Learning to Assess the Cognitive Capacity of Human Partners

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ABSTRACT

We demonstrate that a robot is capable of learning to recognize the behavioral indicators that a complex, rapidly-evolving task has exceeded the cognitive capacity of a human partner and make an informed decision based upon this assessment. The robot is trained to associate human directions with task quality for a well-understood task, in this case, the navigation of a maze. The robot may then apply this learned model to a different problem while still being able to evaluate a human operator's cognitive load. Even without the ability to understand the end goal of this new task, the robot can use the indicators learned previously to estimate the cognitive limits of an increasingly frazzled human partner.. Perhaps even more importantly, the robot may then make an informed decision based on this assessment, switching to an autonomous operation mode for example, in an attempt to reduce operator demand.

Keywords

User modeling and awareness, teamwork and group dynamics, robot behavior design, quantitative field study, learning about the environment

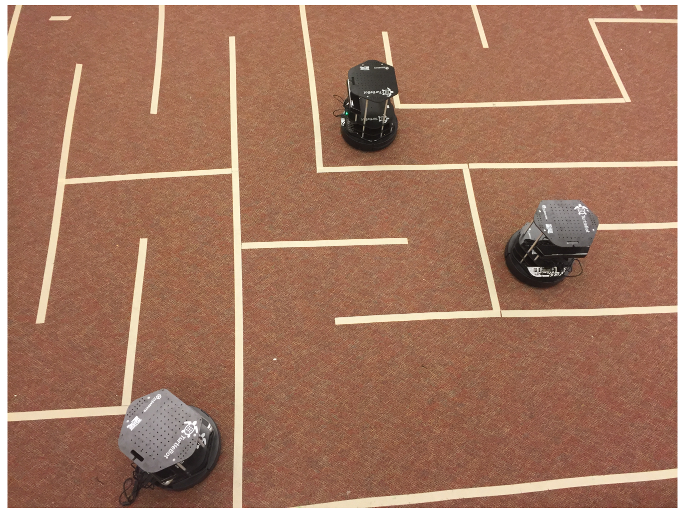

Figure 1: Turtlebots navigate a maze while evaluating human task input.

1. INTRODUCTION

One of the most challenging obstacles facing human-robot teams is the inherent communication barrier between the two. Human operators, at least once they have received training, have some notion concerning the capacities of their mechanized partners, but the ability of robots to assess the limitations of humans has not received adequate attention. Research in this area often focuses on attempting to observe human behavior and predict what action or actions to perform in the future; this renders such systems incapable of making instantaneous or reactive decisions. In contrast, systems which are capable of making split-second decisions, such as the lane drift detection found in some high-end cars, make no inference concerning the user's abilities or frame of mind; they are reacting to a well understood world state without consulting their human partners. This is not true interaction; the robot is learning to work *around* the user instead of with them. Human assistance should enable complex multi-robot tasks in situations where the robots themselves are unable to assess their environment fully, but this lays a heavy burden on the operator in a dynamic, dangerous, rapidly-changing environment with many cognitive demands. Human operators and robots each have complementary capabilities and limitations; that both groups have the ability to know the limits of the other is crucial for cooperation and ultimately success. [8].

Our research allows robots to form models of human behavior during well-understood tasks, and then apply these learned models during unknown tasks. We show that these models allow the robot to make an effective determination of the cognitive capacity of a human partner, even when the robot cannot directly assess the task it is being asked to perform. This provides the robot with the ability to fall back to safe autonomous operation mode whenever the task demands begin to exceed the ability of its human partner. The operator may then assume direct control at their discretion as they are able.

Why is this understanding between human and robots so important? As previously mentioned, both members have advantages and limitations. It easy to see that a robot with limited sensors and actuators may be unable to perform a task, owing to a failure to perceive information about its environment. Merely cramming improved components into a robots does not guarantee any significant improvement on the robot's ability to accomplish a task – a great many tasks require contextual information far beyond what machines are currently able to muddle out. Thus for the foreseeable future, many of these complex tasks will require assistance from human teammates, co-processors if you will. Humans are able to integrate data, rely on experience to predict the effects of actions on world states, and produce effective long-term plans far better than any current robot.

