Robotic Activity Support (RAS)

A Cognitive Assistant for the Smart Home

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Introduction

The Problem:
- 50% of adults age 85+ require assistance with activities of daily living (ADLs)
- Cognitive impairment necessitates a robotic aid to offer automated assistance for completing ADLs with an elder-friendly user interface

The Goal:
- Design and build a robot to serve as a cognitive aid for ADLs
- Coordinate with our smart home sensor network for activity learning capability
- Elder-friendly user interface to support aging in place

Robot Design

Requirements:
- Interface for prompting resident whether assistance is needed (see Figure 4)
- Visually recognize human and objects, keeping track of last-seen locations
- Navigate to human and object locations in the house

Components:
- Hardware: Turtlebot (see Figure 1)
- Software: (see Figure 2)
  - ROS Components connected by manager node
  - RabbitMQ to communicate with CASAS smart home

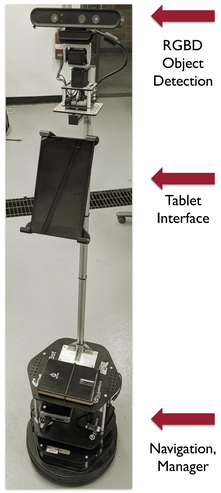

Figure 1. Robot hardware

Navigation:
- Cartographer with 2D LiDAR for SLAM (see Figure 5)
- Dijkstra's for fast interpolated navigation
- Linearization of paths for complex environments

Object Detection:
- Train Convolutional Neural Network (CNN):
  - Create labeled image dataset of objects of interest
  - 20k human images from Microsoft COCO dataset
  - 2.5k images of smart home-specific objects
  - Split into 80% train and 20% test
  - Train an object detection CNN (see Figure 6 for results)
- Run CNN live on robot RGB/depth images:
  - Run the RGB image through the CNN to predict bounding boxes (see Figure 7)
  - Find 3D center of each bounding box using depth point cloud
  - Transform into map location and store last-seen object location
  - Only SSD networks run on robot due to memory constraints (~10 fps)

Error Detection:
- Create directed acyclic graph (DAG) for each activity's steps
- Use smart home sensors to detect non-DAG-supported step order

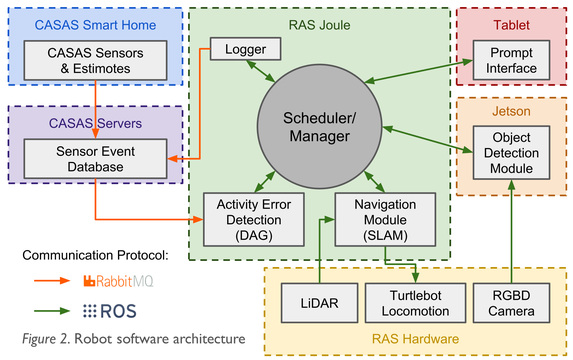

Figure 2. Robot software architecture

Activity Assistance Evaluation

Participants:
- 26 healthy young adults (11F, 15M, mean age 24 years)

Procedures:
- Participants complete three representative ADL scenarios, interacting with robot prompts:
  - **Tasks:** (1) Prepare to walk the dog, (2) Take medication with food and water, (3) Water plants
  - **Error Conditions:** Complete once without error, three times with different omission errors
  - **Prompts:** Robot navigates to participant and prompts upon error detection (see Figure 3)
  - **Participant Response:** Accept help with one of three options: (1) Lead to task-relevant object, (2) Show video of how to complete missing step, (3) Show video of how to complete entire task
  - **Finish:** Participant fixed their error and completed the rest of the task

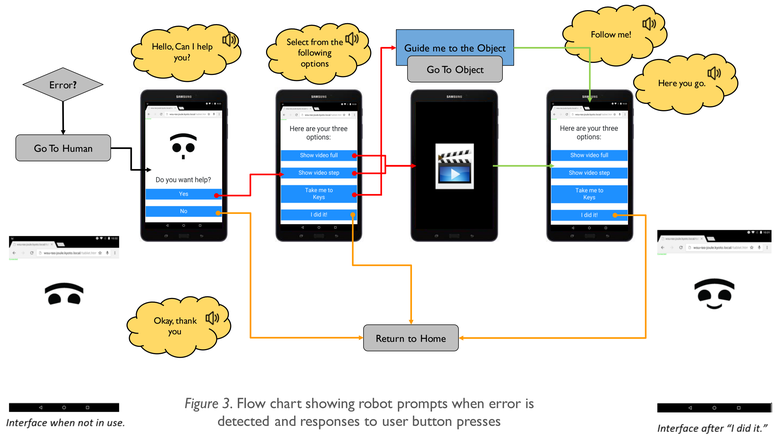

Figure 3. Flow chart showing robot prompts when error is detected and responses to user button presses

