Locating Items Using a Mobile Robot in a Domestic Environment

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***Abstract*— In this paper, I present how a home service robot can be built for locating misplaced items in a smart home environment. The robot uses the historical human trajectory which is obtained from the smart home environment for generating an optimized path planning for object finding. The object is detected using a real-time object detector which works on the principles of convolutional neural network. The experiment is performed on a smart home testbed and accuracy and efficiency are provided.**

I. Introduction

A. Motivation

As the technologies develop, there's an increase in the need for services that can assist in everyday activities. One such need can also be for the old age people who often forget where they keep their household things and then struggle to find, especially the ones with dementia. In the USA, the prevalence of dementia among individuals aged 71 and older was 13.9%, comprising about 3.4 million individuals in the USA in 2002. The corresponding values for Alzheimer's disease were 9.7% and 2.4 million individuals. Dementia prevalence increased with age, from 5.0% of those aged 71–79 years to 37.4% of those aged 90 and older [1]. Hence it is imperative to develop solutions that can help older people. Along with that, almost everyone would misplace his/her things frequently, like car keys, and the busy lifestyle of almost every working professional would benefit from something that can assist them with the search.

In recent times, there are plenty of services that now an intelligent home service robot can provide, such as vacuum cleaning. One other service a mobile home service robot can provide is to assist people to locate misplaced items in the household. One way to design such a robot is to perform a visual search in every section of the house for object detection. We can localize the house into regions and the robot can learn the places where the object is usually located,and such localization can be done using SLAM algorithm. However, if something is recently misplaced then the new mapping will not be found. Also as the houses get bigger, the search gets exhaustive and can take very long to find an item. Thus just a localization and visual search solution will not be sufficient. An efficient path planning of the robot for search is a good way to go about it to reduce the search time. For this purpose, we can make use of a smart home environment to get additional information to aid in planning. From our daily experiences, we know that the location of a common item and human movement are highly correlated because the location of an item is usually changed by human use [2]. Understanding the trajectory of human movement across the house can be used to understand how the user moves and how probable is it for him to drop things in the trajectory he usually follows.

Therefore, in this study, an approach for locating items in a smart home environment is described which goes as 1) Human trajectory information is collected using a wearable sensor on human and multiple sensors across the home, which we refer to as a smart home. 2) Search path planning is done using data from step 1 and applying a modified genetic algorithm. 3) Real-time object detection is performed using CNN.Using the given details, this work can demonstrate how robots can make use of the smart home environment for better performance and efficiency.

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B. Related Work

There are several technologies which are developed for misplaced object detection. One was using active radio frequency identification (RFID) tags that were attached to both the user and the items, and the positions of misplaced items could be obtained by the relative distances between them. In 2011, an item search system called IteMinder was proposed using passive RFID tags and an autonomous robot [3]. In 2017, a service robot was proposed which takes in user voice and performs visual search[4], similar to what is proposed in this article, although they do not perform a path planning using the smart home environment and that can result into a very long search time. In a recent research done in 2020, a gadget model is proposed wherein an article is followed that interfaces with Android cell phones to find objects utilizing android application through Bluetooth and Arduino. [5]

In all the approaches, the search was completely relied upon the robot sensors which can consume a significant amount of the robot's resource. Therefore, it is desirable to develop approach for locating misplaced object that can use the contextual information provided by the smart home environment.

II. Basics

Here are some concepts and sensor descriptions that will be useful while you read the paper:

- **Sensors**:
  - **Passive infrared sensor-** It is an electronic sensor that measures infrared light radiating from moving objects in its field of view. They are most often used in PIR-based motion detectors.
  - **Laser range finder-** it is a rangefinder that uses a laser beam to determine the distance to an object.
  - **RGB D camera-** These are a specific type of depth-sensing devices that work in association with a RGB (red, green and blue color) sensor camera. They are able to augment the conventional image with depth information (related with the distance to the sensor) in a per-pixel basis.
  - **SensorTag v2 -** The SensorTag operates as a Bluetooth low-energy (BLE) peripheral slave device based on the low-power and high-performance CC2650 multistandard wireless microcontroller unit (MCU) platform.

