Learning to Assess the Cognitive Capacity of Human Partners

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ABSTRACT

One of the most challenging obstacles facing human-robot teams is the inherent communication barrier between man and machine. Human operators have some notion concerning the limitations of their mechanized team-mates, but the ability of robots to assess the limitations of humans is limited at best. Research in this general direction often focuses on attempting to observe human behavior and predict what action they will perform next. This is not true interaction; the robot is learning to work *around* the user instead of with them. To determine if it is possible for a robot to

Categories and Subject Descriptors

H.4 [**Human Robot Interaction**]: Human AssistanceMultiple Robots

General Terms

Cognitive Limitation, Trust, Mobile Robot

Keywords

Robotics, Human Operator, Multiple Robot, Maze game, Learning, Human Robot Teams, Cognitive Stress, User Stress, Problem Solving

1. INTRODUCTION

One of the most challenging obstacles facing human-robot teams is the inherent communication barrier between man and machine. Human operators have some notion concerning the limitations of their mechanized team-mates, but the ability of robots to assess the limitations of humans is limited at best. Research in this general direction 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 lane drift detection found in some high-end cars, make no inference concerning the user and operate only on a case-by-case basis. This is not true interaction; the robot is learning to work *around* the user instead of with them. Multiple robots with human assistance have great potential to perform tasks which are difficult, or even impossible, for a single, more robust robot. Fundamentally, the reason behind this is the fact that both human operator and robots have complementary capabilities and limitations. With the advancement of technology the capabilities of the robots have been increased in many ways. However, discovering cognitive capacity of human operator in human-robot team is also essential[12]. We believe that there is more scope to discover this fact more explicitly in terms our experiments and to use the result for the better understanding the assistance that the robots get from human operator in different circumstances.

Why human and robots need to interact with each other? The answer is that they both have limitations. It is easy to understand that a robot with flawed sensors and actuators may not perform a simple task because of loss of useful information that it could not perceive. But it is not necessarily the case that a robot with high precision sensors and actuators will be able to do a task efficiently in proportion to its superiority in hardware in human robot team. One reason why it may not perform well is that its efficiency in a task depends not only on the underlying hardware and technology but also the assistance it gets from the human operator. Human assistance with multiple robot has been demonstrated in different practical situations. For example they have been used as customer assistance in shopping mall[20, 11] where human operator occasionally assisted robots. Human robot interaction has been used to assist robot as tour guide in a museum[18] and warehouse inventory management [19]. Just like a very well build robots with finest hardware does not necessarily ensure better performance, human, being very superior to robots in term of sensor and intelligence, may not assist robots as efficiently as it could. Several issues regarding human robot interactions in literature[2]. Some of the obvious reasons are noisy communication between human operator and robot, accidental damage of robot sensor and so on. However, in this paper we witness the problem from a different aspect which is cognitive capacity of human operator. For obvious psychological reason, tiredness and other natural reason human mind can often be stressed. .We believe understanding this cognitive stress by the robot in any given task carried out by a human-robot team is very important. For example for a remote pilot controlling multiple military unmanned air vehicles cognitive stress can be

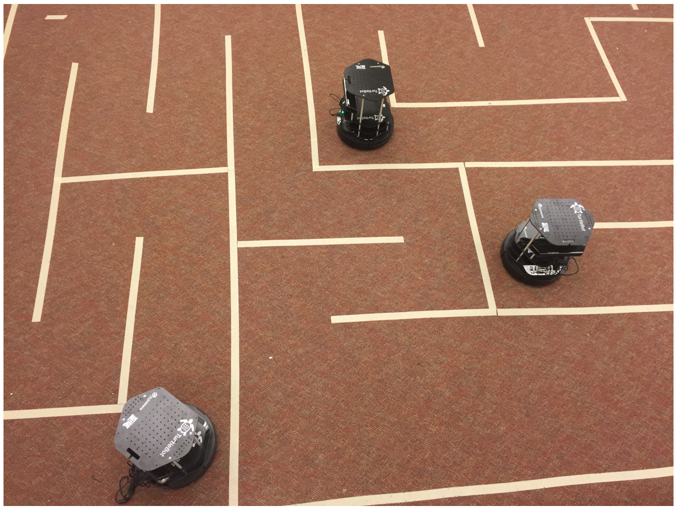

Figure 1: Turtlebots[7] running the maze.

