Effects of Robot Motion Timing on Human-Robot Collaboration and Trust

Deanna Kocher
Cornell University
Ithaca, USA
drk225@cornell.edu

Jijie Zhou
Cornell University
Ithaca, NY
jz888@cornell.edu

***Abstract*—We evaluate robot path timings with cost function algorithms to optimize a mobile robot's ability to express its internal state. Path timing, like the path itself, can convey a great deal of information to a human collaborator. These timings, however, are often hand generated, and algorithms are specific to set robot tasks and configurations. To address this, we apply two cost function algorithms that were developed on a robot arm (confidence and naturalness) [1] and implement them on a mobile robot with automatically generated timings. We further propose a new cost function to combine both of these metrics. We evaluate the algorithms' effectiveness with a human-robot collaboration study. In our analysis, we measure participant's perceptions of the robot motion and their trust in the robot, as well as objective measures of their performance during the task.**

Keywords—motion timing, expressive motion, human-robot collaboration

I. Introduction

The difference in the trajectory and the timing of a robot's motion can lead us to make different interpretations of that motion. When a robot is completing a task with a human or interacting with a human, the human is forming inferences about the robot and its motion as it moves. A path that is followed with a consistent, slow velocity will be perceived differently than one with a consistent, fast velocity or one that has a number of pauses along the way. Such interpretations can have significant impacts on human-robot collaboration, and on an individual's understanding of a robot. Therefore, metrics that can help map the robot motion timing to human's perception are crucial to help improve interactions between human and robots.

Past research focused mainly on the kinematic of robot motion and for this reason motion planners primarily focus on trajectory optimization. Planning algorithms such as RRT [2] and visibility roadmaps [3] are examples of ways to search for efficient trajectories for a robot to complete a motion in a known region. In addition, there are a number of algorithms, such as CHOMP [4], for trajectory optimization. Early studies on optimizing path timing are limited, focusing only on designing time-optimal trajectories [5].

Zhou et al. [1] presented a human-centric approach to path timing by concentrating on the way individuals interpret different timings along the same trajectory. They focused on a simple but common task in human-robot interaction (HRI): a hand-over. They tested a number of different hand-over timings, varying the robot's speed, number of pauses, and changes in speed. Participants then evaluated the robot's competence, confidence, disposition, naturalness and the weight of the object the robot is holding. They found that different timings over the same path can greatly impact how people think of the robot's intention and capability. From there, they developed mathematical models for a robot's confidence, naturalness, and the weight of the object it is carrying.

Such models, however, may be limited to handovers and robot arm configurations. In addition, their implementation utilized only hand-crafted path timings that were developed specifically for their experiments. It was not clear how the magnitude of the velocity was decided and why the velocity patterns chosen were sufficient to study the effects. Moreover, the mathematical model they designed was mapped only to their experimental data; there was no evaluation of new timings with these models, and there is no validation that these models will work in other scenarios.

To address this, we implement the mathematical models from Zhou et al. [1] in a more general HRI scenario, with a new robot configuration. Our implementation is demonstrated in ROS Turtlesim, and the experiment could be done with any mobile robot, such as a Turtlebot or a Vektor Robot. We apply two of the cost functions from Zhou et al. [1]: naturalness and confidence. A combined metric is introduced, which allows for the two cost functions to be combined into a single metric. In our implementation, we divided an experiment-specific trajectory into waypoints and automatically generated random timings rather than using hand-crafted timings. We then designed a collaborative human-robot task that allows for objective and subjective analysis of the impact of these timings, to verify and improve the models.

II. Cost-Functions for Path Timing

The cost functions developed by Zhou et al. [1] have a basis in Bayesian inferences. Individuals watching a robot movement form inferences about the robot's internal state as they watch the motion, and update that inference as they receive new evidence from the robot. The full formulation can be found in Zhou et al. [1]; our formulation focuses on the application of two specific cost functions: confidence and naturalness. The generalized form that we arrive at, after applying Bayes' theorem, is

$$P(T|q,\theta) \propto e^{-\lambda C(T;q,\theta)} \quad (1)$$

where C(T; q,θ) is the cost function.

