Autonomous Robotic Exploration and Mapping of Smart Indoor Environments With UWB-IoT Devices

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Abstract

The emerging simultaneous localization and mapping (SLAM) techniques enable robots with spatial awareness of the physical world. However, such awareness remains at a geometric level. We propose an approach for quickly constructing a smart environment with semantic labels to enhance the robot with spatial intelligence. Essentially, we embed UWB-based distance sensing IoT devices into regular items and treat the robot as a dynamic node in the IoT network. By leveraging the self-localization from the robot node, we resolve the locations of IoT devices in the SLAM map. We then exploit the semantic knowledge from the IoT to enable the robot to navigate and interact within the smart environment. With the IoT nodes deployed, the robot can adapt to environments that are unknown or that have time-varying configurations. Through our experiments, we demonstrated that our method supports an object level of localization accuracy ($\sim 0.28m$), a shorter discovery and localization time ($118.6s$) compared to an exhaustive search, and an effective navigation strategy for a global approach and local manipulation. Further, we demonstrated two use case scenarios where a service robot (i) executes a sequence of user-assigned tasks in a smart home and (ii) explores multiple connected regions using IoT landmarks.

Intruduction

Within our surrounding environment, the ad-hoc tasks which we take for granted are often complex for robots because of their limited perception capabilities and underdeveloped intelligence algorithms (Kemp, Edsinger, and Torres-Jara 2007). Despite the commercial successes of mobile robots, particularly in warehouses, they are mostly specialized in handling simplified and pre-defined tasks within controlled environments often with fixed navigation pathways. Further, many of the AI advances in navigation are in simple settings with many assumptions, and are not useful in realistic environments (Savinov, Dosovitskiy, and Koltun 2018). On the other hand, the rapidly emerging IoT ecologies bridge our physical world with digital intelligence. In contrast to ongoing advances in vision, we propose an integration of robots into the connected network, where they can leverage information collected from the IoT, and thus gain stronger situational awareness (Simoens, Dragone, and Saffiotti 2018) and spatial intelligence, which is especially useful in exploration, planning, mapping and interacting with the environment without relying on AI/vision-based navigation only.

Recent advanced computer vision technologies, such as SLAM algorithms and depth sensing, have empowered mobile robots with the ability to self-localize and build maps within indoor environments using on-board sensors only (Cadena et al. 2016), (Newcombe et al. 2011). Although these systems provide good maps under favorable conditions, they are very sensitive to calibration and imaging conditions, and are not suitable in changing dynamic environments. Therefore, to fully support navigation and interaction with the environment, we need to extend robots' perception from a vision-based geometric level to a semantic level. Although researchers have made substantial progress in scene understanding, object detection and pose estimation (Salas-Moreno et al. 2013), vision-based approaches largely rely on knowing the object representations a priori (Wu, Lim, and Yang 2013) and keeping the objects of interest in the camera's view. That said, vision-only approaches may be more suitable for local and specific tasks. Thus, mapping key parts of the environment and identifying the objects of interest, and especially finding means to interact with them using vision-based methods, usually do not have well-developed solutions.

In contrast, within a smart environment, wireless techniques such as Bluetooth, Zigbee, and WiFi allow for instant discovery of the connected objects via the network. Further, the robots could naturally access the semantic information stored in the local IoT devices which contributes towards understanding the environment and results in intelligent user interactions. Still, resolving the spatial distribution of the IoT-tagged devices or objects remains challenging. Using the wireless communication opportunistically, received signal strength indicator (RSSI)-based methods for localization of the sensor node have been studied extensively in the wireless sensor network (WSN) field (Heurtefeux and Valois 2012). Yet, the low accuracy of the results (a few meters) may prevent them from being employed for in-

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door mobile robots. Other researchers have developed UHF RFID-based object finding systems (Deyle, Reynolds, and Kemp 2014). However, these systems introduce an extra bulky and expensive UHF antenna, suffer from a limited detection range ($\sim$3m), and, using their approach, a robot must perform a global search before navigating to and interacting with the IoT tags.

