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"Me and You Together"
Movement Impact in Multi-user Collaboration Tasks

Miguel Faria[1] Rui Silva[2] Patrícia Alves-Oliveira [3] Francisco S. Melo[1] Ana Paiva[1]

Abstract— **This paper presents a study on collaborative manipulation between an autonomous robot and multiple users. We investigate how different motion types impact people's ability to understand the robot's goals in a multi-user scenario. We propose an approach based on Collaborative Probabilistic Movement Primitives to generate the robot's movements, exploiting predictability and legibility of movement to express intentions through motion. We compare the impact on the interaction of using only either predictable or legible movements, and propose a third approach —hybrid motion—that selects, in each situation, whether to execute a predictable motion or a legible motion, depending on what the robot perceives as more efficient for the multi-user collaboration effort. To test the impact of the three motion types in the context of a collaborative task, we run a user study using a Baxter robot that autonomously serves cups of water to three users upon request. Our results show that, in the particular case where all users simultaneously request water, the hybrid motion performs better than the other two.**

I. Introduction

As robots become more widely used in different aspects of our daily life, they should be able to interact successfully with the multiple human users with which they share their environment. In particular, social interactions require that the humans be able to interpret the robot's intentions, so that the actions of the latter do not cause confusion, surprise or even fear upon the humans. Such ability to interpret the robot's intentions is critical in situations where humans and robots co-operate, so that the humans can quickly adjust to the robot's actions, thus yielding more efficient interactions.

In this paper we investigate how different motion types impact the transmission of intent during a collaborative manipulation task between an autonomous robot and multiple users. Specifically, we study the effect of different motion types in both the *fluency* of the collaboration and in the *efficiency* of the intention transmission by the robot.

Our scenario involves an autonomous robot serving as a "bartender", pouring a cup of water to one of several customers. If the robot performs an unexpected motion, human users may become confused regarding whom the robot is trying to serve, which may eventually cause the wrong person to be served. On the other hand, if the intention of the robot is clearly perceivable, the chances of confusion decrease and the efficiency of the task improves.

In our approach, we use Collaborative Probabilistic Movement Primitives [1] to generate new movements for the robot, and rely on established notions of *legibility* and *predictability* [2] to express intention through motion. We contribute a novel approach that combines both legibility and predictability, depending on the situation, and thus leverages the advantages of both.

II. Related Work

Human-robot collaboration has been extensively investigated in the HRI community, both in terms of robot motion [3]–[6] and in terms of the interaction and communication of intentions [7]–[10].

In terms of robot motion for collaboration, existing works explore how a robot can safely move close to people during collaborative tasks [4], [11]. Such approaches use information about the movement of the humans and the layout of the environment to predict how the users will move. The robot then plans its own motion accordingly. Other works explore alternatives to the use of planning to determine the best movement to perform in a collaboration task [3], [5], [12], [13]. The robot learns from demonstration a set of movement primitives that are then generalized (modulated) to new targets. The learned movements primitives can be compactly represented as a dynamical system [5] or using a probabilistic representation [3]. In our work, we adopt a probabilistic representation in the form of Probabilistic Movement Primitives (ProMP) [14].

In terms of interaction for collaboration, several works have investigated the impact of communication during task execution, both implicit and explicit [10], [15], [16]. These studies show that different forms of communication (e.g., through body movement, touch, gaze, etc) play an important role during collaboration, because people tend to look for cues allowing them to infer the movements and intentions of their partners and adapt accordingly.

Driven by such conclusions, several mechanisms have been deployed on robots to facilitate interaction. In one approach, the robot identifies cues from humans to anticipate their actions and respond accordingly [17]. In another work, the robot movements were designed to be *anticipatory*, thus allowing humans more time to respond to the robot [8].

