Indoor Navigation for Assistive Robots using EEG Signals as Feedback

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Presentation outline

- Introduction
- Motivation and Overview
- Background
- Methodology
- Results
- Conclusion and Future work

Assistive Robots

A branch of robotics that assists people with physical disabilities with physical interaction.





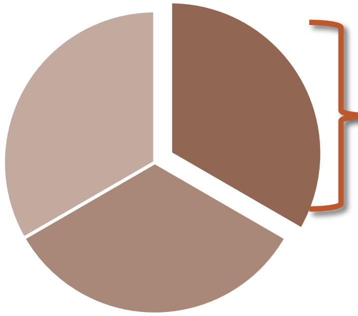
Human Robot Interaction :

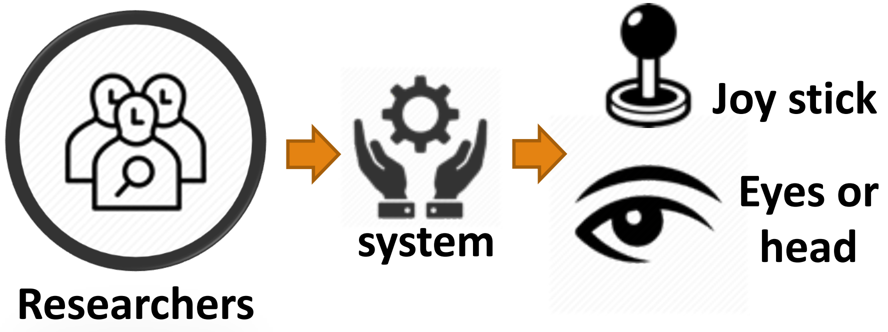
A study of interactions between humans and robots, with contribution from brain computer interaction, artificial intelligence, robotics, natural language understanding, design and social sciences.

Interaction or the exchange of information can be verbally or non-verbally

Communication

Motivation



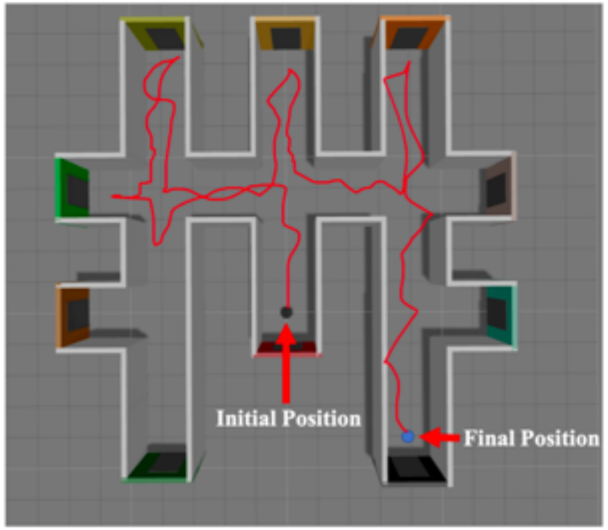


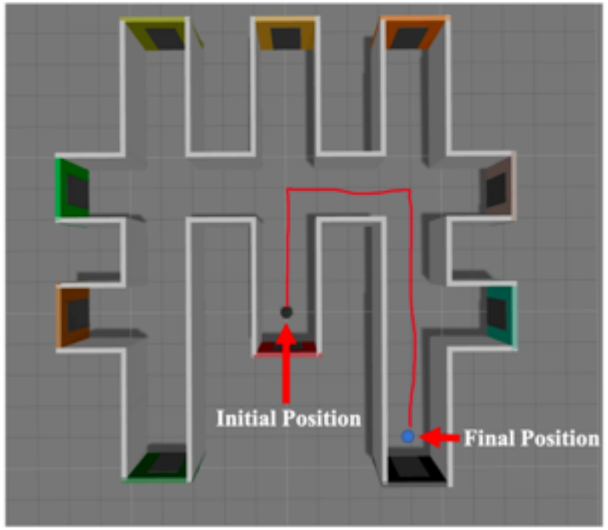
Locked-in syndrome

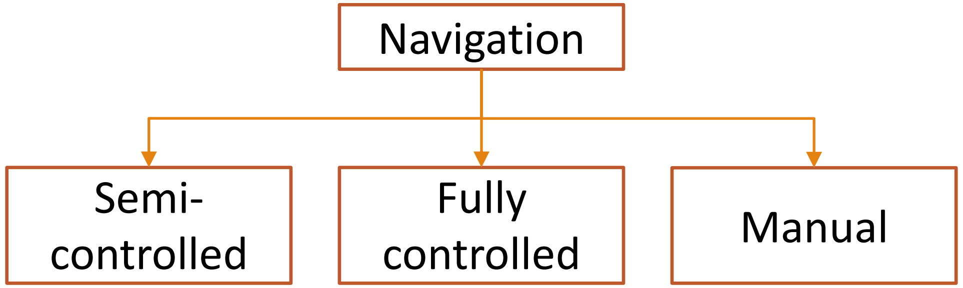
- **Complete loss of control over their voluntary muscles where patients are unable to speak and move but are conscious and can think and reason.**

Examples: Stroke, severe cerebral palsy, motor neuron disease, ALS

- Our research focus is on patients who are affected by Locked-In Syndrome and to help physically challenged people to achieve **greater independence by making technologies such as BCI/HRI** accessible which provides an alternative communication bridge between human brain and robot/computer.







We present an introductory navigation algorithm that allows an individual to control an assistive robot using EEG signals in order to navigate from a starting location in a structured building to an ending location.

