of these trajectories form the navigable spaces. These Wi-Fi based approaches are most suitable for generating navigable spaces, and cannot gather intricate details about the objects in the indoor space, unless expensive Wi-Fi tags are used. Therefore, these approaches are not suitable for generating a detailed object level indoor map.

Passive RFID based systems allow the objects in the indoor space to be tagged in a scalable and cost effective manner, and help identify an object in the indoor space. RFID based approaches are proposed for effectively localizing the tags in the indoor environment [7][8][10]. These use various methods such as reference tags, probabilistic methods, Kalman filters, variation of power level and simplex method to reduce the error. The localization of the tags can be looked at as a possible method to build an indoor map at object level by localizing each and every tag attached to the object present. Due to expensive hardware and long localization time, these methods prove to be costly both in terms of hardware and time. Additionally such techniques work best in the presence of reference tags which adds to scalability issues and costs.

Some techniques combine multiple technologies to map an environment. For instance laser range scanner and RFID on-board a mobile robot have been used together to map an indoor environment [11]. But this approach suffers from line of sight issues which cause high localization error. It also leverages on the fusion of complex sensors which adds to the infrastructure cost. Also these approaches use fixed readers which necessitates the requirement of electricity i.e., infrastructure dependent.

Other approaches use infrared and sonar to map an indoor environment. In one such method, a smart phone and an IR sensor is used to map an indoor environment [12]. The smart phone is used to determine the position of the user and the IR sensor is used to map the indoor space. In another solution, head-mounted inertial and laser range scanners are used to map an environment [13]. But these laser and IR based approaches work only in a static environment where there are no disturbances. Sonar based approaches use sonar data for generating a map of an environment [14]. Therefore, infrared and sonar based approaches suffer from the drawback of occlusion, signal rebounding and back-scattering in chaotic environments.

Infrastructure dependence, scalability, computational complexity and localization delays are the major drawbacks of the approaches discussed above, if they are used for indoor map generation at object level. We address some of the drawbacks of these existing approaches by proposing a robust method, which treats each of the objects as an individual entity and by using one or more passive Ultra High Frequency(UHF) RFID tags to uniquely identify them. Hand held RFID reader and inertial sensors are used to generate a detailed map of an indoor space with minimal human effort and reduced computational complexity. This approach aims to reduce the required infrastructure and the need for an ideal environment to be present. Since each object is tagged using passive RFID tags, there is no external power source required other than the battery source for the portable RFID reader. Due to minimal infrastructure requirement the chances of its failure due to infrastructure loss during rapid response situations is very minimal. The only overhead is in tagging the objects with passive RFID tags. The cost of tags is much lower than other infrastructural costs, and tagging objects serves a purpose in asset management and tracking. This proposed method can accommodate crowd-sourcing to collect data from the indoor space for mapping. This decreases the time and human required to generate an object level map even when the indoor space is huge.

III. Object mapping framework

The RFID and Positional sensor (RAPS) system comprises the portable handheld RFID reader and the Inertial Navigation sensors (INS). As the user moves inside an indoor environment, the gyroscope and the accelerometer present in the INS module help track the position of a user in real-time. The portable RFID reader is used to detect the tags within range of the user's current position that is provided by the INS. At each position of the user RFID readings are taken at multiple power levels. The interactions among different readings from different power levels at various points in the indoor environment are exploited to effectively localize the tags.

A. Sensor Data Modelling

As described above, the user moves within the indoor space and takes readings at multiple points. The data collected from each point is stored as a triplet (p_i, Θ_i, RD_i). Here p_i is the

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position of the user, Θ_i is the orientation of the user at p_i and RD_i is the RFID module data. In our approach we have a necessity to detect the tags present in a particular read range. Usage of varied power levels in the RFID reader is better suited for this requirement. The indoor environment consists of N tags. List $T = \{t_1, ..., t_n\}$ contains the list of tags that are detected, when the user takes reading at power level ρ_j, assuming there are $j = 1, ..., k$ power levels. RD_i contains the information regarding the list of tags detected in each and every power level ρ_j at position p_i.

B. Object Modeling

Indoor environments are often comprised of major objects (objects that impact the indoor map) with complex geometric structures. These structures can be approximately modeled into simple geometric shapes, for efficient representation. Bounding boxes are drawn around these complex structures to model them as simple shapes. The number of tags used to represent an object is dependent on the number of lateral faces of the simple geometric representation of the object o_i. If there are M objects $o_1, ..., o_M$ present in the room, each object is tagged with one or more tags t_i, which represent the object and its dimensions. Usage of multiple tags to represent an object is owing to the fact that, orientation of the object is of primary importance while building the indoor map. By representing an object using multiple tags, the RAPS system resolves the orientation of the object. The tag t_i contains an unique EPC (Electronic Product Code) value, which points to the object o_i and the side s of the object o_i on which they are placed. For those objects, whose orientation does not matter, one tag will suffice.

Huge indoor environments generally have uniformity in the structure of objects present inside them. This property can be leveraged to create generic templates for object modeling. These templates can then be seamlessly used to approximately measure the dimensions of the objects, which are required to be given as an input to the RAPS system. The templates for different objects present in the indoor space are shown in Fig 1.

