Learning to Assess the Cognitive Capacity of Human Partners

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Objectives

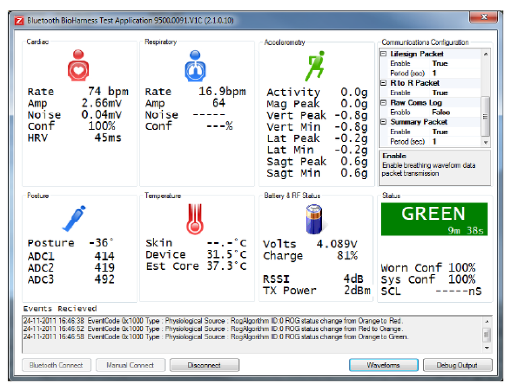
Our goal is to build a model for robots so that they can

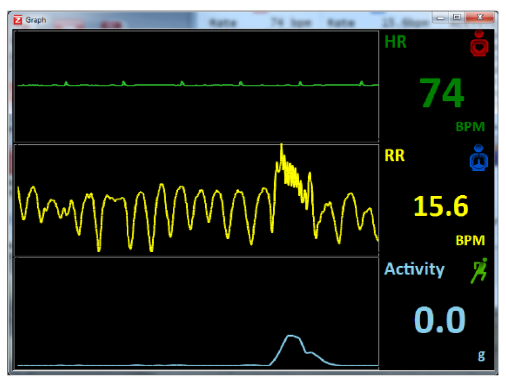
- learn to assess cognitive capacity of a human partner.
- can act autonomously based on that.
- reduce the human decision burden.
- help improving task performance.

Motivations

- Overcome inherent communication barrier between human robot
- Controlling multiple robots becomes impossible: cognitive load, heterogeneous robots
- Complete automation impossible: new task environment
- Robots must asses human cognitive load in human robot-team
- Robots need to assess cognitive capacity of human robot team

Trivial Methods





Trivial fundamental metrics[1] of measuring the behavioral indicators (i.e. ECG,EEG) has following drawbacks:

- hard to set up in generic task environments
- a generic method to assess cognitive load should work with simple metric
- can be useful as baseline

Feature Metrics

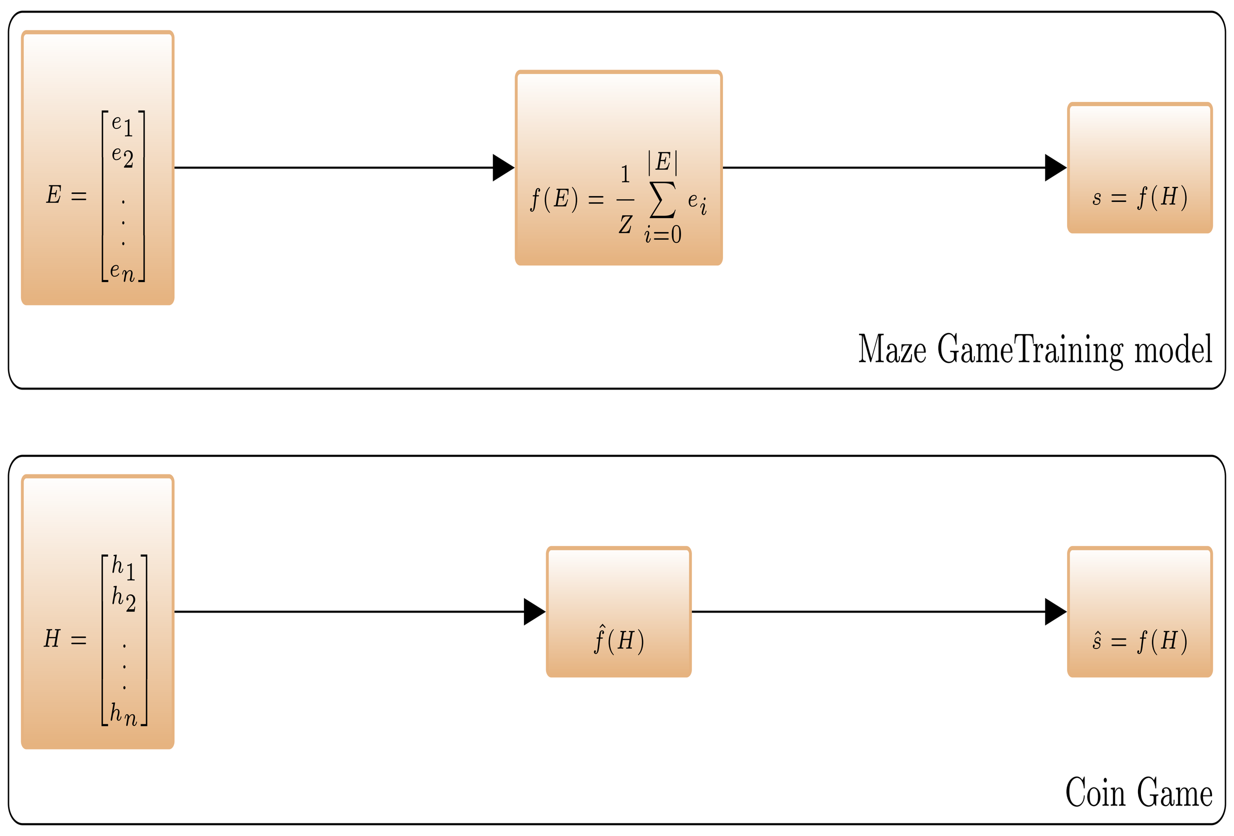
E is measurable environmental features of task success