Recently, researchers have been investigating distance-based localization methods using an ultra-wide bandwidth (UWB) wireless technique which provides accurate time-of-flight distance measurements (Di Franco et al. 2017). Such techniques have been further applied to enable users to interact with smart environments (Huo et al. 2018). Inspired by these works, we propose a spatial mapping for IoT devices by integrating UWB with SLAM-capable robots. We build highly portable and self-contained UWB-IoT devices that can be labeled and attached to ordinary items. The SLAM-capable robots simply survey in a small local region and collect distance measurements to the IoT devices for a short time, and then our mapping method outputs the global locations of the devices relative to the SLAM map. Our method supports navigation and planning in previously unseen environments. We leverage the discovered IoTs as spatial landmarks which essentially work as beacons that help the robot familiarize itself with a complex environment quickly without accessing any pre-stored and static databases. Centering upon this mapping method, our contributions are three-fold as follows.

- A method to build a smart environment with spatial and semantic information by deploying UWB-IoT devices.
- A navigation pipeline that drives a robot to a target globally and then refines the object localization, for example with object handling and manipulations.
- Demonstration of our method with a prototype service robot (i) working with users through a task-oriented and spatially-aware user interface and (ii) exploring an unknown environment referring to IoT landmarks.

Background

The Internet of Robotic Things

The concept of IoT has gained recent importance because of connectivity and low-cost electronics for communication. Mobile robots are being increasingly explored because of their mobility given by computer vision and falling costs, but vision alone is not reliable or scalable. However, the concept of Internet of Robotic Things (IoRT) has been not been that widely explored in practice across the IoT and robotics communities (Simoens, Dragone, and Saffiotti 2018). As we demonstrate, the intrinsic pervasive sensing from IoT platforms could enhance robots' perception by building and referring to a comprehensive model of the smart environment (Sanfeliu, Hagita, and Saffiotti 2008). IoT-aided robotics applications have been explored in health-care, industrial plants and rescue operations where heterogeneous equipment and assets are closely monitored (Grieco et al. 2014). Prior work proposed to leverage perceived information from the IoT for context-aware material handling in smart factories (Wan et al. 2017). Moreover, the assistive robots in human environments rely heavily on overseeing human-involved activities and/or medical conditions from the IoT platform (Simoens et al. 2016). Essentially, these extended perception and cognitive capabilities lead to a larger degree of autonomy and adaptability, and thus better facilitate human-robot interactions and collaborations (Nguyen et al. 2013). On the other hand, compared to stationary and simple actuators such as doors, coffee makers, manufacturing machines, and elevators in an IoT ecosystem, the mobility introduced by robots serves as an essential complementary-element in IoRT. From this perspective, self-localization and mapping becomes fundamental to navigate the robot to complete any spatially-aware tasks in indoor environments such as factories, hospitals, and houses. While on-board vision-based sensors support SLAM well for navigation, semantic mapping remains challenging using only on-board sensors (Cadena et al. 2016). In our paper, we emphasize an IoT-facilitated mapping of the smart environment by employing an autonomous discovery and localization of the IoT devices and associating them spatially on the SLAM map.

Mapping of Smart Environments

To access locations of smart devices, researchers have developed environmental models which associate the metadata and spatial information of the IoT with the geometric map of the environment (Dietrich et al. 2014). However, these models largely remain static, which indicates low flexibility against the environment changing, e.g., newly added or moved assets. By equipping the robots with on-board active sensors, researchers further investigated approaches towards autonomous and dynamic discovery and mapping of IoT. Utilizing UHF RFID technologies, a probabilistic model and a filtering-based localization method have been proposed to map the distributed passive tags (Hahnel et al. 2004), (Joho, Plagemann, and Burgard 2009). Although RFID tags carry some basic information, they are not connected to the network or Internet. Therefore, the discovery of the tags often requires the robots to traverse the entire environment (Deyle et al. 2010). Further, previous works have investigated leveraging wireless communication techniques to localize the nodes in a WSN, e.g., WiFi, Bluetooth, and Zigbee (Heurtefeux and Valois 2012). Compared to the RSSI-based probabilistic models, recent works started to employ direct distance measurements with a high accuracy ($<$0.1m) using UWB technologies (Di Franco et al. 2017). Here, we adopt a mobile anchor assisted approach which exploits the mobility of the robots and immediate navigation capabilities from the SLAM (Han et al. 2016), (Huo et al. 2018). Further, our approach allows the robots to access the real-time status from the surrounding IoT and therefore supports rich interactability with the environment. Moreover, based on the mapping of smart environments, we create a task-oriented and spatially-aware assignment interface for users to easily deploy robotic tasks.