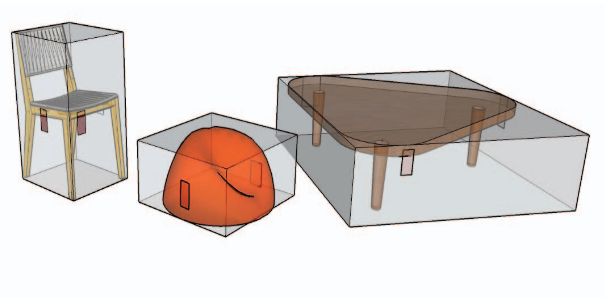

Figure 1: Object bounding box

C. User Tracking

All positions inside the indoor space are represented using a coordinate system (x, y), which denotes a unique point in the indoor space. The user position p_i represents the point where the user takes readings during the procedure and hence p_i is represented as (x, y) and the collection of all p_i, is the set P. The initial point p_0 is where the user commences the map building procedure. All the subsequent points $p_1, ..., p_n$ are calculated relative to p_0, using the data streamed from the gyroscope and accelerometer. The accelerometer gives a signal when the user takes a step and gyroscope gives us the direction in which the step is taken. The average distance covered by the user in a single step is experimentally determined to be $0.5m$ and the total distance covered is the aggregate of all steps. Initially the angle θ at which the user takes readings is noted and the subsequent angles are dynamically calculated using the calibration module. The orientation θ in which user moves combined with distance d gives us the displacement S, which in turn gives the next position p_{i+1} of the user from his current position p_i. If a user takes a reading at a point p_i, then p_i is added to the set P.

When given with a large indoor environment that needs to be mapped, it is cumbersome for a single user to cover the entire area. In the algorithm we propose, the process of mapping an object is only dependent on its immediate vicinity. Leveraging on this property, the same algorithm can be used in a crowd-sourced fashion to map an indoor environment simultaneously using multiple users. Each user maps a part of the indoor space. If the readings of different users are redundant, then the user with the latest readings are considered. The final map is generated by combining the readings from all the users.

D. Power Level-Range Modeling

Our algorithm for dynamically generating a map largely relies on the area covered by the RF signals emitted by the RFID reader at a particular power level. When a tag has been detected at a particular power level, it implies that the detected tag is present within the range of RF signal at its corresponding power level. The power level has a correlation to the maximum area of coverage of the RFID reader. In order to facilitate efficient computation, there is a requirement to model the exact shape and area covered by the RF signals of the RFID reader at all the power levels used.

For initial calibration, the RFID reader is fixed at a particular position in space. The power level of the reader is fixed at the basic power level supported by the reader. At every 10^0, starting from 0^0 (from the right of the reader) to 180^0 (left of the reader) passive tags are placed. Each and every tag's position is adjusted so as to find the maximum distance at which a tag gets detected at a threshold frequency. Threshold frequency is the minimum frequency of the readings required to distinguish the stray tag readings from the tags, which are actually present. This is repeated for multiple power levels like $15dB$, $20dB$ and $22dB$. These power levels have been chosen experimentally to produce optimal results, because higher power levels have relatively bigger range, which increases the localization error. By tracing the position of the tags, we get the area and the shape associated with the range of the reader for each power level as shown in Fig 2. As shown in Fig 3, the shapes of the ranges were found to be ellipses of different major and minor radii by curve-fitting the irregular shapes. This approximation to an ellipse is performed to enable easier processing for localization purposes. The equations of each of the ranges i.e ellipses e_i at each power level pw_i were experimentally determined to be as follows:

$$e_1\, at\, 15dB \;:\; \frac{x^2}{(60.96)^2} + \frac{y^2}{(32.258)^2} = 1$$

$$e_2\, at\, 20dB \;:\; \frac{x^2}{(80.772)^2} + \frac{y^2}{(46.736)^2} = 1$$

$$e_3\, at\, 22dB \;:\; \frac{x^2}{(106.934)^2} + \frac{y^2}{(70.612)^2} = 1$$

$$e_4\, at\, 25dB \;:\; \frac{x^2}{(145.542)^2} + \frac{y^2}{(94.996)^2} = 1$$

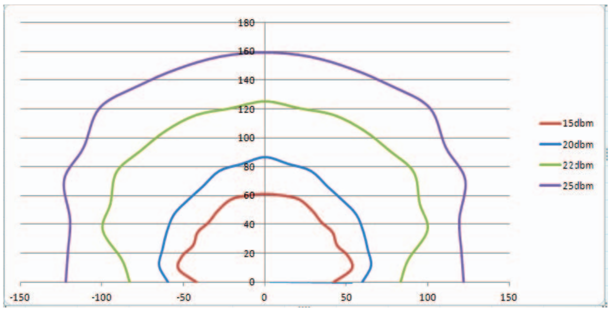

Figure 2: Power level range depiction

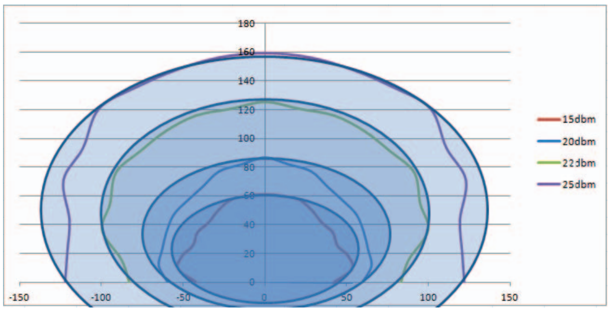

Figure 3: Curve-Fitting

This calibration process is performed only once for the device, and works irrespective of the environment. Once we model the region of influence of the reader at a certain power level as an ellipse, we can determine the area where the tag has been detected. When a user takes a reading at a point, multiple ellipses are superimposed. Many such ellipses can overlap in a region as the user takes multiple readings.