A. Confidence

Confidence, τ, increases with speed and decreases with pauses [1]. However, higher speed also decreases the opportunity for individuals to observe the robot and update their belief states. Thus, the following function is proposed:

$$C(T;q,\tau_0) = kT_N + \frac{1}{\tau_f} \quad (2)$$

where τ_f is the final confidence, T_N is the overall time to complete the motion, and k balances the relative importance of speed versus the observations individuals can make while the robot moves (included in τ_f [1]).

For our implementation, we initially used the values for k, and λ from Zhou et al. [1], but found that this was not a good fit for our mobile robot. Thus, we updated k and λ experimentally, such that none of the path timings were driven to 0. We found that k = 0.1 and $\lambda = 1.9$ met this requirement. No other adjustments were made, as we were interested only in the ranking of each timing (maximum and minimum confidence) and not their specific confidence scores.

B. *Naturalness*

The naturalness model is more straightforward, seeking only to minimize jerk along the path. It is presented as the sum of the total trajectory time, T_N, and the squared jerk along the path.

$$C(T; q, k) = kT_N + \sum_i \|J_i\|^2 \tag{3}$$

We found that the suggested k value [1] for the naturalness algorithm was also driving values to 0, so k was revised to k = 0.5. This value will vary depending on how timings are generated, as our timings were generated randomly and thus had low naturalness scores.

C. *Combined Metric*

Because the confidence and the naturalness algorithm seek to optimize different behaviors, their resulting optimal motion timings are significantly different. Thus, we sought to combine these two functions into a single metric to provide a path that was relatively fast with minimal jerk. This combined score was created with a multiplicative objective function,

$$f(\hat{x}) = \prod_i v_i {a_i}^{w_i} \tag{4}$$

where a_i represents the objectives (confidence and naturalness). We balanced the weight of each objective, such that the maximum combined score was not the maximum confidence nor the maximum naturalness timing, but a path timing that was high scoring in both. The same logic was applied to the minimum scores. This resulted in the following equation for our combined scores

$$f(n, c) = n^{\frac{1}{10}} * c \tag{5}$$

where n is the naturalness score and c is the combined score.

D. *Generating Random Path Timings*

Rather than hand-crafting different path timings, we opted for automatically generating random timings, within a set of constraints. Our path timings consisted of 17 Turtlesim velocities, that moved the turtle between a set of 18 waypoints (Figure 1).

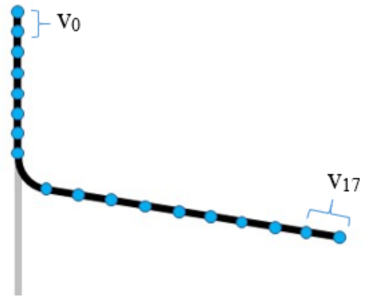

Fig. 1. Turtlesim motion path with waypoints and velocities

All Turtlesim velocities were limited to a range of 0.1 to 0.9, at increments of 0.1. We generated 550 random sequences in this manner, but found that most paths were still significantly jerky, yielding low naturalness scores. To address this, for half of those sequences, we added an additional smoothing calculation (Equation 6). Because this limited the maximum speed the robot could achieve (and thus decreased the confidence scores) the other half of the timings were not smoothed.

$$f(v) = \begin{cases} \sqrt{v} & if\ v < 0.5 \\ v^2 & if\ v > 0.5 \end{cases} \tag{6}$$

E. *Timing Selection*

For our implementation, we focused on the maximum and minimum scores for each of our cost functions: naturalness, confidence, and combined scores. Because the minimum scoring paths for each metric were all fairly similar (primarily low velocities, with some jumps to high velocities), we chose only to execute the minimum combined score. The median combined score was used as our baseline motion condition. The mean was not used as our data was subject to outliers and was not representative of a centralized path timing.

III. Hypotheses

We anticipate that the path timing participants experience will impact their performance in the collaborative task and subjective interpretations of the robot.

H1. Preferred Path Timing. *The maximum combined score will be the most preferred timing, as it integrates both naturalness and confidence. Between the other two maximum scores, maximum naturalness will be preferred over maximum confidence.*

H2. Objective vs Subjective Metrics. *While individuals will have significantly different subjective interpretations of the robot motion, their behaviors will not see the same degree of variation.*

H3. Trust in the Robot. *Individuals trust in the robot will be positively correlated with the naturalness of the path timing. Increased jerkiness will lead to a decrease in trust.*

IV. Experimental Design

To explore the effectiveness of this motion timing algorithm, we conducted a within-subjects study wherein participants collaborated with a mobile robot in a food service task. In the task, the human is responsible for the physical process of steeping the tea, while the robot is responsible for "taking orders" and relaying them to the participant.

