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TASC: Teammate Algorithm for Shared Cooperation

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Abstract— **For robots to be perceived as full-fledged team members, they must display intelligent behavior along multiple dimensions. One challenge is that even when the robot and human are on the same team, the interaction may not *feel* like teamwork to the human. We present a novel algorithm, Teammate Algorithm for Shared Cooperation (TASC). TASC is motivated by the concept of shared cooperative activity (SCA) for human-human teamwork, developed in prior work by Bratman. We focus on enabling the robot to prioritize certain SCA facets in its action selection depending on the task. We evaluated TASC in three experiments using different tasks with human users on Amazon Mechanical Turk. Our results show that TASC enabled participants to predict the robot's goal earlier by one robot move and with greater confidence. The robot also helped reduce participants' energy usage in a simulated block-moving task. Altogether, these results show that considering the SCA facets in the robot's action selection improves teamwork.**

I. INTRODUCTION

As robots weave into people's daily lives, they will need to act as teammates to human users. These robotic teammates must be able to reason about teamwork, for example, with multi-dimensional models of the different elements that make an effective team. By doing so, they can interact with human users in ways that *feel* team-like. That is, a human and robot working in proximity to each other or sharing the same workplace are not necessarily a team. In particular, the interaction may not *feel* like teamwork to the human user. To enable robots to become full-fledged team members, we apply the concept of shared cooperative activity (SCA), developed by Bratman [1] for effective human-human teams to human-robot teams. Our work provides a computational structure to this multi-dimensional sociological model for understanding teamwork.

Bratman defines three facets that must all be present for an activity to be considered teamwork: mutual responsiveness (MR), commitment to the joint activity (CJA), and commitment to mutual support (CMS) [1]. *Mutual responsiveness* is appropriately reacting to the intentions and actions of the other while assuming that the other will do the same in favor of the joint activity. *Commitment to the joint activity* means aligning the team members' sub-plans so they are all participating in the same joint activity. Lastly, *commitment to mutual support* is the willingness to help each other if there are breakdowns. Inspired by SCA, we present a novel robotic teammate algorithm that extends the SCA facets to human-robot teaming, Teammate Algorithm for Shared Cooperation (TASC), and evaluate its performance. TASC has three weighted parameters that map to the SCA facets: *legibility*, which enables mutual responsiveness by recognizing and communicating intent; *effort*, which demonstrates commitment to the joint activity by taking actions that appear effortful to the human; and *value*, which shows commitment to mutual support by providing assistance towards achieving the team's goal. We evaluated TASC in three user studies via Amazon Mechanical Turk: two cooperative navigation tasks and a tower assembly task. These tasks were implemented in a Markov Decision Process (MDP) framework with discrete states and actions.

The first navigation study provided insight into the relationship between the parameters. We found that prioritizing *value* or weighting all parameters equally resulted in significantly better performance in comparison to prioritizing *legibility*. Results from the second navigation study showed that giving weight to *legibility* allowed participants to make accurate goal predictions earlier by seeing one less robot action and with more confidence. Participants did not perceive teamwork to be significantly different between the Legibility and Value conditions but did significantly prefer the Legibility condition. In the towers study, we saw that giving weight to *effort* enabled participants to use 6% less energy and positively influenced their perception of MR. Our results show that TASC enables the robot to exhibit behavior consistent with the SCA facets resulting in improved teamwork when the weights on *value*, *effort*, and *legibility* are tuned for the given task.

II. RELATED WORK

In this section, we describe the relationship between existing computational techniques for human-robot collaboration and the three facets of SCA. Teamwork has been an area of interest in computational HRI [2], but no prior algorithm incorporates all three facets of SCA. Most research includes at most two facets: mutual responsiveness and commitment to mutual support, while commitment to the joint activity is assumed, typically because the experimenter gives directions to the participants.

To display *mutual responsiveness*, the robot must be able to consider the human's intentions and actions and respond

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in a timely manner. Our prior work showed that a robot that is able to recognize and communicate intent improves team performance [3]. Another approach used spatial augmented reality to convey the robot's intent and eye gaze for the robot to understand the human's intent [4]. A probabilistic graphical model of the structured tasks has also been proposed to allow the robot to appropriately time its actions ([5], [6]).

Besides understanding the human's intent, *mutual responsiveness* also requires robots to be able to communicate their own intentions. Prior HRI work in intent communication was inspired by animation techniques and focused on designing human-like robot behavior so that the robot is intuitive to understand ([7], [8]). Gielniak and Thomaz showed that the spatiotemporal correspondence of actuators can be used to generate motions that better convey intent [9]. Researchers also investigated the concept of legibility of motions to help the human to predict the robot's goal ([10], [11]).