IV. Architecture and Prerequisites of the RAPS System

This section highlights the architecture of the mapping system described in the previous sections. The mapping system includes the following components namely, the RAPS module, Calibration system, Refinement engine, Rendering system, Regionizer and Positioning system as shown in Fig 4. The RAPS module consists of RFID reader (ATID AT370), accelerometer and gyroscope (in common tablets). This module is responsible for keeping track of the position of the user. The RAPS module undergoes a calibration process, in which the initial position of the user is determined. After the calibration process, the co-ordinates and the angle of every position where the readings are taken are streamed from the RAPS module to the regionizer. The regionizer facilitates faster computation by splitting the area under consideration into various regions, thereby reducing the complexity to calculate the positions of the objects under consideration. These regions are independently sent to the positioning system to estimate the object's position. Since each region is considered as an independent problem, they can be solved either sequentially or in parallel.

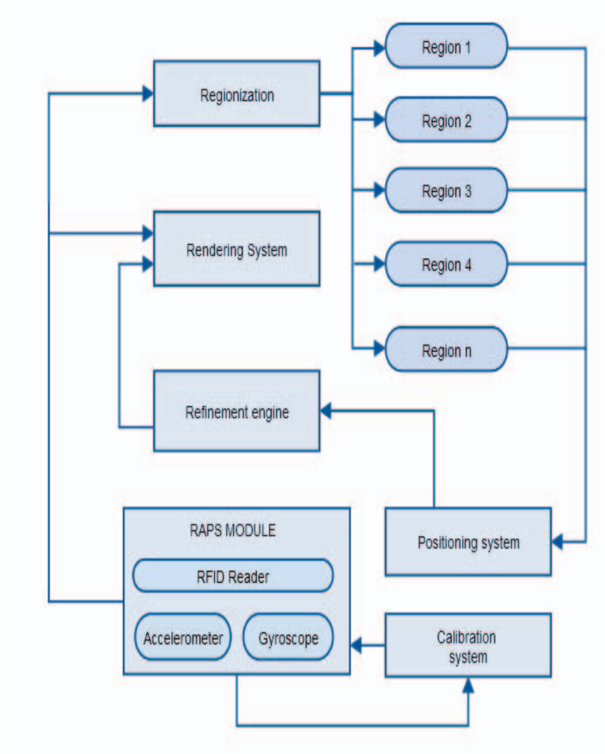

Figure 4: RAPS Architecture

A filter is generated based on a set of rules pertaining to all indoor environments. The results of the computation in each region are then sent to the refinement engine, which applies the filter on top of existing results to enhance the accuracy. The refined results are then sent to the rendering system, which displays the final position of tags on the screen.

Since indoor environments are diverse in nature, there exist certain minimal prerequisites that must be met and pre-processing steps to be completed, before using the RAPS system to generate the map and the following list enumerates them.

1) Initially the user has to identify all the major objects which are present in the indoor space. An object is considered as a major object if it can significantly vary the map of an indoor environment by its placement. For attaining higher accuracy the user has to make sure that all the major objects have been identified.
2) As described in section III, all the major objects are modeled and tagged based on their geometric constraints.

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3) Each object may be tagged with one or more passive RFID tags, which enables us to resolve the orientation of the object. A correlation between EPC values of various tags belonging to the same object and the corresponding object's ID is established.
4) The orientation of the RAPS system has to be calibrated to conform with the user's perspective of the indoor space as shown in the Fig 5.
5) Dimensions of the indoor environment under consideration must be known beforehand and given as an input to the system.

Lets consider an indoor space of dimensions 5.1×4.76 meters as shown in Figure 5. In this indoor environment six major objects have been identified, which are represented as solid black rectangles. Initial orientation of the user with respect to the indoor environment is marked as 0^0 counter-clock wise. The orientations for the rest of the readings are determined relative to the newly defined 0^0.

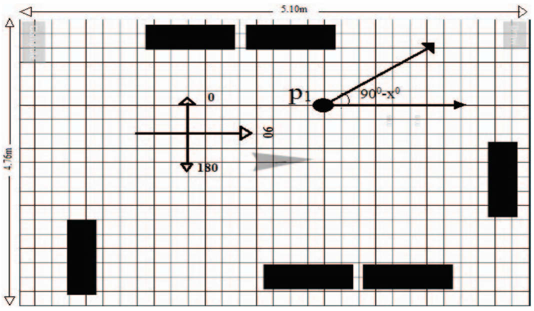

Figure 5: RAPS system calibration

V. Proposed Mapping Algorithm

Our algorithm comprises of three major modules namely the regionizer, the estimator and the indoor mapping filters. Indoor environments can sometimes be very large with a lot of major objects which need to be mapped. In such scenarios, computation can be really expensive and it is not optimal to estimate the position of all the objects at once. In order to solve this problem, our algorithm tries to separate the total indoor space under consideration into non-overlapping distinct regions. Theoretically, a region is an area inside the indoor space, where a set of ellipses overlap and are disjoint from the other groups of ellipses.