Constructing a Smart Environment

To construct a smart environment with spatial and semantic information, we develop an IoT module consisting of a WiFi and a UWB communication component. A commonplace use case scenario involves a set of IoT devices spanning an indoor environment and a SLAM-capable robot with an IoT module attached. The robot connects to the IoT through a WiFi network and the UWB network then primarily provides distance measurement capabilities. When entering an unknown environment, the robot surveys in a local small region ($1.5m \times 1.5m$) and collects the distance measurements to the IoT devices. A distance-based method is then used to estimate the multiple IoT locations simultaneously and register them within the SLAM map, namely, mapping the smart environment. Depending on this semantic map, the robot navigates close to the targets and finishes tasks locally.

Mapping of UWB-IoT Devices

In a traditional WSN, all of the nodes are distributed to designated locations. A typical distance-based localization method involves two steps: (i) resolving relative positions of the nodes in an arbitrary coordinate system, and (ii) transforming the positions into the desired coordinate system (Dokmanic et al. 2015). To resolve the relative positions, an optimization problem is formulated to minimize the mismatches between the distance measurements and the calculated distances from the estimated positions. Then, referring to a set of four non-planar *anchor* nodes, i.e., nodes with known positions beforehand, a rigid body transformation between the arbitrary coordinate system and the absolute one can be derived.

In our case, we introduce a robot which is capable of self-localizing with respect to the environment as a *dynamic anchor*. Consider we have n nodes to be localized, i.e., n IoT devices, and m *dynamic nodes*, i.e., m samples along the the surveying path. The on-board SLAM algorithm provides coordinates of the robot on the path. We denote the unknown coordinates of the n nodes and the known ones of the m anchors as $\mathbf{X}_u = [\mathbf{x}_1, \ldots, \mathbf{x}_n]^T \in R^{n\times 3}$, and $\mathbf{X}_a = [\mathbf{x}_1, \ldots, \mathbf{x}_m]^T \in R^{m\times 3}$, respectively. We can further estimate $\mathbf{X}_u$ by minimizing the following stress function:

$$\min_{\mathbf{X}_u} \mathrm{S}(\mathbf{X}_u) = \min_{\mathbf{X}_u} \sum_{i\le n, j\le m} \omega_{ij}(\hat{d}_{ij} - d_{ij}(\mathbf{X}_u, \mathbf{X}_a))^2 \quad (1)$$

where $\hat{d}_{ij}$ is the distance measurement, $d_{ij} = \|\mathbf{x}_i - \mathbf{x}_j\|$, and the weight, ω_{ij}, is defined based on the quality of the measurements. We choose ω_{ij} in Eq. 1 to be 1 in our prototype. To this end, we formulate the localization as a nonlinear least-square problem which can be solved by existing methods, e.g., Levenberg-Marquardt algorithm (Ranganathan 2004). It is worth noting that, in general, this method is applicable to estimate the 3D locations as long as the samples remain non-colinear on all three dimensions. Yet, we degrade the formula to a 2D case since, in this work, we focus on a grounded moving platform. Further, the estimated positions from the optimization are already in the desired coordinate system, i.e., the SLAM map frame, which is not the case with traditional WSN with only stationary nodes.

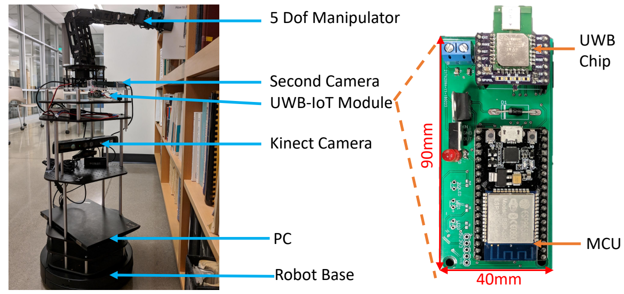

Figure 1: The robot platform and UWB-IoT module.

Navigation and Interaction

To complete a manipulation task, our robot needs a navigation strategy through three phases: (i) surveying movements to collect enough distance samples in a local region, (ii) globally approaching into the proximity of the IoT object, and (iii) locally adjusting poses for executing the manipulation.