As defined earlier, *commitment to the joint activity* consist of each teammate performing the joint action in accordance with sub-plans that align. Hoffman and Breazeal [12] proposed a hierarchical goal-oriented task execution system based on SCA, Joint Intention Theory and Dialog Theory. They achieved commitment to the joint activity by meshing sub-plans and commitment to mutual support by asking the human teammate for help when needed. They tested the system in a collaborative, turn-taking button task with a human-robot team and showed that by exhibiting behavior that shows its commitment to the joint activity and mutual support, this produced fluid and efficient collaboration. CJA may also be influenced by a team member's perception of the other's effort level. Chai et al. [13] investigated the influence of the robot's effort level on establishing common ground in a situated human-robot dialogue setting. They defined low effort as the robot's minimum effort in accepting or rejecting a presentation from its human teammate via solely explicit confirmation. High effort was defined as the robot's extra effort in proactively describing what it perceives from the environment after it accepts or rejects a presentation. Results showed that low effort may incorrectly lead the human teammate to believe a common ground has been established.

Lastly, *commitment to mutual support* is each teammate's willingness to provide assistance to the other when needed. One method to achieve CMS is task allocation, which has been well studied in the HRI domain [2]. Shah et al. used insights from human-human teaming to design Chaski, a goal-oriented task level controller that enables the robot to take initiative to choose and schedule its own activities and adapt real-time to the human teammate in a manner that minimizes the human's idle time [14]. Another task allocation solution used hierarchical task networks [15]. Another capability that is needed to achieve CMS is the ability to reason about when and how to be helpful. Mangin, Roncone, and Scassellati proposed a high-level, hierarchical task model that enables a robot to automatically determine when and how to help the human [16].

Existing techniques focus on only one or two of the SCA facets. Our approach incorporates all three SCA facets and uses them as the foundation in the design of our TASC algorithm. In three user studies, we show that TASC enables the robot to exhibit behavior that correspond to all the SCA facets leading to better team performance.

III. ALGORITHM DESIGN

We propose TASC, Algorithm 1. We model the interaction as a Markov Decision Process (MDP):

- S = a finite set of states, with possible goal states $G = [G_0 ... G_n] \subset S$,
- A_R = robot actions,
- A_H = human actions,
- $a_R \in A_R$ = most recent robot action,
- $a_H \in A_H$ = most recent human action,
- T = $(s, a_R, a_H) \to s'$ = transition function,
- $R = [R_0 ... R_n]$ = n separate reward functions for reaching each goal,
- γ = discount factor, $0 \leq \gamma \leq 1$.

We represent the facets of SCA as follows:

Mutual responsiveness: We aim for the robot to predict the human's goal $G_H \in G$ in order to take actions that reach the same goal. To predict this goal, we define a classifier $C_G(s, a_H)$ that takes the current state $s \in S$ and the most recent human action $a_H \in A_H$ and returns $\Pr_G$, the probabilities for each possible goal state $G_i \in G$: $C_G(s, a_H) \to \Pr_G(G_i \in G)$.

Legible actions are introduced to convey the robot's intended goal. In order to take legible actions, the robot sets its goals equal to the predicted human goal, $G_R = G_H$. $\Pr[G_R | s, a]$ is defined as the probability that a person will predict goal G_R after viewing action a from state s. This legibility calculation is task dependent, but uses the notation

$$L(s, a) = \Pr[G_R | s, a]. \tag{1}$$

Commitment to the joint activity: We aim for the robot to take actions that appear effortful to the human. We define $\Pr[E|, a]$ as the probability that a person will perceive action $a \in A_R$ in state s as effortful, which can be determined through data collection on human perception of effort. We use the following notation for effortful actions

$$F(s, a) = \Pr[E | s, a]. \tag{2}$$

Commitment to mutual support: We aim for the robot to take actions that, along with the human's action, take the team to the highest-valued state. This enables the robot to provide assistance towards finishing the task. We define a classifier, $C_A(s, Pr_G) \to (a_p \in A_H)$, that predicts the next human action, a_p, given the current state $s \in S$ and the current probabilities of each goal $G_i \in G$, $\Pr_G$. The robot solves for MDP values V_G for each G_i using the reward function in R_i corresponding to G_i. The robot takes the action $a \neq a_p$ that maximizes the expected value of the next state, s', given $\Pr_G$ and a_p. We define change in value for our algorithm as

$$\Delta V_{G_i, a_p, a} = V_{G_i}((s, a_p, a) \to s') - V_{G_i}(s). \tag{3}$$

Algorithm 1 Teammate Algorithm for Shared Cooperation (TASC)

w_V, w_F, w_L = weights on value, effort, and legibility
$(S, A_R, A_H, T, R = [R_0 ... R_n], \gamma)$ = initialize MDP
$G = [G_0 ... G_n]$ = possible goal states
$V_{G_i}(s \in S)$ = solved MDP value of s given goal $G_i \in G$
$a_H \in A_H$ = idle
$C_G(s, a_H) \rightarrow \Pr_G(G_i \in G)$
$C_A(s, \Pr_G) \rightarrow (a_p \in A_H)$