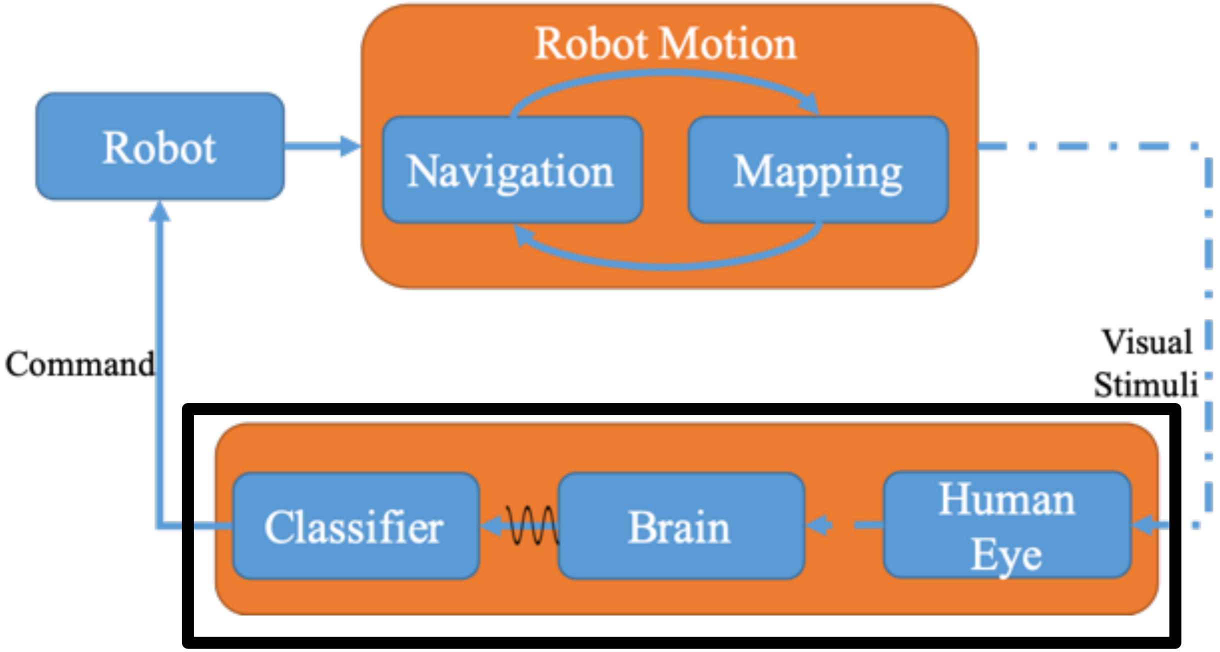
This work focuses on:

- Enabling to some degree the ability for individuals to self navigate buildings
- Reducing the amount of input required in order to accomplish this navigation

Focus on global navigation

- Starting point known by assistive robot but ending point unknown
- Utilize the history of user decisions when navigating a structure to minimize decision that must be made by the user
- Leverage navigation algorithm to determine most likely path to destination

Overview



Stimuli in this case refers to intersection exits or colored doors.

Goal Description

- Provide a **proof of concept for a semi-autonomous navigation scheme**
  - Allow a user with **locked-in syndrome** to navigate from a start location to an end location in a structured building structured building with minimum inputs

- Utilize assistive robot such that user need to **make the least amount of decisions while still maintaining global navigation control**
  - Assistive robot only requires user input at hallway intersection and potential end destination (doors)
  - Build a memory of previous paths such that the assistive robot will attempt to re-tread common paths
    - Such as a daily lunch routine

- **Assistive robot proposes an intersection exit to user**
  - User provides a negative ErrP response if intersection exit is incorrect

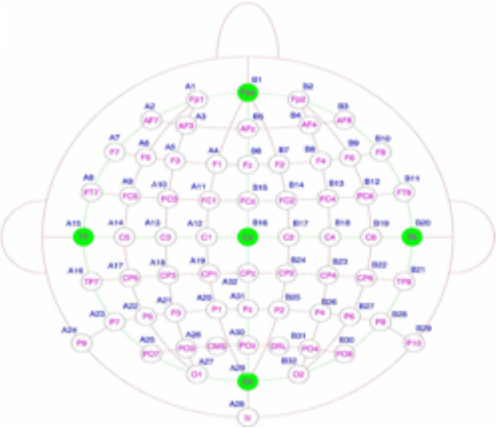
Background - EEG

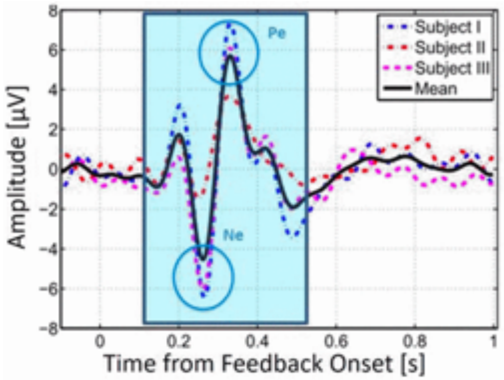
Electroencephalography (EEG):

A group of electrical potentials generated by neural activities in human brain.

Event Related Potential:

Derivative of EEG which are produced by human brain in response to external stimuli or specific event





P50 wave	N400 wave
N100 or N1 wave	Movement related cortical potentials
P200 or P2 wave	Contingent negative variation
N200 or N2 wave	Post imperative negative variation
N300 wave	
P300 wave	

Categorized according to latency and amplitude after the stimulus

<u>Error Related Potential:</u> Characterized by an initial positive peak occurring at 200ms and large negative between 200-250ms and positive peak

Classifier

Raw EEG → Preprocessing → Feature Selection → Classification

Simulated Human Brain with EEG signal | Temporal (Bandpass) & Spatial filtering (CAR) | Electrode Selection based on Spatiotemporal Maps | ‘FCz’ and ‘Cz’ was used with ConvNets

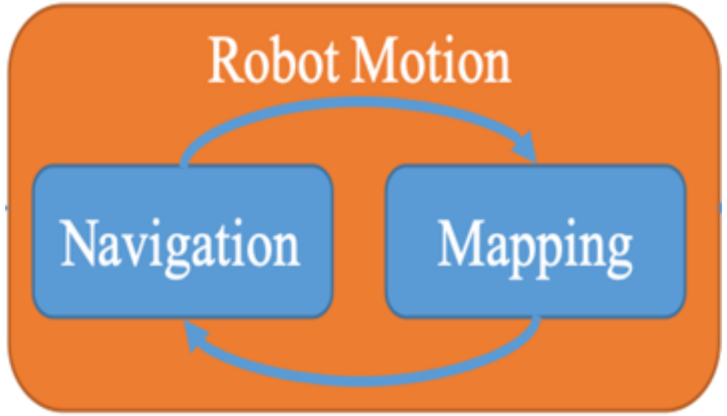
- Dataset was collected from BNCI Horizon 2020 (EPFL, Switzerland) [1]
- Overall Accuracy Achieved: 86.1% for two sessions [2]