the difference between life and death[3]. Or if it is a commercial robot it may define the margin of profit and loss for the business organization. In this paper, we have tried to quantify the human cognitive capacity by making a computer program learn the correlation among several quantifiable metrics and human operators cognitive capabilities. We have designed a maze game Fig 1 in office environment where multiple robot's were operated by a single human operator. The objective of every robot was to complete the maze. We developed a model to learn the human operators trustworthiness based on some metrics that we believe relates to the operator's cognitive stress. Then we observed the effect of the learned model of cognitive stress of human operator in a another experiment of coin collecting game.

2. RELATED WORK

In this section, we will briefly discuss related work on assessing cognitive capacity of human operator of multiple robot. Several research projects recently have investigated cognitive capacity of human operator using different methods.

Learning effectively navigating maze game thas been demonstrated in literature[4]. Research showed that robot learns better navigation through maze from human operator if the learned was trained in the context of features that robot can easily understand. It has been shown that robot learned to navigate maze better from human operator when they instructed robot using tags without actual visual of the environment than with the live video feedback of the environment. Although it seemed counter-intuitive that a human will choose not to see what is happening, it turned out that because of the metrics for example collision with walls the interaction without seeing leaned a better navigator. In our research we have shown that along with collision damage other metrics also affects the learner. However, we also tried to show that by observing these metrics carefully the robot can also learn cognitive boundary of the human operator.

Recent literature[5, 10] presented a model for assessing attention level of human based on eye contact and detection of moving gaze towards robot. Based on the attention level it could generate appropriate signal to seek attention of targeted human. Whereas, in this paper, we intend to learn the cognitive threshold of human operator. We also want to show that the leaned model is transferable to a different HRI problem.

One of the research works[14] has defined some fundamental metrics to evaluate human robot interactions. This metrics are also related to cognitive capacity of human operator for obvious reason. For example, one metric has been defined as task effectiveness (TE) which is describes how efficiently the robots operated by human completes a given task. This can be measured in various quantities. For example, task effectiveness can be measured using the speed of the robot. In navigation experiment, it may be the time taken by the robot to reach the goal. If we consider a human robot operation the effectiveness can be difference between the time taken with and without the human assistance. In object recognition problem it may be the number of object the robot can recognize correctly, given a set of objects. Another important metric that they have defined is neglect tolerance (NT) which denotes how much autonomous a robot is. In office environment several turtlebot[7] mobile robots can navigate autonomously. Even in complex environment with dynamic obstacles state of the art[13] showed that vehicles can 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 than other metrics. They have also defined some useful formula like, robot attention demand (RAD), free time (FT), fan out (FO) and interaction time. In contrast, instead of strictly defining a formula we tended to learn the expected behaviour of the robot by measuring the effectiveness of the robot from different aspect. In another research paper[8] with very similar concepts of metrics described in[14] they have presented seven principles for making human robot interaction efficients. These principles includes implicitly switch modes between user interfaces, using human operators natural cues, directly manipulating the world, manipulating the robot-world relation, supporting attention management and so on. Using the similar terminologies described above, another research work[3] has discovered how neglect time impacts some important properties of a human robot team. They have shown a relation between the neglect time and the maximum number of robot that a single human operator can handle. This is a good estimation of human operator's cognitive capacity as well.

In another social experiment[20] where autonomous humanoid robots have been deployed to investigate their social acceptance, a scheduling algorithm has been used to facilitate human operator. The set up for that experiment was multiple humanoid with single assistance. For this experiment they developed an algorithm that can prioritize the the human operator assistance for a particular robot from a multiple robot team. The robots task was to make conversation with interested shopping mall customer and to guide them to particular shelf corresponding their requirement. The shopping mall map was already known. There were some critical section in the shopping mall environment where the robot needed assistance, for example, regions with glass walls or unsafe region, from the human operator. As there were multiple robots a single operator could not assist them all simultaneously. So operator allocator algorithm picked the robot which is more likely to fall in a critical region for assistance. Here the operator was assumed to be able to assist the robot without considering the cognitive capacity. In contrast, we tried to develop a model that, in a sense, can make robot understand the mind of the operator and then perform the task accordingly.