Human assistance with multiple robots has been demonstrated in different practical situations. For example, they have been used as customer assistants in shopping malls [16, 7], where human operators occasionally assisted robots. Human-robot teams have assisted each other in museum tour scenarios [14] and in warehouse inventory management [15]. Just as robots, regardless of their hardware capabilities, do not necessarily perform well without assistance, humans do not always assist robots as efficiently as they might, despite their superiority in context sensitivity and general intelligence. Several issues arise in this regard [1], including obvious problems such as noisy communication between human operators and robots, accidental damage to robot sensors and so on.

In this paper, we focus on one problem which can cause difficulties in a human-robot team: the cognitive capacity of the human operator. Humans often find their ability to function effectively challenged, due to psychological stress, tiredness, or overwhelming task demands. A robot's ability to participate constructively in a human-robot team will benefit immensely from understanding and accommodating this cognitive stress appropriately. For example, for the pilot of an unmanned aircraft, cognitive stress can be the difference between life and death [2]. If such a robot can detect the emergence of cognitive stress in its operator, it can increase its level of autonomy and reduce its demands on the operator's attention. Hopefully, such a robot would wait safely for a more opportune moment or decide to engage in a less cognitively challenging task, rather than continue to follow the direction of a human who is no longer able to provide appropriate assistance.

In this paper, we have designed robots that learn the correlations between quantifiable behavior metrics and the cognitive capabilities of human operators. We designed a maze game (Fig. 1) where multiple robots are given directions by a single human operator. At first, the robots' objective was simply to complete the maze, a task that they were capable of executing without human assistance using autonomous path planning. They were therefore able to determine whether the instructions of their operators were sound or questionable, and associated these outcomes with measurements of their operator's behavior. We observed the output of the learned cognitive stress model in a different task, this time with the robots engaged in a coin-collecting game inside the maze. Although the robots had no knowledge of the rules or objectives of the coin-collecting game, and had no ability to sense the game's context, their learned models enabled them to determine the cognitive stress of their human partner. In this way, they were able to evaluate the trustworthiness of the actions they were being asked to perform. The cognitive stress discerned by the robot correlates with the true stress experienced by the human operators, as quantified by their self-reporting and by expert evaluation.

2. RELATED WORK

In this section, we will briefly discuss work related to cognitive capacity assessment and human operation of multiple robots. Several research projects recently have investigated human cognitive capacity using different approaches.

Effectively navigating a maze game has been demonstrated in literature [3]. This research showed that robots learn more effectively from human operators if the learning took place in the context of features that the robot can easily understand. Counterintuitively, restricting the information available to a human operator led to better demonstrations and more effective learning. In this research, we show that similar metrics can be employed by the robot for the purpose of learning the cognitive threshold of a human operator.

Recent work [4, 6] presented a model for assessing a human's attention level, based on eye contact and gaze detection towards a robot. Based on the perceived attention level, the robot could generate an appropriate signal to obtain the attention of a targeted human. Attention is an important component of a human agent's cognitive capacity, but in our work, the robot learns a general behavior model to identify the operator's cognitive threshold, rather than relying on the specifics of gaze.

Human-robot interactions can be evaluated using fundamental metrics [10]. Such metrics relate to the cognitive capacity of human operators in obvious ways. For example, task effectiveness (TE) describes how efficiently robots complete a given task under human direction. For example, task effectiveness can be measured using the speed of the robot. In a navigation experiment, it may be the time taken by the robot to reach the goal. It could be defined as the difference between the time taken with and without human assistance. Another important metric is neglect tolerance (NT), which denotes a robot's level of autonomy. In static indoor environments, simple robots such as Turtlebots can easily engage in autonomous navigation. Even in complex environments with dynamic obstacles, clever algorithms [9] can enable such vehicles to navigate autonomously. Thus although it is a very important metric, we have focused on mostly TE because we think that that is the metric which can be exploited more consistently across different problems. Other potentially useful metrics include robot attention demand (RAD), free time (FT), fan out (FO) and interaction time. All of these could conceivably be included as inputs into a learned model such as ours.