while completing task **do**
  $G_H = \arg\max_{G_i \in G}(C_G(s, a_H))$ {predict human's goal}
  $G_R = G_H$
  $(a_p) = C_A(s, \Pr_G)$ {predict human action}
  $L(s,a) = \Pr[G_R | s, a]$ {*legibility*}
  $F(s,a) = \Pr[E|, a]$ {*effort*}
  $V(s, a_p, a) = \frac{1}{2}\left(\frac{\mathbb{E}_{\Delta V_{G_i, a_p, a}}}{\max_{\alpha \in A_R, G_i \in G}(|\Delta V_{G_i, a_p, \alpha}|)} + 1\right)$ {*value*}
  $a_R = \arg\max_{a \in A_R}(w_F \cdot F(s,a) + w_V \cdot V(s, a_p, a) + w_L \cdot L(s,a))$ {robot action}
  a_H =human action
  $s = T(s, a_R, a_H)$ {update state}
end while

$$\mathbb{E}_{\Delta V_{G_i, a_p, a}} = \sum_{G_i \in G} Pr_{G_i} * \Delta V_{G_i, a_p, a} \tag{4}$$

$$V(s, a_p, a) = \frac{1}{2}\left(\frac{\mathbb{E}_{\Delta V_{G_i, a_p, a}}}{\max_{\alpha \in A_R, G_i \in G}(|\Delta V_{G_i, a_p, \alpha}|)} + 1\right) \tag{5}$$

Equation 3 calculates the change in MDP value between the current state s, and the expected s' when taking action a and a_p from s for $G_i \in G$. To find the relative change in the MDP value, this is divided by the maximum value change expected when taking other actions $\alpha \in A$ (Equation 5). This keeps the impact of V similar as the team is closer to the goal by using the difference in MDP value between s' and s. V is scaled in the range $[0, 1]$.

Depending on the task, different parameters (legibility, effort, and value) may be more important than others. Thus all three parameters must be assigned weights, $w_V(value), w_F(effort)$, and $w_L(legibility)$, summing to one to denote desired importance of each component. The robot takes the action that maximizes the weighted sum of these three parameters.

In the next sections, we present our evaluation of TASC in three user studies. We assessed TASC in collaborative scenarios where both teammates have the same capabilities in terms of the possible actions. Since we are interested in investigating the effects of value, effort, and legibility on teamwork, our controls include keeping the number and duration of all actions taken by each teammate to be the same. While these tasks use synchronous human-robot actions, TASC can be extended to scenarios where the teammates take asynchronous actions via modifications to the goal classifier and action classifier.

IV. ALGORITHM IMPLEMENTATION

Algorithm 1 shows the general form of the TASC algorithm. We list here the implementation details used in our evaluation of TASC, which may be changed based on the desired task. In this work, the settings for our MDP solver, MDPtoolbox [17] are the same for all evaluations: the discount factor is set to 0.9, the stopping criterion is set to 0.01 (default value), and the maximum iterations are set to 1000 (default value).

The robot solves the MDP for each possible goal G_i by using the reward function for goal G_i and solving for V_{G_i} and policy P_{G_i} using value iteration for the navigation experiments and policy iteration for the tower assembly experiment. The transition and reward functions are deterministic for all tasks in this work.

The classifier $C_G(s, a_H)$ predicts a human goal G_H by comparing the potential values of the next state s' for different goals $G_i \in G$, where $(s, a_R, a_H) \rightarrow s'$. The classifier outputs the probability of all goals and gives a prediction G_H, the goal with the highest expected increase in state value. For the current state s and next state s' after the human action a_H, the probability of some goal $G_i \in G$ is

$$\frac{\max(0, V_{G_i}(s') - V_{G_i}(s))}{\sum_{G_j \in G} \max(0, V_{G_j}(s') - V_{G_j}(s))}. \tag{6}$$

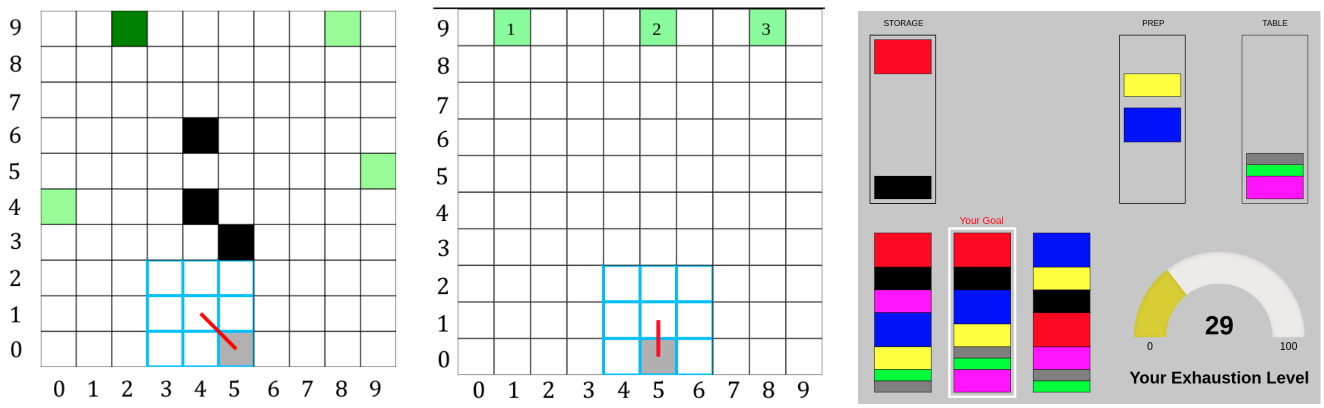
Thus the probability increases with the difference in MDP value between s and s'.

