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Toward Human-like Teleoperated Robot Motion: Performance and Perception of a Choreography-inspired Method in Static and Dynamic Tasks for Rapid Pose Selection of Articulated Robots

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Abstract— **In some applications, operators may want to create fluid, human-like motion on a remotely-operated robot, for example, a device used for remote telepresence. This paper examines two methods of controlling the pose of a Baxter robot via an Xbox One controller. The first method is a joint-by-joint (JBJ) method in which one joint of each limb is specified in sequence. The second method of control, named Robot Choreography Center (RCC), utilizes choreographic abstractions in order to simultaneously move multiple joints of the limb of the robot in a predictable manner. Thirty-eight users were asked to perform four tasks with each method. Success rate and duration of successfully completed tasks were used to analyze the performances of the participants. Analysis of the preferences of the users found that the joint-by-joint (JBJ) method was considered to be more precise, easier to use, safer, and more articulate, while the choreography-inspired (RCC) method of control was perceived as faster, more fluid, and more expressive. Moreover, performance data found that while both methods of control were over 80% successful for the two static tasks, the RCC method was an average of 11.85% more successful for the two more difficult, dynamic tasks. Future work will leverage this framework to investigate ideas of fluidity, expressivity, and human-likeness in robotic motion through online user studies with larger participant pools.**

I. Introduction

Robot operation in dynamic environments requires that a human can communicate complex movement designs to a robot. In particular, many tasks can leverage surface contact with a particular shape of robot arm, such as folding a large piece of paper, using proximal joint linkages to hold wide swaths of paper in place before creasing. Additionally, the expression of the robot and the relationship between the operator, robot, and any humans in the vicinity of the platform are valuable aspects of teleoperation. To this end, we suggest that rapid joint-space control for robots may offer increased flexibility in dynamic environments, including applications where the specific shape of the robot arm offers greater functionality for task completion, and more success in human-facing environments where a human-like, fluid quality to the robot motion may be desired.

Teleoperation presents various challenges for human operators, including remote perception and manipulation [1]. Determining the best way to transfer user input to robotic output given a set of constraints is something that demands attention and researchers are investigating several methods of controlling a robot, including traditional joystick, body part tracking [2], and whole-body teleoperation [3].

Articulated surgical robots such as the Zeus and the da Vinci are guided by a surgeon via remote control that translates the hand movements of the surgeon to the end-effector [4]. If given a specific end-effector position, inverse kinematics (IK) may be used to determine the joint angles for the robot. This analytical problem is well studied and several numerical solvers exists for IK [5], [6], [7]. However, if used by itself, IK may present singularities in which a specific end-effector position may be reached with various joint angles. Thus, the corresponding joint angles for a specific position may be difficult to find [8]. Furthermore, the greater the number of degrees of freedom of the robot, the more computationally expensive IK becomes [9].

Moreover, innovative interface techniques have improved performance, e.g., a "point-and-click" interface that gives users better situational awareness [10]. Gesture-based interfaces have also been proposed [11]. For teleoperated articulated robots with pose specification available, such as the PackBot, commands are usually created in a joint-angle-by-joint-angle fashion, which is often labor intensive and results in low command frequency [12].

Robot motion generation may also focus on the ability for the framework to produce engaging, variable motion. This is often done by developing a library of poses that define the position of the robot in either two-dimensional or three-dimensional space. One such example of pose control is shown in [13], where a motion library is used to develop a desired trajectory of a quadrotor while an additional adaptation algorithm corrects the path within its desired accuracy. This consideration has been discussed in telepresence, where the way the artificial body looks and moves affects the perception of the remote human [14].

Thus, we differentiate between end-effector and joint-space control for mobile and articulated robots and have chosen to focus on joint-space control for articulated robots with the goal of having human-like motion that improves performance on complex, dynamic tasks. Specifically, we present a comparison between a joint-angle-by-joint-angle (JBJ) method and a choreography-inspired method named Robot Choreography Center (RCC) of controlling an articulated robot to complete one-arm and two-arm static and dynamic tasks. Performance metrics such as rate of success and duration of task are compared with preference scores.