There are also literature[16, 17] where human-operator act as a teacher in interaction with robot. In their paper they have shown that human operator helping robot in kitchen environment. The human acts as a teacher to contribute to reward functions. Based on the observation that human guidance considers future reward along with past reward, they modified Reinforcement learning method. And they have found improvement in the learning of the robot behabior. The nature of human cognition somewhat contributed here to the improvement of robots operation.

We have mentioned several related research works those are related to ours in many ways. But what most of the research if not all did not explore is the fact that although humans are much more intelligent than a robot, in terms of assisting, humans have significant limitations as well. One aspect of the limitation in assisting a robot is that a human operator can have is that the operator may become psychologically stressed. Some of the research works mentioned above learned human behaviour in assisting the robot. Whereas, we are particularly focused on human operator's behaviour pertaining to cognitive stress. Although learning human assistance in general is helpful, we argue that the only learning the behaviour is not enough. We believe that behaviour should also provide a notion of trustworthiness in the human assistance. And that is how it can give a meaningful direction regarding what the robot might decide to do.

3. TECHNICAL DETAILS

In this research project, we have designed two experiments to assess cognitive stress of human operator. The first experiment is the Maze Game experiment and second one is the Coin Game experiment. Both of them are executed in a similar map environment and robots but with different constraints. Basically the result of our first experiment was tested and verified using the second experiment.

The experiments were set up in office room environment in the lab. We used three TurtleBots[7] mobile robots. The experiments were done using Robot Operating System (ROS)[15] which a open source operating system. We used one workstation as master machine to communicate with all the TurtleBots as slave machines.

The master machine also served the purpose of user interface between the robots and human operator. The human assistant can use a graphical tool in the master to interact with the robots using a tool called rviz. As rviz may seem to be foreign to many novice human operator who has no experience with ROS, we developed a novice user friendly interface using HTML5 and JavaScript to bring the interface in the web browser which may not scare a novice human operator.

4. MAZE GAME AND TRAINING

Fig 2 shows the actual representation of the maze on the floor. The maze is $4.63m$ long and $3.2m$ in width. The visual markers are treated as the boundary of a maze path. So a valid pathway for the robot is between the two parallel markers. Although the marker represents the maze visually to the human assistant, it is not recognized by the robot. To

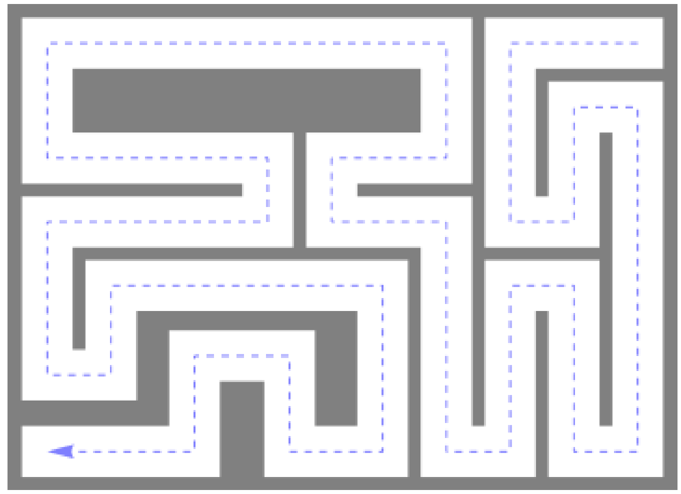

Figure 2: Map of the maze, arrow indicates path direction.

Figure 3: Representation of the path through the maze in RViz.

represent the maze to the robot we have designed the map showed in Fig **??**.

The map was built from the autonomous navigation of the mobile robot on the floor using Simultaneous Localization and Mapping (SLAM). The original map from the SLAM was then edited using image editing tool to get a more perfect map of the floor shown in Fig 4. The final map in Fig **??** of the maze was developed by careful measurement of the maze markers.

There 32 turning points in the maze are indexed from $0 - 31$. Some index and corresponding coordinates have been shown in the Table 1

The map is a 146x177 pixel image. Every pixel in the map represents $0.05m$ distance in the real world. The pixel values represent the cost in the occupancy grid which is used by the ROS path planner for autonomous navigation from current location to given goal. The pixel values ranges from 0 to 255. The occupied threshold for a pixel to considered as an obstacle is 0.65 which means any pixel greater than or equal to 166 is considered as an obstacle by the planner. Similarly threshold for pixels free from obstacles is defined as 0.196.