- e_0 is the *disparity*
- e_1 is the *collision*
- e_2 is the *time delay*

H is human behavioral metrics which are ecologically valid for a navigation direction task

- h_0 is the *decision interval*
- h_1 is the *error correction*
- h_2 is the *franticness*

Overview of the Model



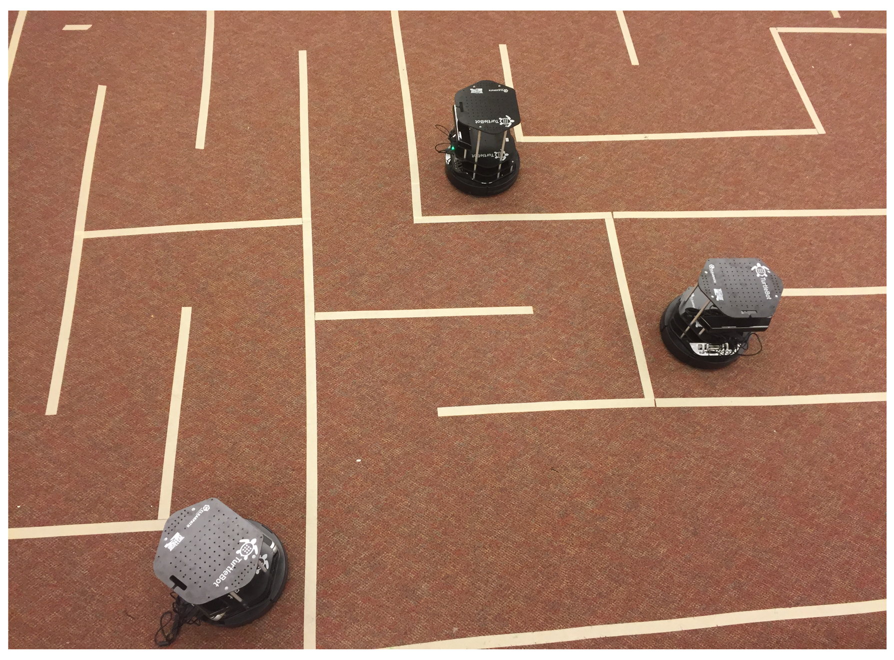


Figure 1: Experimental setup of Maze Game experiment for training

Experiments and Results

Our experiments consisted of two games, maze navigation[2] and coin collection.

Mage Game:

- The task in this game is to complete a maze(Fig.1) by instructing Turtlebot robot
- The game is 2 min. long and collision with walls are negatively rewarded
- The games complexity evolves in succession
- Mage Game was used to collect the metrics in E and calculate the success score s
- The underlying function was modeled using E and s by using Random Forest learner

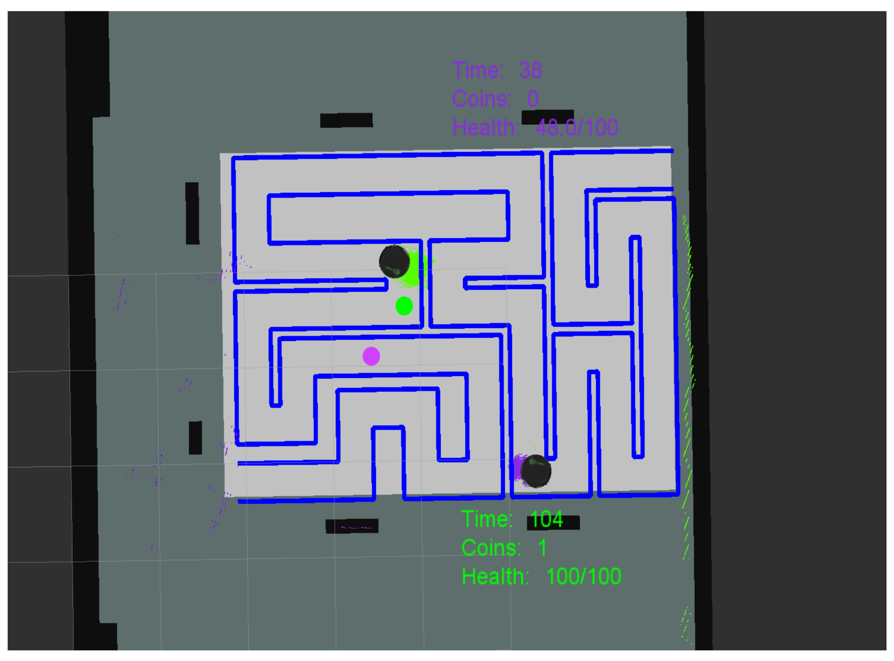


Figure 2: Interface to human operator for Coin game.