The rest of the paper is structured as follows: Section II

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reviews the high-level, embodied ideas about motion that inspire this work, Section III discusses the procedure for the user studies, and Section IV presents the performance and preference data comparing the methods used to control the robot. Finally, Section VI concludes the presentation of work and proposes future directions.

II. Development of Human-like Movement Teleoperation Scheme

Prior work developed a motion specification scheme that showed promise for creating human-like motion across multiple platforms [15]. That method was then extended into a teleoperation scheme and tested against a benchmark method on a single user across four tasks in [16]. This paper will extend the analysis of the two methods, reviewed in this section, to a pool of in-lab participants. This section will also introduce concepts from the Laban/Bartenieff Movement System (LBMS) used in this work and to train participants.

The LBMS taxonomyintroduces the concept of high-level commands. Despite each human body being a unique platform of varying geometries and force outputs, dancers are often asked to perform the same movements in unison – and are seemingly successful at this task. This requires a movement idea or abstraction with flexible bodily execution rather than a prescribed joint angle. Through the right set of compromises, thought of as choreographic abstractions, dancers seem like they are *doing the same thing* when onstage. The method presented leverages this idea as operators of robots may be thought of as trying to synchronize an internal model of motion with the device they are operating.

A. Space-Body Maps Developed from LBMS

The Space component of LBMS describes the spatial orientation of a motion, or *where* a movement takes place. Rudolph Laban developed *movement scales* to create an understanding of balance in motion [17]. Similar to musical scales played by musicians, these movement scales involve a series of complex, but related movements that span the space of typically used spatial pulls (in dance) or notes (in music). These scales are in LBMS as referential points to understand and characterize movement [18], [19], [20], [21] and are used to "install" new platforms into the RCC system [15] and index pose commands [16]. In this paper, they are used to train participants for the teleoperation method.

Four distinct categories of kinesphere sizes were introduced to the participants of this study: near-reach, middle-reach, far-reach, and further-reach. The near-reach kinesphere is defined for movements that are close to or touching the body. Middle-reach spans the region between near-reach and the arm being fully extended. Some examples of a task performed in middle reach would be typing on a computer or taking notes. Far-reach is the kinesphere that correlates to the arm being fully extended, while further-reach requires whole-body translation to occupy the desired space. All four of these kinesphere sizes were introduced to the participants; however, only near-reach, middle-reach, and far-reach were utilized (given that the Baxter platform cannot locomote).

In addition to the concept of kinesphere sizes, this work also utilizes spatial pulls, which exist within any given kinesphere and are comprised of both plane and direction. Within each kinesphere, three longitudinal planes exist: high plane, middle plane, and low plane. Within a single plane, eight spatial directions can be specified: forward, backward, right, left, and the diagonal directions in between.

B. Description of Teleoperation Methods

This section describes a novel teleoperation scheme under development (RCC) based on ideas outlined in the prior section, as well as a method used as a benchmark based on current PackBot controllers used by the military (JBJ). The mappings between motion concepts and buttons on the Xbox One controller for each method are provided in Fig. 1. Both methods are also described and utilized in [16].

1) Description of JBJ Method: The JBJ method is used as a benchmark method where commands are delivered to individual joints in a sequential fashion. This allows the user more precise control over the shape of the robot, not just the the position of the end-effector. This method allows for the command of a single joint at a time and averages about one joint moving at a time in the tasks developed in [16] and described in the next section. In this method, the desired pose can eventually be reached through the sequential input of each parameter, with the movement of the robot in between each command aiding in construction of these commands.