Navigation and Mapping

- Navigation is semi-controlled

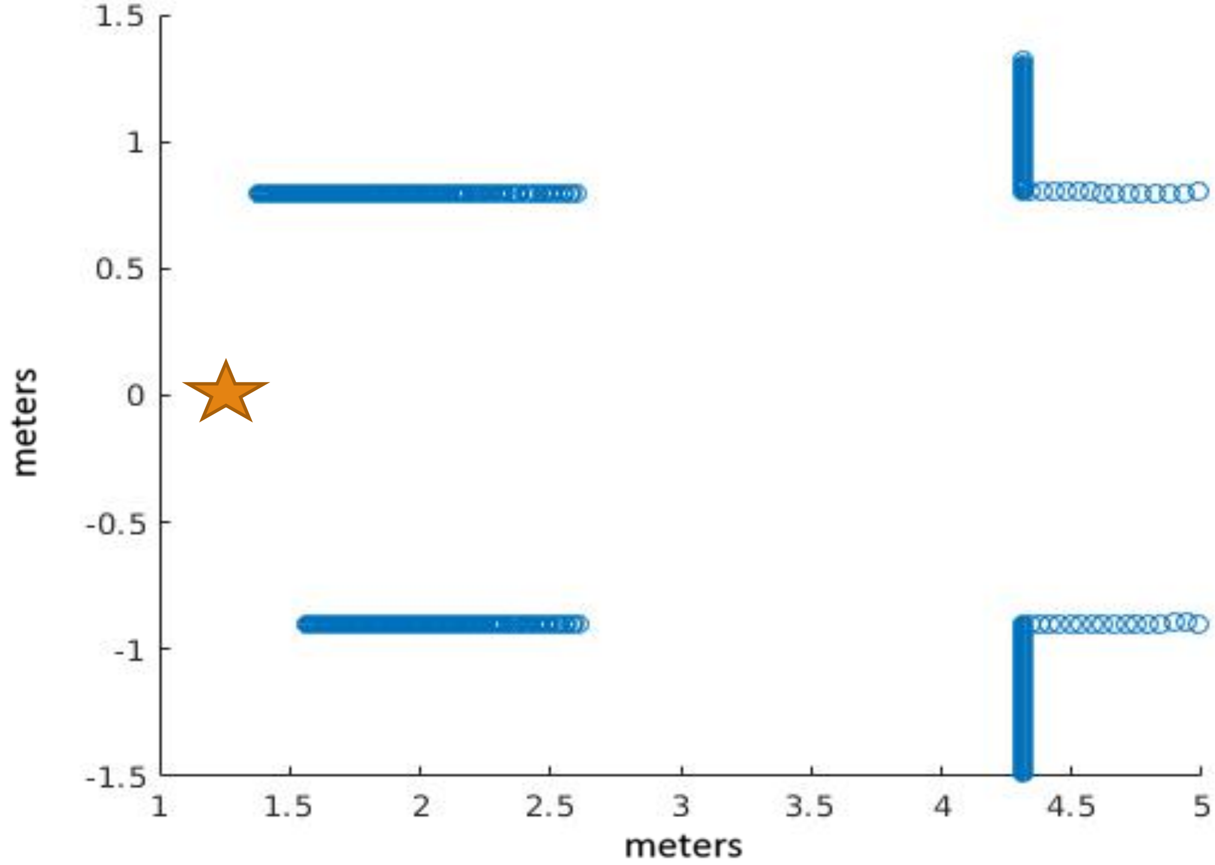
- User makes decisions at key points while navigating
  - Key points are determined to be hallway intersections and colored doors for this work

- Robot utilizes user input to refine global navigation
  - ex) If exiting intersection 3 from the north after entering from the south, then the most likely next intersection exit is…



Intersection Identification

Range measurement of four-way intersection gathered by robot.

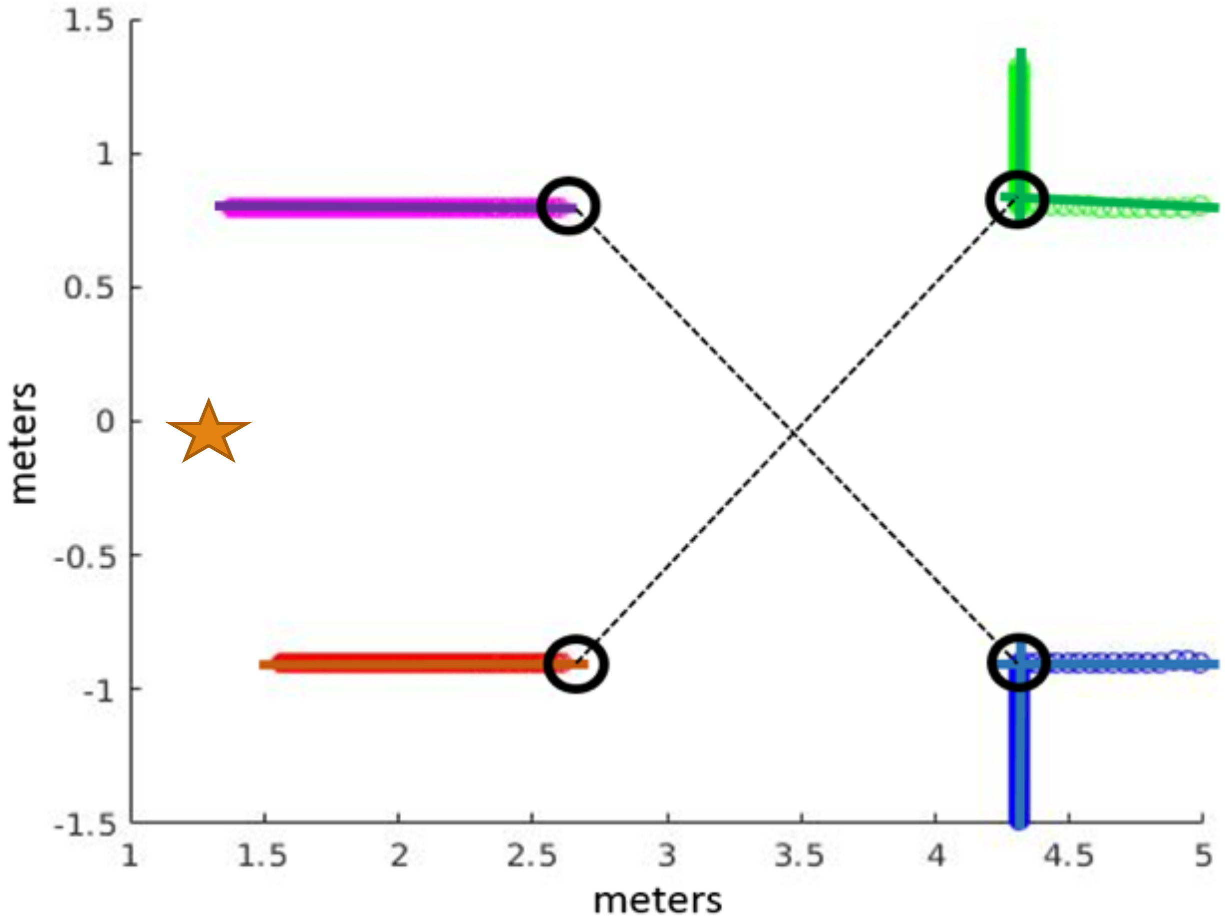


Intersection Identification

- Range measurement of four-way intersection gathered by robot.