A. *Task*

The tea-making task is set up such that the participant cannot see into the room where the confederate students are, and the participant is required to stay at the supply table while the robot enters the room, takes a tea order, and relays it to the participant via two floor markers (Figure 2). While the participant will be told that the robot takes orders verbally, the robot is in fact hard coded to follow set paths and timings. There is one practice trial, where the robot takes the main researchers request and drives to the earl grey marker. Four experimental trials follow this, executing the maximum naturalness, maximum confidence, maximum combined, and minimum combined path timings.

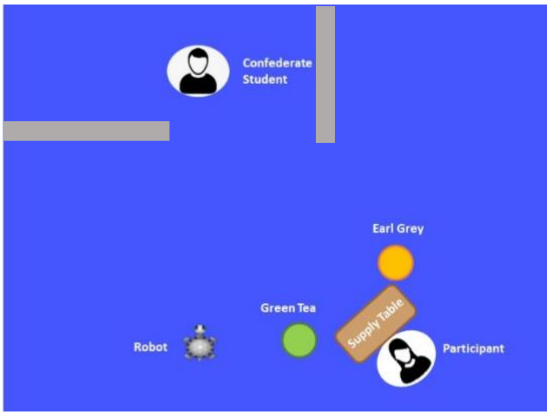

Fig. 2. The experiment setup with the robot at its intial position

B. Procedure

Participants were brought into the study room and shown the tea-making setup for the task (Figure 2). The materials for making tea were on the table for the participant to access, while markers for each of the two types of tea were laid out on the floor for the robot. The participant was told the following:

"This robot has been programmed to take tea orders from students, and it can relay orders to you by driving over to the markers on the floor. There are four different graduate students in the study room who love tea and are going to give the robot their tea orders. Since they are in a study room, however, they will have to tell the robot their order quietly, and the robot has trouble understanding orders at low volumes. The robot can convey how well it understood the order by the way it drives over. If at any point you feel the robot took the order incorrectly, you can send the robot back to re-take the order, or you can simply select the other type of tea."

The participant is then shown a button to press to send the robot back, and the robot motion is demonstrated with a trial run, wherein the researcher tells the robot they prefer black tea (Figure 3). At this point, the robot executes the median combined score path timing and drives across the room and over to the black tea marker.

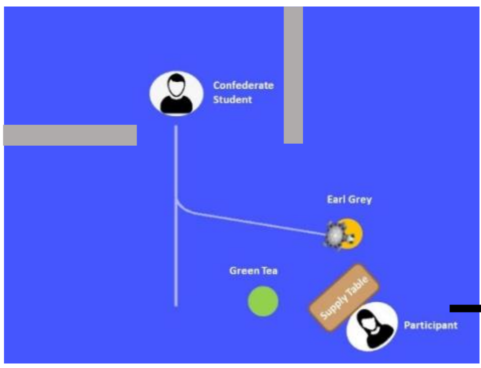

Fig. 3. The experiment setup with robot path, after the practice trial

After the robot arrives at the marker, the participant is asked to make the black tea so that they are familiar with the hot water heater, the different types of tea, and the requirements for steeping. While the robot takes orders and comes back to the markers, the participant will be asked to make and steep the tea. This tea steeping period is critical, as it allows the participant to have a clear task, while also allowing them ample time and motivation to watch the robot motion. Once they have completed the trial run, the test trials begin with the robot driving back across the room to take the first order. This repeats four times. Between each trial, the participant will be asked to fill out a short survey about how the robot motion and interaction. The interaction will be videotaped, for analysis of participant behaviors.

C. Participant Assignment Method

A total of 35 participants will be recruited from the community to participate in the study. The first ten of these participants will have participated in the pilot, to measure effect sizes and any changes that may need to be made to the final study. If no effect is measured in the pilot, the robot motion timings may be re-generated with a wider range of velocities and a different smoothing algorithm to increase the range of naturalness scores.

