Toward Expressive Multi-Platform Teleoperation: Laban-Inspired Concurrent Operation of Multiple Joints on the Rethink Robotics Baxter Robot in Static and Dynamic Tasks

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ABSTRACT

Human motion calls upon embodied strategies, which can be difficult to replicate in teleoperation architectures. This paper presents a teleoperation method that centers around the Space component of Laban Movement Analysis and may improve the dynamic complexity of teleoperation commands, allowing a trained user to command multiple joint angles at one time via a large database of stored poses, which are indexed by Space parameters. In this paper, this method is compared to a benchmark method, utilizing a joint-by-joint manner of control on a Rethink Robotics Baxter with compliant limbs using a Microsoft Xbox controller. Across four tasks with a trained operator, analysis of the number of active joints at a given point in time and time to completion emphasize the utility that comes with the proposed method. In particular, for the two presented static tasks, the average number of joint angles moving at one time improves and completion times reduce for the proposed method. Plots of behavior show additional qualitative differences in operator strategies and resulting motion, which are also discussed. Future work will extend this initial demonstration to more formal trials with multiple operators. This method may help achieve more fluid, continuous, and improvised motion in teleoperation of robots via gamepads as are currently used in disaster response platforms.

CCS CONCEPTS

• **Computer systems organization → External interfaces for robotics**;

KEYWORDS

Teleoperation, Laban Movement Analysis, Data-driven Methods

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1 INTRODUCTION

Communicating commands to robots is still a limiting bottleneck in teleoperation workflows, especially for dynamic or complex tasks. Teleoperation schemes rely on (and excel at) precise motion of end effector positioning. However, in dynamic environments which require quick, complex movement, which may need to be choreographed on the fly, these interfaces feel impoverished. On the other hand, humans communicating tasks to other humans can be astonishingly quick and effective at providing movement commands to one another. For example, consider how a parking attendant may guide someone to a specific location in a parking garage or finding the correct set of actions to manipulate a parking meter and pay stall. In both of these examples, the attendant will use spatial commands; in the former example, these commands will imply translation through space, while in the latter, the spatial commands imply articulation of limbs and distal digits.

This paper will extend a method for translating spatial commands to articulated poses for various platforms [1]. The aim of this work is to encourage more complex, simultaneous movement *that is directly commanded by a user*. In classifying such tasks, we make a distinction between the number of appendages required as well as the complexity of the task through the following examples. A task like pressing a small button requires pin point accuracy, but does not demand continuous progress or coordination of multiple joint angles. On the contrary, an action like swimming can be general and loose, but calls for constant motion in order to be completed. Thus, we aim to complex tasks with multiple degrees-of-freedom moving at once. We'll show this feature is occurring in our teleoperation method more than in a benchmarking method and that this feature of operation may help accomplish certain kind of tasks.

Prior efforts have leveraged the use of artists to construct variable robotic behavior, capturing artist manipulation of objects that can be actuated, such as ground [2] and aerial vehicles [3]. These are analogous to tools from the learning from demonstration community [4], which allow users to manipulate articulated bodies in order to capture desired user behavior [5]. Such approaches have also been used in a master-slave approach, where users can manipulate a full-size, or scaled, model of the teleoperated device to in order to communicate task; this approach is used in haptic-sensitive instruments for surgery [6], humanoid robot control [7, 8], and exoskeletons [9].

Another approach to generating human-designed motion on robots has been to use motion capture systems and re-targeting methods to generate behavior [10]. Motion capture of hands with gesture detection has been used for pick-and-place tasks [11]. Another source of action data has been EMG systems [12]. Gesture-based control has also been developed [13]. Other methods have looked at eye-tracking as an intuitive source for tele-operation command input, but this work has not translated to articulated motion [14]. These methods, which translate body-activity in a literal way, require lots of space, sensitive instruments, and the immediate mapping between human body action and robot action is not always clear.