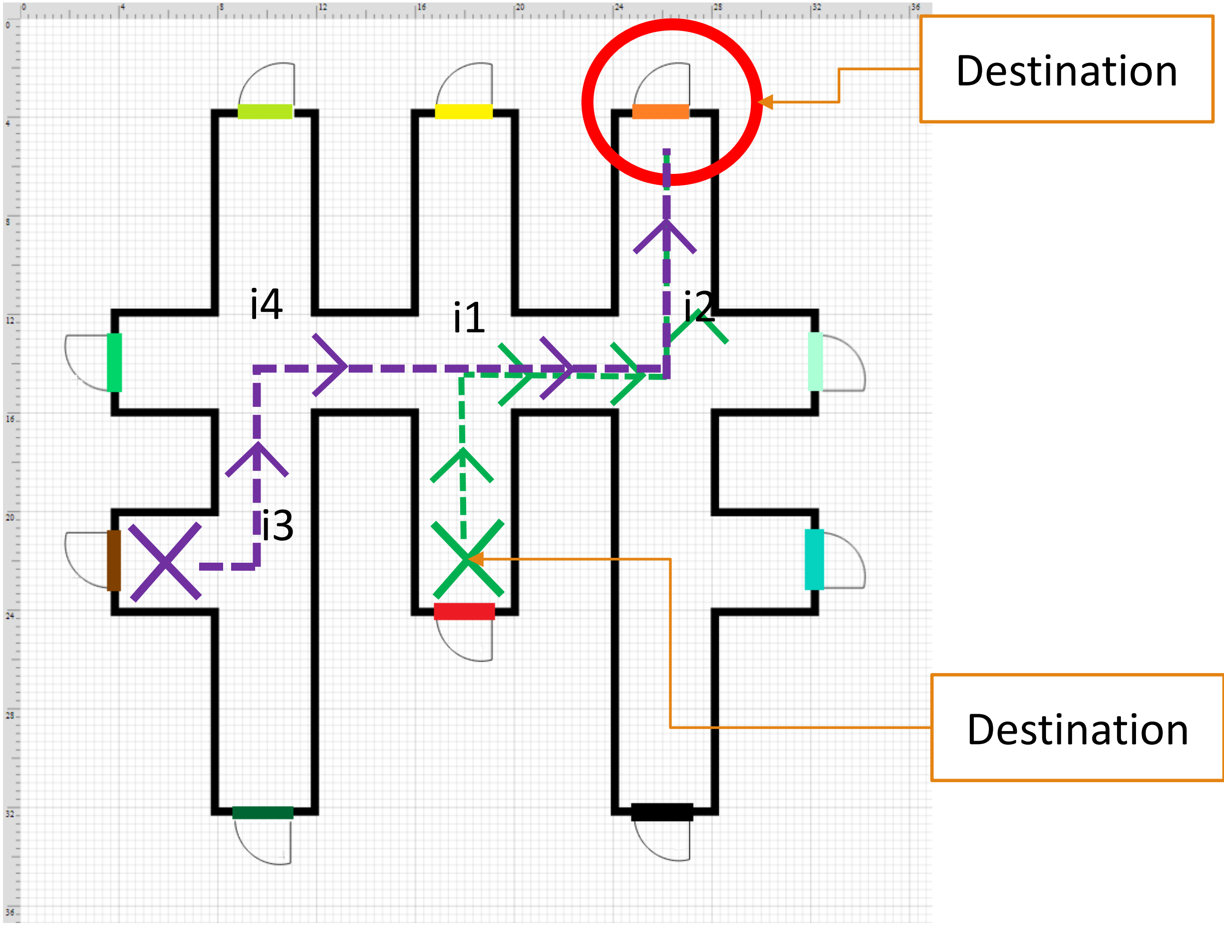
- RANSAC used to identify walls

- Intersection of walls drawn between farthest corners determines intersections center

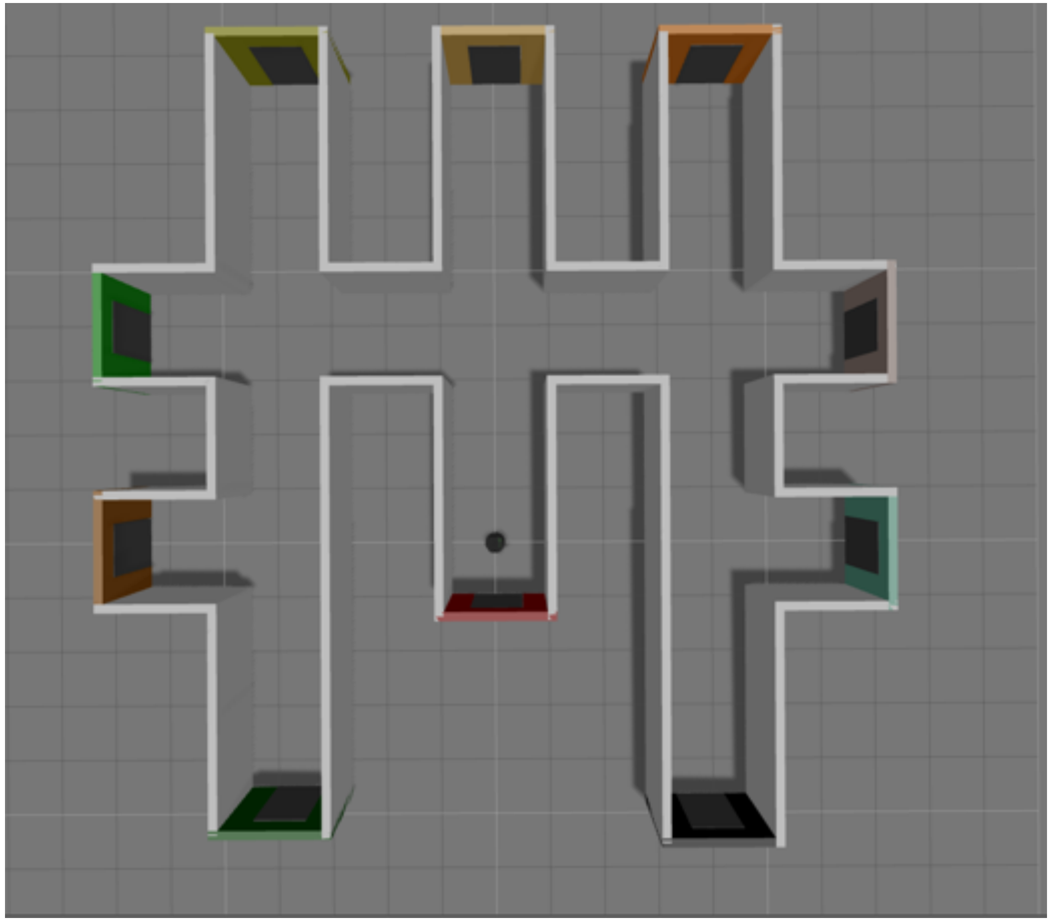


Global Navigation

- **Reducing required user inputs** by examining history of previous intersections navigated
- **Navigate the user to an intersection** and auto-rotate towards the correct intersection exit with **no user input required**
- Halls are mapped using out of the box Simultaneous Localization and Mapping R.O.S Gmapping package [4].
- Intersections are appended to map and intersection exits are used to determine most likely exits