V. USER STUDIES

In this section, we present the three user studies that we conducted to evaluate TASC (Figure 1, accompanying video). For all the studies, we recruited participants from Amazon Mechnical Turk. Only workers who reside in the U.S. and had at least a 85% approval rating were eligible to participate in the study. Instructions were provided to the participants describing the task and study procedure. Each study included a practice session, test session, and then the survey. We analyzed only the test data. To ensure quality data, we preprocessed the data. If a participant completed the study multiple times, we only kept the data from their first session to control for interaction time. We also excluded participants who did not complete all the questions in the questionnaire, selected the same response for all the questions since there were reversed questions, or did not answer the check question correctly. We collected both objective and subjective data. The objective data varied based on the task. The subjective data was a survey that we devised based on SCA [1] as shown in Table I. Since the tasks were different, we slightly modified the survey for each task.

A. Evaluation #1: Navigation Task

Task Description: We evaluated TASC in a shared manipulation navigation simulation in a 10×10 gridworld (Figure 1(a)). In this simulation, the teammate agent and human



(a) study 1: navigation (b) study 2: modified navigation (c) study 3: tower assembly

Fig. 1. We evaluated TASC in three user studies using these tasks.

Mutual Responsiveness
1. The robot perceives accurately what my goals are.
2. The robot does not understand what I am trying to accomplish.
3. I know which goal the robot is going towards.
Commitment to the Joint Activity
1. The robot was lazy.
2. The robot put forth its best effort.
Commitment to Mutual Support
1. The robot tried to help me.
2. The robot did not cooperate with me.
3. The robot wanted to make the task easier for me.
4. The robot did not care about supporting me.
Post-Study
1. Out of the two robot teammate programs, which one do you prefer? Why?

TABLE I

SUBJECTIVE MEASURE (5-POINT LIKERT SCALE).

worked together to move a remote-controlled car to one of four goal states. This gridworld navigation task allowed us to evaluate in a task with distinct visual differences in action paths chosen for *value*, *legibility*, or *effort*.

The robot did not know the human's goal but was aware of the four possible goal states. The human's goal was dark green, whereas the other possible goals were a lighter green. Obstacles were black and the starting position was grey. Both team members were allowed to choose from the same set of actions. At each time step, the human or the robot could choose a single action to control the remote-controlled car, with the two team members taking turns throughout the course of the game. The cells highlighted in blue indicated the possible cells the remote-controlled car could be moved to from the current state. We defined the states $S=$ (x,y) coordinates, possible goals states $G=[(0,4),(9,5),(2,9),(8,9)]$, and actions $A_R=A_H$ as one idle, cardinal, or diagonal movement. Transitions were deterministic and the agents received a reward of 100 at the goal, -1 otherwise.

We set $\Pr[E|a \in A_R]$ to 0.9 for actions that move the remote-controlled car in diagonal directions, 0.5 for actions that move the remote-controlled car in the cardinal directions and 0.0 for idling. The probability of perception of effort was higher for actions that move the remote-controlled car further, and hence the probability was highest for diagonal moves since they carried the combined effect of two cardinal moves. We calculated legibility in the following manner. First, the new state was predicted from each possible action from state s, $s'=(s,a,a_p)$, where a_p was the human action predicted by the agent, and $\Delta dist(G_i)$ was the change in Euclidean distance to G_i from s to s'. Since this task was turn-based, $C_A(s,\Pr_G)$ simply returned a_p as idle. If the car idled or moved further away from every goal, the legibility for each goal was $\frac{1}{|G|}$. Otherwise, the legibility of action a from state s given G_i was defined as

$$\frac{\max(0,\Delta dist(G_i))}{\sum_{G_j\in G}\max(0,\Delta dist(G_j))}. \tag{7}$$

The probability of G_i given an action a from state s that takes the car further away from the goal was set to zero. As a result, we discounted the goals with a negative $\Delta dist(G)$ in our legibility calculation. We note that $\sum_{G_i\in G} Pr[G_i]=1$. Teams moved the remote-controlled car to all four goals in the test session. We randomized the order of the goals.

Experimental Design: We conducted a one-way between-subjects study to investigate the effects of different weights of *value*, *effort*, and *legibility* on teamwork. The independent variable was the setting of the weights, w_V, w_L, and w_F. We focused on three conditions: Value ($w_V=1.0, w_F=0.0, w_L=0.0$), Equal ($w_V=0.333, w_F=0.333, w_L=0.333$), and Legibility ($w_V=0.1, w_F=0.1, w_L=0.8$). All conditions set $w_V>0$ as this kept the robot working towards finishing the goal. We did not test a condition that prioritizes only effort due to the nature of this task. In our pilot study, we observed that if only effort is prioritized, the robot's behavior does not move towards the goal, as there is no incentive to finish the task. This resulted in the human correcting the robot many times which can be frustrating. To control for order effects, we counterbalanced the order of the conditions.