For multi-degree-of-freedom (articulated) robots, adaptive strategies that automatically re-target action using reinforcement learning have been proposed [15]. Techniques that leverage visual servoing have also been developed [16]. These methods can produce dynamic, coordinated action based on the location of an object of interest in a camera view; however, they do not give the operator direct control over the bodily action of the robot, limiting the ability for operator improvisation. In a comparative study of gamepad-like input devices, researchers described this difficulty, writing "Soldiers found that several robotic control functions could not be performed simultaneously (e.g., raise the control arm while turning the sensor head) with the multifunction controller. This necessitated sequential operation which was time consuming and difficult." [17]. Teleoperation architectures tend to have tradeoffs between desired features [18], and the method we propose here may be a possible mode of operation to encourage such improvisational, even creative, actions of operators in dynamic environments with unexpected actions required of the platform.

Specifically, this paper describes an extension of a previously developed user-command architecture [1] to a teleoperational system using an Xbox gamepad as a control input. These input devices are common in robotic teleoperation [19, 20], including used by the military for the Endeavor Robotics PackBot device [21]. This paper presents single-operator trials on a Rethink Robotics Baxter platform as an initial demonstration of the strengths of our method over more precise, traditional methods. This paper does not propose effective user interface design, bandwidth or sampling rates, environment awareness for a distantly located users, or other important factors that contribute to teleoperation system performance [22]. Moreover, the paper does not suggest that this scheme *replace* existing schemes, like the joint-by-joint method we compare to here. Instead, we propose a *complimentary* scheme that excels in certain tasks and may connect better to channels of human embodiment.

Next, in Section 2, we will review Laban theory, on which the prior architecture builds, and describe the prior motion specification architecture and motivating results from user studies. Then, Section 3 describes the mapping of our prior method along with a more common joint-angle-by-joint-angle control architecture that is used as a baseline method. Results and analysis of the operator trials are presented in Section 4, and concluding remarks with future directions of work are outlined in Section 5.

2 LABAN SPACE HARMONY AND PRIOR CONTROL ARCHITECTURE

This section will review a previously developed method for motion specification and the Laban theory that supports it. This method, named Robot Choreography Center (RCC) [1], revolves around the Space component of Laban Movement Analysis. Specifically, the method formally incorporates the idea of the kinesphere: the spherical space around the body that you can move through with your limbs. Within the kinesphere, there are three longitudinal planes: the high plane, the middle plane, and the low plane. Within a single plane, there are eight spatial directions as well: forward, right, backward, left, and the diagonal directions between those four as well.

These so-called "spatial pulls" were proposed by Laban as points of interest around which harmonic movement scales could be designed [23]. These scales continue to be used in the Laban/Bartenieff Movement System as a referential point from which we can understand and characterize movement patterns [24–27] and are used to "install" new platforms into the RCC system.

During operation the RCC method takes advantage of these spatial pulls and utilizes them as areas to move towards, implying full body articulation as well as possible translation, as opposed to simply rotating a joint through a certain angle. This provides much more fluidity to motion by allowing for multi-joint actuation. While one single joint is toggled onto at any given moment, the commands from the RCC method do not restrict the rest of the joints from moving, and other joints will rotate as well to satisfy the given spatial pull. This is implemented through a large database of stored poses as described in [1].

An additional option included in the RCC method is a variable kinesphere size. There are near reach, mid reach, and far reach kinespheres for movements that occur closer to our body, a little further away from our body, and at the very edge of the maximum size kinesphere. We implemented these options into the mapping to allow for differently sized movements.

Motif symbols were leveraged in previous work [1] to index the database of poses used in the RCC method. In this past work, researchers needed to translate these symbols, used by users, to strings of words that could be typed into a terminal and that mapped to poses within the databases. The end product of this was very similar to what the result of the RCC method is, but passing in text-based parameters demanded manual translation.