For the first phase, we design a static random walk trajectory to guarantee the non-colinearity of the sample positions during the surveying. Further, based on our preliminary experiments and results from the previous work (Huo et al. 2018), we keep the footprint of the trajectory sufficiently large ($1.5m \times 1.5m$) to achieve accurate localization in a large room ($\sim 10m \times 10m$). In the second phase, we employ a path planner which integrates a global costmap and a local costmap. Since we emphasize the exploration and navigation in an unknown environment, as the robot marches and the map updates, the planner re-plans the trajectory. The planner utilizes the local costmap to avoid dynamic obstacles during the exploration. Although the UWB-based localization is accurate enough to drive the robot close to the targets, the manipulation task usually requires millimeter-level accuracy. Thus, for the third phase, we employ vision-based tracking for the granular pose adjustment. As the scope of this paper is on phase one and two, we simply use fiducial markers to perform the local manipulation. To handle the transition between phases two and three, we use the distance measurement as a threshold for proximity detection (e.g., less than 1 meter). Moreover, the IoT devices facilitate the manipulation procedure by providing semantic information, such as the offset from the marker and grasping directions.

Implementation

Hardware

Our prototype system consists of a mobile ground robot platform (TurtleBot 2) and a set of UWB-embedded IoT modules as shown in Fig. 1. We equip the robot with a Microsoft Kinect camera for SLAM navigation. Further, a 5-degree-of-freedom robot arm (PhantomX) is affixed on the top chassis to allow for interacting with objects within $40cm$. An extra camera in front of the arm base is used to track the fiducial markers in close range. We use a standalone PC (CPU i7-6500u, RAM 8G) to handle the computation on the robot. The overall size of the robot platform is $\sim 0.32m \times 0.32m \times 0.98m$.

As for the IoT module, we develop a self-contained board with off-the-shelf components. The board includes a microcontroller (MCU), a UWB unit, and peripheral circuits. An ESP32 chip (NodeMCU 32S) has been selected as our MCU since it offers built-in WiFi communication. The MCU connects with the UWB chip (DWM1000) through the SPI bus. Based on the datasheet of DWM1000, we expect a distance measurement with an accuracy of $\sim 5cm - 10cm$ and a maximum measuring range of dozens of meters. In our experiment and use case environments ($\leq 10m \times 10m$), we observed similar measurement accuracy.

Software

Our software system is composed of three major modules: (i) a UWB-IoT firmware running on the IoT board for distance measurements and WiFi communications, (ii) a robot control scheme based on ROS to handle the navigation and manipulator movements, and (iii) a user interface on a mobile phone for task-oriented programming of the robot. The IoT devices, robot, and the user interface are connected to the same local area network.

We employ a two-way asynchronous ranging method which utilizes two round-trip messages for distance measurements. With a one-to-n distance polling, we estimate the update rate to be $1000/(80 + 21n)$Hz based on the current parameters, e.g., one-to-one ranging results in ~ 9.9Hz and one-to-two ranging results in ~ 8.1Hz. The ranging results are transmitted to a ROS node through UDP.

For the navigation and path planning, we adopt a RGB-D based SLAM package from ROS, i.e., RTAB-Map[1]. We configure the package to synthesize a laser scan from the depth camera fused with the odometry. Further, the built-in Dijkstra's algorithm-based global planner and the dynamic window approach-based local planner are used to navigate the robot within the unknown environment. After the robot reaches the proximity of the target, we apply vision-based method to recognize and track the object which has an AR tag[2] attached to it.

We develop a mobile application on an Android device for users to interact with the robot. Once the robot discovers and localizes all of the available IoT devices, the interface is updated based on the spatial relationship between the robot and the devices. By referring to the revealed spatial relationship, users can then schedule and command the robot to finish a sequence of tasks related to the IoT devices.

Experiments

We designed three experiments to study the accuracy of the distance based localization for mapping the IoT devices, the efficiency of our approach compared with an exhaustive search, and the effectiveness of our navigation pipeline in guiding the robot globally and locally for manipulation tasks. We conducted all the experiments in a controlled indoor environment ($10m \times 8m$) as shown in Fig. 2. Based on