2) Description of RCC Method: RCC implements both the kinesphere sizes and spatial pulls outlined in the prior section to construct its movement commands, using them as areas towards which a body part should move, including relative degree or amount of motion, allowing for full body articulation without requiring specific input for each joint. This multi-joint actuation provides more fluid movements, especially as multiple poses are rapidly sequenced together. This method averages about three joints moving at a time in the tasks developed in [16] and described in the next section. This is implemented via a database of stored poses that the user is indexes with the gamepad controls; thus, not every pose in the robot configuration space is accessible.

C. System Implementation

As described in [16], the Robot Operating System (ROS) was used to connect the Baxter platform to the Linux workstation via ROS Kinetic. This system of control allows the user to input the commands themselves as well as receive almost immediate visual feedback as to how the robot is moving. The Baxter Robot acted as the ROS Master and connected to the Ubuntu Development Workstation through an ethernet switch. The Microsoft Xbox One gamepad used a ROS node to connect the gamepad to ROS. Chosen for its robust design and commercial availability, the Xbox One gamepad provided the necessary controls for participants to experience commanding the robot with two separate mental models without developing a new input system, which may be the subject of future work. In order to control and manipulate the Baxter Robot, several API functions from the Baxter SDK were used.

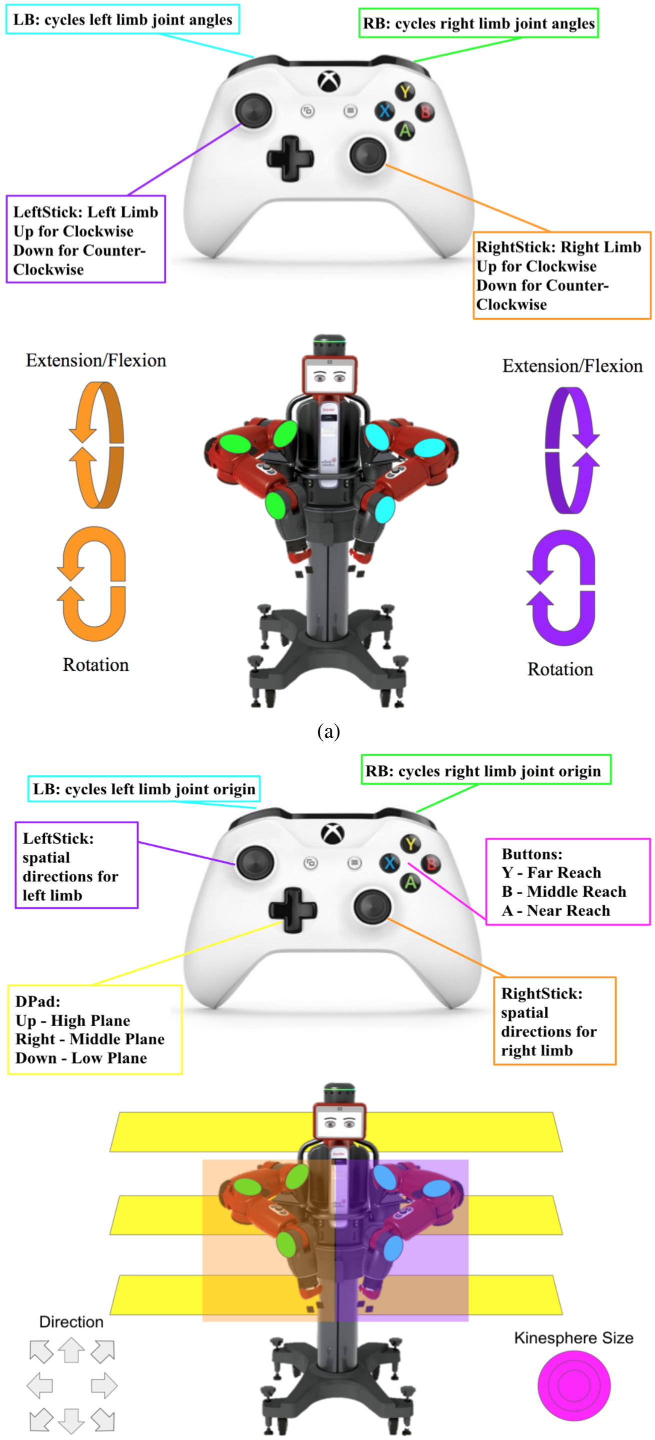

Fig. 1: Description of controls and corresponding visual of the Baxter robot for a) JBJ and b) RCC methods. The left and right bumpers toggle through joint options for both methods and the joysticks correspond to the direction of movement. The directional pad indicated by the yellow line specifies the plane while the face buttons indicated by the pink line provide the kinesphere size of the movement command. Embodied lessons were provided by the researcher to show how these commands would map to the user's body before robot operation and attempting the teleoperation tasks.

III. Experimental Design

To evaluate the performance advantages of each method and to understand preferences of users for each of the methods of controlling the robot, a user study was conducted.

A. Movement Training