Other efforts [5, 10] have presented very similar concepts of metrics for improving the efficiency of human-robot interaction. These principles include implicit mode switching among user interfaces, using human operators' natural cues, directly manipulating the world, manipulating the relationship between the robot and the world, supporting attention management and so on. Using similar terminology, other work [2] discovered how neglect time impacts important properties of human robot teams. They have shown a relation between the neglect time and the maximum number of robot that a single human operator can handle. We leverage this data to inform our robots' estimation of a human operator's cognitive capacity.

In another social experiment [16], where autonomous humanoid robots have been deployed to investigate their social acceptance, a scheduling algorithm has been used to assist the human operator. This experiment developed an algorithm that prioritizes the assitance provided by a human operator for a particular robot within a multi-robot team. The robot's task was to make conversation with interested shopping mall customers and to guide them to particular shelves corresponding to their needs. The shopping mall map was already known. Within critical areas inside the shopping mall environment, the robot needed assistance from humans, for example in unsafe locations or areas with glass walls that confused the robots' sensors. As there were multiple robots, a single operator could not assist them all simultaneously. The operator allocator algorithm therefore picked the robot most likely to encounter a critical region for assistance. In this work, the operator was assumed to be able to assist the robot without considering cognitive capacity. In contrast, we developed a model that enables the robot to make this determination and then perform the task accordingly.

A large amount of work [12, 13] has investigated human operators acting as teachers when interacting with a robot, for example helping a robot in kitchen environment. The human's demonstrations contribute to the robot's reward functions, using a modified reinforcement learning method that is based on the observation that human guidance is able to consider future reward along with past reward. The rich context that a human operator provides and that robots are very poor at reasoning about for themselves leads to improvement in the robot's learned behaviors. This observation only holds, however, as long as the human operator possesses the cognitive capacity to provide good, informative demonstrations. Our work allows robots to make this determination for themselves.

We have mentioned a number of research results that relate to ours in many ways. However, most current work does not explore the fact that, although humans are much more intelligent than robots, they nevertheless face significant limitations in their ability to assist their robot partners. One aspect of these limitations is that a human operator is vulnerable to task overload and psychological stress. Our work focuses particularly on human behavior in the face of this cognitive stress. Although engaging human assistance for the purpose of task learning is valuable, we argue that such a learning task is more effective if the robot simultaneously has the tools to evaluate the trustworthiness of the human's direction.

3. TECHNICAL DETAILS

3.1 Problem statement

Without loss of generality, take $H = [h_1, h_2, \cdots, h_m]$ to be a vector of ecologically valid measurements of human behavior relevant to the problem space. Assume a task for which a robot participant can independently calculate s, a scalar metric of success, which is a function of a vector of measurable environmental features $E = [e_1, e_2, \cdots, e_n]$. Thus, $s = f(E)$, where f is a task-specific function known to the robot. Using f and calculating s, a robot can build its own supervised training set for a learning task, where the human input H is associated with s through a learned function g. Thus, the robot learns to associate the human behavioral metrics H with task success s within a known task, so the output of g is a learned *estimate* of the true success ($\hat{s} = g(H)$). Now, assign the robot a task which

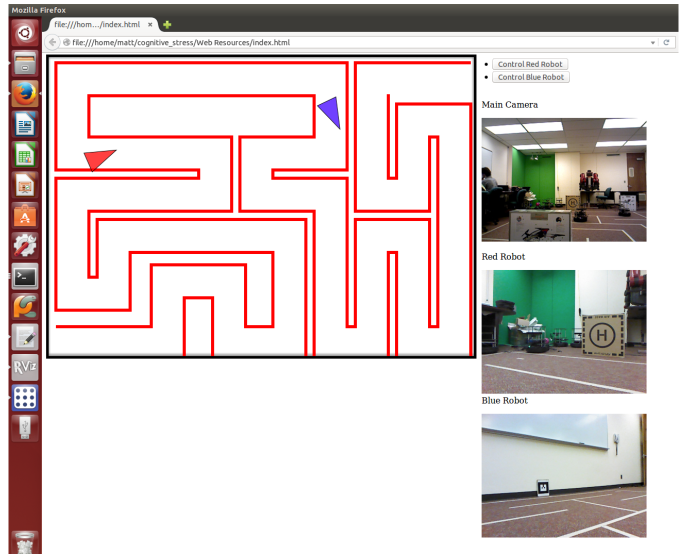

Figure 2: The Rosbridge Web Interface.

requires human input for success, i.e., the robot has no access to an analogue to f or s in this new task. However, it can still measure the components of H, and it has access to its learned model g. We show that computing $\hat{s} = g(H)$ in this new environment allows the robot to estimate not the task success (about which it has no information), but the cognitive load on its human partner and an estimate of the quality of the human's direction.