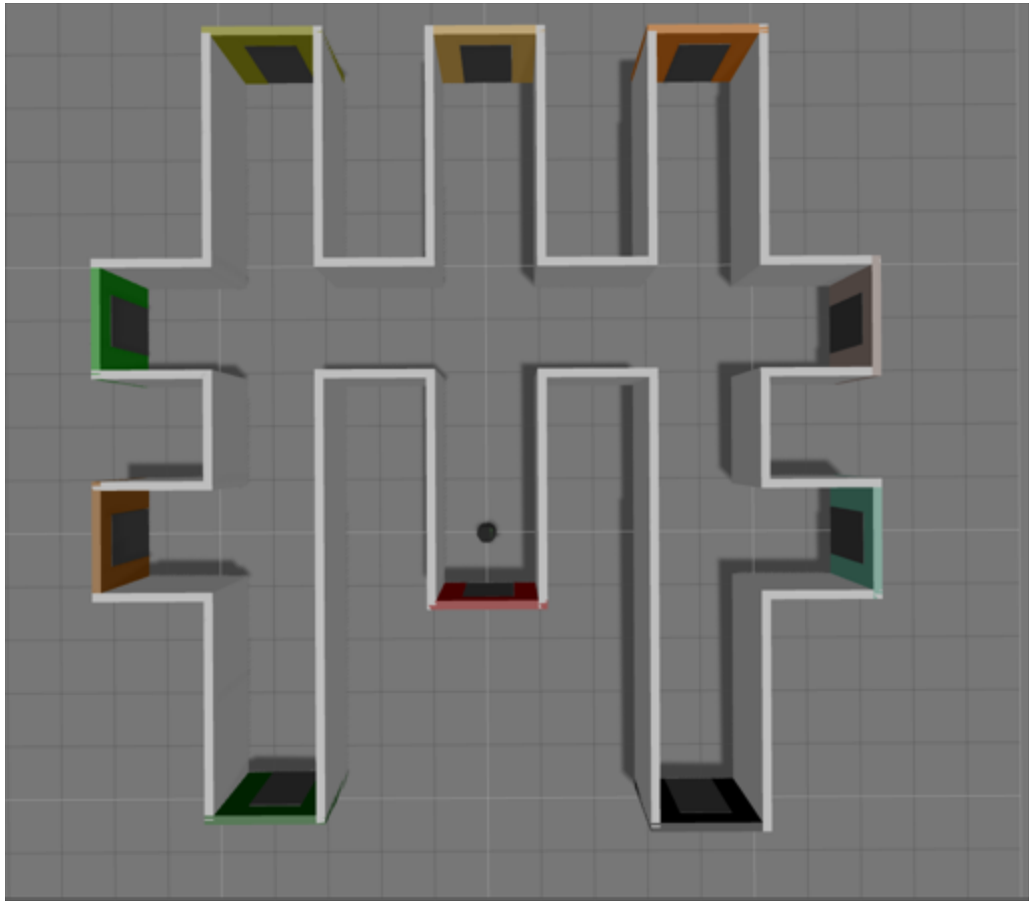


Simulation: Gazebo



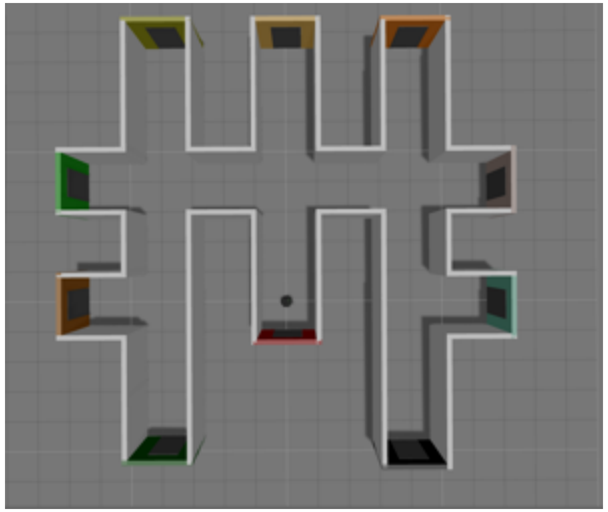
Simulation: Gazebo

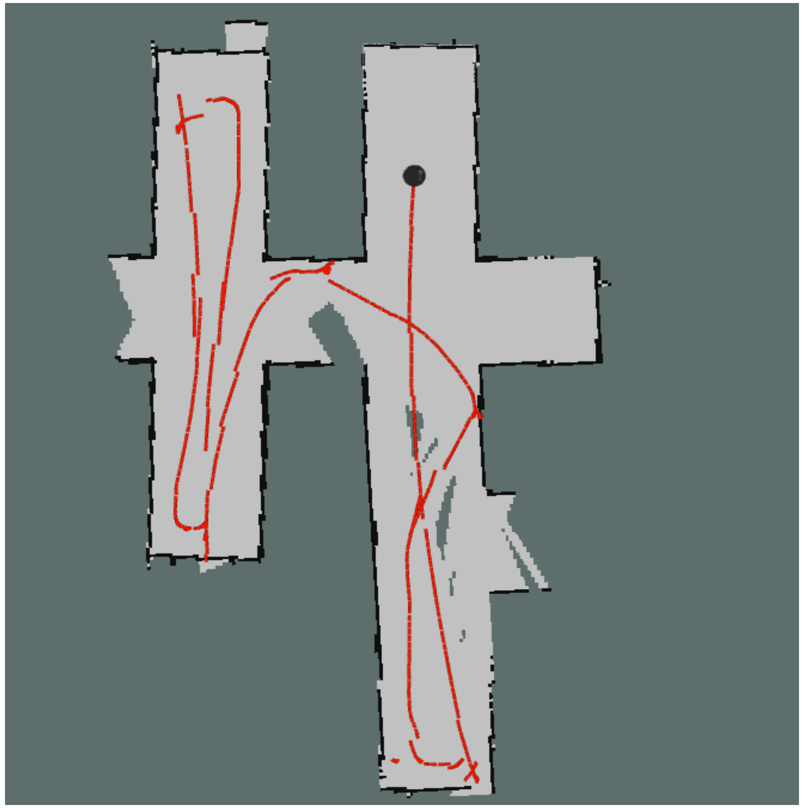
- Simulation Tests
  - **Autonomous Navigation**
    - Randomly move and avoid obstacles until the target orange door is identified
  - **Semi-Controlled Navigation**
    - Identify and navigate to intersections
    - Use pre-generated user inputs determine appropriate exit from intersection
    - Stop once target orange door is identified



