RFID Based Object Localization System using Ceiling Cameras with Particle Filter

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Abstract

In this paper, we propose an object localization method for home environments. This method utilizes RFID equipments, a mobile robot and some ceiling cameras. The RFID system estimates a rough position of each object. The autonomous robot with two modules of RFID antenna explores the environment to detect other objects on the floor. Each object, attached by an RFID tag, is then recognized by utilizing its feature information stored in this tag. Finally, the precise localization of each object is achieved by the ceiling cameras with particle filters. The accuracy and the robustness of the proposed method are verified through an experiment.

1. Introduction

Robots are now involved not only in industrial applications, but also in home services. Especially for elderly or disabled people, robots will be partners that can aid them. However, there are technical problems that should be overcome.

Object localization is one of the typical problems. For a robot that works at home, positions of objects are fundamental information. To recognize and localize objects in an indoor environment, many methods have been proposed. Image-based object localization requires prior object recognition and then localizes those objects in the next measurement step. Object recognition is usually based on some kinds of feature of objects (e.g. lines [1], edges [2, 3], statistics [4, 5], shape [6], etc.). Some studies have also represented features as histograms of shape, or color distributions (e.g. SIFT-based feature [7]). For localization with cameras, stereo-based methods have been studied. In robotics, robots that have attached stereo cameras are utilized [8, 9]. Wireless sensor networks have also been used for object detection and localization [10].

In this paper, we propose a total system that can give positions of objects that should be considered by the robot. Since the uncertainty of measured positions should also be considered when a robot works at home safely, the uncertainty is also given by our system.

They key of such a system is to reduce the human load of implementation. When we use only cameras, for example, the information of what an object is must be given. Since the method of implementation is not standardized, a system tends to work only in a specific environment. For our system, RFID (radio frequency identification) equipments are utilized proactively. It will become common in future and many products will be attached an ID tag, which can store some kinds of features of the object.

When the position of an RFID antenna is known, the rough position of an object can be detected when its tag is sensed. We utilize this property with particle filters [11]. A particle filter can represent the rough position with a probabilistic manner. We also utilize a robot, Roomba made by iRobot, which has a function of sweeping a flat environment. Small antennas are attached on a Roomba. The Roomba becomes an active antenna in the RFID system. Ethernet cameras are also used in this system for reducing uncertainty of object positions.

In Sec. II, the proposed system is presented. In Sec. III, the algorithms in the system are explained in detail. The experiment environment is then mentioned in Sec. IV. In Sec. V, the system is evaluated. The paper is concluded in section VI.

2. Object localization system with RFID and camera

In order to localize the various objects in a room, an RFID system and a camera system are proposed, shown in Figure 1. The RFID system consists of some RFID tags, named RT_1, RT_2,…RT_M, attached on the objects, named Obj_1, Obj_2,…Obj_N . Normally, $M \geq N$, which means that some objects in the room may have more than one RFID tags. Each RFID tag contains the identity and information about the features of the object it is attached on. The system also consists of K RFID antennas, {RA_1, RA_2, … RA_K} placed around the room. The camera system also consist of Q ceiling cameras {C_1, C_2, … C_Q}, set up on the ceiling.

When an RFID antenna RA_k ($1 \leq k \leq K$) senses a tag RT_m, ($1 \leq m \leq M$) attached on an object Obj_n ($1 \leq n \leq N$), the information stored in RT_m , describing the object Obj_n, is transferred to the system. Furthermore, it is also implied that the object Obj_n is in a small area within the range of the antenna RA_k. Therefore, the system can estimate the rough position of Obj_n in advance and also acquire the information about the Obj_n's features, stored in RT_m.

If none of the antennas can detect Obj_n, Obj_n is on the floor , or somewhere out of range of any RA_k. In that case, a mobile robot is proposed to estimate the rough position of Obj_n. The mobile robot, named MR, which is capable of wandering around the room, is attached by mobile J RFID antenna(s), {RA_{K+1}, RA_{K+2}, …RA_{K+J}}. While the robot is wandering around the room, if an RA_j ($K+1 \leq j \leq K+J$) can detect Obj_n, it is implied that Obj_n is somewhere around the robot. Therefore, in this case, the system can estimate the rough position of Obj_n . The object's features, stored in RT_m , are also acquired.