A. Regionizer

1) **Cell Mapping:** Initially the total area under consideration is represented as a single region R as shown in Figure 6. In order to facilitate faster computation the region R needs to be divided into independent regions $r_1, r_2, ..., r_n \in R$. Region R can be represented as a matrix of dimensions $m \times n$ where each element of the matrix is a grid cell of unit dimensions. When the user takes readings at a certain point, the range covered by the RFID reader is modeled as an ellipse. This ellipse when rendered to scale on the grid covers a certain number of grid cells as shown in Fig 6. The value of these cells is set to 1. In a quad-tree based fashion, we recursively divide the total region into four sub-regions each of dimensions $m/2 \times n/2$, until we find a sub-region fully filled with either 1 or 0 as shown in Fig 7.

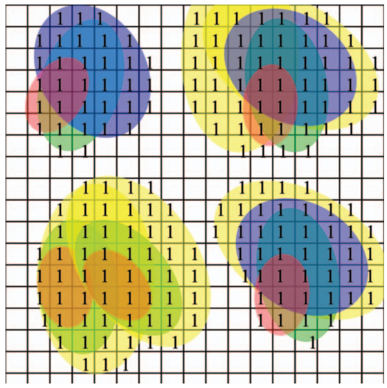

Figure 6: Cell Mapping

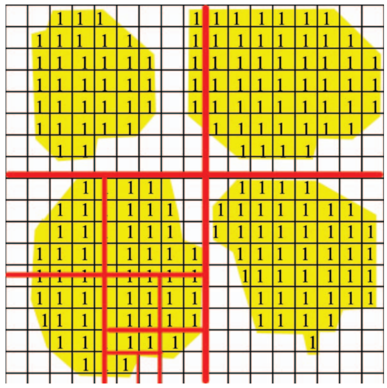

Figure 7: Recursive Regionization

2) **Graph Modeling:** The sub-regions identified in the above step can be represented as nodes in a graph $G(V, E)$ where V is the set of nodes (sub-regions). There exists an edge e_{ij} between two sub-regions when there exists a possibility of interaction between tags present in those sub-regions. Existence of these interactions can be detected when the boundaries of these sub-regions are adjacent.
3) **Connected Component Analysis:** After modeling the graph G, it comprises of a distinct connected components as shown in the Fig 7. Each of these connected components is in turn a sub-graph $g_i \in G$. Each $g_i \in G$ is disjoint from the set $G - g_i$, hence we can run the estimator module in parallel on all distinct connected components of graph G.

B. Estimator

The connected components generated by the **Regionizer** are passed as input to the estimator module. The estimator module's function is to find the most probable cells for each tag in the indoor environment. The estimator module can perform its task on all components in parallel as they are disjoint. To estimate the probable cells, the estimator module uses a scoring algorithm.

Algorithm 1 Regionizing the region R

function REGIONIZE(x,y,$length$,$breadth$)
$l \leftarrow \frac{length}{2}$
$b \leftarrow \frac{breadth}{2}$
if *checker(x,y,l,b)≠true* **then**
    $Regionize(x, y, l, b)$
    $Regionize(x + l, y, l, b)$
    $Regionize(x, y + b, l, b)$
    $Regionize(x + l, y + b, l, b)$
end
else
    $Create\_node(x, y, l, b)$
end
end function

Figure 8: Regionizing the region

Algorithm 2 Creation of Connected Components

function CONNECTED_COMPONENTS(NodeList)
length $\leftarrow$ NodeList.length
i $\leftarrow$ length
while $i \neq 0$ **do**
    j $\leftarrow$ length
    while $j \neq 0$ **do**
        if *NodeList[j]* $\neq$ *NodeList[i]* **then**
            Dif$_x \leftarrow$ NodeList[j].x $-$ NodeList[i].x
            Dif$_y \leftarrow$ NodeList[j].y $-$ NodeList[i].y
            if *Dif$_x \equiv$ NodeList[i].length* **then**
                CreateNode(NodeList[i],NodeList[j])
            end
            else if *Dif$_y \equiv$ NodeList[i].width* **then**
                CreateNode(NodeList[i],NodeList[j])
            end
        end
        decrement j
    end
    decrement i
end
end function

Figure 9: Creation of Connected Components

Data which is collected in the form of triplets (P_i, Θ_i, RD_i) from the indoor space is analyzed by the RAPS system to produce a map. Initially as shown in the Fig 5 the indoor space is represented in the form of a grid cells. The first task of the RAPS system is to find the most probable cells in which a tag t_i can exist. This has to be done for each tag t_i in the indoor space. Each cell in the indoor space will contain a list of numerical quantities called scores corresponding to each tag t_i. The score for each tag t_i in every cell is calculated as:

$$\sum_{i=1}^{n} \frac{1}{(number\, of\, cells\, covered\, by\, the\, ellipse\, e_i)}$$

This implies that the cell which contains the maximum number of ellipses over it has the maximum score. The higher score indicates that the tag is more likely to be present in that cell.