Simulation: Autonomous Navigation Results

- Autonomous Navigation
  - Randomly move and avoid obstacles until the target orange door is identified
- Primary sources of error
  - Taking exits at intersections not connected to target door

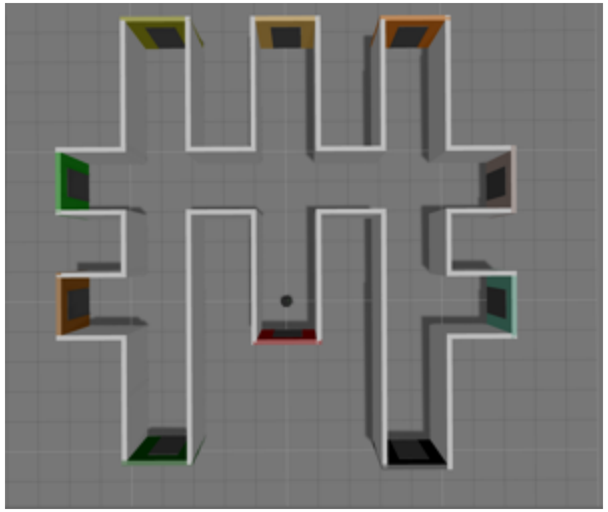




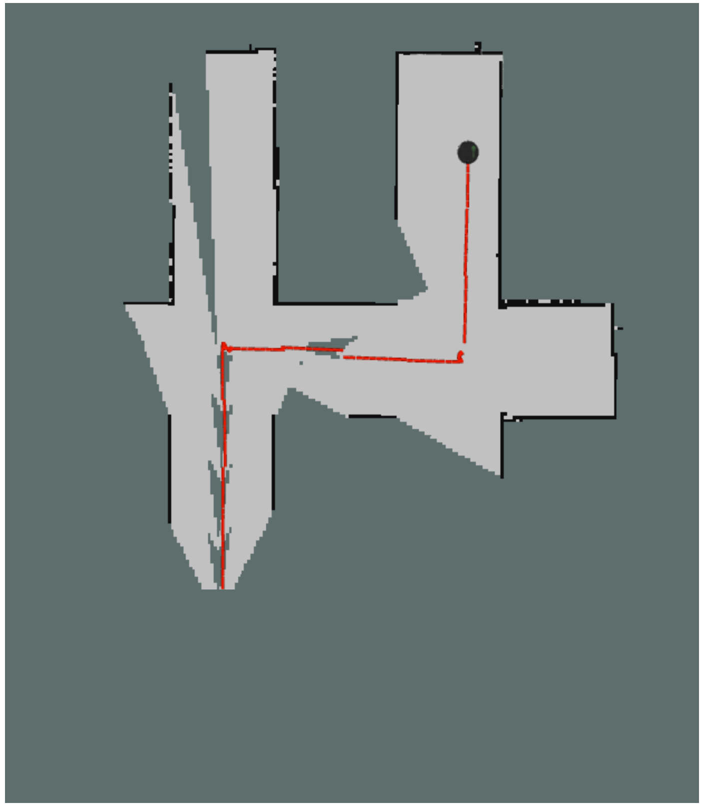
Time taken to reach target door --> 6min: 15sec

Simulation: Semi-Controlled Navigation Results

- Semi-Controlled Navigation
  - Identify and navigate to intersections
  - Use pre-generated user inputs determine appropriate exit from intersection
  - Stop once target orange door is identified
- Note
  - No intersection exits were misidentified
  - Misidentifications could increase time