When the Obj_n's rough position is estimated, the system can recognize it by the ceiling cameras using its features. Then, Obj_n can be precisely localized by the ceiling cameras using a particle filter.

3. Object localization method

In order to recognize and localize the objects robustly, an RFID system and a camera system are proposed in this paper, described in the previous section. The rough position of each object is initially estimated by the RFID system. Then the camera system recognizes the object in its existing area and finally localizes its precise position by a particle filter.

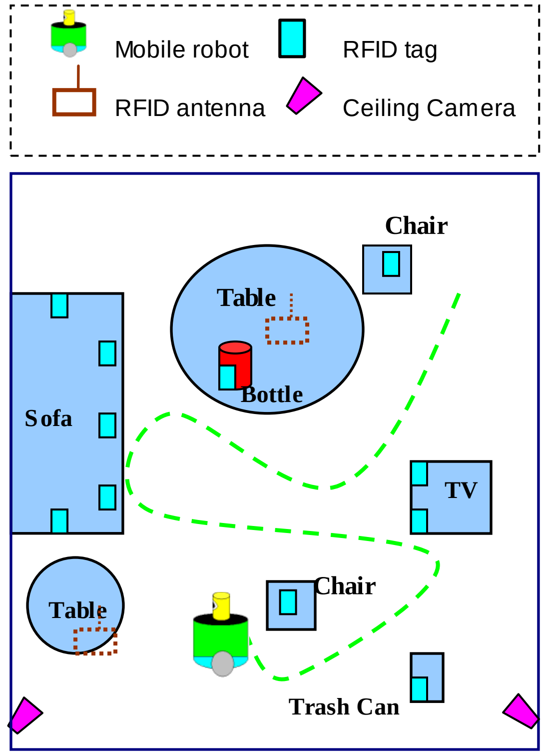


Figure 1. An example environment

The proposed method consists of 3 main steps:

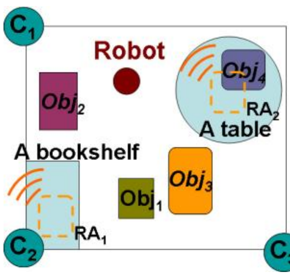
1. Estimate a rough position of the object by the RFID system.
2. Recognize the object in its *existing area* by the camera system using object features information.
3. Localize it precisely by the camera system using a particle filter.

3.1. Object localization method

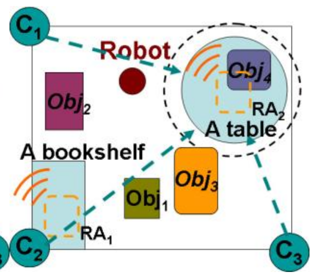
In order to estimate the rough position of an object, Obj_n, the RFID system is introduced.

K RFID antennas, {RA_1, RA_2, … RA_K}, are placed around the room. Let us assume that there are N objects, {Obj_1, Obj_2,…Obj_N}, in this room. The position of Obj_n is denoted as δ_n ($1 \leq n \leq N$). RFID tag(s), {RT_1, RT_2,…RT_M}, are also attached on objects, and store objects' features, denoted as f_n. Once an object Obj_n is detected by an RFID antenna RA_k, the RFID system can acquire f_n via the RFID system. It is also implied that δ_n is in a small area within the range of the antenna RA_k. We use the term "*existing area*", for this rough estimation of δ_n .

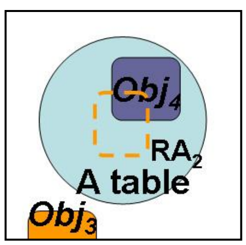
In case none of the antennas can detect Obj_n, δ_n is estimated by mobile RFID antenna(s), $\{RA_{K+1}, RA_{K+2}, \ldots RA_{K+J}\}$, attached on the mobile robot. While the robot is wandering around the room, if an RA_j ($K+1 \le j \le K+J$) can detect Obj_n, it is implied that δ_n is somewhere around the robot. Therefore, in this case, the *existing area* is the area within the range of RA_j. The f_n can be acquired via RA_j as well. The object's position estimation steps are shown in Figure 2 and Figure 3.