The experiment is set up to be within-subject, so that each participant can make comparisons between the different path timings. The timings will be randomized for each participant to control for order effects. Over the four trials, the robot will alternate going from the earl grey marker to the green tea marker (Figure 4). This pattern is consistent for all participants and only the timings will vary.

Fig. 4. Task trials alternating types of teas, randomizing the timing conditions, and showing the send back option.

D. Dependent Measures

1) Objective Measures

The experiment is designed to give participants multiple ways to express doubt or trust in the robot through their behaviors during the task. They have the option to a) delay when making a tea bag decision b) choose to send the robot back to re-take the order and c) choose the opposite tea back indicated by the robot. These are discussed in detail below.

a) Decision-making time and task completion time

Decision-making time will be determined through a frame by frame video analysis of the time between the robot's arrival at the target and the participant's decision to either steep the tea (when they select a tea bag) or to send back the robot to repeat the trial. If a participant sends the robot back, the time it takes to make this decision will be summed with the time it takes to select a tea bag after the robot returns. We will also record the overall task-completion time to evaluate the efficiency of the collaboration.

b) Number of repeating trials and choice of teabag

This will be recorded as the number of times the participants sends the robot back, and whether their final teabag choice agrees with the robot (1) or not (0).

2) Subjective Measures

Since our participants will not be aware of the timing condition for each trial, we will not use comparative subjective metrics such as the User Experience Questionnaire (UEQ)and NASA Task Load Index (TLX) to evaluate the effects of the timing. Instead, we designed the following questions to assess the quality of this cooperative task.

1) *How do you describe the motion of the robot?*
2) *If you sent back the robot to repeat the trial, why?*
3) *How much did the robot contribute in this task?*
4) *How much did you trust the robot?*
5) *Is the robot competent to finish the job?*
6) *Of the four trials, which would you prefer to work with?*

Question 1 and 2 are open-ended question, so participants will not be biased on how to interpret the motion and their decisions. Questions 3, 4, and 5 will be on a Likert Scale. Participants will assign scores ranging from 1 to 5 (from not at all to a lot) to represent the degree of each feature. A score of 3 will represent a neutral point of view.

Participants will answer these questions between trials (while the tea is steeping) so they can accurately report on their experience immediately after seeing the path timing. At the end of the task, participants will be asked question 6. If the participants are willing to elaborate, the recorded answer will be used for further qualitative analysis.

V. Analysis

We first analyze the effects of the combined score based on naturalness and confidence. We will use a regression analysis to see if participants tend to select trials with higher combined scores in question 6. A positive correlation will indicate H1 is confirmed.

To validate H2, we will need to analyze the results from both subjective and objective measures. We will first look at the objective metrics of decision-making time, T_d, and the number of repeat trials, n_{repeat}, among all the sessions. For T_d, we will test for significance with a one-way repeated measures ANOVA. For repeat trials, we anticipate that participants will not send the robot back more than once, and so we will treat n_{repeat} as a binary variable and test for significance with Cochran's Q. In addition, the mean and standard deviations of these two values will be computed respectively for each of the timing conditions. A smaller value of T_d will be interpreted as a higher degree of trust in the robot. Likewise, a smaller n_{repeat} can be seen as a higher efficiency in completing the task. The objective results will then be compared with the subjective responses to Q3, Q4, and Q5. We will analyze these Likert Responses with a two-sample t-test. While this assumes a continuous distribution, this parametric analysis has been shown to yield similar results to non-parametric analyses [6]. To confirm H2, we would expect to see small differences in the means of T_d and n_{repeat} and larger differences in the means from Q3, Q4, and Q5. These data should be negatively correlated, where longer decision times and more repeat trials are associated with lower subjective scores. H2 would also be validated if there are significant differences in subjective responses, but no significance in the objective metrics.

For question 3-5, we will compute the average, median and standard deviation for each of the timing condition and plot the data. If the variations of each term match the variation in the value of T_d and n_{repeat}, for example, when the trust value is lower, the value of T_d and n_{repeat} are greater, then we see a consistency in the way people perceive the robot and the reaction they behave. Otherwise, H2 is confirmed that human's behavior does not directly tell how they think about the robot.