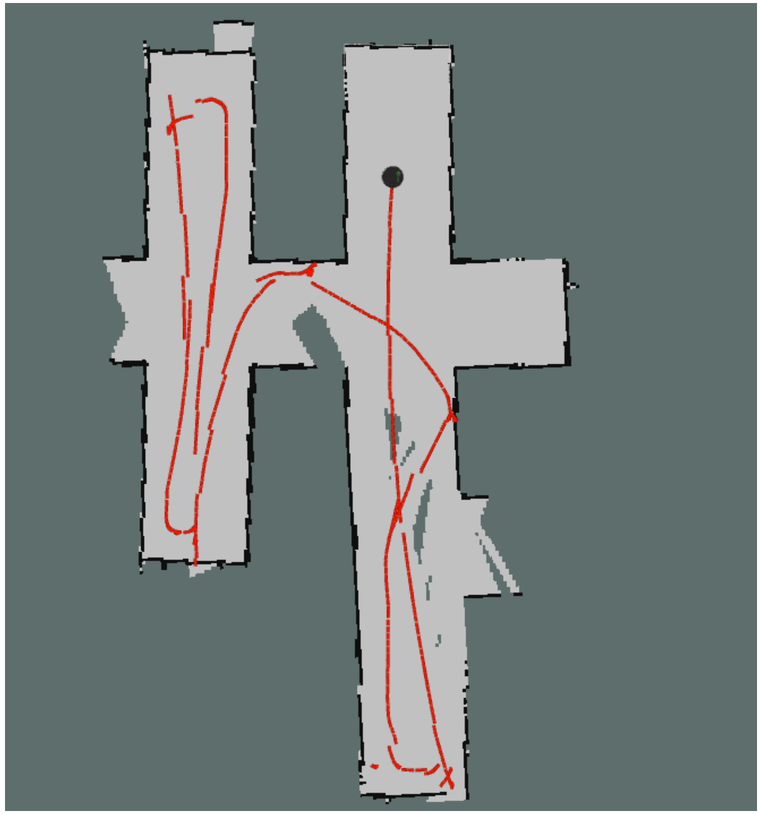


Time taken to reach target door -->
2min: 34sec



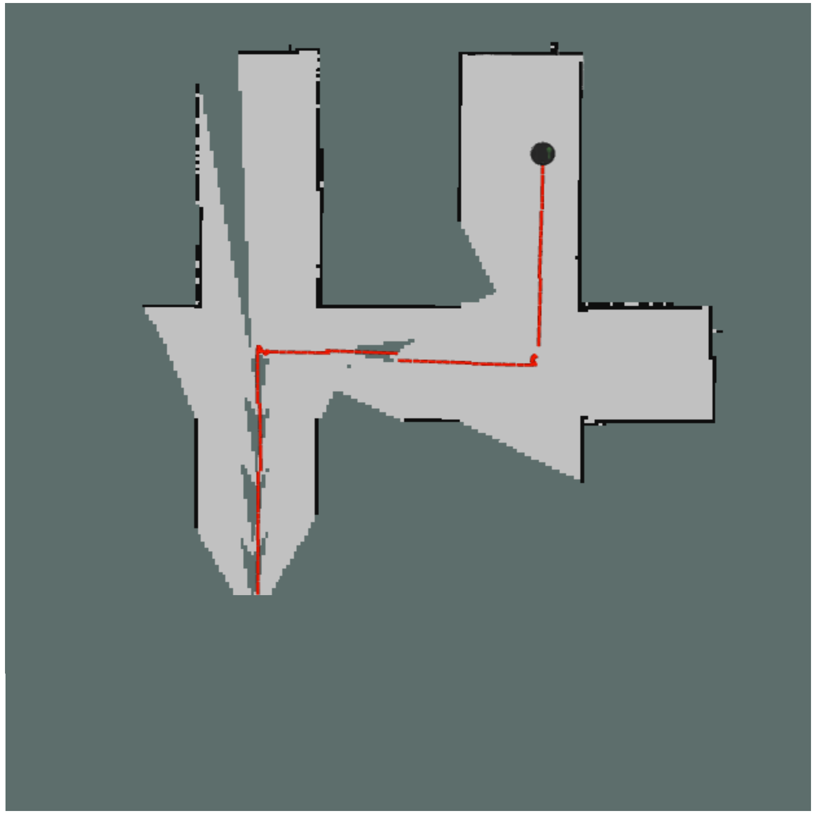
Simulation: Results

Simulated Autonomous Navigation Results



6min: 15sec

Simulated Semi-Controlled Navigation Results



2min: 34sec

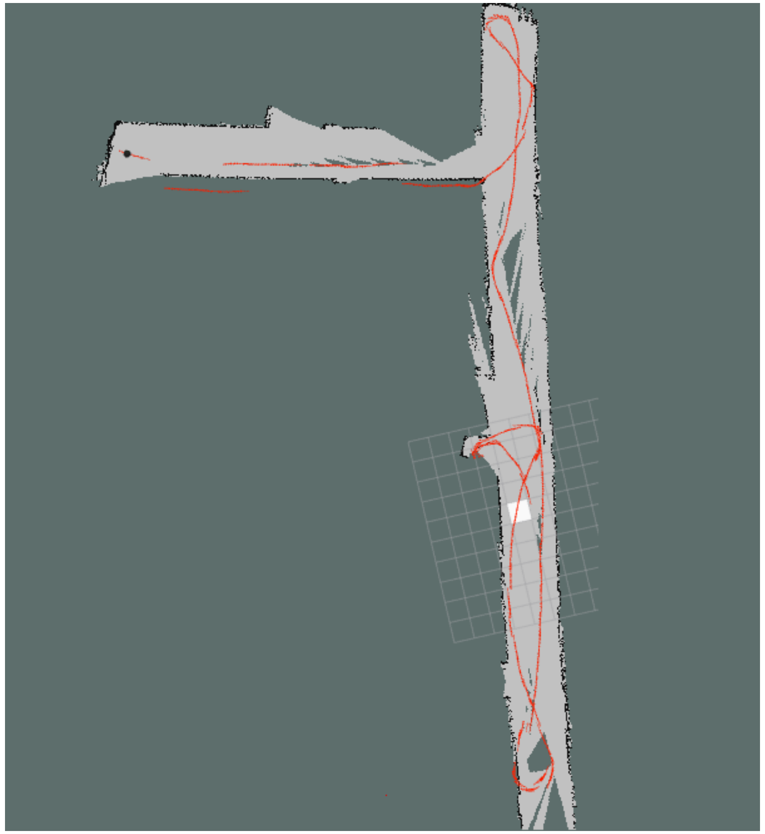
Real World: Setup

Real World: Autonomous Navigation Results

- Autonomous Navigation
  - Randomly move and avoid obstacles until the target orange door is identified

- Primary sources of error
  - Incorrect turn at possible door

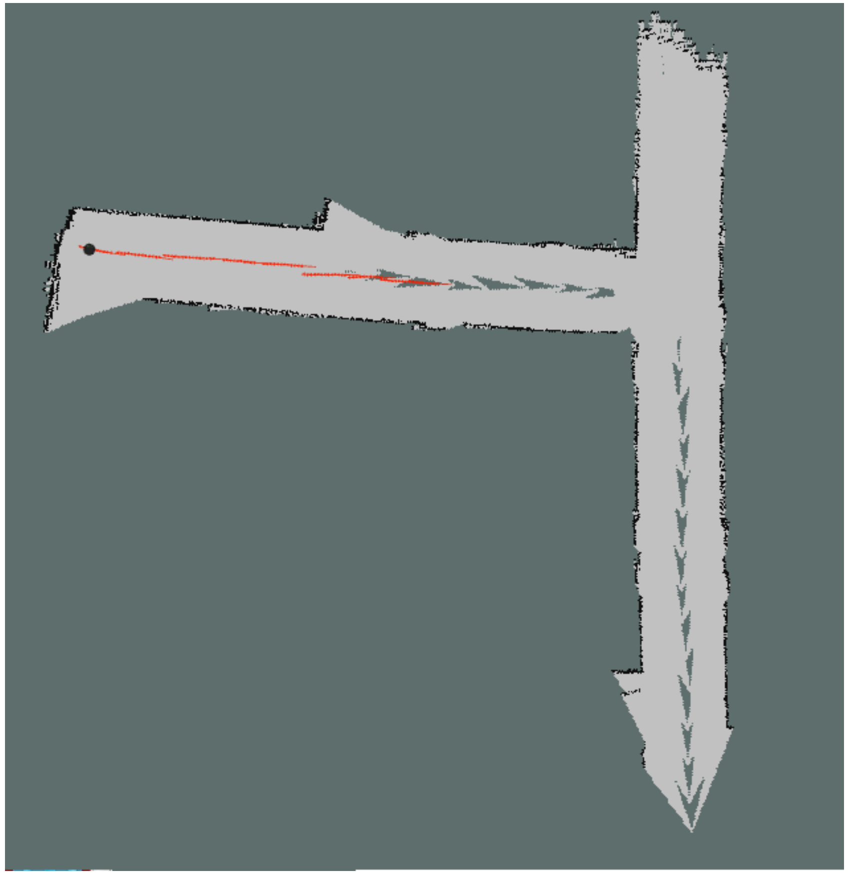
Time taken to reach target door --> 14min: 32sec