(a) RA_2 sensed Obj_4

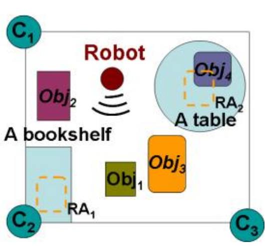


(b) C_1, C_2, C_3 focus on the existing area

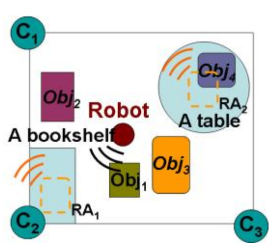


(c) The existing area

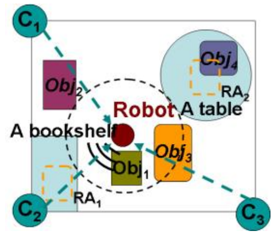
Figure 2. Estimating rough position of an object by an RA_k ($1 \le k \le K$)



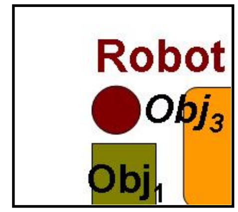
(a) The robot wanders around



(b) It found RT_m on Obj_1



(c) C_1, C_2, C_3 detect the robot



(d) C_1, C_2, C_3 zoom in

Figure 3. Estimating rough position of an object by an RA_k ($K+1 \le j \le K+J$)

3.2. Recognize object in the existing area

In order to recognize Obj_n in its *existing area*, f_n is stored into RT_m attached to Obj_n. The feature used in this paper is 1D Hue Color Histogram values. To recognize the object, whose f_n has been received via RT_m, each ceiling camera (C_q) in the room detects Obj_n in its *existing area* using that histogram. This is done by creating the back project of the histogram using as input the image of each camera. The backproject is created by replacing the value of the observed pixel of the input image by the value of the probability of that pixel given the distribution (histogram). Then, the image is thresholded and the largest connected component is selected.

Some studies also used color histogram as object's features [12, 13] because it is independent of the angle and size of the object in the image. Moreover, storing object's color histogram does not require large storage.

3.3. Precise object localization

In order to find the precise δ_n, a particle filter with ceiling cameras is used. The particle filter represents the posterior distribution by a set of random state samples drawn from this posterior. It represents a distribution by a set of samples, called *particles*, drawn from that distribution. Here, the distribution of each Obj_n is represent by a set of particles, named X_n. Let us assume that there are I particles in this set. Each particle is represented by its position ($x_n^{[i]}$) and its weight ($w_n^{[i]}$).

The position of C_q is denoted as a vector $\mathbf{S}_q$ ($1 \le q \le Q$), and the center of the image received by C_q is denoted as a vector $\mathbf{S'}_q$. Therefore, the direction of each C_q can be represented as a vector $\mathbf{S'}_q - \mathbf{S}_q$. This vector, looking at Obj_n, is used as a measurement of the particle filter. According to the particle filter, $w_n^{[i]}$ of each particle is updated by the direction of C_q. Such a representation is approximated, but it is nonparametric, and therefore can represent a much broader space of distributions than, for example, Gaussians [11]. Additionally, it takes full advantage of the information gained from all ceiling cameras focusing on the existing area of each Obj_n.

Since we have already estimated the *existing area* of each Obj_n, δ_n should be somewhere around RA_k ($1 \le k \le K+J$) that detected the RT_m attached on Obj_n. Therefore, X_n is sampled randomly in 3D space around RA_k. Each $w_n^{[i]}$ is then modified by the direction of C_q, pan (θ_q) and tilt (β_q). The coordinate system is shown in Figure 4.