Particularly relevant to our work are the works of Dragan et al [2], [6]. These works investigate the use of both animation principles and anticipatory motion to create movements

[1]M. Faria, F.S. Melo and A. Paiva are with INESC-ID and Instituto Superior Técnico, University of Lisbon, Portugal. E-mail: miguel.faria@tecnico.ulisboa.pt and {fmelo,ana.paiva}@inesc-id.pt.
[2]R. Silva is with Instituto Superior Técnico, University of Lisbon, Portugal, and Carnegie Mellon University, Pittsburgh, USA. E-mail: rui.teixeirs.silva@tecnico.ulisboa.pt
[3]P. Alves-Oliveira is with INESC-ID and Instituto Universitário de Lisboa (ISCTE-IUL), CIS-IUL, Lisboa, Portugal. E-mail: patricia.alves.oliveira@inesc-id.pt

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that allow humans to quickly discern the robot's intentions. Dragan formalizes the notions of *predictability* and *legibility* in robot movement, and investigates how both types of movement (predictable and legible) impact collaboration between humans and robots. Their studies show that predictability and legibility can be used to improve a user's understanding of the robot's intentions [7], even in scenarios where the robot's objective is not easily identified. In this work we explore those same notions of legibility and predictability but in scenarios involving *multiple human users*, which increase the collaboration complexity given the fact that the collaboration is multi-sided making the motion decision more complex.

III. Scenario and approach

In our scenario, a Baxter robot interacts simultaneously with multiple users, successively pouring water in the cups held by the users (see Fig. 1). As the human users tend to approach the bartender when they believe that they will be served next, interaction is more effective if the motion of the robot can be easily interpreted by the different users.

In order to address this scenario, we developed an interaction control system for the Baxter that comprises three modules: a *vision module* that identifies the position of each cup using a Kinect camera; a *decision module* that selects which cup to fill next and generates the corresponding movement; and a *social interaction module*, responsible for making the interaction feel more natural by using facial expressions and/or speech.

The decision module uses Probabilistic Movement Primitives to generate the robot's serving motion. Serving motions are learned from demonstration and designed to take into account principles of predictability and legibility. In particular, at each moment the decision module decides whether to generate a *predictable movement* or a *legible movement*.

A. Predictability and Legibility

As described by Dragan et el. [2], predictability and legibility describe two distinct properties of a movement. *Predictability* is the property of a motion to match the movement that a person would expect if they knew the objective of the motion. *Legibility* is the property of a movement that allows a human partner to quickly infer the objective of the motion. While a predictable motion is more efficient, a legible motion allows another party to quickly understand its goal.

B. Movement Learning

We use an instance of Probabilistic Motion Primitives especially designed for collaborative interactions [1]. Collaborative Probabilistic Movement Primitives (CoPMP) build a probabilistic model of the intended motion correlating both the degrees of freedom of the robot and additional degrees of freedom foreign to the robot (for example, of a human user). This probabilistic model is typically learned from demonstration, and provides a compact representation for a set of (similar) demonstrated trajectories in both spacial and temporal terms. The consideration of the DoF of the human user allows the robot to naturally modulate its motion depending on the pose of the human user. Additionally, CoPMP are also very sample efficient [1], allowing the robot to capture a motion from a couple of demonstrations.

In this work, we use CoPMPs to model, separately, predictable and legible movements. At run time, one type of movement is selected and the trajectory generated from the corresponding CoPMP. The trajectories used to build the CoPMP were demonstrated using kinesthetic teaching and designed from the principles in [2]. Predictable trajectories are more direct and "unsurprising"; legible motions seek to explicitly communicate the movement's target, generally by performing wider movements that steer away from the other possible targets as much as possible. The CoPMPs obtained for both motion types were then validated by human users.

C. System Architecture

The overall system is built over ROS. The vision module uses the data sent from a Kinect v2 camera to determine the 3D position of the target cups. In particular, the color image is segmented to determine the position of the different cups in the image and the depth image is then used to determine the centers of mass for each cup in real world 3D coordinates.

The movement decision module uses the data from the vision module to decide which cup to serve next. The decision is based on the distance of the different cups: the system selects the closest reachable cup that has not been served yet. After the cup is selected, the serving motion is generated conditioning the CoPMP model to finish slightly above the computed center of mass of the selected cup. The movement is then executed using the joint trajectory action server on Baxter. The decision module also communicates with the social interaction module whenever some specific interaction with the user is necessary for the task to complete.