- **Path planning**:
  - **Genetic algorithm**: it is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. This algorithm reflects the process of natural selection where the fittest individuals are selected for reproduction in order to produce offspring of the next generation.
  - **SLAM algorithm-** In computational geometry and robotics, simultaneous localization and mapping (SLAM) is the computational problem of constructing or updating a map of an unknown environment while simultaneously keeping track of an agent's location within it.

Object recognition:
  - **YOLOv1**: YOLO, short for You Only Look Once is a convolutional neural network architecture designed for the purpose of object detection and is very fast in doing so.

III. Scenario

In this section, the main components of the robotic system is defined in detail, which includes the service robot, the smart home, and the user interface.

A. Smart home

1) Smart home testbed: The smart home testbed was established in a 5.72 m × 6.85 m (19 ft × 22 ft) room. It simulates a home environment that consists of a living room, a bedroom, a kitchen, and a bathroom. Fig 1 shows an example of the smart home testbed [2].

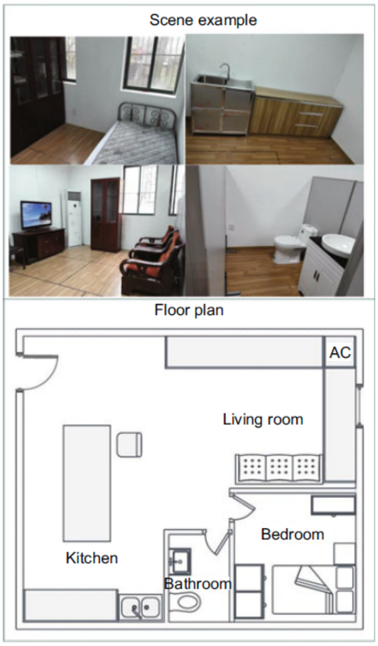

Fig. 1. An example scene of the smart home (top) and the floor plan (bottom)

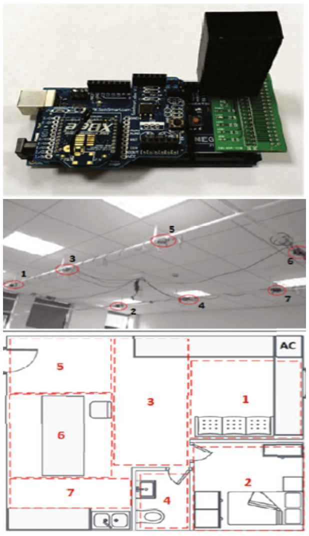

Fig. 2. A passive infrared (PIR) sensor node

2) Passive Infrared Sensor network: A passive infrared (PIR) sensor is an electronic sensor that detects infrared light radiated from moving objects. The PIR sensor used in this system is the Panasonic EKMC1601111, which is capable of detecting human movement when the resident is in its field of view (FoV). Fig. 2 shows one PIR sensor node. The PIR sensor is connected to an Arduino microcontroller board. An XBee shield, along with the XBee module, is mounted on the Arduino board, which is used to transmit the sensor data over the ZigBee protocol to the gateway node. The PIR sensor network consists of seven PIR sensors in total. [2]

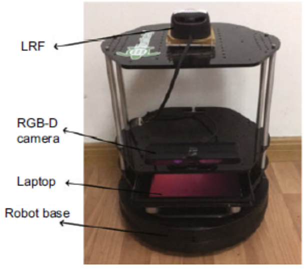

Fig. 3. Mobile service robot

3) Wearable sensor node : We used the wearable sensor node SensorTag v2 from TI (http://www.ti.com/lit/ug/tidu862/ tidu862.pdf). The SensorTag operates as a bluetooth low-energy (BLE) peripheral slave device based on the low-power and high-performance CC2650 multistandard wireless microcontroller unit (MCU) platform. Inside the MCU platform, there is a nineaxis motion MPU-9250 sensor (inertial measurement unit, IMU) that provides the motion data including three-dimensional (3D) accelerations, 3D angular velocities, and 3D magnetic field data. The CC2540 universal serial bus (USB) dongle acts as a central device (BLE master). It connects to a Windows PC USB port and is preloaded with necessary software to collect the sensor data. This sensor node is attached to the user's waist [2].