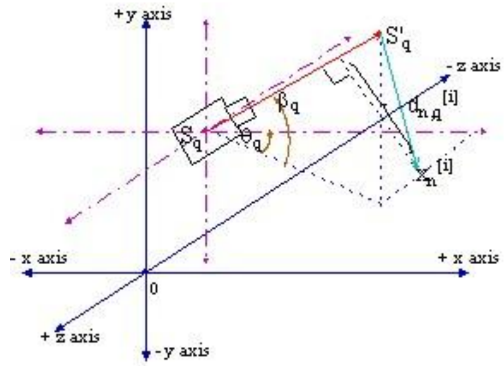


Figure 4. Coordinate system

Since the position of C_q is denoted as the vector $\mathbf{S}_q$, and the center of the image received by C_q is denoted as the vector $\mathbf{S'}_q$, the direction of C_q can be defined as follows.

$$S'_q = S_q + (at, bt, ct) \quad \text{where } t \in R \tag{1}$$

And a, b, c are defined as

$$\begin{aligned} a &= \cos\beta_q \cos\theta_q \\ b &= \sin\beta_q \\ c &= \cos\beta_q \sin\theta_q \end{aligned} \tag{2}$$

Then, for each particle, $w_n^{[i]}$ is updated according o the distance between the direction vector of C_q and each $x_n^{[i]}$. Therefore, the distance, denoted as $d_{n,q}^{[i]}$, for each $x_n^{[i]}$, can be calculated as follows

$$d_{n,q}^{i} = |(S'_q - x_n^{[i]}) x (S'_q - S_q)| / |(S'_q - S_q)| \tag{3}$$

At the next step, each particle will be sampled again. The probability of each particle is given by its weight. The system will keep resampling every particle until all particles are stable. The δ_n is then estimated by the mean value of all $x_n^{[i]}$ (for every I, where $1 \le i \le I$).

The proposed method can be implemented in the pseudo code in Table 1.

Table 1. The pseudo code of the proposed localization method

1: *if* (RA_k *found an* Obj_n)
2: *read* f_n *via* RA_K
3: *create an existing area around* RA_K
4: *for* $q = 1$ *to* Q *do*
5: C_q *focuses on the existing area*
6: C_q *recognizes* Obj_n *using* f_n
7: *endfor*
8: $X_n = \phi$
9: *for* $i = 1$ *to* I *do*
10: *sample* $x_n^{[i]} \sim$ *the existing area of* Obj_n
11: $w_n^{[i]} = d_{n,q}^{[i]}$
12: $X_n = X_n + < x_n^{[i]} , w_n^{[i]} >$
13: *endfor*
14: *for* $i = 1$ *to* I *do*
15: *draw I with probability* $\propto w_n^{[i]}$
16: *add* $x_n^{[i]}$ *to* X_n
17: *endfor*
18: *endif*

From line 1 to line 3 the first step of the proposed method is implemented: A rough position of the object is estimated by the RFID system. When an RA_k detects an Obj_n in the room, the features of Obj_n are acquired via the RFID system. Then, the *existing area* of Obj_n is estimated as a small area around the position of RA_k

From line 4 to line 7 the second step of the proposed method is implemented: The object is recognized in its existing area by the camera system, using the object features information. When the existing area of Obj_n is estimated, all ceiling cameras recognize Obj_n by using its features acquired from the RFID system. The result of this step is a 2D coordinate in the screen coordinate system of each ceiling camera.

Line 8 to line 18 consist the last step of the proposed method: localizing the objects precisely by the camera system using particle filters. First, particles are sampled randomly around the existing area of Obj_n , shown in line 10. The weight of each particle is also updated using the distance from that particle to each camera's direction vector. Then, all particles are resampled. The probability of each particle is given by its weight, shown in line 15. Therefore, the result of this step is a new set of particles, which represents the probability distribution of the position of Obj_n. The δ_n is then estimated by the mean value of all $x_n^{[i]}$.

The proposed method is simple and easy to implement and, according to the experiment result described in next section, it can localize the objects in an indoor environment accurately and robustly

4. Experiment environment

In order to evaluate the efficiency of the proposed method, the proposed system was set up in a room. The whole system consists of an RFID system and a camera system, described below.

4.1. The RFID system

The RFID system, proposed in this paper, is used in the first step of the proposed method; estimating a rough position of the object. The proposed RFID system consists of RFID tags, RFID antennas and mobile robot(s). The RFID system used in the experiment is described below.