We formed two hypotheses:

H1.1 - Objective Measures of Teamwork: The Equal condition will result in the best performance in terms of the objective measures.

H1.2 - Subjective Performance Rating: Participants will rate the Equal condition significantly higher than the Value and Legibility conditions.

We collected data from a total of 184 participants and after data pre-processing, a total of 153 participants remained, 51 in each condition (64 F, 85 M, and 4 preferred not to answer, age: $Mean = 35.07$, $SD = 10.59$). We calculated the average of the following metrics across all four goals: reward earned, task time, path length, and human counter moves, i.e., human actions that directly undo the robot's actions such as left and right moves.

B. Evaluation #2: Modified Navigation Task

Task Description: Next, we modified the first navigation task to investigate the influence of *mutual responsiveness* and *commitment to mutual support* on teamwork. We reduced the total number of possible goals to three, changed the goal positions, and removed all the obstacles (Figure 1(b)). The main difference was that the robot is now given the goal and the human does not know the goal *a priori*. This removed the need for $C_G(s, a_H)$. We modified the MDP from the first navigation task (Section V-A) as follows: the possible goals $G = [(9,1),(9,5),(9,8)]$, and the agent received a reward of 100 for reaching the goal, otherwise -1 for taking cardinal actions, and -2 for taking diagonal actions. We penalized diagonal actions more than cardinal actions to encourage straighter paths to goals. At the end of each robot move, we asked the participants to make a prediction of the robot's goal: "Which goal do you think the robot is heading towards? How confident are you in your prediction?" (5-point Likert scale). Teams completed all three goals during the test session. The goal order was randomized.

Experimental Design: We used a one-way within-subjects design to investigate the effects of incorporating MR (w_L) and CMS (w_V) in the robot's action selection on teamwork. The independent variable was the setting of the weights. We tested two conditions: Value ($w_V = 1.0, w_F = 0.0, w_L = 0.0$) and Legibility ($w_V = 0.7, w_F = 0.0, w_L = 0.3$). Similar to the previous study, we set $w_V > 0$ to enable the robot to work towards finishing the task. We counterbalanced the order of the conditions.

We made the following hypotheses:

H2.1 - Objective Measures of Teamwork: The Legibility condition will enable participants to correctly predict the robot's goal earlier in the interaction and with higher confidence than the Value condition.

H2.2 - Subjective Performance Rating: Participants will rate the Legibility condition significantly higher than the Value condition.

We collected data from 48 participants. For data pre-processing, besides the standard protocol, we also excluded participants who did not give a correct answer for the goal prediction of the final time step as it indicated data quality. After data pre-processing, we used the data from 34 participants (17 M, 17 F, age: $Mean = 34.50, SD = 9.98$). The following objective measures were averaged across the three goals: reward earned, task time, first correct goal prediction (number of robot moves needed for the human to make the first correct goal prediction), and confidence change (number of times the goal confidence rating increased or decreased).

C. Evaluation #3: Tower Assembly Task

Task Description: In the last study, we evaluated TASC in a simulated joint assembly task in which the robot and human worked together to build a tower using blocks (Figure 1(c)) to investigate the influence of *commitment to the joint activity* and *commitment to mutual support* on teamwork. While the navigation task was turn based, in this task, the human and robot were both able to take an action at every time step. At the start, the human was given one out of the three possible towers to build. The robot did not know the human's goal but did know the three possible towers. Both team members were capable of performing all the actions. All the blocks for the three towers were in the storage container. The preparation area (prep) was a staging area for building the tower. Blocks in storage must be moved to prep and then stacked on the work station table. In addition, any blocks taken off of the tower must be placed in prep before they can be moved back to storage.

In this task, the effort of an action was conveyed via the drag speed of the block and the distance between the initial and final areas. The drag speed of a block was inversely proportional to the block's size. We also introduced an exhaustion meter for the human to incentivize participants to behave cooperatively and to raise awareness of the robot's work. The level of the exhaustion meter increased with the time that the human spent moving blocks. For each tower, the team needed to complete assembly before the exhaustion level reached 100%, or else they had to start the task over from the beginning. We defined the MDP as follows:

- $S = [storage, prep, table] \ \forall \ blocks$,
- $G \in [G_0 ... G_n] = [tower_1, tower_2, tower_3]$,
- $A_R = A_H = [place_{prep}, place_{table}, idle,$ $removeblock_{table}, removeblock_{prep}] \ \forall \ blocks$,
- $T = (s, a_R, a_H) \rightarrow s'$ = deterministic transition function,
- $R = [R_0 ... R_n]$:

$$R_i = \begin{cases} 100 & s = G_i \\ \text{sum of correctly placed blocks} - 8 & otherwise. \end{cases}$$

In S, blocks could either be in storage, prep, or stacked on the table. The classifier $C_G(s, a_H)$ functioned the same as in the navigation task. In this task, the robot's action classifier $C_A(s, \Pr_G)$ used intent recognition, implemented here as tracking of the human's mouse position. The subset $A \subset A_H$ was chosen based on the position of the mouse at the click. The action a_p and probability p_A was determined by comparing the values of taking each action in A.