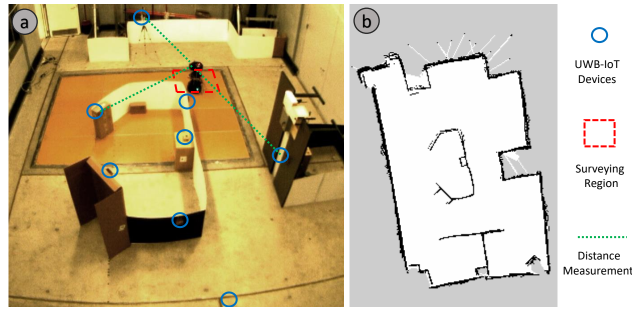

Figure 2: Experiment setup: IoT devices distributed in a room with manually placed obstacles (a), and a pre-scanned map of the environment (b).

our preliminary investigation, we set the sampling number at 200 to reach an accurate localization result. Also, to achieve a uniform sampling, we kept drawing samples every $2cm$ on the surveying path. The maximum speed of the robot has been limited to $0.2m/s$ for safety concerns.

IoT Localization Accuracy

To evaluate the accuracy, we compared the localization results and the ground-truth result from a Vicon tracking system. We attached IR reflective markers on the robots and the IoT modules. From previous work (Huo et al. 2018), we learned that the number of IoT devices does not significantly affect the accuracy. Therefore, we decided to examine the accuracy test with a constant number of IoT modules, e.g., 3 in this paper. We first identified 8 possible positions spread within the Vicon tracking volume. For each trial, we randomly selected a set of 3 out of the 8 positions to place the IoT devices and started the robot roughly at the same location. In total, we executed 10 trials, yielding a total of 30 localization results.

Results. We computed the absolute errors on the x and y axes as well as the root mean square distances between the localization results and the ground-truth (Fig. 3). We observed two outliers with distance errors larger than $1m$. Since we conducted our experiment without referring to an existing map of the environment, these outliers may be caused by the unstable SLAM during the local surveying. After removing those two outliers, the average errors yielded $0.20m$ (SD=0.19), $0.16m$ (SD=0.10), $0.28m$ (SD=0.17) for the x, y, and distance, respectively (Fig. 3). We confirmed the localization accuracy with our robot platform was similar to previous work (Huo et al. 2018). We expect such a sub-meter localization accuracy to support the global navigation module to drive the robot within close proximity of the target.

Localization Efficiency

Although previous works have used UHF RFID to find and navigate to passive tags, the discovery of all of the tags still requires traversing the environment (Deyle, Reynolds, and Kemp 2014). To finish such a global search, a pre-built map and search path of the environment have been used for the path planning. As shown in Fig. 4, we simulated the search

[1] http://wiki.ros.org/rtabmap_ros
[2] http://wiki.ros.org/ar_track_alvar

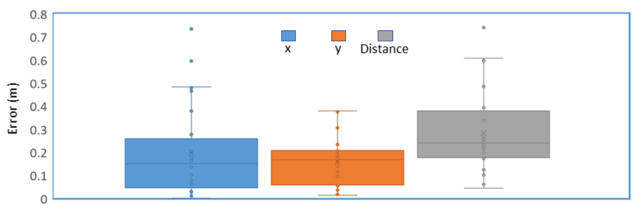

Figure 3: Results of localization accuracy test.

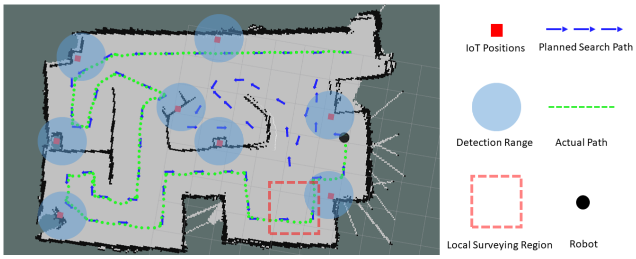

Figure 4: Map with a global search setup where the robot traverses the environment with a predefined path, compared to a local surveying region that is only needed in the proposed approach.

and defined a successful detection of one tag if the robot passed by the tag position within a certain range, e.g., $1m$. The global search was terminated after all tags were detected. Whereas in our case, UWB units are capable of measuring distances within a large range. In our controlled environment, we did not observe any accuracy degradation for the distance measurements. Using our approach, the robot surveyed a small local region ($1.5m \times 1.5m$) and localized all of the IoT devices at once.