4.1.1. RFID tag. In order to recognize an object, its features are stored in a passive RFID tag which is attached on it, as shown in Figure 5 (a). The information stored on the tag consists of the object's name and some features describing it. These features are extracted from an image containing various postures of that object. In this experiment, object's color histogram values are stored in the RFID tag, as a representation of the object's features as shown in Figure 5.

(a) RFID tag put on an object. (b) Its color histogram.

Figure 5. An RFID tag and information stored in it

4.1.2. RFID antenna. In order to estimate the rough position of an object and obtain its information, the RFID antennas are needed. When an RFID antenna senses a passive RFID tag attached on an object, it is implied that the object is around this RFID antenna. The object features' information is also transferred to the RFID system.

In this experiment, two Bluetooth RFID antennas and two wired RFID antennas are used, shown in Figure 6. The wired RFID antennas are attached under the tables in a room; therefore, objects put on the tables can be detected by these RFID antennas. The Bluetooth RFID antennas are attached to a mobile robot which is capable of wandering around the room. Therefore, while the robot is moving, objects on the floor with attached RFID tags can be detected as well.

(a)Wired RFID antenna (b) Bluetooth RFID Antenna

Figure 6. The RFID antennas

4.1.3. Mobile robot. In order to estimate the rough position of an object on the floor, RFID antennas are put on a mobile robot which is able to wander around the room. While the robot is wandering, once the RFID reader attached on it senses an RFID tag, the information of that object is read. The object, whose name is contained in that information, should be around that area.

In this paper, *Roomba*, a robotic vacuum cleaner made by iRobot, is used as a mobile robot, shown in Figure 7. Roomba was first released in 2002 and updates and new models were released in 2003, 2004, 2005 and 2006. [14] It was used in our experiments, as it is capable of wandering around the room and can be easily detected by ceiling cameras. Two RFID antennas were attached on it, as shown in Figure 7. While the robot is wandering around the room, objects on the floor can be detected by these RFID antennas.

Figure 7. Roomba with bluetooth RFID antennas

4.2. The camera system

The camera system, proposed in this paper, is used in the second and the third step of the proposed method; recognizing the object in its *existing area* using object features information and localizing it precisely using a particle filter.

In the experiment, three ceiling cameras at are set up in three corners of the experiment room, shown in Figure 8. The cameras used are capable of rotating, zooming and auto focusing as well. The system can acquire images from these three ceiling cameras via UDP. The resolution of images and the frame rate, acquired from the cameras, are 320x240 [$pixel^2$] and 30 [fps] respectively.

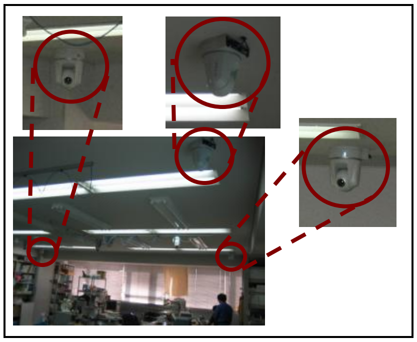
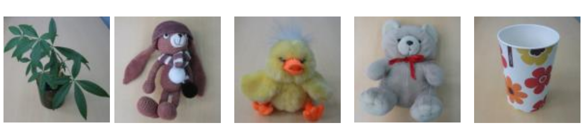


Figure 8. The Camera system set up in the experiment room.

4.3. The experiment environment

In the experiment, an indoor environment was set up in order to localize 10 various objects in the experiment room, shown in Figure 9 and Figure 10. According to the first step of the proposed method, in order to estimate the objects' rough position, the name of each object was stored into each of the RFID tags. Then, one or two tags were attached on each object. One wired RFID reader was placed under a table and another under a desk, in order to detect objects placed on them. Two mobile RFID readers were also attached on the front side of the roomba, which was used as a mobile robot, in order to detect the objects on the floor. In the second step of the proposed method, HUE color histogram values of each object were stored into the corresponding RFID tags. In the last step, three ceiling cameras were used in order to find the objects' precise position by using the Particle Filter algorithm.