This paper extends that prior work [1] by including a Microsoft Xbox gamepad to operate the robot. In prior work, we demonstrated the method across several platforms, but in this paper we focus only on the Rethink Robotics Baxter platform. With this new controller, the user still needs to be trained to understand what each and every control means in terms of Laban Movement Analysis, as did users in [1], but the action of utilizing a gamepad to move a robot allows for direct operation of the robot through these concepts.

This prior work [1] also verified these methods through user studies where users were trained by certified movement analysts, and then they were shown videos of movement tasks being performed by themselves and robotic systems alike; overall, users expressed satisfaction with the robots recreating the tasks using the RCC methods. Thus, this method can be seen as a way to translate the mental model humans have of how spatial direction should correspond to coordinated joint action, by approximating the explication of some of Laban's ideas about Space Harmony.

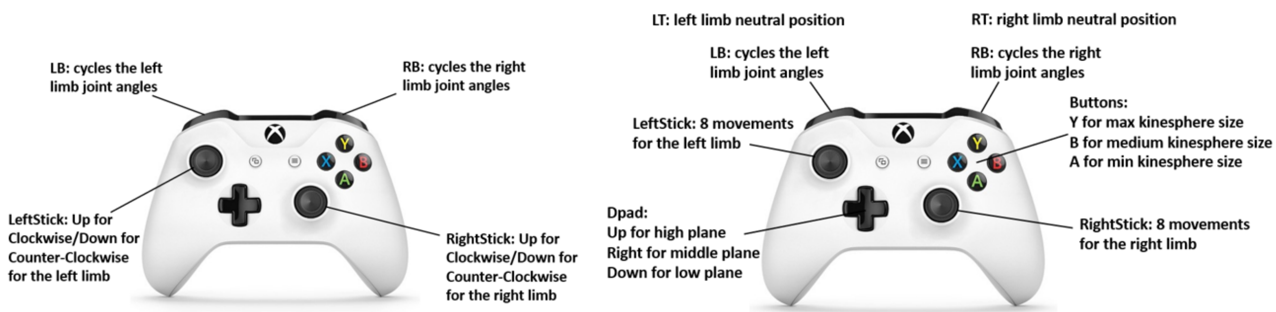

Figure 1: Gamepad layout of the two methods. Left: joint-by-joing control (JBJ); right: the Laban-inspired method (RCC).

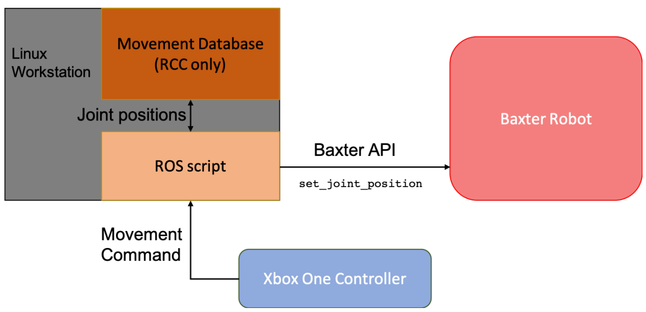

Figure 2: Architecture for teleoperation control.

3 GAMEPAD CONTROL EXTENSION AND TASK DESIGN FOR EVALUATION

This section describes the implementation of an external input device on the RCC method, extending the framework for teleoperation. We also established a benchmark method where commands are delivered from the external gamepad to the Baxter platform in a joint-by-joint fashion. In this method, which we refer to as joint-by-joint (JBJ), the user has more control over the robot and can eventually reach an pose in the robot's configuration space, through sequential input of commands through the input device. On the other hand, the RCC method is limited to executing the set of poses that are saved in a database. Four tasks designed to demonstrate the differences in this performance are, thus, also presented in this section.