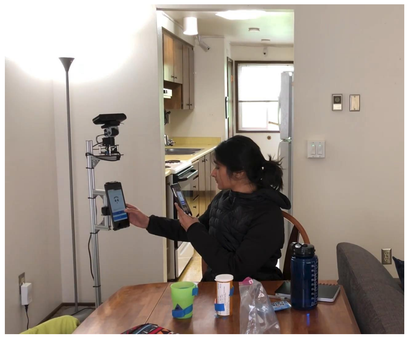

Figure 4. Human-robot interaction after a mistake was made during the take medication task.

Figure 5. Cartographer map of the smart apartment, green dots show current lidar scan, the green rectangle represents the robot footprint

Precision by Class	Faster R-CNN	R-FCN	SSD Inception	SSD MobileNet
Food	0.69	0.97	0.94	0.90
Cup	1.00	1.00	1.00	1.00
Keys	0.90	1.00	1.00	1.00
Pill Bottle	0.96	0.97	0.87	0.89
Plant	0.99	0.96	0.99	0.97
Umbrella	0.98	1.00	0.96	0.97
Water Can	1.00	1.00	1.00	1.00
Human	0.47	0.46	0.43	0.34

Figure 6. Smoothed average precision @ 0.5 IoU on testing set of all the classes for each of the 4 TensorFlow-trained object detection networks

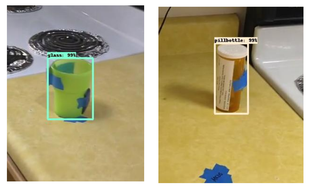

Figure 7. Two objects recognized by the object detection and the predicted bounding boxes from the CNN, showing the Estimote sensors mounted on the sides of each object

Results and Conclusions

Participant Surveys:
Participants were asked to evaluate their interaction with the robot

Usability Questionnaires		
Category	**Mean Rating**	**Standard Deviation**
PSSUQ[1]	**Lower** is more useful	
Overall	4.55	1.95
System Usefulness	4.37	1.89
Interface Quality	4.83	1.94
Information Quality	4.66	2.23
QUIS[2]	**Higher** is more satisfied	
Screen	7.96	0.97
Terminology	7.74	1.42

[1]Post-Study System Usability Questionnaire (1=more useful, 7=less useful)
[2]Questionnaire for User Interface Satisfaction (1=less satisfied, 9=more satisfied)
Note different scales for PSSUQ vs QUIS

Usability:
- Usefulness ratings mostly neutral, but responses varied widely among individuals
- Satisfaction ratings favorable of the tablet interface

Preferred Prompt Type			
Rating Category	**Guide to Object**	**Next Step Video**	**Full Video**
Most Liked Prompt	32%	**60%**	8%
Most Helpful Prompt	40%	**52%**	8%
Least Effective Prompt	12%	8%	**80%**

Note: N=25 (one participant did not answer)

Prompt Types:
- Next step video both most liked and most helpful
- Full video of entire task was least effective
- Participants rated next step video most helpful to someone with cognitive impairment

Successes:
- Robot intervened when errors occurred
- Overall participant impressions favorable
- Next-step video found to be helpful

Challenges:
- Human detection accuracy low (false positives)
- Delayed network communication and slow robot movement (assistance may be too late)
- Sensor firings (misfired sensors lead to missed errors)

Future Work

- Evaluate system with older adults and those with cognitive limitations (Fall 2018)
- Improve object detection (track humans in home and update object locations)
- Improve error detection:
  - Quicker detection speed
  - Utilize more CASAS smart home sensors (motion, door, etc)
  - Detect more activity types and multiple simultaneous errors
- Evaluate system in real-world scenarios
  - Test in users' homes for multiple days with non-scripted activities (planned: Spring 2019)
- Develop self-docking system to allow long-term usage