In our experiment, the room's size was $30m^2$ * 2.5 m (surface * height). All 10 objects were randomly put in the room as shown in Figure 10. The computer used had a 3.2[GHz] Pentium D CPU, 2.0[GB] RAM and 150[GB] HDD.



(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Figure 9. Objects used for localization

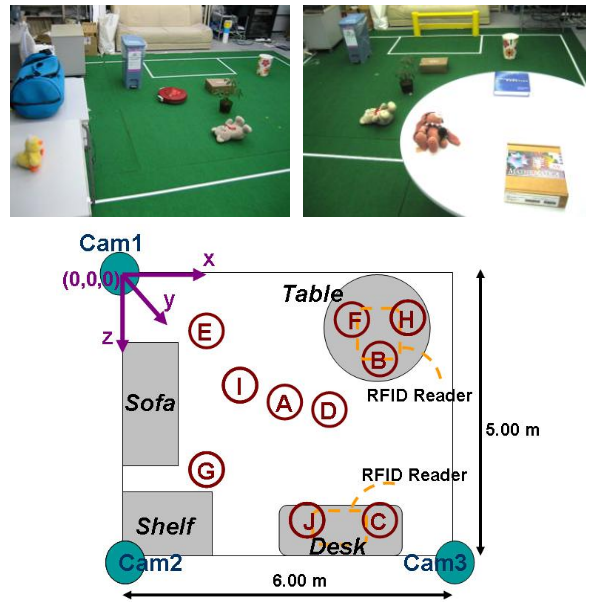


Figure 10. Experiment environment

5. Experiment evaluation

The purpose of our experiment is to evaluate the efficiency of the proposed method by localizing 10 various objects, shown in Figure 9. The result is evaluated in terms of recognition and localization efficiency. The recognition accuracy with and without using the RFID system is also compared, in order to evaluate the importance of the RFID system to the proposed method.

5.1. Efficiency of object recognition

In order to evaluate the object recognition efficiency of the proposed method, each object was placed on a total of 100 different positions in the experiment room. At each position, the ceiling cameras tried to recognize the object focusing on a small area, estimated by the RFID system. Then, the same experiment was done again without using the RFID system information, thus without the focusing of the cameras.

The results of both experiments are evaluated considering both recognition accuracy and computational time. When the RFID system was used, recognition accuracy was larger and computational time was lesser, as shown in Table 2.

Table 2. Time consumption for object localization

Object	Recognition Accuracy [%]		Computational Time [s]	
	with RFID	without RFID	with RFID	without RFID
A	96	89	0.17	0.41
B	91	31	0.23	0.55
C	94	82	0.19	0.46
D	93	81	0.19	0.50
E	97	96	0.18	0.47
F	91	48	0.25	0.61
G	88	35	0.26	0.63
H	96	79	0.20	0.44
I	93	83	0.22	0.48
J	92	62	0.23	0.48
Average	93.1	68.6	0.21	0.49

According to the experimental result, the average recognition accuracy when and without using the RFID system is 93.1% and 68.6%. The average computational time is 0.21 [s] and 0.49 [s], respectively. Therefore, use of the RFID system can increase recognition accuracy by 34.5% and decrease computational time to less than a half.

As object's 1D HUE color histogram is used as object's feature information, the system could hardly distinguish the difference between objects of similar color, like (f) and (i) in Figure 9. Thus, when two objects of similar histograms were put at a very close distance to each other, object detection failed. This actually rarely occurred, as all objects were placed randomly and the cameras focused on a small area around the RFID reader. Thus, the error of object recognition in the experiment was small.

5.2. Efficiency of object localization

In order to evaluate the object localization efficiency, 10 objects were randomly placed on various positions in the experiment room. Three of them were placed on the table and two on the desk of the room (Figure 10). RFID readers were attached under the table and the desk. The other five objects were randomly put on the floor. These objects were out of the range of the RFID readers under the table and the desk, but were detected by the RFID readers attached on the Roomba mobile robot.

The Object Localization experiment was performed 10 times. Since the motion of roomba is random, each time the order of localized objects was different. The average error and localization time are shown in Table 3.