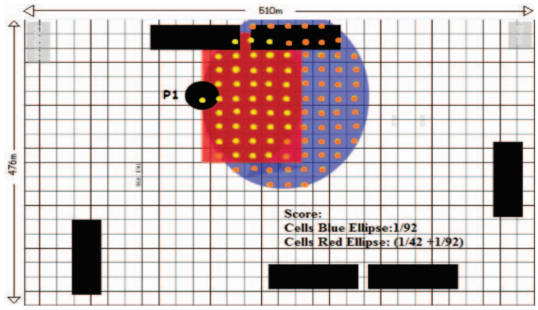

Figure 10: Scoring function

In Fig 10, the point p_1 represent an instance of data collection phase where the user takes the reading at power levels $15dbm$ and $20dbm$. When a Tag t_i is detected in these power levels, the RAPS system generates appropriate ellipses and updates the score for t_i in the cells which are covered by these ellipses. The orange points indicate cells which are overlayed by the $20dbm$ ellipse. The yellow points indicate the cells which are covered by ellipses of both $15dbm$ and $20dbm$. The total number of cells covered by the ellipse of power level $20dbm$ is 92. In accordance with the scoring algorithm, the score of the cells which are covered by the ellipse of power level $20dbm$ for tag t_i will be $1/92$. When another ellipse is rendered, it might occupy cells which already contain scores for certain tags. In that case, the new score is added to the existing score. So, cells with the yellow points have score $(1/41 + 1/92)$. The tag is more probable to be present in the cells marked with yellow dots rather than the one's marked with orange dots. This analysis is performed on all the regions in the indoor space. In this manner, the most probable cells for each tag are identified.

C. *Indoor Mapping Filters*

By observing certain trends in the data collection patterns and spatial existence of indoor environments, three filters have been designed. They are Traversed path filter, hidden tag filter and geometric filter. These filters aim at improving the accuracy at which the objects are localized.

Traversal Path Filter: As the user covers the expanse of the indoor environment, the trajectory of his path is recorded. The minimum space required for a human being to move inside an indoor environment is around 0.5 meters. So, we can safely assume that none of the tags can be present along the path covered by the user of width 0.5 meters. Traversal path filter introduces this correction by reducing the scores of the cells covered by the user's path to zero. This is depicted in the Fig 11, with cells colored in red.

Hidden tag Filter: Hidden tag filter comes into play, when a certain object has been tagged with N tags, but the number of tags reflected in the readings are less than N. From this behaviour, we can infer that either those tags are obscured by the presence of indoor obstacles like walls or are being

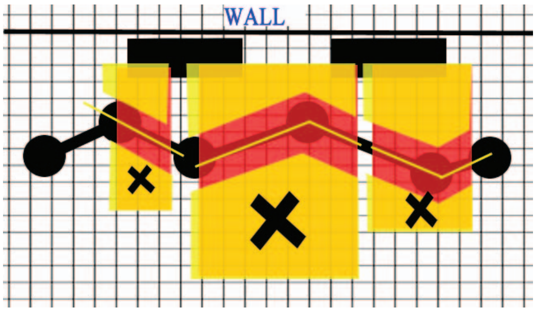

Figure 11: Application of filters

blocked by other objects. The possibility that the user has not covered the area in which that specific tag was present can be eliminated because covering all the navigable spaces is a mandatory constraint imposed by our algorithm. Hidden tag filter introduces these corrections by setting the weights of the cells which are away from the obstacle (i.e., tags which are not read) to zero. This is depicted in the Fig 11, by the yellow regions marked with cross.

Geometric Filter: Geometric filter aims at improving the accuracy by looking at the geometrical aspects of the object. Based on the dimensional constraints of the tag placement on the object, geometric filter reduces the localized area of the tag by setting the cells in the quadrants which are away from the rest of the tags(i.e., other tags belonging to the same object) to zero. These filters can be applied in any order, but in order to reduce the complexity, it is desirable to apply them in the order given.

1) Updating Score: When the filters are applied score of each cell belonging to the ellipse for a tag t_i has to be updated. The score of the cells where the tag cannot exist according to the filters is reduced to 0. The score of potential cells where the tag can exist should be increased. Let us represent the cells overlayed by the ellipse whose score is 0 as $zero\_cell$. Note this is all in reference with one tag t_i. The function for updation of score is for tag t_i is:

$$\sum_{i=1}^{n} \frac{1}{(number\,of\,cells\,covered\,by\,the\,ellipse\,e_i) - (zero\_cell)}$$

This updation clearly shows that the score of the cells increases after application of filters. This shows that the probability of existence of the tags t_i in these cells increases. Since the number of cells has reduced the accuracy also increases.

D. Map Generation Algorithm

After applying all the filters on the results generated by the estimator module, each object has a set of equally probable cells in which the object can be placed. Let us consider an object o_i which is tagged with four tags t_1, t_2, t_3, t_4. Each tag has a set C_i of equally probable cells in which the tag can be placed. In order to accurately place an object, we need to employ a method to select a set c_i of cells, where one cell is chosen from each of the sets C_1, C_2, C_3, C_4. A number of different sets c_i are possible. So, we need a methodology to select a specific set c_i from the different possible combinations. We cannot bias our tag placement to a specific cell out of all possible cells, because all of them are equally likely. This restriction leads to two ways of making this decision. These decisions can be made either using a greedy strategy or in a randomized manner.