We assigned $\Pr[E|a \in A_R]$ based on the relative size of the block the robot moves as well as the distance that the block is moved. We calculated legibility in the same manner as the navigation task except with a relaxed problem heuristic in place of Euclidean distance. Given a current state and a goal state, the heuristic compared the location of each block between the two and estimated the minimum number of moves that would be required to reach the goal state based off of that. In the test session, teams built all three towers where the order of the towers were randomized.

Experimental Design: We used a one-way within-subjects design to investigate the effects of CJA (w_F) and CMS (w_V) on teamwork. The independent variable was the weight settings. We focused on two conditions: Value ($w_V = 1.0, w_F = 0.0, w_L = 0.0$) and Effort ($w_V = 0.6, w_F = 0.4, w_L = 0.0$). Again, we set $w_V > 0$ to enable the robot to work towards reaching the goal. We counterbalanced the order of the conditions to control for order effects.

We formed the following hypotheses:

H3.1 - Objective Measures of Teamwork: The Effort condition will perform significantly better than the Value condition in reducing the human's exhaustion level.

H3.2 - Subjective Performance Rating: Participants will rate the Effort condition significantly higher than the Value condition.

A total of 59 participants took part in the study. We used the standard pre-processing method with the addition of removing participants who made more than 14 moves building any of the towers in the test session, since it took one agent 14 moves to build the tower alone. In other words, one agent making more than 14 moves means there is no teamwork. After data pre-processing, we ended with 28 participants (10 F, 17 M and 1 preferred not to answer, age: $Mean = 29.14, SD = 6.00$). For the objective measures, we averaged the reward earned, task time, total actions taken per teammate, and percentage of exhaustion.

VI. RESULTS

The objective results of all the studies are in Tables II, III, and IV. For the subjective scales shown in Table I, we calculated Cronbach's α. Cronbach's α was higher than 0.6 for these scales.

A. Navigation Study Results

Condition	Reward	Task Time (sec)	Path Length	Human Counters
Value (M)	91.33	31.12	34.51	0.10
(SD)	3.34	32.12	12.83	0.36
Equal (M)	90.65	35.49	36.98	0.49
(SD)	3.11	46.75	11.54	1.05
Legibility (M)	87.32	37.48	50.37	0.53
(SD)	2.73	20.32	10.35	1.36
$F(2,150)$	24.92	0.45	27.52	2.83
p	< 0.001	0.64	< 0.001	0.06

TABLE II

OBJECTIVE RESULTS FOR THE FIRST NAVIGATION STUDY.

For the first navigation study, a one-way ANOVA was calculated on the average reward (Table II). The ANOVA result was significant, $F(2,150) = 24.92, p < 0.001$. We conducted post-hoc comparisons using Tukey HSD test. The post-hoc test revealed that the average reward was significantly higher in in the Equal condition ($M = 90.65, SD = 3.11$) compared to the Legibility condition ($M = 87.32, SD = 2.73$), $p < 0.001$. The Equal and Value ($M = 91.33, SD = 3.34$) conditions were not significantly different from each other, $p = 0.51$. For task time, there was no significant difference between the conditions, $F(2,150) = 0.45, p = 0.45$. However, the analysis was significant for path length, $F(2,150) = 27.52, p < 0.001$. Participants took longer paths when they interacted with the Legibility condition ($M = 50.37, SD = 10.35$) as in comparison to the Value ($M = 34.51, SD = 12.83$) and Equal ($M = 36.98, SD = 11.54$) conditions, $p < 0.001$. The path lengths in the Equal and Value conditions were not significantly different, $p = 0.53$. Next, we analyzed the team's efficiency as measured by the average number of human counter moves and the results were marginally significant, $F(2,150) = 2.83, p = 0.06$. These results do not provide support for our H1.1 hypothesis that the Equal condition would outperform both of the other two conditions.

Our H1.2 hypothesis predicted that the Equal condition would be rated the best in terms of the SCA facets. We found partial support for this hypothesis. The ANOVA results were significant for MR, $F(2,150) = 3.54, p < 0.05$. The post-hoc results showed that MR scored significantly higher in the Equal ($M = 3.78, SD = 0.90$) condition compared to the Legibility condition ($M = 3.30, SD = 1.03$), $p < 0.05$. The MR ratings for Equal and Legibility ($M = 3.69, SD = 0.98$) were not significantly different from each other, $p = 0.11$. Moreover, results for participants' ratings of CJA was significant, $F(2,150) = 4.03, p < 0.05$. CJA was rated marginally higher with Equal ($M = 4.25, SD = 0.90$) compared to Legibility ($M = 3.87, SD = 0.93$), $p = 0.08$. Participants did not perceived CJA to be significantly different between Equal and Value ($M = 4.33, SD = 0.77$), $p = 0.86$. For ratings of CMS, the results were significant, $F(2,150) = 5.54, p < 0.01$. Participants perceived CMS to be significantly higher when interacting with Equal ($M = 4.02, SD = 0.76$) vs. Legibility ($M = 3.58, SD = 0.87$), $p < 0.05$. Participants' ratings of CMS for the Equal and Value ($M = 4.03, SD = 0.71$) conditions were not significantly different, $p = 0.99$. In this study, we did not administer the post-study question regarding which teammate programs participants prefer.