Results. We compared the completion times of detecting and localizing 3 IoT devices with two different approaches: the global search and our local surveying. Similar to the accuracy test, we randomly chose 3 positions from the 8 predefined locations to place the IoT devices. We conducted 5 trials for each approach. The results indicated that our local surveying, which had an average cost of $118.6s$ (5 successful trials), was significantly faster than the global search which had a cost of $251.0s$ (4 successful trials). Additionally, to perform a global search in practice, we need to take the time to scan a full map of the environment into account that is not included in the cost calculation in our result.

Navigation and Manipulation

Further, to validate the full workflow, we conducted a third experiment, where the robot (i) localized the surrounding IoT targets, (ii) navigated itself within close proximity, (iii) searched for the fiducial marker and finished the manipulation task. In each trial, we placed two IoT targets randomly in the environment as shown in Fig. 5. We observed the accomplishments of the full workflow and timed each step. In this experiment, we assumed an unknown environment and did not use any pre-built maps.

Results. We conducted 6 experiments where the robot finished the entire task successfully 4 times, and failed on navigating to the second target in the other 2 trials. In general, the robot was able to complete the whole task within $450s$. As illustrated in Fig. 6, the local searching for AR tags and manipulation took similar time ($68s$) across all experiments, whereas the navigation time varied depending on the locations of the targets ($28s - 176s$). In some extreme cases, the navigation failed due to poor SLAM mapping.

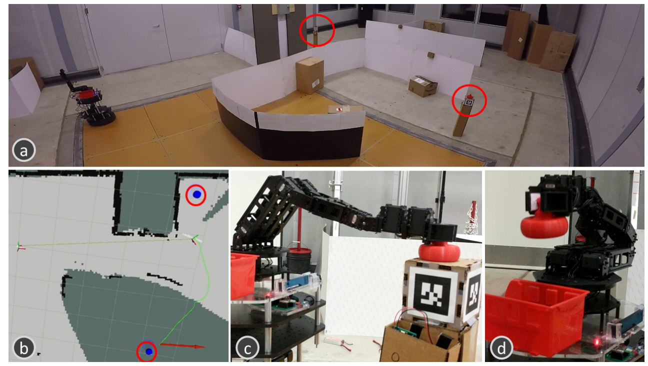

Figure 5: Setup for navigation and manipulation test: our robot visited two IoT targets (a, b) according to the localization results, then grabbed the target (c) and placed it to the basket (d).

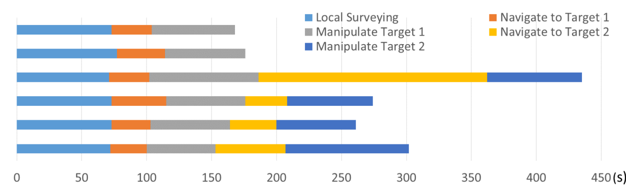

Figure 6: Time profiles for navigation and manipulation trials.

Use Cases

Our workflow emphasizes autonomous mapping and interacting with the smart environment. We envision that the robot will be empowered with spatial awareness of the distributed IoT devices. Here, we selectively demonstrate two use cases leveraging the enhanced spatial intelligence of the robot.

Task-Oriented and Spatial-Aware Programming

Our approach in general contributes to a higher level autonomy for robots to interact with a smart environment, e.g., general purpose service robots interacting with a smart home. As shown in Fig. 7, to command such a robot to conduct a sequence of tasks, a user simply uses a mobile user interface to schedule the IoT-indicated tasks. Then, the robot is capable of localizing the targets and accessing the backend knowledge from the IoT network. The real-time spatial relationship between the robot and the IoT targets is updated to the users for better task planning.

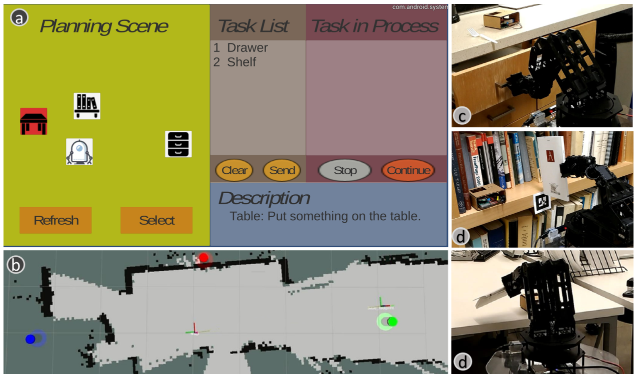

Figure 7: Through a spatial-aware programming interface (a), a user schedules a robot to perform a sequence of tasks: cleaning the kitchen table (c), delivering a book from a bookshelf to a desk (d, e).