The greedy strategy is to presume that the first possible set c_i will contain cells which represent the actual position of the object, but the probability that this approach will give optimal results is very minimal. Now, we are left with cells which when chosen for set c_i have different error percentages. There exist many cells which are closer to the actual position of a tag. These cells incur relatively less error. In scenarios like these, randomized strategies are proven to perform better in reality (the average case). So, instead of a greedy strategy, the process of selecting the set c_i will yield better results if a randomized strategy is used.

So, we take a randomized approach to select the set c_i, in which the object can be placed for generating a map. This randomized approach is followed to optimally place all the objects in an indoor environment and generate a map.

VI. Experiments and Evaluation

The accuracy of the RAPS system predominantly depends on the behavior of the user and the density of the objects present in the indoor environment. The object density of an indoor environment is defined as :

$$Object\,density = \frac{No.\,of\,cells\,covered\,by\,objects}{No.\,of\,cells\,present\,in\,the\,environment}$$

When no constraints are in place to restrict the way user takes readings, we cannot predict the user's behavior. So, it is essential to take into consideration, the different possible ways in which a user can take readings and analyze how it impacts the accuracy of the RAPS system. Having a higher object density in an environment is desired, because it can help us develop a better understanding of the indoor environment. So, there is also a necessity to understand the impact of various object densities on the RAPS system.

Distinct regions generated by the regionizer module are independent. Hence, only one region of a large indoor environment is considered in all the experiments. All the possible scenarios in an indoor environment have been discussed. The dimensions of the indoor space considered for all the scenarios is 5.1×4.76 meters. This indoor space consists of a number of steel cuboidal cabinets labeled as $o_1, o_2..., o_N$, where N is the number of cabinets present in each scenario. These cabinets are tagged with passive UHF RFID tags on all the four sides. $p_1, p_2, ..., p_M$ are the points at which the user takes the readings, where M denotes the number of unique points at which the readings are taken. The following sections have screen-shots from a prototype of RAPS system, which visualizes the placement of objects in the indoor environment. Initially before applying the filters, the potential regions for placing the tags are represented by solid red rectangles. Solid black rectangles are used to represent the original position of the objects. As mentioned in the section V.D the randomized map generation algorithm is responsible for associating a final position to every object in the map. The images in the following sections depict the worst case behaviour of the map generation algorithm, which is indicated with the yellow rectangular outlines.

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The error for each tag is calculated by finding the euclidean distance between the tag's actual position and the position assigned by the RAPS system. The aggregate error of each object is found by the average of the errors incurred in each tag's position belonging to the object. The average of all the object's aggregate error is the total error of the map generated by the RAPS system for a given scenario. Worst case error from the randomized map generation algorithm is calculated, by placing the objects at the farthest possible group of cells at which the algorithm could position the object.

A. *User behavior*

The user's behavior is defined by the manner in which the readings are taken. The user has the option of either taking the readings in a dense or sparse fashion. The RAPS system provides the user with the liberty to selectively take readings at only certain power levels, but this may reduce the accuracy. The accuracy in all these scenarios has been discussed in the following sections.

1) Dense points: In this scenario, the number of points at which the user takes readings is more than what is sufficient for the RAPS system. More importantly the points at which the readings are taken are very close to each other. Readings are taken at fifteen unique points ($M = 15$) in the indoor space for mapping objects $o_1, o_2, o_3, ..., o_6$ as shown in Fig 12. This scenario gives a better accuracy because, the RAPS system can take advantage of multiple readings taken at nearby points. The possibility of a same tag being detected at different points is very high. So the number of most probable cells for a tag can be narrowed down to a greater extent and hence the error incurred is minimal. The maximum and minimum error incurred for an object in this scenario is $0.35m$ and $0.17m$ respectively. The average error incurred in the worst case behaviour of the randomized map generation algorithm was experimentally determined to be $0.26m$.

[8][10][7] were able to achieve this level of accuracy, but these techniques rely heavily on the usage of reference tags. By employing the RAPS system, we can achieve similar accuracy without relying on reference tags.

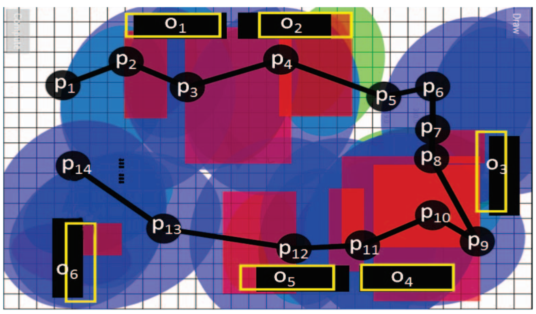

Figure 12: Dense points

B. *Moderately Sampled Points*

This scenario consists of an indoor environment, where the density of the points at which the readings are taken is relatively lesser than the dense points scenario. Readings were taken at points $p_1, p_2, ..., p_{13}$ for all six cabinets ($N = 6$ and $M = 13$) as shown in Fig 13. The maximum and minimum error incurred for an object in this scenario is $0.70m$ and $0.11m$ respectively. The error incurred in this scenario is $0.35m$. The accuracy of the RAPS system in this scenario is comparable to the accuracies achieved in other existing techniques [7][10][8]. This scenario is most desirable because, reasonable accuracy is achieved without taking readings at too many points.