Every robot in the maze starts from the index 0. The user can use the web interface to guide the robot from on point to any other location in the map. For the maze game experiment the objective is to complete the maze. A screen

Figure 4: Origianal representation of the floor to the robot before designing the map.

Table 1: Coordinates of turning points

Index of point	x	y
0	6.73	6.0
1	5.73	6.0
2	5.73	4.6
3	6.23	4.6
28	4.00	3.55
29	3.25	3.55
30	3.25	2.8
31	2.10	2.8

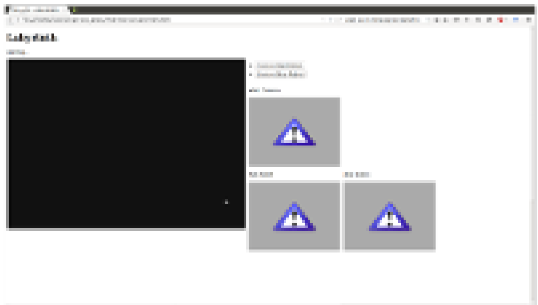

Figure 5: Web interface for novice human assistant.

shot of the web interface is shown in Fig 5.

Six non-paid human assistants were used to run the experiments. All of them were novice human user. They could either choose from web interface or reconfigured rviz interface to send directions to the robot.Both of interfaces were easy to understand and use for most of the human assistants. Most of the human assistant understood the task very well after a brief description.A human assistant were able to select only one robot at a time. After selecting a particular robot an operator can send a goal in the maze by clicking the mouse inside the maze map to indicate the location of the goal. Along with location the human operator can also send the orientation of the goal.

We were interested in three useful metrics in this experiment. For all the turning points (we also call them key points) $0 \leq i \leq 32$, we have defined some metrics as following:

Disparity is the distance between the goal set by human assistant and the goal robot actually achieved. It is given by the following Eq. 1.

$$disparity_i = \sqrt{(x_{expected} - x_{robot})^2 + (y_{expected} - y_{robot})^2} \quad (1)$$

Health Damage Percentage is the percentage of robots health that was damaged during an navigation through the maze. It is measured using Eq 2

$$damage_i = \frac{health_{initial} - health_{current}}{health_{intial}} \quad (2)$$

Time Delay is the difference between ideal time to arrive at a point from the initial position by robot autonomously and the time taken when it is assited by the human operator. It is calculated using Eq 3

$$delay_i = \frac{time_{autonomous} - time_{assited}}{heath_{intial}} \quad (3)$$

Having defined this these metrics we can hypothesise about a function defined by Eq. 4 that describes how good or bad a human assistant is actually assisting a robot navigating through the maze game.

$$\mu(i) = disparity_i + delay_i + damage_i \quad (4)$$

Eq. 4 express our idea about untrustworthiness of human operator because all the three terms on the right hand side of the equation negatively affects the effectiveness of maze navigation task. For example, we want the robot to reach the intended key point as much closer as possible. Thus, an absolute trustworthy value of *disparity* is zero. It is also easy to see that disparity is always non negative. Another important thing to notice here is that *delay* can be negative or positive. However, a positive delay negatively affects the the effectiveness of the task because we want the robot to reach certain goal with human assistant to be quicker than it does autonomously. The last term *damage* is calculated in a different way than the previous two terms. The metric health is quantifiable but it is somewhat an abstract term with respect to other tow metrics that we previously discussed. At first a $health_{initial}$ is randomly assigned between 0 and 10000. Then whenever the robot hits the wall of the maze its health value is decreased to a random value between 0 and $health_{intial}$. So it gives an quantity that denotes how much consistently the robot was able to follow the human assistance.