Finally, the social interaction module is responsible for displaying facial expressions that relate to the task stage. For example, the robot displays a happy face after performing a successful movement. It also follows the movement of its own arm during the serving motion, much like humans do when pouring a drink. Additionally, the robot also interacts through spoken utterances to greet the users, explain the task, or ask the user to reposition the cup when out of reach.

D. Hybrid Movement

In this work, we investigate for the first time how legibility and predictability impact the interaction between a robot and *multiple users*. In particular, in the context of multi-user interaction, the robot should be able to select, *in runtime*, whether a legible motion or predictable motion is more adequate, depending on the current context of task. We thus developed an approach that, given a target cup and the task context (e.g., the state of the other cups and the position of the different users), decides whether to perform a legible or a predictable motion. The selection is done by checking whether a legible movement towards the target cup would be more expressive than executing a predictable movement. This verification relies on the following criteria:

- When the intended target is closely surrounded by other possible targets, a more direct (predictable) movement is preferable to a wider (legible) movement;
- When the intended target has other possible targets on one side alone, a legible movement from the side with no other targets is preferred to a more predictable movement;
- When the target has other possible targets nearby, on the side that the robot will approach—e.g., when the robot is reaching the leftmost cup with the right arm and there are other cups on the right of the objective cup—a predictable movement is preferred to a legible movement;
- Finally, if there is only one target remaining or there is no ambiguity regarding intended target, a predictable movement is preferred.

To determine when a target is sufficiently close to affect the expressiveness of a legible movement, we tested different configurations and found that, for distances smaller than 50cm between possible targets, people find legible movements to be more confusing than predictable movements. We used this value as the minimal distance that a cup should be from other cups on the side of the executing robot arm for the robot to execute a legible motion. We also concluded that when the distance between targets is close to the diameter of a cup, a predictable motion is preferred to a legible one.

IV. User Study

We conducted a user experiment using the system described above, where a Baxter robot interacted simultaneously with three users, successively serving water to the different users. A total of 33 participants, recruited from the Lisbon area, participated in the study, out of which 22 were male and 11 were female. Their ages ranged from 19 to 33 years old, with a mean age of 23 years old. The participants were randomly matched in groups of three, according to the availability of each participant.

A. Experimental Design

The task was designed to test how the users' perception of robot motion is affected when they have to collaborate with a robot to achieve a common goal (having the respective cup filled with water) while other people try to achieve a possibly concurrent goal. Ideally, the users should collaborate both with the robot and one another, so they are served as soon as possible and without anyone being served out of order.

Figure 1 illustrates the setup during an experiment. Each group of three participants interacted with the robot three times, one for each motion type (predictable, legible and hybrid). The order of the different motion types was randomly selected, to prevent influence across groups of users.

Each interaction consisted of three movements of the robot, one for each cup. For the purpose of the study, and to prevent a serving pattern that the participants could exploit, the robot randomly selected the next cup among those that were reachable and not yet served. Such random selection also forced the participants to be focused on the motion of the robot, giving it a leading role in the interaction and emphasizing the importance of the robot's movement. The participants were asked to individually figure out who the robot was serving next and facilitate the task, either by moving their cup slightly away (if they thought they were not being served) or by complying with the robot's movement (if they thought they were being served). After each interaction the participants answered a questionnaire to evaluate the most recent interaction.

Fig. 1: Scenario layout. The robot on the right serves each of the users on the left. The cups are filled by no particular order and the participants should respond to the robot's movement.

In order for the participants to be familiarized with the robot's motion and its motion and reduce the novelty effect, each group performed a training interaction with the robot, before starting the evaluation process. In this training interaction the robot always performs predictable movements, since they are more direct and expectable.

B. Hypotheses

In our study, we investigate the following hypotheses:

- **H1** The type of movement impacts the collaboration.
- **H2** Participants prefer hybrid motions to legible motions and legible motions to predictable motions.
- **H3** Hybrid motions are seen as more legible and predictable and result in more efficient task execution.
- **H4** Hybrid motions will not be perceived as more confusing than the other two.
- **H5** The type of movement will not impact the perceived intelligence of the robot.