3.1 Implementation of Gamepad Control

The Robot Operating System (ROS) was used to connect the Rethink Robotics Baxter Robot and the Linux workstation. The ROS version we use is ROS Kinetic. In this case, the Baxter Robot is acting as a ROS Master and connected to the Ubuntu Development Workstation through a Gigabit Ethernet Switch. For the Microsoft Xbox One gamepad, we use a ROS node called Joy to connect the gamepad to ROS. For controlling and manipulating the Baxter Robot, we used several API functions from the Baxter SDK such as `set_joint_position` to set and read the joint positions.

For the JBJ method, we change the angle of a single revolute joint each time. Each analog joystick controls the movements of the two robot limbs. In this method, we set joystick moving up for clockwise and down for counter-clockwise. See the left side of Figure 1 for this mapping to the input device.

We used a distinct mapping to Xbox One controller for the RCC method (right side of Figure 1). Based on the Laban Movement Analysis, we obtained a database describing each movement by the parameters of kinesphere size, plane and joint angle. There are twenty-seven movements in the database, the high, middle and low planes each has nine movements. Among the nine movements, there are forward, backward, left, right, forward left, forward right, backward left, backward right and the neutral. After we set the plane by the Xbox One controller, we let each analog joystick control eight movements except the neutral movement. Every time we get the command of movement from the Xbox one controller, we would extract the corresponding data from our database and send them to the Baxter robot through the rosnode. The Baxter robot would then set the positions of the joints based on the information we give. This architecture is illustrated in Figure 2.

3.2 Tasks for Demonstration of the Method

Four tasks were designed to showcase and compare the JBJ and RCC methods. The tasks utilized in this demonstration can be categorized, as shown in Table 1, into the following partitions: one-arm and two-arm and static and dynamic. These tasks provide a breadth of activity with which to demonstrate the performance of the JBJ and RCC methods in order to compare the types of tasks where each method will excel.

	One-arm	**Two-arm**
Static	Task 1	Task 2
Dynamic	Task 3	Task 4

Table 1: Structure of tasks.

In this paper, we define a static task as one characterized by a postural objective. This means that the task can be completed by achieving a specific posture with the robot and, thus, the overall goal of the task is to move one, in a "one-armed" task, or both in a "two-armed" task, of the limbs of Baxter to a certain configuration. The first two tasks established fit this criteria, and the first requires the use of one arm while the second requires the use of two.

For Task 1, the objective is to move the right arm of Baxter through a hula hoop that is suspended in the air in front of Baxter. The plane of the hula hoop is perpendicular to the direction that