JBJ and RCC were randomly assigned "Method 1" and "Method 2" for each participant so that no information about the method could be inferred from the name. Seventeen participants were given the JBJ method as Method 1 and twenty-one participants were given the RCC method as Method 1. Participants began the study with a short embodied training on the concepts related to each method. For the JBJ method, this involved completing tasks such as touching the left hand to the left shoulder or putting a hand on a hip by moving a single joint at a time. For RCC, the relevant concepts discussed in Section II-A were explained. Participants were asked to move in each kinesphere and explore the spatial pulls of the Space category of LBMS. Participants were then shown how the method was mapped onto the gamepad. After the movement training, participants had to pass a verbal test to prove that they understood the concepts of the method to move on to controlling the robot.

B. Teleoperation Tasks

The four tasks that were designed in previous work [16] were used in order to compare the JBJ and RCC methods. Each task was categorized as either a one-arm or two-arm task, as well as a static or dynamic task. These tasks provided a range of activity with which the performance of the JBJ and RCC methods could be tested in order to compare the types of tasks in which each method would excel. In this work, static tasks are characterized by a postural objective, meaning that achieving a particular configuration with the robot satisfies the task requirements. Meanwhile, a dynamic task requires movement and momentum in order to achieve a desired effect. Task 1 was static and required only one arm to complete; Task 2 was static and required both arms to move; Task 3 was dynamic and required only one arm; and Task 4 was dynamic and required two arms to complete.

The participant was given four training tasks so that the they would have time to grow accustomed to the method of controlling the robot via a gamepad. Users were given a maximum of five minutes to complete each training task. Once the user completed the training task or five minutes had passed, the robot was reset and the participant moved onto the next training task. After completing the training tasks, the participant was asked to fill out a post-training survey for the method. The participants then moved onto the actual tasks, where the performance of the user was evaluated for a monetary value. Three minutes was given for each of these tasks. The laboratory setup for each task is shown in Fig. 2.

Task 1 involved moving the right arm of the robot into a 23.5" diameter hula hoop hanging from the ceiling in front of the robot. The bottom of the hula hoop was taped to the floor to promote stability. Task 2 required that both the right and left arms of the robot be moved into 23.5" hula hoops