Real World: Semi-Controlled Navigation Results

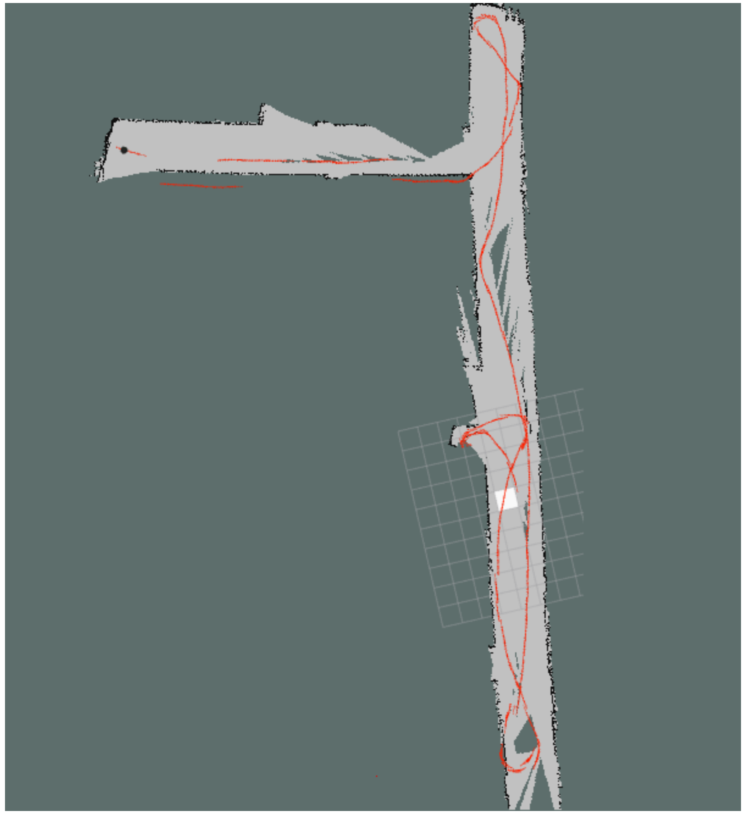
- Semi-Controlled Navigation
  - Identify and navigate to intersections
  - Use pre-generated user inputs determine appropriate exit from intersection
  - Stop once target orange door is identified

Time taken to reach target door --> 5min: 32sec



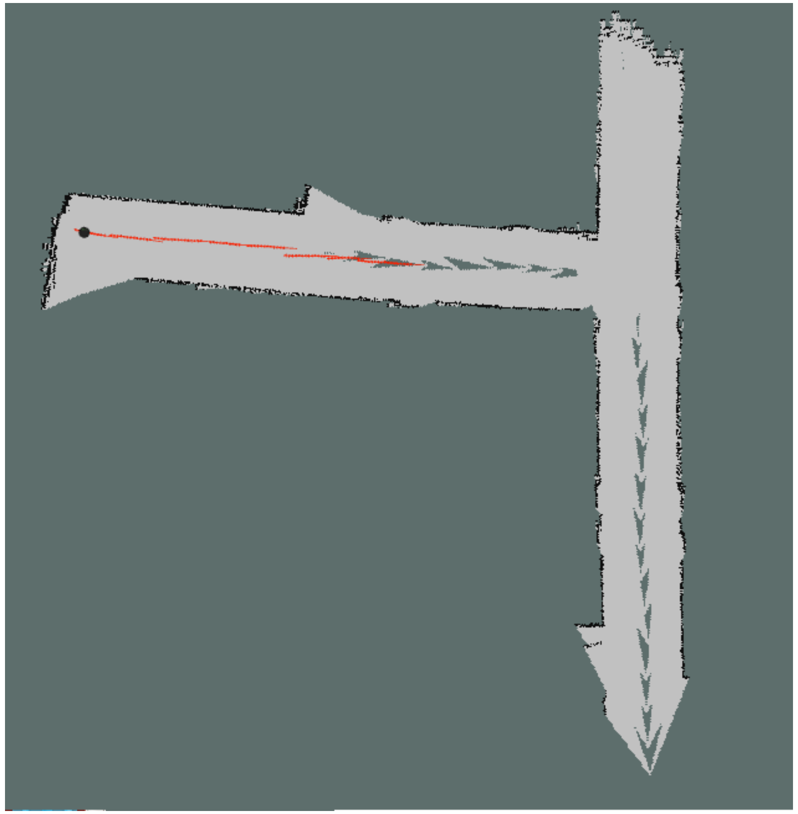
Real World: Results

Real World Autonomous Navigation Results



14min: 32sec

Real World Semi-Controlled Navigation Results



5min: 32sec

Conclusion

- The proposed navigation scheme outperforms a base autonomous navigation scheme.
- Has the potential to aid those suffering with locked-in syndrome
- Provides validation and the onus for future work

Future Work

- More extensive testing in a variety of environments

- EEG signals gathered in real-time

- Comparison against more complex navigation algorithms

References

[1] X. Perrin, R. Chavarriaga, F. Colas, R. Siegwart, and J. d. R. Millˊan, “Brain-coupled interaction for semi-autonomous navigation of an assistive robot, ”Robot. Auton. Syst., vol. 58, pp. 1246–1255, Dec. 2010

[2] R. Chavarriaga and J. d. R. Millan, “Learning from eeg error-related potentials in noninvasive brain-computer interfaces, ”IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 18, pp. 381–388, Aug 2010.

[3] S. A. S. Bellary and J. M. Conrad, “Classification of error related potentials using convolutional neural networks,” in9th International Conference on Cloud Computing, Data Science and Engineering, Noida, India, January 2019.

[4] B. Gerkey and V. Rabaud, “Ros – gmapping.” http://wiki.ros.org/gmapping, 2019. [Online; accessed 20-June-2019].

Thank You

Appendix A

Layer	stage	kernel	num of filters
Input	-	-	0
Convolution	1	2x64	16
Convolution	2	1x64	32
ReLU activation	2		0
Max Pooling	2	1x2	0
Convolution	3	1x32	32
ReLU activation	3		0
Max Pooling	3	1x2	0
Convolution	4	1x16	64
ReLU activation	4		0
Max Pooling	4	1x2	0
Fully Connected	5	2	2
Softmax activation	5		0
Total Learnable Parameter			239938

Subjects	**Train Sess1 & Test Sess2**		**Train Sess2 & Test Sess1**	
	ConvArch1	*ConvArch2*	*ConvArch1*	*ConvArch2*
1	86.62%	87.62%	77.42%	85.35%
2	80.52%	80.13%	79.2%	82.77%
3	78.84%	79.40%	81.32%	80.01%
4	71.81%	78.46%	78.64%	83.28%
5	73.34%	70.92%	77.63%	78.59%
6	72.13%	78.76%	70.83%	76.46%

Simulated 'Brain'

To simulate a user attached to a Brain Computer Interface we utilize the training data that our utilized deep neural network was trained on.

A correct path from the robot start position to the end position is pre-generated. EEG signals from the test set with appropriate ErrPs are then fed to the neural network when a decision must be made at an intersection