3.2 Experimental design

In keeping with the problem statement, experiments were carried out in two parts: the Maze Game and the Coin Game experiments. In the first phase, the robot collected the data needed to build a model g for evaluating the trustworthiness of user input H. The robot is able to do this for the first phase because in the case of the Maze Game it has access to f and E and can calculate s. It understands the problem sufficiently to make such judgements; the robot requires no human aid to solve this problem.

In the subsequent Coin Game, the robot is placed in a different scenario, one in which it had no access to success measures or even rules; beyond the fact that it was moving in a similar environment to the Maze Game, it is wholly reliant on human direction to succeed in the task. Even so, with no independent means of measuring task success, it can still calculate $\hat{s} = g(H)$, and can therefore evaluate the quality of instruction, and hence the cognitive capacity, of its human partner.

Communication between operators and robots was achieved using the Robot Operating System (ROS)[11]. Users sent navigation goals to the robots by using a web interface developed for the project, which allowed the experiment to be conducted remotely (Fig 2).

4. MAZE GAME AND TRAINING

As previously mentioned, the first step of our experimental design was to identify a task simple enough for the robot to complete unaided, yet complex enough to potentially benefit from human input. The problem also need to be readily tape_map.jpg

Figure 3: The final map laid out on the lab floor.

scalable to include additional robots. This led us to select autonomous navigation through a maze using Adaptive Monte Carlo Localization (AMCL). The maze consisted of a single path with multiple 90° turns. The final design, seen in Fig 3, consists of 32 waypoints and measures $4.63m$ by $3.2m$. It is important to note that the maze traced out on the floor serves only as a convenience for human operators and does not serve as a navigation guide for the robot. In fact, the robot does not treat the walls of the maze as physical obstacles, and will happily pass through them if instructed to do so.

In the Maze Game, the robot is able to evaluate the success of the directions it is given by its human operator. This is a function of a vector of environmental measurements $E = [e_0, e_1, e_2]$, which in this particular context have been defined as follows:

- e_0 is the *disparity* term, the distance between the navigation directions provided by a human and the route that the robot would have planned for itself,
- e_1 is the *collision* term, which penalizes collisions with walls, and
- e_2 is the *time delay* term, the amount of time taken for the human to guide the robot through the maze, compared with the robot's estimate of the time it would have taken under its own power.

The computation of $s = f(E)$ to obtain a success metric is straightforward:

$$s = \frac{1}{Z} \sum_{i=0}^{|E|} e_i \tag{1}$$

where Z is a normalization constant.

By computing this value s, the robot can label its own data in order to train a supervised learning algorithm which will relate the success of a human-directed task (and, presumably, the cognitive capacity of the human partner) with a set of measured behaviors H.

$H = [h_0, h_1, h_2]$ is a set of human behavioral metrics which are ecologically valid for a navigation direction task. For this particular experiment, these are the following:

- h_0 is the *decision interval* term, which measures the time elapsed between the robot reaching a navigation goal and the human providing a new one,
- h_1 is the *error correction* term, which measures the tendency of a human operator to provide a navigation goal and then subsequently provide another before the task is complete, and
- h_2 is the *franticness* term, which characterizes erratic behavior for the control inputs.

These features were chosen because they are contextually valid for a navigation problem, while remaining general enough to not be tied to our a specific instance. It is worth noting that there is no reason to assume that the features selected are uniquely suited as members of H. Appropriate features for inclusion in H should be easy to identify in a wide variety of tasks.

4.1 Maze Game and Training Results

Now we will show that the robot is able to learn the model $\hat{s} = g(H)$, and that it reflects the cognitive capacity of humans correctly, based on the described metrics. Fifteen test subjects performed runs of the maze game, resulting in approximately 1000 data points used for training.