Coin Game:

- The goal is to collect 5 coins instead of completing the maze
- The timeout for completion next goal is decremented after each coin collection
- We collected H metrics from the experiment which was input to the model to estimate stress $\hat{s}$
- On detection high stress robot started navigating autonomously

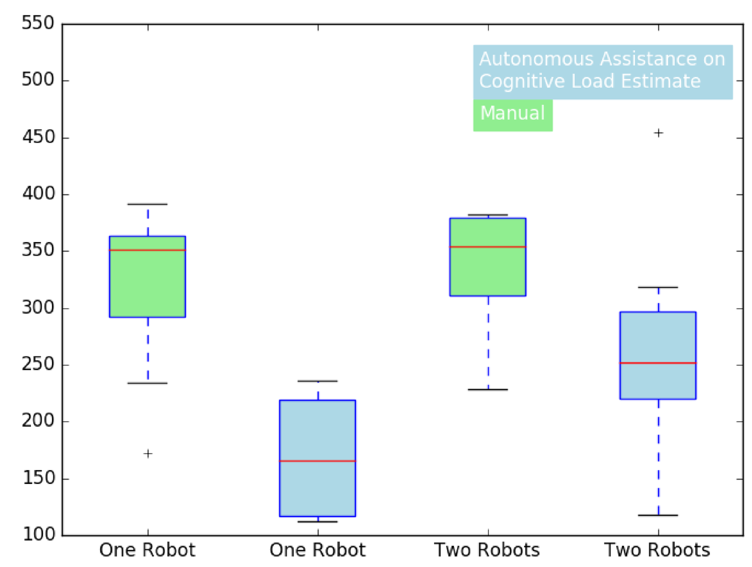


Figure 3: Learned model's contribution to task success: Coin game task penalties in manual vs. autonomous assistance modes across 34 test subjects. $p < 0.05$ in both instances.

Prediction vs Evidence

The robot correctly predicts an operator's cognitive load. Figure Fig. shows modest correlation between physiological evidence of an operator and the robot's estimation of stress.

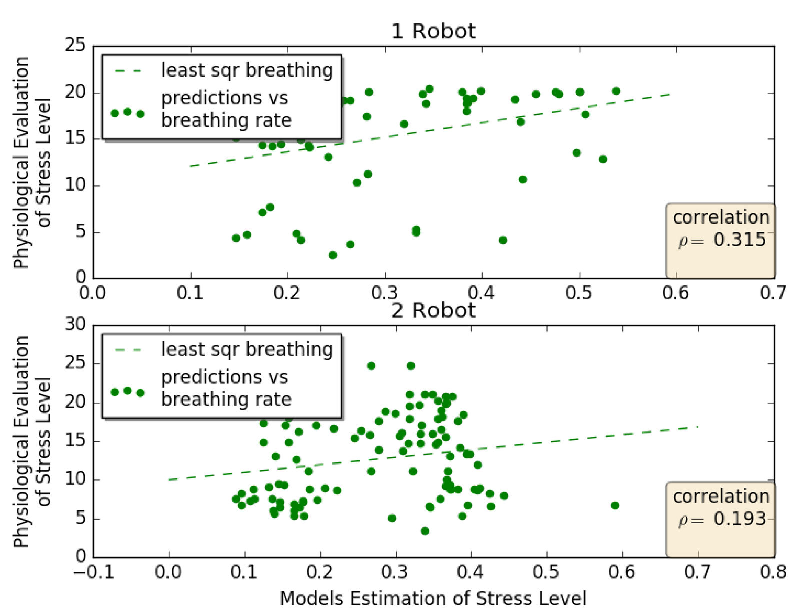


Figure 4: Robot's estimated cognitive stress level modestly correlates with physiological metrics (breathing rate measured with a Bioharness).

References

[1] Dan R Olsen and Michael A Goodrich. Metrics for evaluating human-robot interactions. In *Proceedings of PERMIS*, volume 2003, page 4, 2003.

[2] Christopher Crick, Sarah Osentoski, Graylin Jay, and Odest Chadwicke Jenkins. Human and robot perception in large-scale learning from demonstration. In *Proceedings of the 6th international Conference on Human-Robot Interaction*, pages 339–346. ACM, 2011.

[3] Jacob W Crandall, Michael Goodrich, Dan R Olsen Jr, Curtis W Nielsen, et al. Validating human-robot interaction schemes in multitasking environments. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, 35(4):438–449, 2005.