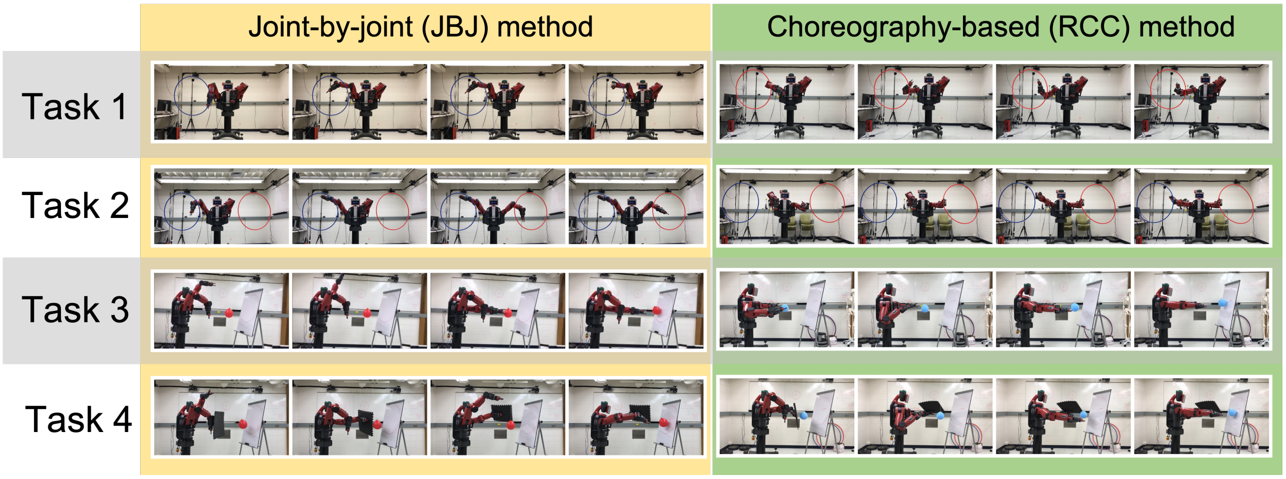

Figure 3: The above figure contains eight series of screenshots that demonstrate the trajectory of Baxter's limbs through the two versions of the four tasks detailed in this paper. The RCC method extends Baxter's limbs in much more natural and familiar ways, and this is especially noticeable in the completion of the first and second tasks. For the RCC methods, the arms open and extend outwards in a more radial manner, but for JBJ method, the way in which the arms expand is extremely mechanical and stunted. This trend also arises in tasks three and four. For the joint-by-joint method, Baxter's arm begins by extending vertically and then rotating downwards, closer to the target. However, the RCC method involves a much more fluid and radial extension of the limbs. Tasks three and four for the JBJ method were the only instances in which the tasks were not successfully completed.

Baxter's arm extends in so that the arm just has to stretch forward to reach through the hula hoop. Task 2 is very similar to, but instead of having just one hula hoop suspended in the air, there are two. The overall objective of the task is to reach one arm through the hula hoop on its respective side, and the other arm through the other hula hoop.

We characterize a dynamic task as one that has a velocity-based, or even force-related, objective. That is, such a task cannot be completed by holding a particular posture; it requires some moving speed of (transferring momentum to) the object being manipulated. This type of task was constructed by requiring the operator to use the platform to strike a primary object to provide it with enough velocity so that it hits a secondary object.

For Task 3, this involves hitting a balloon that is strung from the ceiling so that it hits within a large circle that is drawn on a whiteboard in front of the balloon. Task 4 is again similar to task three, but there is now the introduction of an intermediary obstacle. There is now a square flap, a rubber mat, suspended in the air between the balloon and the whiteboard. This is meant to force the user to utilize both of Baxter's arms: one to move the obstacle out of the way, and the other to hit the balloon into the whiteboard.

Completion (or attempt thereof) of each task by one of the researchers is shown in Figure 3. This researcher was trained in Laban Space Harmony, was provided the structure of the RCC, and had implemented the Xbox input device. Through this process, the researcher had accumulated around 20 hours of experience teleoperating the Baxter platform in the JBJ and RCC methods. The performance of the researcher on these distinct tasks is presented in the next section as an initial evaluation of the proposed method.

	Task1	**Task2**	**Task3**	**Task4**
Joint-By-Joint	31.4s	70.6s	99.8s	(103s)
RCC	21.2s	42.8s	86.8s	87.8s

Table 2: Task completion time.

4 RESULTS AND ANALYSIS

This section presents the results of typical trials in the lab with a skilled researcher. These trials were selected as typical in the best judgement of the research team and are meant as an initial demonstration of the RCC method compared to a more traditional teleoperation method (JBJ). The four tasks described in the previous section (Task 1: static, one-armed; Task 2: static, two-armed; Task 3: dynamic, one-armed; Task 4: dynamic, two-armed) are presented.

One measure of performance is whether or not the task was completed. Tasks 1, 2, and 3 were completed successfully by both methods; Task 4 was only completed successfully by the RCC method. In previous trials, both methods have been used to complete all four tasks, but it is extremely tricky to complete the dynamic tasks with the JBJ method due to the time it takes to create desired movement through serial commands to each joint actuator.