Eq. 4 thus gives an quantity that tells us how much untrustworthy a human assistant was. However, there is a problem with this formula. The terms that constitutes the formula are not numerically in the same scale. Thus it may not provide us good intuition about untrustworthiness. Moreover, we are interested in calculating the trustworthiness of the human operator, not the untrustworthiness of it. Although, they are complimentary to each other, it turns out that there is a nice way to calculate the trustworthiness with all the metrics scaled in a range 0 to 1. We can take the normalized value between 0 and 1 for all the metrics defined as follows instead of Eq. 1, 2 and 3 respectively:

$$d_i = \frac{disparity_i}{max(disparity) - min(disparity)} \quad (5)$$

$$h_i = \frac{damage_i}{max(damage) - min(damage)} \quad (6)$$

$$\Delta t_i = \frac{delay_i}{max(delay) - min(delay)} \quad (7)$$

Now we can also describe our trustworthiness function as:

$$\tau'(i) = 1 - (disparity_i + delay_i + damage_i) \quad (8)$$

However, we also want the trustworthiness function to be normalized so that we can manipulate this data effectively while interpreting this data. Finally, our hypothesis regarding about trustworthiness of human operator is the function:

$$\tau(i) = \frac{\tau'(i)}{max(\tau'(i)) - min(\tau'(i))}, 0 \leq i \leq 31 \quad (9)$$

We can also define a decision function δ based on the trust value. The decision function decides whether an human assistance is trustworthy or not based on τ and a threshold θ .

Figure 6: Comparison between histograms of $d, h, \Delta tand\tau$ after and before normalization.

Figure 7: Disparity, Damage, Time delay vs. Trustworthiness.

$$\delta(i) = \begin{cases} True, & \text{if } \tau(i) \geq \theta \\ False, & Otherwise \end{cases}$$

One of the concern regarding normalization of $d, h, \Delta tand\tau$ is that by normalization are we loosing considerable amount of information that might affect the classifier to classify the input. We have plotted the histogram distribution of all the metrics and the τ. From the side by side comparison of the histogram plot in Fig 6 we can see that the distribution of metrics and the trustworthiness visually looks very similar.

One important constraint in Maze Game experiment is that the robot can be allowed to move only towards a forward key point. The program internally keeps a position index count of the position of the robot. The index is incremented if it reaches the next key point. Therefore, a good assistance from the human operator will be next key point in the maze. A bad assistance by human operator can be punished by several metrics. For example, if a human operator points the robot to reach a goal which is across the wall of the maze then the robot will hit the wall several times which will affect the health of the robot and thus affect the trustworthiness. Similarly, a human operator who is not paying attention to interact with the robot will take time to give next instruction to the robot. Thus it will take more time for the robot to reach the goal. This will basically result in a poor time delay which will affect the trustworthiness of the human operator as expected. Similarly, if the operator instruct the robot to reach distant goal from the next key point it will affect the trustworthiness by contributing to disparity metric.From above discussion it becomes clear that our chosen metric intuitively very effective in determining the trustworthiness of the human operator. We will formally show the evidence of our claim in the next sections.

4.1 Maze Game and Training Results

Now we will show that Eq. 8 indeed reflects the trustworthiness of human correctly based on described metrics. To show that we have learned model that can predict the trustworthiness of a human operator in a different correctly. After several run of the experiment we have got around 1000 instances of the trustworthiness defined by Eq. 8.

Fig. 7 shows a 4 dimensional scatter plot that give an idea about how trustworthiness is related to the metrics according to our hypothesis. After that we have tried to find correlations among the metrics and trustworthiness to learn the our hypothetical function. We have used a visual data mining named Orange[1] for this purpose. We have used

Figure 8: A screen shot of visual machine learning tool orange.

Table 2: Accuracy of the classifier in the maze game experiment.

Training Size	Accuracy of classification
45%	95%
50%	95%
55%	95%

Support Vector Machine(SVM) which is a popular machine learning technique to learn classifier using Orange. The reason behind using SVM is that SVM can capture a classifier hyperplane even in high-dimensional hyperspace. SVM has been used in learning enormous classifiers in very complex feature spaces including cancer cell detection, spam email classification and so on[9, 6]. If we observe the plot in Fig. 7 then we can see that the classifier that we want to learn is a two dimensional plane in three dimensional feature space. Therefore, it SVM can very effectively learn the classifier from our experimental data. Fig. 8 shows a snapshot of how data mining tool Orange was used to train the trustworthiness classifier using our experimental data.