B. Service Robot

The robot consists of a mobile robot base, a laptop, and several peripheral sensors. The robot base is the TurtleBot platform, which is a safe, reliable, robust, and feature-rich mobile chassis. The computation engine of the robot is a laptop equipped with a dual-core processor, which runs the Robot Operating System (ROS, 2018). For perceiving objects in the environment, we equipped the robot with various sensors. A fixed-focus RGB-D camera captures the scene images necessary for object detection. A laser range finder (LRF) mounted on the top of the mobile base measures the obstacles for mapping and localization purposes. The same has been shown in Fig 3 [2].

C. User interface design

To provide a friendly interface for the user, we integrated an Android application as a remote control interface. It can display the realtime positions of the robot and the resident on the home floor plan. The speech-to-text service offered by the Xunfei online voice recognition platform is also implemented in this application [2].

IV. Approach

Describe the approach used in the experiment.

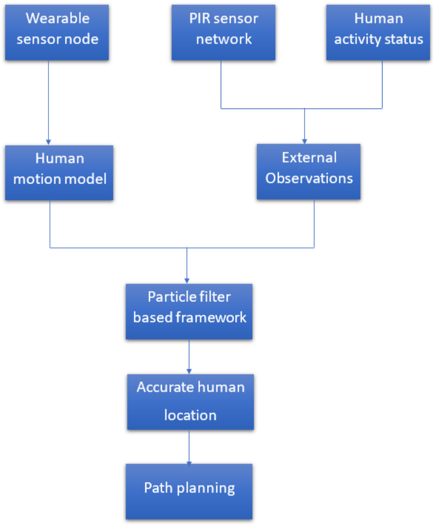

Fig. 4. Location estimation process

A. Input through user interface

The user's voice command is taken as input. The approach is to parse natural language into a high level specification of robot behavior, which can then be executed in the context of an arbitrary environment. Differentiating context and meaning in this way lends itself well to tasks in robotics, where full knowledge of the environment is rarely available[7].
A user can tell two commands in order to find the object: 1) What do you want to find? 2) Do you know where it could be? Through the first question the robot understands what item it has to search which is used for object recognition. For the second question, the user can give two kinds of answer: either the room name(kitchen, bedroom, etc.) or that he doesn't know. This response will be taken into consideration when doing path planning. The set of lexical entries and their weights will be used to train the model for understanding the location name and the object name provided by semantic parsing. When the results are obtained after search, the same will be provided to the user.

B. Human location estimation

There are two models that are used for obtaining human trajectory information. First one is a human motion model is generated that takes the data from the wearable sensor. The second model takes the external observation data that is collected from PIR sensor and human activity status. The data obtained from these two models are then fused using particle filter based framework for obtaining accurate human location estimation. This information is eventually used in the path planning of robot. The process is described in Fig 4

1) Motion model: PDR(pedestrian dead reckoning) algorithm is used for estimating coarse human location by measuring the movement distance and heading angle. This can be further improved when the initial location is known, and that can be obtained using WiFi location. We can use these two location information and fuse them to generate an indoor location algorithm that is based on WIFI and PDR according to the characteristics of PDR algorithm and WIFI location algorithm [8].

- Location from WiFI:
  For generating WiFi location, support vector machines (SVM) is used as a location algorithm, in which first a location fingerprint database is constructed according to the map grid and a certain amount of WIFI sample data is collected at each grid center. This data is used by SVM algorithm to construct the learning model. The real time WiFI data is calculated and the grid coordinate value is set as the WIfi location coordinates, which are the initial location coordinates.
- Location from PDR:
  PDR algorithm is used for estimating pedestrian trajectory using inertial sensors. It takes the single foot movement from the sensor as step and uses that for the calculation of steps, step length and heading angle. This walking step detection can also be considered as an acceleration detection problem, where the X and Y axis acceleration and the acceleration magnitude is taken and filtered, and normalized to get a_v. The features are extracted using sliding window size of 32 with an overlapping size of 16 between two consecutive windows. At a sampling rate of 10 Hz, each sliding window represents the data of 3.2 s, which is sufficient to capture the cycles in activities like walking [2]. For adapting different users and walking modes, adaptive threshold based algorithm is used with the acceleration in which signal valley threshold(T_v) and the signal peak threshold (T_p) are calculated as follows:

$$T_v = \frac{V_k + V_{k-1} + -1}{2} + (K - \frac{V_k + V_{k-1} + -1}{2})C_1 \quad (1)$$

$$T_p = T_v + \sqrt{(K - T_v C_2} \quad (2)$$

  where K is the limiting condition to renew the threshold which goes as:

$$K = \begin{cases} P_k, & P_k < P_{k-1}, \\ P_{k-1}, & P_k \geq P_{k-1}. \end{cases} \quad (3)$$

  where P_k and V_k are the maximum and minimum acceleration values of walking step k respectively, P_{k1} and V_{k1} are of walking step $k-1$, and C1, C2 are the parameters determined experimentally [2].
  The heading angle change is obtained as follows:

$$\theta_k = \theta_{k-1} + \Delta\theta, \quad (4)$$

$$\Delta\theta = \int_t^{t-1} \omega_t \, dt \quad (5)$$

  where $\Delta\theta$ is the accumulated heading angle change between walking steps $k-1$ and k.
  Combining the walking steps and heading angle, the human motion model can be derived as:

$$L_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix} = \begin{bmatrix} x_{k-1} + d_k cos\theta_k \\ y_{k-1} + d_k sin\theta_k \end{bmatrix} \quad (6)$$

  where L_k are the coarse location coordinates at walking step k, d_k is the walking step length which remains constant for a certain user, and n_k is the process noise. [2]
- Fusion:
  WiFi location can be easily disturbed as it is absolute position information and hence can lead to inaccurate location. However, by using the PDR algorithm, the next step coordinates can be calculated using step length and heading angle of pedestrian. But the error is easily accumulated in PDR algorithm. Therefore, a fusion location algorithm based on Extended Kalman filter(EKF) is adopted to fuse WIFI fingerprint location and PDR location. During walking, WIFI location is conducted after each 5 steps. If the location error between the WIFI and the PDR results is in the range of 4 meters, then, the EKF algorithm is used to fuse the result of WIFI fingerprint location and the PDR calculation result and obtains the final location. Otherwise, the final location result is calculated by PDR[8]

2) Human Location by PIR sensor: The PIR sensors in the testbed detect the user movement and maintains a queue for its triggered identifiers. These triggers are used to calculate user location as follows:

$$P(z_k^{PIR} = 1 | L_k^i) = \begin{cases} 1, & L_k^i \in PIRsensor'sFoV, \\ 0, & L_k^i \notin PIRsensor'sFoV. \end{cases} \quad (7)$$

where $P(z_k^{PIR} = 1 | L_k^i)$ is the likelihood function of location L_k^i, and $z_k^{PIR} = 1$ represents the PIR sensor being triggered. L_k^i may be one of two conditions: the user is either in the same room or in a different room that the particle represents.

3) Human location by activity status: Every room of a house is usually associated with certain kinds of activities that humans do and these are very limited. For example in bedroom a human would be lying, in living room a human would usually walk, etc. This additional information can be used for measuring human activity recognition. If a_k represents different activities of human in daily life(standing, walking, lying, sitting, others), then the measurement model would be defined as:

$$P(a_k|L_k^i) \tag{8}$$

which is the likelihood function of location.
Moreover, these activities have some acceleration information associated with them the activity can be analysed by these acceleration observations.