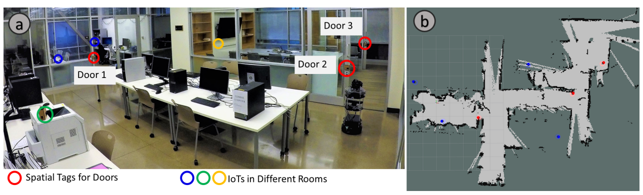

Figure 8: A robot explores an environment which includes multiple rooms by referring to spatial tags on the doors.

Autonomous Exploration Using Spatial Tags

Although UWB-based localization suffers less in non-line-of-sight (NLOS) scenarios compared to approaches using computer vision, a heavy NLOS condition such as walls still degrades the accuracy. To mitigate this issue, we propose to use UWB-IoT as spatial landmarks and references for the robot to navigate and explore multiple rooms in a continuous manner. As illustrated in Fig. 8, we showcase a robot navigating through three IoT-tagged doors and exploring three rooms. Each tag on the doors provides spatial knowledge about a local region. Finally, we localize all IoT devices in the rooms and register them onto a single SLAM map. With our autonomous exploration, we foresee greatly lowering the barriers to deploy the robots in realistic environments.

Discussion and Future Work

Localization Accuracy. Our experimental results suggested our SLAM + UWB mapping approach has strong potential towards accurate and fast localization of smart objects. However, we still observed some unstable localization especially in an unknown cluttered scene. We suspect some possible causes for this to be non-robust SLAM tracking in an unknown environment and inaccurate distance measurements under NLOS conditions. In the future, we plan to employ a visual-IMU fused SLAM alternative to examine the SLAM tracking quality. Further, it will be interesting to develop a data-driven model for the NLOS detection so that we can better address the inaccurate samples.

Scalability. Since we adopted a two-way ranging scheme between UWB modules, the update rate of the distance measurements limited the number of IoT devices to be localized. In addition, the slow update rate may compound the synchronization between the distance measurements and the SLAM tracking poses of the robots. To achieve a higher sampling rate, it is helpful to investigate a Time-Difference-of-Arrival (TDOA) method by introducing an extra UWB unit for time synchronization across the network (Tiemann, Eckermann, and Wietfeld 2016).

Sophisticated Tasks. Although we demonstrated a service robot being assigned with some chores, the task actions were largely hard-coded and pre-programmed. Instead of an AR tag, we plan to take advantages of the advanced vision based approaches and further closely integrate our global navigation with local tasks. Moreover, as smart devices are proliferating rapidly, it is worthy studying robot-IoT interactions to address more sophisticated and realistic tasks.

Conclusion

Our paper contributes towards the broad goal of empowering robots with a higher level of autonomy and intelligence in a smart environment. We develop a UWB+SLAM approach enabling robots to *autonomously explore an unknown smart environment and map the IoT devices*. We further verified that our method provides localization of IoT-marked targets with an *object level accuracy* ($\sim 0.28m$). With our method, the robot is capable of navigating to the proximity of the targets without using any pre-scanned map. Through this work, we bring robotics closer to our everyday life by leveraging the rapidly growing IoT network.

References

Cadena, C.; Carlone, L.; Carrillo, H.; Latif, Y.; Scaramuzza, D.; Neira, J.; Reid, I.; and Leonard, J. J. 2016. Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age. 32(6):1309–1332.

Deyle, T.; Nguyen, H.; Reynolds, M.; and Kemp, C. 2010. Rfid-guided robots for pervasive automation. 9(2):37–45.

Deyle, T.; Reynolds, M. S.; and Kemp, C. C. 2014. Finding and navigating to household objects with uhf rfid tags by optimizing rf signal strength. In *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems.*, 2579–2586.

Di Franco, C.; Prorok, A.; Atanasov, N.; Kempke, B.; Dutta, P.; Kumar, V.; and Pappas, G. J. 2017. Calibration-free network localization using non-line-of-sight ultra-wideband measurements. In *Proc. of the 16th ACM/IEEE Int. Conf. on Information Processing in Sensor Networks*, 235–246. ACM.

Dietrich, A.; Zug, S.; Mohammad, S.; and Kaiser, J. 2014. Distributed management and representation of data and context in robotic applications. In *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems.*, 1133–1140.