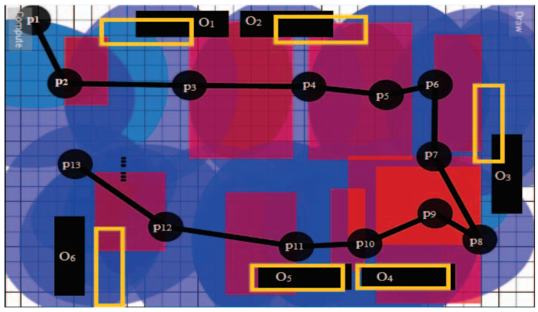

Figure 13: Moderately Sampled Points

1) Sparse points: In this scenario, the number of points at which the user takes readings is much lesser than what is ideally required for the RAPS system. The points at which the readings are taken are relatively far from each other. Readings are taken at ten unique points ($M = 10$) in the indoor space for mapping the same number of objects present in the above scenario (dense points) as shown in Fig 14. Because of the constrained availability of data the average error in this scenario for the worst case behaviour of the randomized map generation algorithm increases to $0.40m$. The maximum and minimum error incurred for an object in this scenario is $0.87m$ and $0.35m$ respectively.

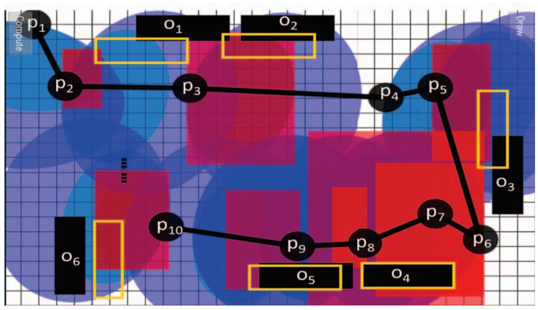

Figure 14: Sparse points

2) Selective power levels: This scenario describes the case where the user selectively takes readings only at particular power levels at each point in the indoor space. In order to get a better understanding of the behaviour of RAPS system while using selective power levels, we need to analyze all the possible ways of taking readings. In order to demonstrate a scenario with dense points, readings were taken at 13 unique points to map 6 objects ($M = 13, N = 6$) as shown in Fig 15. At all the points, readings were only taken at power levels of $15dBm$ and $22dBm$. The maximum and minimum error incurred for an object in this scenario is $0.52m$ and $0.35m$ respectively. The average error incurred in the worst case behaviour of the randomized map generation algorithm

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was experimentally determined to be $0.41m$. Even though readings were taken only at power levels $15dBm$ and $22dBm$, the RAPS system could still give a desired accuracy. This is because dense points has compensated for the usage of selective power levels.

On the contrary, if the points at which the readings were taken have moderate density, like points depicted in the Fig 13, the average error incurred is $0.61m$. In this scenario the maximum error incurred for an object drastically increases from $0.52m$ to $1.05m$.

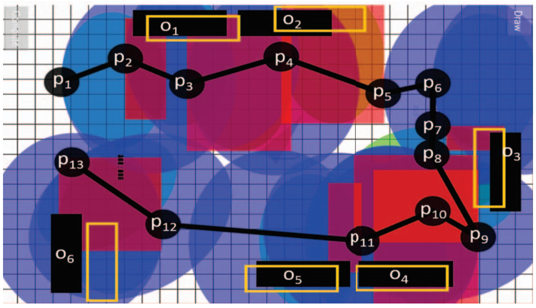

Figure 15: Selective Power Levels

C. Object density

Object density of the environment under consideration can affect the accuracy of the RAPS system. Once the approximate location of certain tags have been determined, the number of cells in which the remaining objects can be placed is reduced. The remaining objects can only be placed in the empty cells. Higher the object density, higher the accuracy of the system. So, there is a necessity to understand the behavior of RAPS system in environments of various object densities. As shown in the Fig 16, the same environment is considered with a reduced object density where objects o_2, o_5 are not considered. $p_1, p_2, ..., p_{12}$ are the points where the readings are taken. The maximum and minimum error incurred for an object in this scenario is $0.53m$ and $0.36m$ respectively. The average error incurred in this scenario for the worst case behavior of the randomized map generation algorithm is $0.45m$. The error incurred in environments with reduced object density is relatively higher.

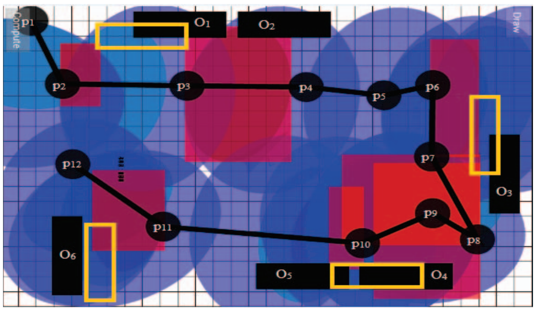

Figure 16: Few major objects considered

D. Impact of filters

The impact of applying filters on the output data from the estimator module of the algorithm is discussed in this section. The estimator module identifies the cells in which the object can be present by using the scoring algorithm. A graphical representation shown in Fig 17 depicts the error incurred when filters are not applied. The error incurred is close to 0.9 meters for every scenario discussed in the previous sections.