4) Particle based sensor fusion: Using the above data of human motion model, PIR observation data and the human activity data, we can use the particle filter based fusion framework that will give us the accurate trajectory of human. Each particle can be thought of as a human location, which has certain weight. The framework would indicate the probability of the location being the real human location. The particle weight ω_k^i is updated by the related likelihood as:

$$\omega_k^i = \omega_{k-1}^i p(z_k^{PIR}|L_k^i)P(a_k|L_k^i) \tag{9}$$

and is normalized as:

$$\omega_k^i = \frac{\omega_k^i}{\sum_{i=1}^{P} \omega_k^i} \tag{10}$$

At last, the mean of the particle's locations is taken to estimate the accurate human location:

$$\tilde{L_k} = E(L_k) = \frac{\sum_{i=1}^{P} L_k^i \omega_k^i}{\sum_{i=1}^{P} \omega_k^i} \tag{11}$$

C. Search Path Planning

The next step in the process is to generate a good search path that can minimize the time of search required. For this, the following steps are applied on a high level:

1) An environmental global map is created using SLAM algorithm.
2) This map is converted into a grid map which is then divided into regions.
3) A modified genetic algorithm is used which takes the prior human trajectory information.

SLAM algorithm is used for generating a global map. This global map is converted into a grid map and these grids are are divided into several regions. While dividing regions, the maximum detection range of the robot camera has to be considered else the item detection step will not work accurately. The robot then moves in the regions to perform a visual search.
As homes have several rooms and these rooms may have multiple regions, following a random path for search may take a lot of time and may also consume robot's resources. So in order to make the search sequence in regions robust, we will use an algorithm which can provide us the best sequence for object search.
In the first step, we had received the input from the user if he could suggest where the item could be. This can be used as the first preference to search. This is done to facilitate the search process even further to have a higher chance of finding the object where the user suggested. Regardless, We then use a modified genetic algorithm(GA) to continue our search in other rooms in case the object was not found in the suggested region or if no such information was provided.
For GA, information about the genes and chromosomes are required. We will consider the regions in numerical form(0-9) and use them as genes and the different transition sequences possible can be taken as chromosomes. Then a fitness function is constructed which considers the traveling time, the rotation time, and the probability of the region and is written as:

$$f = \sum_{n=1}^{N-1} \frac{D(s_{n-1}, s_n)/\nu + T(s_{n-1}, s_n)/\omega}{\rho_{s_n}} \tag{12}$$

where N is the total number of regions in a given region transition sequence, $D(s_{n-1}, s_n)$ and $T(s_{n-1}, s_n)$ denote the moving distance and the rotation angle between two consecutive regions respectively, and ν and ω represent the robot's linear and angular speed respectively [2]. We assume that the user drops things with the uniform probability while he/she is walking around, so the probability ρ_{s_n} is dependent on the human historical trajectory knowledge that was calculated in the section above and can be represented as:

$$\rho_{s_n} = \frac{L_{sn}}{\sum_{n=0}^{N-1} L_{sn}} \tag{13}$$

where L_{sn} is the number of human trajectory points contained in region s_n. This equation is used in equation 12 to get the correct value of fitness function. In this way, the historical trajectory information is included in search path planning.

D. Vision based processing

1) Object Recognition: :
The item name is obtained from the UI which is taken for processing and the images are acquired by the robot using the RGB-D camera. The workstation on the robot is integrated with fast object detector, YOLOv1 which is based on pre-designed convolutional neural network(CNN). The CNN generated 3 types of outputs from the images- 1) class probability 2) the bounding box coordinates which gives the point of refernce and 3) a confidence value. Evaluation is performed based on these outputs and gives results as the two classes: 'item' and 'no item'. The misplaced item is considered detected if and only if all the object-description information matches the item. The evaluation flowchart is described in Fig 5 [2].

2) Wall and door detection: Some domestic object classes that are not suited to this approach such as doors and walls. We use a framework of fusing 2D local and global features such as edges, textures and regions with geometry information obtained from

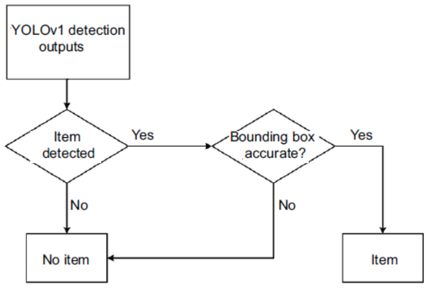

Fig. 5. Evaluation flowchart

pixel-wise dense stereo for reliable 3D indoor structural scene representation. Door detection is again based on the robots knowledge about its vertical pose. The main idea is to post process the 3D lines obtained from stereo processing. Doors are detected where two vertical parallel lines have a distance between 0.6 m and 1.4m, and both lines have a height of more than 1.5 m. [9]

3) Obstacle detection: A 2D light detection and ranging (LiDAR) is used for detection of an obstacle in it's field of view. However, if objects are below the scanning sight, obstacle detection may not work. For this, we will use a combination of two sensors: an inclined laser rangefinder (LRF) and a 360 all-round visibility LiDAR. This system would leverage the navigation stack capabilities of using multiple observation sources to increase the accuracy of both navigation and obstacle avoidance and will be able to avoid an obstacle below the scanning sight.