Qualitative analysis will be done by grouping the answers into different categories to find out if the resulting effects match with our hypothesis and explore other crucial factors. First, representative adjectives and nouns will be clustered from the transcribed answers for each open-ended question. For example, for the first question about motion, we expect to see adjectives such as 'smooth' or 'jerky'. From there, synonymous adjectives (stop-and-go, seamless, fluid) will be clustered into these two categories. We are also expecting categorizations like 'fast' and 'slow' to describe the motion.

To assess H3, we will first test if there were significant differences in trust by condition (using a two-sample t-test). We will then compare differences in trust with the difference in the algorithms scores for naturalness and confidence. That is, we would compute the differences in trust between each condition, and then compute the difference in naturalness score and confidence score between the same two conditions. Because the range of naturalness and confidence scores vary in our implementation, the differences measured between conditions would be normalized by the overall range of naturalness and confidence scores (Figure 5). To confirm H3, we would expect to see that larger increases in trust between conditions are correlated with larger increases in naturalness score between those conditions. H3 would still be confirmed if there is a correlation with the difference in confidence score as well, if the difference in confidence score is less than the difference in naturalness score.

TABLE I. Sample Table for Trust and Naturalness

Condition	***Difference in Trust (Sample Data)***	***Naturalness***	***Confidence***
Combined Min – Combined Max	3.1	$\alpha_{nat} * (n_{c.min} - n_{c.max})$	$\alpha_{con} * (c_{c.min} - c_{c.\max})$
Combined Min – Naturalness Max	3.3	$\alpha_{nat} * (n_{c.min} - n_{n.max})$	$\alpha_{con} * (c_{c.min} - c_{n.max})$
Combined Min – Confidence Max	2.0	$\alpha_{nat} * (n_{c.min} - n_{con.max})$	$\alpha_{con} * (c_{c.min} - c_{con.max})$

Fig. 5. Table showing comparison of trust to differences in computed naturalness and confidence

From the last question, we will expect the participants to bring us potential factors brought by the timing issue that will greatly affect the task efficiency. There may be perceived motion characteristics that are yet to be discovered such as the fluency of the cooperation. Moreover, the answers to the last question will help eliminate data when repeating trials happen for other reasons aside from decisions based on the perceived robot motion.

VI. Discussion

Our experimental setup presents an opportunity to validate two previously proposed cost functions [1] and one new combined metric for confidence and naturalness. In addition, the collaborative experiment provides opportunities to assess both objective and subjective metrics of how participants experience robot path timing, and the effect size of the impact on each of these types of measures. We expect to find that subjective metrics will vary more than the objective metrics, as people will likely have stronger impressions of the robot but will be unlikely to send the robot back except in extreme cases. This, however, may be balanced by the concern for making someone the wrong type of tea, as participants believe that their actions have real-life consequences.

We also expect that timing will have a large impact on trust in the robot and its perceived competence. Movement that is jerky and unnatural may lead to a higher possibility that individuals' subjective perception will affect their behavior towards the robot. The motion smoothness may be a crucial factor that make individuals to change their objective behaviors and decisions.

There are a few limitations to this implementation and study. The first is that the paths between the two types of tea are of different lengths in the setup, and this may have a minor effect on how participants experience path timings, given that some participants may see a specific timing with the earl grey tea, and others may see it with the green tea. Second, our randomly generated velocities are not reflective of real robot constraints, though they were set up to be within a range of relatively safe speeds for collaboration. These random velocities may not be reflective of actual robot movement, and thus limit the generalizability of our results. Further, there may be a floor effect, wherein participants do not send the robot back or choose the opposite tea bag, regardless of path timing. This would leave decision time as our only objective metric, which would limit our understanding of participant's behaviors. While we hope to balance this with high consequences as the tea they are making is 'actually' being made for a graduate student, this still needs to be assessed in the pilot study.

VII. Conclusion

In this study, we validate two previously proposed algorithms by applying them to a new robot configuration and evaluating them with a human-robot collaboration experiment. Our findings may suggest that such algorithms can be implemented with only minor adjustments to the parameters. Additionally, our implementation suggests that the challenge in developing robot timings is not in applying these cost functions to rank timings, but in generating the timings themselves.

The full implementation code [7] and a demonstration video [8] can be found online.

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