A second measure of performance is how long the completed tasks took. It is preferable to see quicker task completion, and in all four tasks, the RCC method facilitated quicker task completion. The Table 2 contains the time to completion of the tasks using both methods. For the trial of Task 4, using JBJ method exceeded a reasonable time limit and were cut short after about 100 seconds of effort (the actual times of data recorded are given in Table 2).

In order to further analyze the performance of the two methods, we also collected the number of joints moving simultaneously for both methods. This number was measured empirically using the encoders at each joint of the Baxter platform. While the JBJ method can only command motion of one actuator at the same time, the compliant, series-elastic actuators used in this platform do exhibit movement when neighboring joints are activated, and this motion is captured in this analysis.

We measured the motion of all the joints using commands from the Baxter API and collected data every 0.2 seconds. Due to the subtle collisions of the actual robot, we set the threshold to detect motion between a multiplicative factor of 0.9 to 1.1 of the joint's prior position in order to capture changes of 90% to 110% of the position at the previous time step. The total number of joints moving is plotted in Figure 5 and which joints were moving when during the trial is plotted in Figure 6. These plots show the different physical performance of the robot under the two different methods. Overall, the RCC method facilitated more simultaneous action of joint angles. This is shown in Table 3, which presents the average number of joints moving during each task.

	Task1	**Task2**	**Task3**	**Task4**
Joint-By-Joint	1.1	1.2	1.1	1.0
RCC	2.7	2.6	3.0	3.0

Table 3: Average number of joints active.

4.1 Discussion

Teleoperating Baxter through the four tasks utilizing the two presented methods highlighted several consistencies as well as innate benefits. Beginning with Task 1, the main type of movement that occurred within this task was taking Baxter's arm from the neutral pose within the near space out to a region close to the periphery of the kinesphere. The joint-by-joint method performed this common task in a very hinge-like way: initially swinging the arm out to the side of Baxter, like a crane, and then rotating a distal joint until the limb has broken the plane of the hula hoop. On the other hand, the RCC method performed this task quite differently.

While both methods begin in the same position, using the RCC method, the operator immediately unfurls the arm outwards, leaving the arm in a concave-up orientation. From there, the arm then extends forward, spoking into space, to pass through the hula hoop. If a human was told to put their arm through a hula hoop from a similar starting position, it is easy to argue that this would look much more similar to how the RCC method performed this task. Similar to how inverse kinematics moves an end-effector to a desired location, the spatial pulls and pre-stored poses allow for the robotic limb to reach the desired location in a more fluid, natural way. Similar activity is observed in Task 2 as well since both tasks require the same movements for success.

Tasks 3 and 4 are especially interesting because for the two prior tasks, despite the large differences in how the methods performed the task, they both resulted in successes. However, the JBJ method succeeded at Task 3, but failed at Task 4 whereas RCC succeeded at both. In terms of behavior exhibited in these tasks, the best approach we have found using the JBJ method began by rotating a proximal joint so that one of the arms was pointing upwards and as high vertically as it could get. Then, the operator swung the arm downwards in hopes of striking the balloon with enough momentum to hit it into the target. The arm would then remain at the periphery of the kinesphere, attempting to string together multiple "bobbles" of the balloon so that it would hit the target.

As in the static tasks, using the RCC method, the operator approached this task in a much different manner: quickly making an attempt at hitting the balloon, which was possible because of the RCC's ability to spoke radially. The operator started Baxter's arm within the smaller-sized kinesphere, curled closer to the body of the robot, and then moved the arm straight outwards towards the balloon by activating a larger kinesphere size in the same spatial direction. This resembled a much more head-on attempt, and it was also much easier to replicate or retry as opposed to the JBJ's method of extending the arm vertically and then swinging it downwards for the sake of initial momentum. The JBJ's inability to complete Task 4 was a great point of interest because as the screenshots in Figure 3 show, there was no problem moving the obstacle, it was rather that enough speed could not be built up to swing the primary object into the secondary one.