B. Modified Navigation Study Results

Condition	Reward	Task Time (sec)	1st Correct Prediction	Confidence Change
Value (M)	88.75	46.41	2.65	2.24
(SD)	1.37	25.24	0.87	0.94
Legibility (M)	88.75	42.76	1.49	1.73
(SD)	2.36	19.24	0.54	1.03
$t(33)$	0.00	0.88	9.61	2.73
p	1.00	0.39	< 0.001	< 0.05

TABLE III

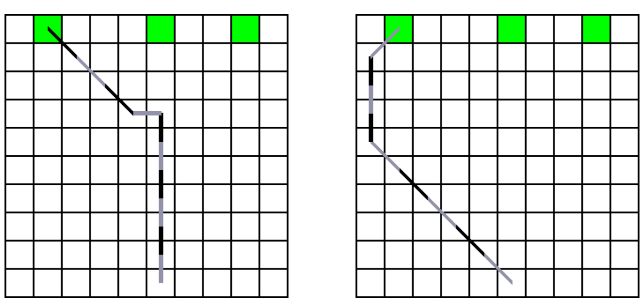
OBJECTIVE RESULTS FOR THE MODIFIED NAVIGATION STUDY.

We used a repeated-measures t-test to analyze the modified navigation study data (Table III). Our H2.1 hypothesis posited that the Legibility condition will enable participants to correctly predict the robot's goal earlier and with greater confidence than the Value condition. We found full support for this hypothesis; those interacting with the Legibility condition ($M = 1.49, SD = 0.54$) made their first correct goal prediction with significantly less robot moves than those interacting with the Value condition ($M = 2.65, SD = 0.87$), $t(33) = 9.61$, $p < 0.001$. Also, participants who used

Legibility ($M = 1.73, SD = 1.03$) were more confident in their goal predictions than those interacting with Value ($M = 2.24, SD = 0.94$) as shown by the significantly smaller number of confidence rating change: $t(33) = 2.73, p < 0.05$. Results of the repeated t-test were not significant for the average reward and task time. Figure 2 shows example paths from the Value and Legibility conditions.

Participants did not perceive MR to be significantly different between the Legibility condition ($M = 4.01, SD = 0.99$) and Value condition ($M = 3.72, SD = 1.04$), $t(33) = 1.00, p = 0.33$. Comparing participants' rating of CJA in the Value ($M = 3.99, SD = 1.08$) and Legibility ($M = 4.18, SD = 1.06$) conditions, the t-test was not significant: $t(33) = 0.86, p = 0.40$. The ratings for CMS were also not significantly different between the conditions (Value: $M = 3.66, SD = 0.0.99$; Legibility: $M = 3.70, SD = 0.97$; $t(33) = 0.21, p = 0.84$). These subjective results did not provide support for our H2.2 hypothesis regarding ratings to be higher for Legibility in comparison to Value.

We analyzed participants' responses to the post-study question, "Out of the two robot teammate programs, which one do you prefer? Why?". The majority, 76% (26 participants), preferred the Legibility condition, and 18% (6 participants) preferred the Value condition. One participant indicated having no preference, and another indicated not noticing a difference between the conditions. One participant's reason for preferring the Legibility condition was "because it was clear what it's intentions were from the start. It even overshot the goal to make sure it was clear where it was going". On the other hand, a participant who preferred the Value condition commented, "I think I liked the second one (Value) because it didn't make wasteful moves. The first one (Legibility) moved too far left or right sometimes for no real purpose".



(a) $w_V = 1.0, w_F = 0.0, w_L = 0.0$ (b) $w_V = 0.7, w_F = 0.0, w_L = 0.3$

Fig. 2. Examples of paths from the modified navigation user study. The Value condition is (a) and Legibility condition is (b). Goals are green, robot actions are gray, and human actions are black.

C. Tower Assembly Study Results

We analyzed the tower assembly study data using a repeated-measures t-test (Table IV). There was not a significant difference in the average reward, task time, or total actions between the Value and Effort conditions. Comparing the human exhaustion level between the conditions, results of the repeated-measures t-test was significant: $t(27) = 3.72, p < 0.001$. Consistent with our prediction, participants were significantly less exhausted while working in the Effort condition ($M = 58.87, SD = 11.61$) compared to the Value condition ($M = 65.17, SD = 11.59$).