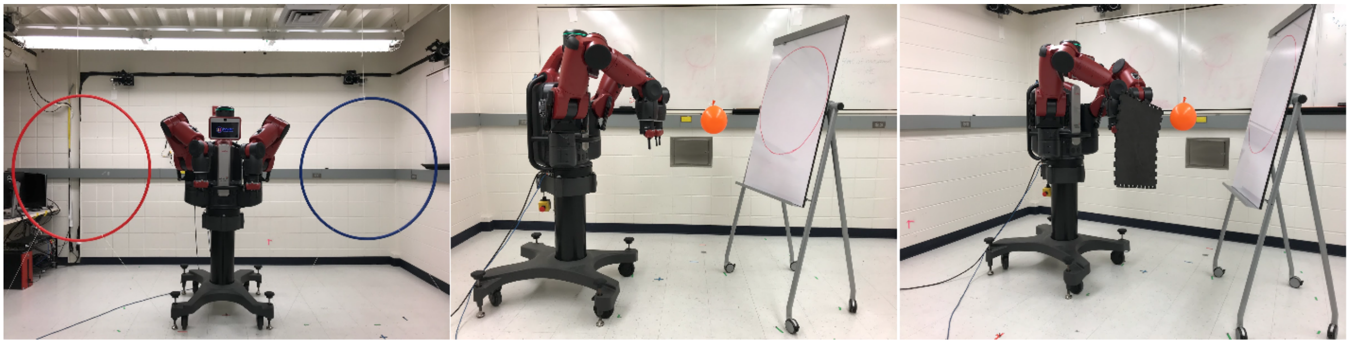

Fig. 2: The initial setup of each task in the user study conducted: left – Task 1 and Task 2; middle – Task 3; right – Task 4.

hanging from the ceiling. For each of these tasks, the user was told not to touch the hula hoop with the arm of the robot. If the hula hoop was touched three times or it was detached from the ground, the robot was reset and the participant was given one additional attempt to complete the task.

Task 3 required the participant to move either arm of the robot such that it struck a balloon of 6.5” diameter hanging 42.5” from the ceiling into a 27” diameter circle on a whiteboard placed in front of the robot. Due to the length of the string and distance of the balloon from the whiteboard, a transfer of momentum between the arm of the robot and the balloon was required. Task 4 added a barrier in front of the balloon that first had to be moved before hitting the balloon. In both dynamic tasks, the user could not change the orientation of the balloon or touch the string.

C. Incentive Structure

Participants were provided a base compensation of roughly $15 per hour ($30 for a study that took approximately 2 hours to complete). If the participant completed the task, he or she earned an additional $5. For Task 2 and Task 4, waypoints were identified (placing one arm in a hula hoop and moving the obstacle to the side, respectively) such that the participant could earn $2.50 if he or she was able to complete the waypoint, but not the entire task within the three minute period. A discussion of successful methods of approach for each task is provided in [16].

D. Hypotheses About Performance and Perception

Based on the experience of the research team in using each method, we hypothesized that the JBJ method would not perform as well on Task 3 and Task 4. We knew that learning to use both methods successfully would take time. Therefore, we hypothesized that the 2 hour study structure would provide enough time to learn both the more straightforward JBJ method as well as the RCC method. Additionally, we hypothesized that participants would judge the JBJ method to be more precise and the RCC method to be more fluid, a term more often associated with natural, human motion than artificial, robot motion. The questionnaire detailed in the next section was developed to test whether or not the hypothesis about perception of the two methods would be correct.

E. Questionnaire Design

After each task, the participant was asked to fill out a survey containing a NASA TLX questionnaire [22], [23], which rates six different categories – mental demand, physical demand, pace, success, amount of effort, and insecurity or discouragement – on a scale from 0 to 20. Once the final task was finished, the user completed a post-method survey and then moved onto embodied movement training for Method 2. The training tasks, tasks, and surveys were then repeated for the opposite method. Once both methods were completed, the participant answered an exit survey asking for demographic information such as age, gender, educational and movement backgrounds, and familiarity with the Xbox One controller. Additionally, the following thirteen questions were asked:

1) Which method was **faster**?
2) Which method was more **precise**?
3) Which method produced more **fluid** movements?
4) Which method was **easier** to use?
5) Which method felt **safer**?
6) Which method felt more **expressive**?
7) Which method felt more **articulate**?
8) Which method did you feel a more **embodied** connection to the robot?
9) Which method did you prefer for **Task 1**?
10) Which method did you prefer for **Task 2**?
11) Which method did you prefer for **Task 3**?
12) Which method did you prefer for **Task 4**?
13) Which method would you prefer for **future** tasks?