The classifier was trained using two different methods; cross-validation and leave-one-out. We have got good classification accuracy using both of the ddata sampling methods. In cross-validation method we have sampled 70% data from the resulted instances of our first experiment as training data. We have got 95% accuracy in the classification on test data sample. In leave-one-out method all the instances except one is selected for training the classifier. After that the test data set is classified using the learned model. All of the instances is selected at least once as a test data. The total accuracy is of the classification is calculated using by counting percentage of data that has been selected and classified correctly against the total data set. Using this method we have also got 95% data was successfully classified correctly. The result of the classifier on the test data using different sampling size using cross validation method in the first experiment is shown in Table **??**

This shows that we have a got well trained classifier. Another way to observe the confidence of the classifier is the confusion matrix. The confusion matrix for the classifier using cross-validation and leave one method is shown in Table 3 and Table 4 respectively. The diagonal elements of the classifier says how accurately the classifier has worked on a given data set. From the two table we can see that the classifier was confident in classifying the test data set. Another, depiction of confidence of classifier using cross validation and leave one out method has been plotted in Fig. 9 and Fig. 10 respectively.

5. COIN GAME EXPERIMENT

To prove our hypothesis regarding the learned function for trustworthiness we have devised the second experiment which we call the Coin Game experiment. The second experiment has very similar set up to the first experiment.

Figure 9: Chart showing the confidence in classification using cross validation.

Figure 10: Chart showing the confidence in classification using leave one out method.

We have used the same workstation machine and the same TurtleBot robots to perform the second experiment. The map for navigation is very similar as well. The map for this experiment is based on the map shown in Fig. 4 and **??**. However, the experiment introduces some new rules regarding navigation of the robot. For example, in this experiment the goal is not defined by the human operator rather the goals are given randomly in the maze. We call these random goals as "coins". Unlike, the previous experiment the goal or coin may pop-up in either forward or backward direction to the robot. As the goal is generated randomly and not under the control of the human operator, it puts more cognitives stress on human operator than the previous experiment; as we will see in the result section for this experiment. Another aspect of cognitive stress for human operator is that in this experiment the goal is not represented in the real world rather the goal in shown in the computer screen as a yellow circles denoting the coin. The coin can pop up between any two key points. The map of this experiment has been shown in Fig.11. Matching the location in the map and real world may pose some additional challenge on human operator. In short, although the second experiment has very similar set up to the first experiment, it is indeed different problem. But it is a suitable problem to test our learned model because many of all of the metrics here has the same implication as it had in the previous experiment.

The human operator points the mouse to a location the map. As the goal is random, the human operator now have to switch between robots more frequently. Research work[14] has shown that this switching time can affect the effectiveness of a task performed by the human robot team. Thus the second experiment is more challenging in terms of cognitive stress.

Even though, all the metrics used in the first experiment has the same implication in this experiment, they are not calculated in the similar fashion. For example the the ideal arrival time to a key point can be calculated by finding out the path segments from robots current position and then adding corresponding required ideal time. However, calculating it differently does not change a human assistance neither more trustworthy or less trustworthy. The learned classifier will classify the the human assistance based on the disparity, damage and time delay it produces. But this time we have not use any formula to calculate the trust. Rather we feed the current metrics to the classifier that we have already learned and the classifier produced a yes or no message using ROS to indicate whether the assistance was trustworthy or not.

We have set two scenarios in this experiment. The first scenario, is the single human operator one or more robots team. In this scenario only one human operator was allowed to assist the human-robot team. We have set a timer for the human operator as 2 minutes and also set maximum 5 coin collection limit. 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 the second scenario, multiple one or more robots were teamed up with two human operators. The initial timer was set to 1 minute and a maximum of ten coins were allowed to collect. Either condition satisfied he end of the game.

Table 3: Confusion matrix of the classification using cross validation method.

		Prediction	
		True	False
Actual	True	72	10
	False	10	72

Table 4: Confusion matrix of the classification using leave one out method.

		Prediction	
		True	False
Actual	True	72	10
	False	10	72

Figure 11: Maze map of the Coin Game experiment with coin goals.