C. Metrics

To evaluate the collaboration between the robot and the humans we used both objective and subjective measures.

In terms of objective measures we analyzed the reaction time and number of errors for each participant across all conditions. The reaction time was measured for each participant, in each condition, in two ways: the time it took, from the beginning of the robot's movement until the participant understood the robot was moving to him, when the robot was moving to that participant; the average time it took, from the beginning of the robot's movement until the participant

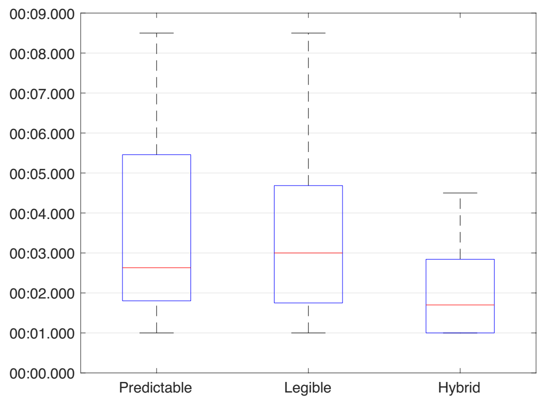

Fig. 2: Average time that each participant took to understand that the robot was serving him/her, organized per movement type.

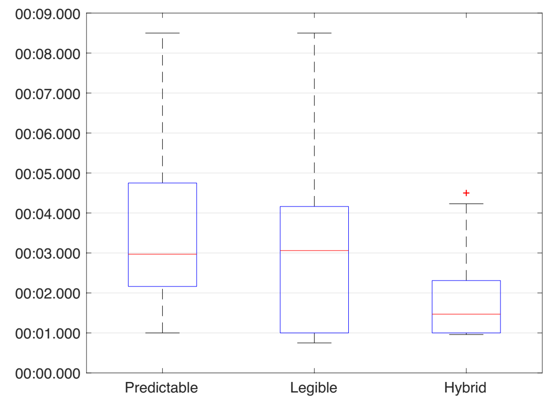

Fig. 3: Average time that each participant took to understand that the robot was *not* serving him/her, organized per movement type.

understood the movement was not for him, when the robot was moving to another participant.

Regarding the number of errors, we considered an error when a participant was wrongly served. In these cases both the participant supposed to have the cup filled and the one that got the cup filled were considered as having failed and their reaction time was considered 8.5 seconds (the time it took for the robot to complete a full movement).

The subjective measures intended to evaluate the perceived collaboration and fluency of the task, the perceived legibility and predictability of the movements and the perceived animacy and intelligence of the robot.[1] All subjective measures were taken once for each participant for each condition.

Finally, after the three interactions, the participants answered four forced-choice questions about which of the movements was their favorite, less confusing, easier to work with and with which they were faster with.

V. Analysis of the Results

A. *Objective Measures*

The analysis in terms of the objective measures considered the following occurrences for each condition: reaction time to understand the robot is moving towards the participant; reaction time to understand the robot is moving to another one of the participants; number of times people wrongly understood the robot's movement.

Figure 2 presents the average time it took each participant to understand that the robot was serving him/her, for the three types of motion. The data does not follow a normal distribution because of two occurrences: participants wrongly understood that the robot was moving towards another participant; and participants served last already knew they were next and immediately started collaborating with the robot. Given the non-normality of the data, we performed the Friedman Test concluded that there is a statistically significant difference in the time it took depending on the type of movement executed, with $\chi^2(2) = 11.546, p = 0.003$, which is in line with **H1**.