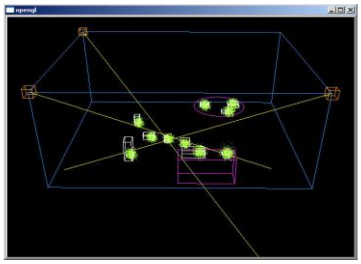
The result of the proposed method is evaluated in terms of localization accuracy and localization time. The average error is 0.079 [m], which is around 0.96% of the room's diameter. The origin of the coordinate system is defined as the top left hand corner of the room in Figure 10.The direction of the positive x axis is rightwards and that of the positive z axis downwards.

The localization time defers significantly, depending on the object's position. If an object is put on the table or the desk, it can be immediately detected by the RFID readers placed under them. Therefore, for the objects put on the table or desk, the average localization time is around 1.1 seconds as shown in Table 3. When an object is placed on the floor, the RFID readers under the table or the desk can not detect it. Instead, it is detected when the roomba wandering around the room "encounters" the object, and the roomba's RFID readers sense one of the object's RFID tags. As shown in Table 3, Roomba needed a lot of time for random wandering until it found an object. This is the main disadvantage of the proposed method.

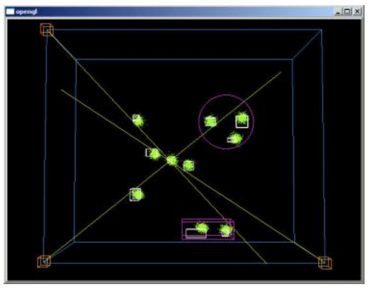
Table 3. Error of object localization

object	Size (L x W x H)[mm]	avg. error [mm]	avg. localization time [s] (on the table/ on the floor)
A	(230 x 200 x 50)	36	1.1 / 34.4
B	(280 x 230 x 70)	62	1.0 / 31.7
C	(100 x 200 x 70)	91	0.9 / 41.3
D	(150 x 150 x 100)	58	1.0 / 45.2
E	(500 x 180 x 200)	145	1.3 / 32.8
F	(250 x 240 x 150)	69	1.2 / 33.5
G	(130 x 130 x 280)	97	1.2 / 28.7
H	(300 x 170 x 560)	114	1.3 / 29.0
I	(300 x 200 x 120)	73	1.1 / 31.8
J	(80 x 80 x 200)	43	0.9 / 34.2
Avg.	----	79	1.1 / 35.3

The result of one of the 10 experiments performed is illustrated in Figure 11 below. The biggest blue box represent the experiment room of size 30[m^2] x 2.5[m] (surface x height). Three orange boxes represent three ceiling cameras at the corners of the experiment room, while three yellow lines represent the current direction of the ceiling cameras. Two purple boxes represent the table and the desk in the room. Ten white boxes and green particles represent the real and estimated position of objects.



(a) The localization result (Front view)



(b) The localization result (Top view)

Figure 11. Object localization result represented by sets of particles

6. Conclusion and future works

In this paper, an object localization method based on RFID system has been proposed. This method can increase recognition accuracy and reduce the computational time in the object recognition process by estimating the object's rough position in advance.

The concrete data obtained from this study is as follows:

- An RFID system and a mobile robot are used to localize 10 various objects in a room with an average error of 0.079 [m]. With the RFID system, which is set up in the room and on a mobile robot, an initial estimation of the position of each object is achieved and feature information of that object is received.
- HUE color histograms values, used as a representation of object's features, are small enough to be stored in the 256 bytes of the RFID tag and efficient enough for object recognition in a small search area. The recognition process is computationally fast, as it can be done in real time. However, the wandering period of the Roomba spent on finding the objects on the floor is quite long
- Particle Filter with ceiling cameras is used for high-precision localization of the objects. It takes full advantage of the multiple camera directions and limits the localization error to 0.96% of the room`s diameter.

In this paper, we assume that there are no similar objects at the same area of interest. As color histogram is only used as object's feature, if there are two (or more than two) similar objects in the same area, the system mostly fails to distinguish the difference between them and thus localize them In the future, we intend to add additional information as object's features in order to solve this problem.

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