IV. User Study Results

Thirty-eight participants (9 females and 29 males) from the University of Illinois were recruited through fliers. The ages of the participants ranged from 19 to 34 with an average of 22.9 and a standard deviation of 3.7 years. While two participants had educational backgrounds in business and psychology, the rest of the participants were from STEM fields such as computer science, chemistry, biology, physics, and engineering. Thirty-six out of thirty-eight participants responded that they had engaged in sports such as soccer, swimming, and running throughout their lives; however, nineteen out of thirty-eight participants also answered that they had no specific movement training. Other participants listed movement practices such as yoga, dance, and martial arts. None of the participants were familiar with LBMS.

A. Performance Measures

The first measure of performance is task completion. Fig. 3a shows the success rate of the pool of participants for each of the four tasks and Fig. 3b shows the distribution of compensation over the entire pool. While Task 1 and Task 2 were completed by over 80% of participants for both methods, Task 3 and Task 4 were more difficult for users, with RCC being more successful for dynamic tasks. One user was able to complete all tasks for both methods; however, no other participant achieved this level of performance and those who were able to complete the dynamic tasks were more likely to do so with the RCC method.

The second measure used to evaluate performance is the amount of time that was required to complete the task. The requirement was to complete each task within three minutes, but we consider it preferable to see quicker task completion. The average duration of successful tasks is shown in Fig. 3a. The speed at which a task was completed demonstrated the strengths and limitations of each method. Although Fig. 3a shows that the JBJ method had a lower average task duration for Task 3, it is important to note that only two users were able to complete Task 3 with the JBJ method while eight were able to complete the task with the RCC method.

This analysis demonstrates the strengths and weaknesses for each of the methods of control. While JBJ is shown to be mildly more effective with static tasks, it is also shown to be slower and less successful for dynamics tasks such as Task 3 and Task 4. Additionally, RCC is more useful for dynamic tasks in which the movement of several joints must happen quickly. This is shown by the success rates of Task 3 and Task 4. Although RCC is shown to be slightly less effective at static tasks, user performance on Task 1 indicates that the RCC method is still a viable method of control for tasks requiring a particular end-position configuration.

B. Perception and Preference Measures

In addition to quantitative performance metrics, the average self-reported NASA TLX scores provided by the participants demonstrated that there was no statistically significant difference between the average scores for the two methods, except in the level of success and perceived amount of effort required for Task 2. Participants rated themselves 21.05% more successful with the JBJ method for Task 2 and rated the amount of effort required for Task 2 using the RCC method to be 13.56% greater than that needed when using the JBJ method. This aligns with the data provided in Fig.3a, since the JBJ method was shown to have a higher success rate for Task 2, as well as the JBJ method taking approximately 20 seconds less to complete Task 2 than the RCC method.

Fig. 3c depicts participant responses to the questions listed in Section III-E. Furthermore, the orange shaded area represents a confidence interval of 95%, which was calculated using the following equation:

$$\bar{x} \pm Z \cdot \frac{s}{\sqrt{N}} \tag{1}$$

where $\bar{x}$ is the mean of the data, Z is the value from the standard normal distribution (1.96) for a 95% confidence level, s is the standard deviation, and N is the pool size. If columns extend either above or below the confidence interval, then they can be considered statistically significant. Therefore, users found the JBJ method to be more precise, easier to use, safer, and more articulate while the RCC method was viewed as faster, more fluid, and more expressive.

C. Preferences of Users With Similar Performance Levels

These preferences were then categorized by level of performance: 25^{th} percentile and below, between 25^{th} percentile and 75^{th} percentile, and 75^{th} percentile and above. Fig. 3 shows several cases in which preference varies with performance. Overall, Fig.3c depicts a trend that lower bracket performers preferred the JBJ method, particularly regarding Questions 9-13. Furthermore, it demonstrates an increased preference for RCC within the top performance bracket.

