Assistive AI with Headset Control for Limited-Mobility Users

Validation Framework

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The Objective

As this thesis deals with the development of an assistive AI, the intuitive expectations are clear (perform as an intelligent agent would), though quantifying such behavior can prove difficult. Wheelchairs are inherently used in dynamic, populated environments, which can be simulated, but it is important to ensure that the platform is not optimized to known test cases. One of the situations that made this quite clear was a difficulty highlighted with the RHINO platform [1]. Though it was endowed with a rather expensive laser ranging system, initial versions had the unexpected limitation of being unable to perceive glass panes which were quite prevalent in its environment. Humans do not generally encounter difficulty in avoiding glass, but augmentation of laser ranging data with SONAR was required to bring this capability to the RHINO platform. Being able to respond consistently well across different environments is important to this platform and enumerating potential areas of difficulty will be an on-going task during development.

Evaluating the autonomous mode

The responsibilities of the autonomous mode are delegated among a variety of independent agents. Apart from integration tests to ensure their collective behavior is in keeping with the goal of “intelligent” action, they are also good candidates for unit testing independently. These agents, or more likely, clusters of agents, will also need to reach a consensus with agents acting on behalf of the user.

Long Range Path Planning

The path planning robot must be able to situate itself and the platform’s destination according to GPS. Depending on the environment, this agent must be capable of bird’s-flight planning, or waypoint based navigation. Test cases which confirm positioning and bearing calculations will provide a base level of confidence. Heuristics will also need to be developed for weighing accuracy and deviation from the current plot, which will likely need experimental validation.

Obstacle Avoidance

Since this system relies heavily on computer vision, reference images can be captured with known metrics and be run through the system for calibration and testing at any time. The resulting 3D disparity maps can also be compared to measured properties of the room and objects therein. To validate decision making during development, image sequences can be captured and run through the system, and then comparing the output with the expected decisions. If it is determined that a laser system is still required, data capture and replay could still be used to ensure the correct function of the obstacle avoidance system. Implemented heuristics for dense environments, like those in the social wheelchair platform, can also be validated by experiment as was done for that platform originally [4].

Integration Tests

After testing occurs to ensure the correct operation of each component, it is then important to verify that the agents as a collective take appropriate action. A recurring practical metric for this task was distance traveled over the optimal distance. The autonomous platforms surveyed all exhibited a degree of overhead (unnecessary distance traveled), and the reduction of this number was considered an increase in performance. Set tasks, like travelling down a corridor or circumnavigating a building, can have a known optimal reference distance and be compared against the robot's odometry. Reissuing obstacle avoidance tests after integration will also be helpful to ensure that agents do not override each other inappropriately (as the laser system did to the SONAR on the RHINO platform) [1].

EEG as Input

EEG as a primary input mechanism adds another important facet to testing. Since EEG packages rely heavily on training sets, ensuring reproducible state transitions will be crucial before integration. Fortunately, Emotiv's SDK has integrated packages for building and testing training sets. After the test subject is confident in their ability to interface with the EEG device, the agent tasked with EEG filtering needs to be tested to ensure that it neither permits excessive false-positives through, nor becomes so restrictive that user input is largely disregarded. As was the case with the computer vision system, EEG streams are able to be recorded and played back at a later time for verification. If intents are manually logged by either the user or researcher along with their timestamp, these can be compared with the output of the user interface agent to measure its performance in terms of false positives and denied commands. The EEG agent should also be subject to validation after integration with the other agents for the same, previously outlined concerns.

References

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