5.1 Result of Coin Game Experiment

Six people who participated in first experiment also participated in the second experiment. We have found that the learned model of classifier was able to understand good and bad assistance very efficiently. We did not allow the robot change its behaviour based on the trustworthiness, it is just keeping a log of which of the assistance came from the human operator were trustworthy and which were not. While running the second experiment we manually kept a log to indicate which particular human assistance were seemed to be trustworthy in the naked eye. After the experiment we collected the log from the robot and then compared with our human judged interpretation of trustworthiness. We have found that the 95% and 97% of robots prediction matches with the two human interpretations. This is a very promising result to support our hypothesis in Eq. 9. The result also showed a 10% decrease in trustworthiness from the previous experiment which also support our assumption about the second experiment to be harder in terms of cognitive stress. Another important result is that by changing the threshold θ to a produced interesting result. The result on matching classification on different threshold is shown in the following table:

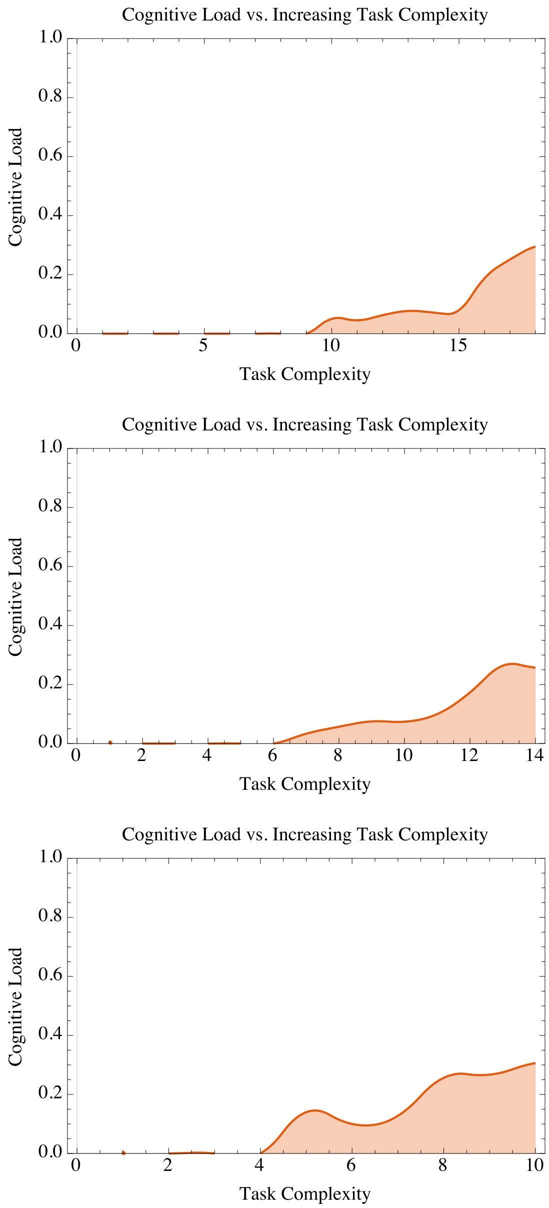

Figure 12: lp

Table 5: Accuracy of the classifier in the coin game experiment.

Threshold	Accuracy of classification
45%	95%
50%	95%
55%	95%

6. CONCLUSIONS

Our research has a profound implication on the way used to look into human robot team. One vital contribution of this paper is that it shows that trustworthiness of human operator in human-robot team can be quantified and learned using useful metrics. We can define it by the term transfer effectiveness of human operator. Besides, defining this novice terminology we have also achieved significant evidence to show transfer effectiveness is possible across multiple problem domain. We have done two experiments on human-robot team to assess cognitive capacity of human assistance. For our a particular problem of maze game, metrics like our disparity, arrival time delay and damage considered as vital metrics in determining the trustworthiness. We have shown that the learned model also implies on Coin Game problem which our second experiment. Although, built on similar set-up, the second experiment was different in many ways from the first. We showed that, although they are different the trustworthiness classifier model can be transferred to this new domain of problem effectively. From this experimental result we try to say that for if several human-robot team problems have metrics those have common implications, may help us to learn the nature of of human assistance cognitive behaviour for those problems. It may also help us to infer the human cognitive stress limitation in another problem. In other words, our research showed that cognitive capacity of human assitant is transferable.

Another, important finding is that based on the problem the cognitive threshold may slightly vary. But if we can define the threshold correctly for two problems correctly, then transferring the cognitive capacity between those two tasks can be understood.

In future, we have plan to extend our research to human and multiple robot team with heterogeneous robot.

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