D. Qualitative Comments

Additional comments comparing the two methods of control and providing additional feedback further supported the hypotheses of this experiment. Users wrote that the joint-by-joint (JBJ) method “requires [that the motion] be broken down into more steps” and is “rigid and well-defined”, giving it a “less steep learning curve”, but also “[requiring] more cycling through the joints” and making it “difficult to achieve complex tasks”. Meanwhile, the choreography-inspired (RCC) method was viewed as “harder to learn” because it is a “whole process”, but “[that it] could be more powerful in the long run since it allows for [coordination] between multiple joints”. Additionally, users wrote that this method “is more natural and comparable to the way humans move”. While some users struggled to understand the concepts of the LBMS in such a short time and thought that the controls felt unpredictable, they asserted that the method “grew to feel more comfortable” and that more training with the method would result in “intuitive and easy control”.

V. Discussion

Thus, teleoperating the Baxter robot via the two methods presented in this paper highlight consistencies in our original hypotheses, as well as the advantages and disadvantages of each method. The two methods were compared by attempting the same four tasks. The quantitative results of this comparison demonstrated that the JBJ method was slightly more reliable and quicker for static tasks such as Task 1 and Task 2, while Task 3 and Task 4 confirmed the superiority of the RCC method with regard to dynamic tasks.

Fewer participants were able to successfully complete Task 3 and Task 4; however, the dynamic tasks were designed to be more difficult. The stark difference between the success rates of static and dynamic tasks is most likely due to lack of training time for the more difficult tasks. Due to the limited time, some participants were unable to explore various strategies and develop a successful motion path. In the future, we suggest a greater amount of training – both with the robot and the LBMS taxonomy – be provided.

Meanwhile, subjective preference data was collected using a thirteen-question survey comparing the two methods, affirming that the JBJ method is more precise, easier to use, safer, and more articulate while the RCC method is faster, more fluid, and more expressive.