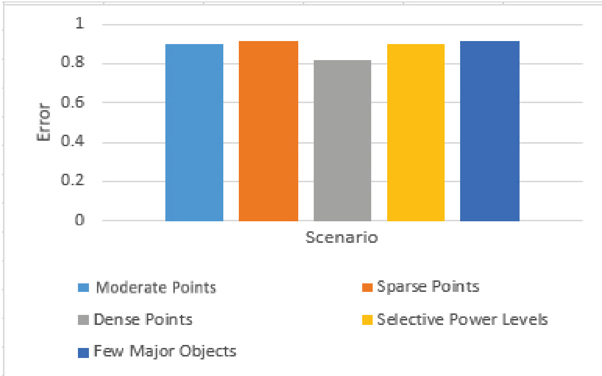

Figure 17: No Filter

1) **Traversal Path Filter:** The score of the cells which are a part of the traversed path of the user is reduced to zero by this filter. Thus reducing the number of cells where the object can be present. This in-turn reduces the error in estimating the position of the object. In the graphical representation shown in the Fig 18, it is observed that traversal path filter reduces the number of probable cells by 40.5% of the output generated by the estimator module. It is also important to note that the maximum increase in accuracy on applying this filter is for **Dense Point Scenario** and **Selective Power Level scenario** performed on dense points.

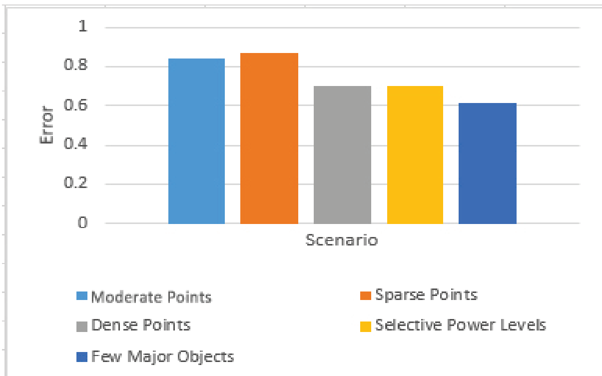

Figure 18: Applying Traversal Path Filter

2) **Hidden Tag Filter:** When some of the tags present on the object are obscured by the walls or other objects, they cannot be read by the RFID reader. Hidden tag filter sets the weights of the cells which are away from the obstacles (i.e., tags which are not read) to zero. After applying the hidden tag filter the error incurred is reduced as shown in the Fig 19. After subsequently applying the hidden tag filter on the output generated by the traversal path filter, there

is a decrease in the number of probable cells by 65.25%. There is a uniform decrease in error in all the scenarios.

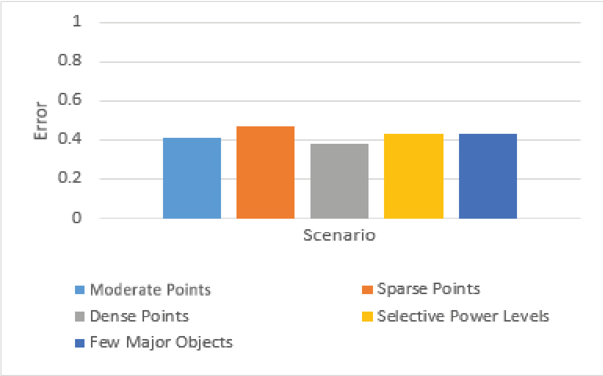

Figure 19: Applying Hidden Tag Filter

3) **Geometric Filter:** Based on the dimensional constraints of the tag placement on the object, geometric filter reduces the error considerably. After applying the Geometric filter, the error incurred is reduced as shown in Fig 20. After subsequently applying this filter on the output generated by the hidden tag filter, the number of probable cells is reduced by 74.5%. Geometric filter reduces the error of an object based on the position of its adjacent objects. There is no prominent decrease of the error incurred in the scenario titled **Object density**, because some of the major objects are not considered.

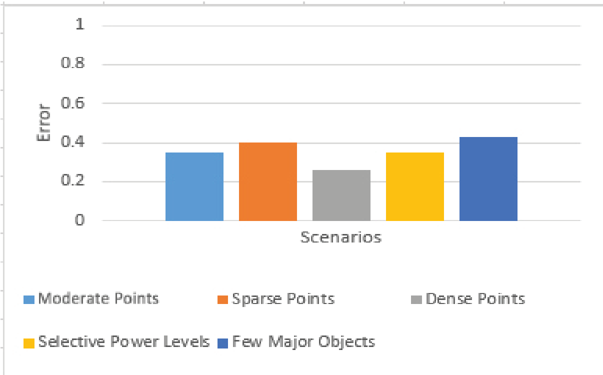

Figure 20: Applying Geometric Filter

VII. CONCLUSION

This paper has presented a robust RFID based method to effectively map an indoor environment at the object level with minimal infrastructure dependence. This method leverages on power level variation of a portable RFID reader and inertial sensors to localize the tags in the indoor environment. This approach is proven to be easily scalable and can be used to map large indoor spaces in a reasonably cost effective manner. Results have shown that a map of the indoor environment can generated with an average accuracy of around 0.35m with desired object density and moderate density of sampled points. The accuracy is limited when the area is sparsely covered with objects, when enough readings are not taken or when two or more major objects are placed on top of each other. Future directions include exploring probabilistic approaches for improving the accuracy, and to view the problem as a three dimensional mapping problem to address the last issue. Addressing the orientation issues with minimum number of tags or when tags are damaged is another challenge to be addressed.

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