Post hoc analysis with a Wilcoxon signed-rank tests was conducted with a Bonferroni correction applied, resulting in a significance level set at $p < 0.017$. Median (IQR) reaction time until a participant understands that the robot is moving towards him/her for the predictable, legible and hybrid motions was 2.63s (1.77s to 5.63s), 3.00s (1.63s to 4.79s), and 1.70s (1.00s to 2.85s), respectively. There were no significant differences between predictable and legible motions ($Z = -0.78, p = 0.946$). However, between hybrid and predictable and between hybrid and legible motions, hybrid motions' reaction times were significantly lower than predictable motions' reaction time ($Z = -2.695, p = 0.006$) and legible motion's reaction time ($Z = -3.940, p < 0.001$). These results are in line with **H3**.

Figure 3 presents the average time it took each participant to understand that the robot was serving another participant, for the different types of motion. Once again, the data is not normally distributed. We performed the Friedman test and found a significant difference between the different motion types, with $\chi^2(2) = 16.464, p < 0.001$.

We again administered a post-hoc test, the Wilcoxon signed-rank tests with a Bonferroni correction, resulting in a significance level set at $p < 0.017$. With this test we concluded that between predictable and legible motions there is no significant difference ($Z = -1.778, p = 0.77$), but between predictable motions and hybrid motions ($Z = -4.076, p < 0.001$) and legible motions and hybrid motions ($Z = -2.790, p = 0.004$) there is a difference. By looking at the median (IQR) the reaction times for predictable, legible and hybrid motions were 2,66s (1,54s to 4,44s), 1,59s (1,00s to 3,08s) and 1,11s (1,00s to 2,08s), respectively. Such conclusion again goes in line with **H3**.

Regarding the number of wrongly perceived movements,

- Out of the 33 predictable movements, 6 (18.182%) caused confusion on two people about who the robot

[1]Perceived collaboration and fluency were evaluated using the Hoffman's questionnaire [18]. Animacy and perceived intelligence were evaluated using the Godspeed questionnaire [19].

was directing the movement;
- Out of the 33 legible movements, 1 (3.03%) caused confusion about the robot's target;
- Out of the 33 hybrid movements, none caused confused regarding the robot's target.

Although there was no statistical difference, our results suggest that predictable motions are more confusing than the others, possibly because they are more direct and lead the participants to react more impulsively to the robot's motion.

B. Subjective Measures

The subjective measures were analyzed in terms of perceived fluency, perceived robot contribution, perceived trust in the robot, perceived safety and perceived robot capabilities to fulfill the task. Of these measures, only the perceived robot contribution had a non-normal distribution of the data. A repeated measures One-Way ANOVA was performed over the combined scores of each item in the fluency, trust, safety and capability metrics and a Friedman test over the combined scores of each item in the robot contribution metric.

The repeated measures One-way Anova tests showed that there were only marginally significant differences in the perceived fluency ($F(2,64) = 3.143, p = 0.050$). The robot contribution metric was analyzed using a Friedman test, which returned that there are no significant differences in terms of the robot contribution perceived by each participant in the different motion types.

These results in part contradict our **H1** hypothesis, because apart from the perceived fluency, the other measures to evaluate the perceived collaboration show that the participants did not notice any differences between robot motion type. Nevertheless, the participants rated the motion types consistently positive, which indicates that they perceived the collaboration between the humans and the robot correct and positive, across every motion type. Another aspect that is interesting is that the hybrid motion was, in average, rated as the most collaborative motion and the predictable motion was rated as the least collaborative one.

The analysis of the results for perceived predictability and perceived legibility was performed using the Friedman test, since both scales have a non-normal distribution. The results for the predictability measure show that there was no significant difference in perceived predictability of the different motions ($\chi^2(2) = 3.429, p = 0.180$). In terms of the perceived legibility, the Friedman test shows a significant difference between different motions ($\chi^2(2) = 7.431, p = 0.024$). A post-hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction applied, resulting in a significance level set at $p < 0.017$ and resulted in a significant difference between perceived legibility in hybrid and predictable motions ($Z = -3.075, p = 0.001$) and hybrid and legible motions ($Z = -2.446, p = 0.013$). Therefore, we can conclude that the hybrid motion was perceived as more legible than both the legible and the predictable motions, which is aligned with our **H3** hypothesis.

The animacy and perceived intelligence metrics were analyzed using a repeated measures One-Way ANOVA. Both tests returned that there were no significant differences among the motion types.The result for the perceived intelligence dimension goes in line with our **H5** hypothesis.