V. Experiment

For image recognition, several kinds of misplaced items are trained on the CNN, including keychains, remotes, slippers, and combs. The sample training images were collected from both the ImageNet dataset (http://www.image-net.org/) and the smart home testbed captured by the robot's camera. The numbers of training samples in the dataset for different classes are shown in Table I [2].

Number of samples				
Category	Keychain	Remote	Slipper	Comb
Training	867	828	638	759
Validation	186	178	137	163
Training	186	178	137	163

TABLE I
Sample number of the dataset for each category

To run our item location experiment, we will ask the user to move around the house and place the keychain in different regions of the house. Two strategies are used to compare our performance- 1) random search where search path transition is generated randomly(benchmark 1) and 2) Predetermined search where the transition sequence is fixed. Both strategies do not have any information of the historical human trajectory(benchmark 2). We will compare our results with these two strategies. Note, the input of location from the user, obstacle detection and location estimation using WiFi location is not included in the robot for the experiment.

Fig. 6. Robot stops when the keychain is found

VI. Results

Fig 6 shows that after a successful search, the robot stopped its movement in front of the keychain.

Three different performance metrics were used to evaluate the efficiency of the proposed approach, including the total time consumption (Tfound), the total length of the path (Len), and the total angle of rotation (Ang). The experiment results on our model are shown in table II. Similar results were also captured for benchmark I and II and the impact of the knowledge on improving the effectiveness of item detection was demonstrated in the comparative evaluation results shown in Tables III and IV.

Performance			
Area	$T_{found}(s)$	Len(m)	Ang(rad)
Bedroom	85.64	7.14	25.71
Living room	85.94	6.82	30.77
Kitchen	85.74	6.01	32.34

TABLE II
Performance on proposed method

Improvement(%)			
Area	T_{found}	Len	Ang
Bedroom	50.37	61.00	55.82
Living room	57.78	64.97	55.87
Kitchen	34.67	55.61	30.90
Average	47.61	60.53	47.53

TABLE III
Improvement over the Benchmark I method

VII. Evaluation

Looking at the tables III and IV, we can observe that the proposed method took approximately 49% less time

Improvement(%)			
Area	T_{found}	Len	Ang
Bedroom	49.43	33.95	60.92
Living room	32.72	-3.65	41.94
Kitchen	68.52	67.53	68.53
Average	50.22	32.61	57.13

TABLE IV

Improvement over the Benchmark II method

to complete the search task The impact of the knowledge on improving the effectiveness of MIF was demonstrated n the comparative evaluation results shown in Tables 4 and 5. It can be observed that the proposed method took 49% less time to complete the search task, and an average of 47% less distance and 52% less rotation, that means that the proposed approach works much faster than the benchmark strategies. The amount of improvement for all the three metrics is almost the same, which is around 50%. The results are obtained for the search of one item, keychain, so the comprehensive analysis of multiple experiments can throw much better light upon how the system actually works.

VIII. Conclusion

The proposed approach has performed well in a smart home environment. Enhancements and further experiments under different circumstances(obstacles present or global map changing) or by using other items for detection are still pending. The robot moves on the ground so there are high chances that it may miss items that are placed high above it's field of view, so an alternative approach can be planned to design a robot for such a purpose, like a drone based robot. Further, multiple human trajectory can also be mapped using pressure sensitive floors and that can be a further research point. Also, the robot is currently equipped to only provide the location of the object. That can be enhanced by mounting a manipulator on the robot to retrieve items. Hence, the robot performs well with many options for improvement.

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Hamburg, January 22, 2021

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