Because the robot understands the maze game and the details of the performance metrics, it is able to generate the training data labels for a supervised model learning task. We have used the Orange data mining API[1] for running the regression. The human behavioral metrics H and the robot's self-generated task success metric s are used to train a Random Forest Regression Learner (RF).RF have been used to learn enormous classifiers in very complex feature spaces. The maze game regression operates only in a low-dimensional feature space, so an RF is able to learn from our experimental data effortlessly, and the approach should scale to much more complex feature spaces. The classifier is trained on H and s. The RF generates an optimized $g(H)$ by performing a regression on the relationship between s and H.

5. COIN GAME EXPERIMENT

The second phase of the project involves a variation on the first experiment dubbed the Coin Game. It uses many of the same principles introduced in the Maze Game, such as the same map, so that the human behavior metric H remains ecologically valid. However, in this task, only the human operator has access to the sensory data required to successfully perform the task. Goals appear appear randomly in the maze, and we call these random goals "coins", with the understanding that the point of the game is to send the robot to the coin locations in order to collect them. Unlike

[1] http://orange.biolab.si

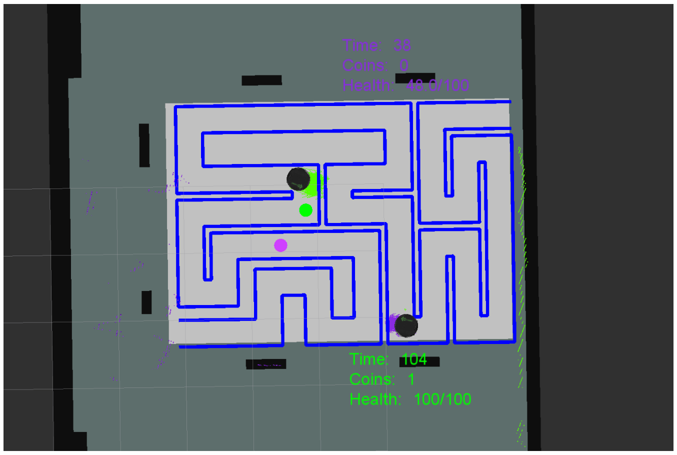

Figure 4: Maze map of the Coin Game experiment with coin goals.

in the previous experiment, where the robot navigated the maze in linear fashion from start to finish, the goals or coins may pop up in any location in the maze, either ahead of or behind the robot. The goal is not represented in the real world; rather the goals are shown on the control interface's computer screen as colored circles denoting the coins. Coins can pop up between any two key points. The interface for this experiment is shown in Fig.4.

The coin game is a very simple game. The human operator points the mouse to a location the map. As the goal is random, the human operator must now switch between robots frequently, in order to marshal the various robots toward their coin goals. Research [10] has shown that this switching time can affect the effectiveness of a task performed by a human-robot team. Thus the second experiment is more challenging in terms of cognitive stress. The task sets a two-minute timer for the human operator and also sets a maximum 5 coin collection limitation. Either condition satisfies the end of the game. Every time the robot collects a coin the timer is shortened by 12 seconds to put more cognitive stress on human operator.

In this instance, the robot has access only to what it can measure about human behavior, in the form of the vector H. It knows nothing about what constitutes success in the Coin Game, as it is not even able to sense the existence of coins. However, it can still compute $\hat{s} = g(H)$, and it can thus calculate an estimate of human cognitive capacity and reliability.

In the coin game the human operator could interact with the robots using two interfaces; web browser (Fig.2) and Rviz (Fig.4). Among human operators ten people interacted with the robot remotely via web browser while playing the coin game. Whereas, ten other participated in the coin game being in the sane room where the game was staged via Rviz interface. While using web interface, in order to compare the robot's estimate of cognitive capacity with reality, test subjects were asked during the experiment to rate their own cognitive stress levels at 12-second intervals using a Likert scale. The human operators who participated using Rviz were given a physilogical activity monitor[2] to attach to their chest to monitor their heart rate, breathing rate, posture, ECG amplitudes and they were also being montitored by a human evaluator who rated and logged their cognitive stress level while they were playing the game. In other words human(coder) evaluator serves here as an subjective evaluator whreas the physiological metrics provides objective evaluation. We have found posture of human operator most likely correlates with subjective correlation with the code evaluation Fig.5. One possible reason behind this is that posture is one of the visible observation that the coder can have while evaluating the operator. The coder rated stress level high when the operator tends to lean toward the screen of the computer when he or lean back on the chair. Other physiological metrics does not higly correlates with coder evaluation of stress level.