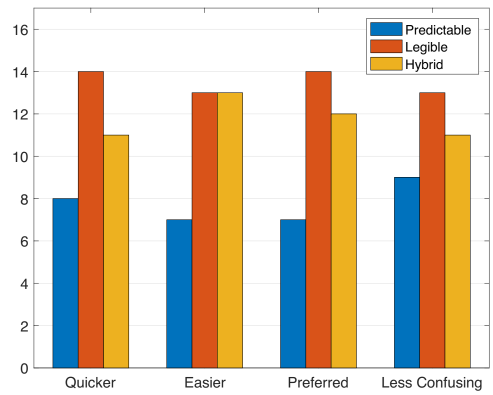

Fig. 4: Results for the forced choice questions.

C. Forced-choice Questions

The results of the forced-choice questions are summarized in Figure 4. The analysis of the forced-choice questions was done by analyzing the frequency that each motion type was selected in each one of the questions. Since we are dealing with nominal frequencies, we performed the Chi-Square Goodness of Fit and obtained that there are no significant differences between the motion types regarding which is preferred or which is less confusing.

In particular, in terms of which is the less confusing motion, the frequencies were very similar with 9 people saying that predictable motion was less confusing, 13 saying legible and 11 saying hybrid. This result is interesting, even more when contrasting with number of wrong inferences of the robot's objective that were presented previously: as shown previously 18% of the predictable movements caused doubts on the participants and the wrong one was served and in 3% of the legible movements the same occurred. However, the fact that hybrid and legible motions had a similar frequency of choice, as the least confusing movement, goes in line with **H4**.

VI. Discussion and Final Remarks

In this paper we evaluate the impact of different motion types in a collaboration task between a robot and multiple people. Following the work of Dragan et el. [2], we investigated the use of predictable and legible motions in the interaction with multiple users, and proposed a third approach that seeks to capture the advantages of both the other two while mitigating their drawbacks. We tested the impact of the different types of movement in the interaction with multiple users through a user study with human users.

While some of our results agree with previous findings reporting in the human-robot collaboration literature, other results provide novel insights on how different types of movement can improve collaborative manipulation tasks.

The first result that we find important is that no significant difference, in terms of time that took between the robot starting to move and people understood the robot's objective, existed between predictable and legible motions. This is interesting because prior work concluded that legible motions contributed for less reaction times and total task times.

This difference in results can lead us to conclude that although legible motions are more expressive, the workspace configuration and the existence of other users play important roles on people's interpretation of the robot's objective based on its movements.

Another result that is important is that allowing the robot the freedom to choose between executing a predictable and a legible motion, depending on the workspace configuration, leads to better collaborations, both in terms of the time it takes for the participants to understand the robot's intentions and in terms of them to "read" the movement and adapt better to it.

The fact that both the perceived capability and intelligence of the robot did not show a significant difference is interesting, since it proves that even if the robot does a less natural or less rational movement - like executing a more wide movement - as long as it behaves as supposed (it fulfills its collaboration role) people think he is capable and intelligent.

Overall, with this work we showed that when there are multiple people engaging the robot simultaneously, and so each person does not focus his attention solely on the robot, executing only predictable or legible motions does not necessarily improve the collaboration. However, allowing the robot to choose between executing a more direct or a more readable movement, depending on the configuration of the objectives in the workspace, leads to less confusion among the humans involved in the task and reduces the time people take to understand if the robot is moving for them or not. All of this without negatively impacting the perceptions of collaboration and the task's fluency.

In the future, we plan to improve the hybrid approach by exploring ways of the system learn to recognize situations were a predictable motion is better than a legible motion and vice-versa and to allow it to generalize such conclusions to situations not predicted. We are also interested in studying the influence of using other communication means besides the robot movement, in how people perceive the robot's objective. Finally, we think that it would be interesting to see if the same results, regarding the hybrid approach, would hold if more complex scenarios, where people would not be just waiting for the robot to move but also were engaged in other activities.

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