Participants rated MR to be significantly higher after interacting with the Effort condition ($M = 4.46, SD = 0.57$) in comparison to the Value condition ($M = 4.15, SD = 0.64$), $t(27) = 3.20, p < 0.01$. For CJA, participants did not perceived a significant difference between the conditions (Value: $M = 4.36, SD = 0.80$; Effort: $M = 4.52, SD = 0.67$; $t(27) = 0.85; p = 0.40$). Participants' rating of MS was not significantly different between Effort ($M = 4.51, SD = 0.55$) and Value ($M = 4.31, SD = 0.64$), $t(27) = 1.51, p = 0.14$. These subjective results partially supported our H3.2 hypothesis that Effort would be rated higher than Value.

We categorized participants' responses to the post-study question and found that 57% of them (16 participants) preferred the Effort condition and 32% (9 participants) preferred the Value condition. One participant liked both conditions equally. Another participant indicated not noticing a difference between the conditions, and one participant did not provide a response. Participants who preferred the Effort condition noticed the robot displaying higher effort as shown by their comments. One participant wrote, "The robot went out of its way to make sure I used as little energy as possible". Comments from participants who preferred the Value condition included, "I felt like the robot knew what I wanted to do better".

Condition	Reward	Task Time (sec)	Total Actions	Exhaust (%)
Value (M)	55.18	49.47	19.38	65.17
(SD)	16.11	12.90	7.80	11.59
Effort (M)	53.56	51.38	18.27	58.87
(SD)	11.68	16.00	5.16	11.61
$t(27)$	0.53	0.85	0.02	3.72
p	0.60	0.40	0.98	< 0.001

TABLE IV

OBJECTIVE RESULTS FOR THE TOWERS STUDY.

VII. DISCUSSION

We present TASC, a robotic teammate algorithm, that enables a robot to select cooperative actions that take into consideration the action's legibility, effort, and value. We expect that a robot that exhibits behaviors that are characterized by all the SCA facets will be perceived by the human teammate as collaborative. We evaluated TASC in three different simulated tasks using human participants.

We first evaluated TASC in a cooperative navigation gridworld study where the participant knew the goal and the robot did not. The results showed that prioritizing *value*, or setting *value*, *effort*, and *legibility* to be equal performed significantly better than prioritizing *legibility*. The Value and Equal conditions collected higher rewards, took shorter paths, and were more highly rated by participants. Our hypotheses were that Equal would outperform Value and Legibility in both the objective and subjective measures, but it only outperformed Legibility. This outcome may be caused by certain aspects of the navigation task, in particular, participants may have preferred reaching the goal faster which the Value condition also satisfied. Most importantly, we found that w_V should be at least equal to w_F and w_L for this particular task domain where the shortest path is the best solution. That is, in the task used, CMS must be weighted highly to ensure teammate performance.

We followed up with another experiment on the same task, for which the robot knew the goal *a priori* instead of the human. These results revealed that giving weight to *legibility* performed equivalently to only weighting *value* on reward and task time. In other words, there was no trade-off between legibility and efficiency. In fact, giving weight to *legibility* improved teamwork, specifically enabling participants to be significantly better at predicting goals, with significantly greater confidence and earlier, supporting our H2.1 hypothesis. Participants also preferred the Legibility condition to the Value condition, although they did not rate it more highly in SCA terms. *Value* and *legibility* both lead the robot to the goal state, which may have influenced participants to rate the SCA components equally. This experiment's result suggest that when the human does not know the goal, CMR need to be given weight to ensure team performance.

Finally, we assessed TASC in a tower assembly task to explore the influence of CJA and CMS on teamwork. Consistent with our H3.1 prediction, our results showed that teams in both the Effort and Value conditions were equally fast at completing the task (i.e., no trade-off with efficiency), while adding weight to *effort* for the robot allowed participants to use significantly less energy. Participants rated Effort more highly in terms of MR, and they preferred it over Value which partially supported our H3.2 hypothesis. Since this task had a large variation in action efforts, the robot needed to weight CJA to ensure the robot's contribution to the team.

These three sets of results together suggest that for different tasks, the weights on *value*, *effort*, and *legibility* need to be appropriately tuned, and thus all three are important facets of human-robot teamwork. All three facets of SCA must be apparent for teammate activity to occur, but different tasks require different weights on the three in order for people to perceive the robot behavior most favorably. TASC provides a method of weighting these facets during a task. Future work should evaluate TASC in user studies with a physical robot and different types of collaborative tasks.

The contribution of our work is applying the SCA concept in human-human teaming to the human-robot teaming domain and mathematically modeling SCA to develop a new robotic teammate algorithm to enable a robot to become a full-fledged team member. Our work opens up a multi-dimensional space for teamwork that can be explored. Learning algorithms, such as reinforcement learning, can be applied to find optimal weight combinations for different types of collaborative tasks.

VIII. CONCLUSION

To achieve effective teamwork, robots must be endowed with intelligent behavior along multiple dimensions since teamwork is a multi-faceted concept. Working towards this goal, we present TASC, a robotic teammate algorithm that is inspired by Bratman's SCA concept for human-human teamwork. We focused on enabling the robot to consider the SCA facets in its action selection. We evaluated TASC in simulated cooperative tasks using human participants and demonstrated that it enables the robot to be a cooperative teammate that displays the three SCA facets resulting in improved teamwork.

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