[2]https://www.zephyranywhere.com/products/bioharness-3

coder_vs_posture-eps-converted-to.pdf

Figure 5: Coder evaluation is a fair proxy of objective evaluation

The coin game also had a autonomous assistant configuration where the robot starts to navigate the maze autonomously not knowing where the coin is. Robot can pick the coin if crossed over it.The autonomous mood was activated by the robot if it found the human operator to be untrustworthy; the stress level is higher than a threshold. The threshold that we have set for our experiment was 55% based on the data that we have collected from the non autonomous or manual mood. If the ignorance time which is the duration while no commands were given to that particular robot was higher than a threshold the robot switched to autonomous mood as well. In autonomous mood robot assumes that the coin can show up anywhere in the maze thus moves towards the optimum way point from where it the expected distance from a coin is minimum.

5.1 Coin Game Results

Analysis of the results from the coin game experiment are in agreement with the original hypothesis. In general, the robot correctly predicts the cognitive load that its operator was under in every scenario. These findings can be seen in Fig 6. Here, the horizontal axis denotes model estimated cognitive stress over time. The vertical axis denotes coder evaluation cognitive load estimate. From our experiments we have found that the cognitive load estimate from the robots using our model correlates with the coder evaluated stress level by a factor $\rho = .336$ and $\rho = .22$ for coin game played with one and two robots respectively. Our experiment also shows that posture of human operator is a suitable objective metric for estimating cognitive stress level of human operator. We could not find any intersting pattern in other physiological objective metrics i.e. heart rate, breating rate, ECG amplitude that correlates to our predictions or coder evaluation. However, that does not mean that they do not capture cognitive stress level of human operator. A better model with more enriched H vector of human behavior metric can certainly produce a better estimate that correlates more with those physiological metrics. But having a H also means the robot can take more sophisticated input from human operators. Whereas in our case we have confined our experiment with simplistic robots. It is critical for interpreting the information in **??** to note that while the robot's cognitive load evaluation and the scoring technique for quantifying self-reported user stress both produce a result between zero and one *their magnitudes are not directly comparable.*Whenever cognitive stress occurs or changes, the robot is able to recognize this increase for most cases in the tested scenarios, and the robot's evaluation agrees with self-reported user stress. In the context of this paper, it also supports the original hypothesis: robots can are able to reliably assess the cognitive strain their human partners are under, even in contexts where the actual tasks they are being asked to perform are opaque to the robot.

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Figure 6: Cognitive load of human operators in Coin Game experiments with differing numbers of robots and steadily increasing task complexity. The robots' predictions fairly correlates with the coder evaluation of cognitive load estimate.

6. CONCLUSIONS

The field of human-robot interaction began by investigating how robots can be designed so that they are comfortable, predictable and understandable to their human partners. Our work investigates an aspect of the other side of that equation: what can robots understand about us? Robots that are capable of understanding the stress or strain their operator is experiencing are vital to safe and efficient teamwork in complex scenarios where the proper level of autonomy and interaction is fluid. Vital communication cues are embedded in the way we behave in particular circumstances, and these implicit indicators do not have to be lost on our robots. Our work's contribution is to demonstrate a quantitative, learnable, generalizable model that allows a robot to determine that a user is behaving in an untrustworthy fashion, even when the robot cannot independently assess the instructions it is being given. Another important finding is that the threshold beyond which cognitive stress produces untrustworthy human assistance may vary from task to task. Nevertheless, general metrics can transfer from problem to problem and still produce meaningful evaluations. In the future, we plan to extend this research into complex heterogenous teams of humans and robots performing real-world tasks.

Every day humans interact with more and more technologies that require us to decide whether or not to trust them; robots should be making similar determinations about us.

7. ACKNOWLEDGMENTS

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