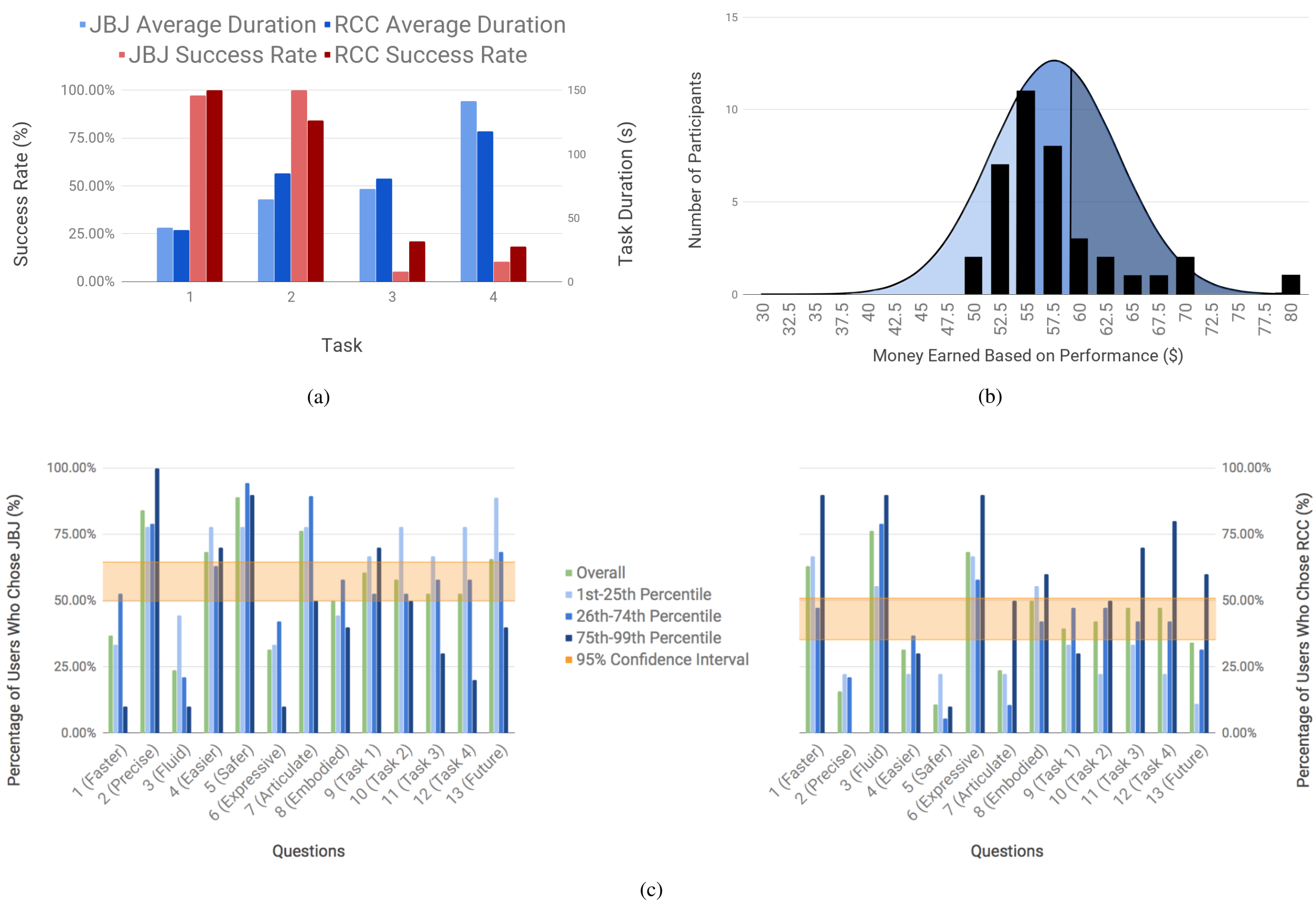

Fig. 3: Measures of method performance. a) displays the success rates and average durations of successfully completed tasks for both JBJ and RCC. b) presents the normal distribution and histogram of the performances of the users, illustrating the performance brackets used in c). c) depicts a comparative evaluation of the joint-by-joint (JBJ) and Laban-inspired (RCC) methods by the participants of the study. The questions on the x-axis refer to those listed in Section III-E. The overall average is shown in green while the performance brackets correspond to those shown in b). The orange shaded area represents a 95% confidence interval. Therefore, any column existing above or below the bar can be considered statistically significant.

VI. Conclusion

In this paper, we have presented a performance evaluation of a novel choreography-inspired teleoperation scheme (RCC), comparing it against a more traditional approach (JBJ). The RCC method utilizes movement commands relating choreographic abstractions from the Laban/Bartenieff Movement System. This system is rooted in the ability of humans to express high-level movement commands with one another such that a group of unique platforms might perform the same movement in unison. Thus, these concepts hold promise for helping to generate human-like artificial motion.

This teleoperation method may be well-suited to supplement existing methods in dynamic environments in which rapid, improvised, full-body actions may be required, including telepresence within the office, disaster response, or space exploration. For example, this scheme could be a new “mode” of operation for a device like the PackBot, utilized by soldiers and first-responders for telepresent activities.

Future work may include analysis of participant background in larger pools to examine correlations between success and prior experience with dance, LBMS, and video games. Additionally, future work may implement input modalities and a system in which this method can be used alongside more traditional teleoperation methods that offer situational awareness and connection to environmental features. If users are able to toggle between multiple methods, it is likely that even better outcomes will be achieved.

Additionally, we are interested in examining the connection between the RCC method and qualitative descriptions of movement such as “human-like” and “natural” that participants used when describing the method as described in [24]. A better understanding of the properties necessary in deeming a motion “natural” will help inspire the development of more expressive robots. Future extensions of the work presented here may further expand the bottleneck between user intent and robot behavior, creating richer interfaces between humans and robots.

Acknowledgment

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