Dokmanic, I.; Parhizkar, R.; Ranieri, J.; and Vetterli, M. 2015. Euclidean distance matrices: essential theory, algorithms, and applications. 32(6):12–30.

Grieco, L. A.; Rizzo, A.; Colucci, S.; Sicari, S.; Piro, G.; Di Paola, D.; and Boggia, G. 2014. Iot-aided robotics applications: Technological implications, target domains and open issues. *Computer Communications* 54:32–47.

Hahnel, D.; Burgard, W.; Fox, D.; Fishkin, K.; and Philipose, M. 2004. Mapping and localization with rfid technology. In *IEEE Int. Conf. on Robotics and Automation.*, volume 1, 1015–1020.

Han, G.; Jiang, J.; Zhang, C.; Duong, T. Q.; Guizani, M.; and Karagiannidis, G. K. 2016. A survey on mobile anchor node assisted localization in wireless sensor networks. 18(3):2220–2243.

Heurtefeux, K., and Valois, F. 2012. Is rssi a good choice for localization in wireless sensor network? In *IEEE 26th Int. Conf. on Advanced Information Networking and Applications*, 732–739.

Huo, K.; Cao, Y.; Yoon, S. H.; Xu, Z.; Chen, G.; and Ramani, K. 2018. Scenariot: Spatially mapping smart things within augmented reality scenes. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 219. ACM.

Joho, D.; Plagemann, C.; and Burgard, W. 2009. Modeling rfid signal strength and tag detection for localization and mapping. In *IEEE Int. Conf. on Robotics and Automation.*, 3160–3165. IEEE.

Kemp, C. C.; Edsinger, A.; and Torres-Jara, E. 2007. Challenges for robot manipulation in human environments [grand challenges of robotics]. 14(1):20–29.

Newcombe, R. A.; Izadi, S.; Hilliges, O.; Molyneaux, D.; Kim, D.; Davison, A. J.; Kohi, P.; Shotton, J.; Hodges, S.; and Fitzgibbon, A. 2011. Kinectfusion: Real-time dense surface mapping and tracking. In *10th IEEE Int. Symp. on Mixed and Augmented Reality*, 127–136.

Nguyen, H.; Ciocarlie, M.; Hsiao, K.; and Kemp, C. C. 2013. Ros commander (rosco): Behavior creation for home robots. In *IEEE Int. Conf. on Robotics and Automation*, 467–474.

Ranganathan, A. 2004. The levenberg-marquardt algorithm. *Tutoral on LM algorithm* 11(1):101–110.

Salas-Moreno, R. F.; Newcombe, R. A.; Strasdat, H.; Kelly, P. H.; and Davison, A. J. 2013. Slam++: Simultaneous localisation and mapping at the level of objects. In *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition*, 1352–1359.

Sanfeliu, A.; Hagita, N.; and Saffiotti, A. 2008. Network robot systems. *Robotics and Autonomous Systems* 56(10):793–797.

Savinov, N.; Dosovitskiy, A.; and Koltun, V. 2018. Semi-parametric topological memory for navigation. *arXiv preprint arXiv:1803.00653*.

Simoens, P.; Mahieu, C.; Ongenae, F.; De Backere, F.; De Pestel, S.; Nelis, J.; De Turck, F.; Elprama, S. A.; Kilpi, K.; Jewell, C.; et al. 2016. Internet of robotic things: Context-aware and personalized interventions of assistive social robots (short paper). In *5th IEEE Int. Conf. on Cloud Networking (Cloudnet)*, 204–207.

Simoens, P.; Dragone, M.; and Saffiotti, A. 2018. The internet of robotic things: A review of concept, added value and applications. *International Journal of Advanced Robotic Systems* 15(1):1729881418759424.

Tiemann, J.; Eckermann, F.; and Wietfeld, C. 2016. Multi-user interference and wireless clock synchronization in tdoa-based uwb localization. In *IPIN*, 1–6.

Wan, J.; Tang, S.; Hua, Q.; Li, D.; Liu, C.; and Lloret, J. 2017. Context-aware cloud robotics for material handling in cognitive industrial internet of things. *IEEE Internet of Things Journal*.

Wu, Y.; Lim, J.; and Yang, M.-H. 2013. Online object tracking: A benchmark. In *Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition*, 2411–2418.