This description can be seen in the plots in Figures 5 and 6. Now, the number of joints moving at a given time is graphed, with JBJ again on the left and RCC on the right. While the graphs may appear similar, the scaling on the y-axis emphasizes that the RCC allows for significantly more complex and fluid motion. The JBJ graph really only operates at two levels: one joint moving, or none moving, with an occasional instance of two joints moving, potentially while the user is cycling through joints. However, the RCC method shows a higher ceiling, peaking at five to six joints moving at a time, but consistently possessing around two to three joints moving. Thus, these plots illustrate that RCC provides a vehicle for more fluid motion characterized by simultaneous action of multiple joints.

5 CONCLUSIONS

In this paper, we introduced a novel method for sending commands to a teleoperated robot (the RCC method [1]). This method utilizes spatial pulls that originate from the Space category of Laban Movement Analysis, a system rooted in choreography and dance, to create movement within a robotic system. Then, we compared this method to a more common, direct method of moving robotic limbs via commands specific to a given joint angle (the JBJ method). We found that when completing the same four tasks, the RCC method was more successful at the tasks (according to completion and completion times) and has more joints concurrently moving than the JBJ method. This suggests that the RCC method facilitates a level of movement complexity that the JBJ method cannot match.

Qualitative analysis of the completion of these tasks also supports this concept: the trajectories of the robot's limbs during the RCC method demonstrates the ability to move between two distant points in space in less time than the JBJ method. Moreover, this simultaneous cooridination of action tends to look more *human-like*. However, the RCC method limits the shapes that can be executed based on the database driving this method; thus, the JBJ method offers more precise movement by allowing for more isolated control over a limb or joint at any given moment as well as the ability to rotate through a specified joint angle as opposed to moving towards a more general spatial pull.

The results of this initial validation suggest that the RCC method can compliment methods employed today, like the JBJ, to improve operator control over robotic platforms. This empirical demonstration is quite limited as it did not recruit a large pool of users. Future work will develop Laban-training (as in [1]) of users and test the ability for a wide-variety users to learn the RCC method and operate a Baxter robot with it. Another area of interest for us is how less experienced users react to the two methods, and whether one "feels" better than the other in practice using metrics like the NASA TLX workload measure. Follow on studies will extend this mapping to other platforms like the SoftBank NAO and Kuka youBot (as in [1]) and even virtual robots as shown in Figure 4. This work would further validate the approach and demonstrate the scalability of the RCC method.

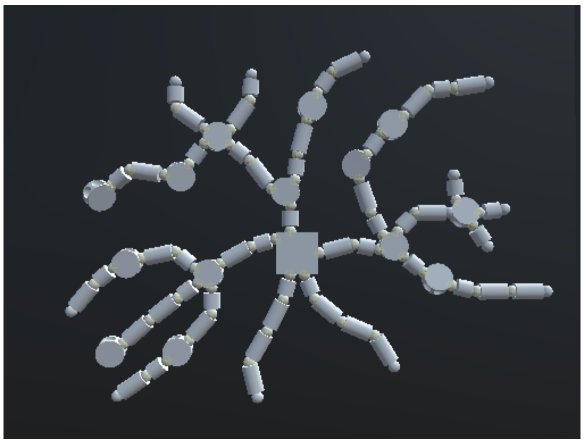

Figure 4: Scalability in teleoperation is especially critical for a robot such as the one above, which possesses a myriad of complex limbs and joints. With a method like JBJ, cycling through each and every DOF would become tedious; however, the spatial pulls leveraged by the RCC method are constant so it can scale to systems such as this.

As an increasing number of increasingly complex robotic bodies are introduced into the world, there will be a greater demand for these systems to have variability in their movement to be able to operate within society with human operators. While a joint-by-joint method may satisfy requirements for a smaller, more simple robotic system, this becomes very restrictive in terms of what types of motion are available. The RCC method offers a greater breadth of motion, although this motion may not be quite as precise, that can scale to more complex bodies.

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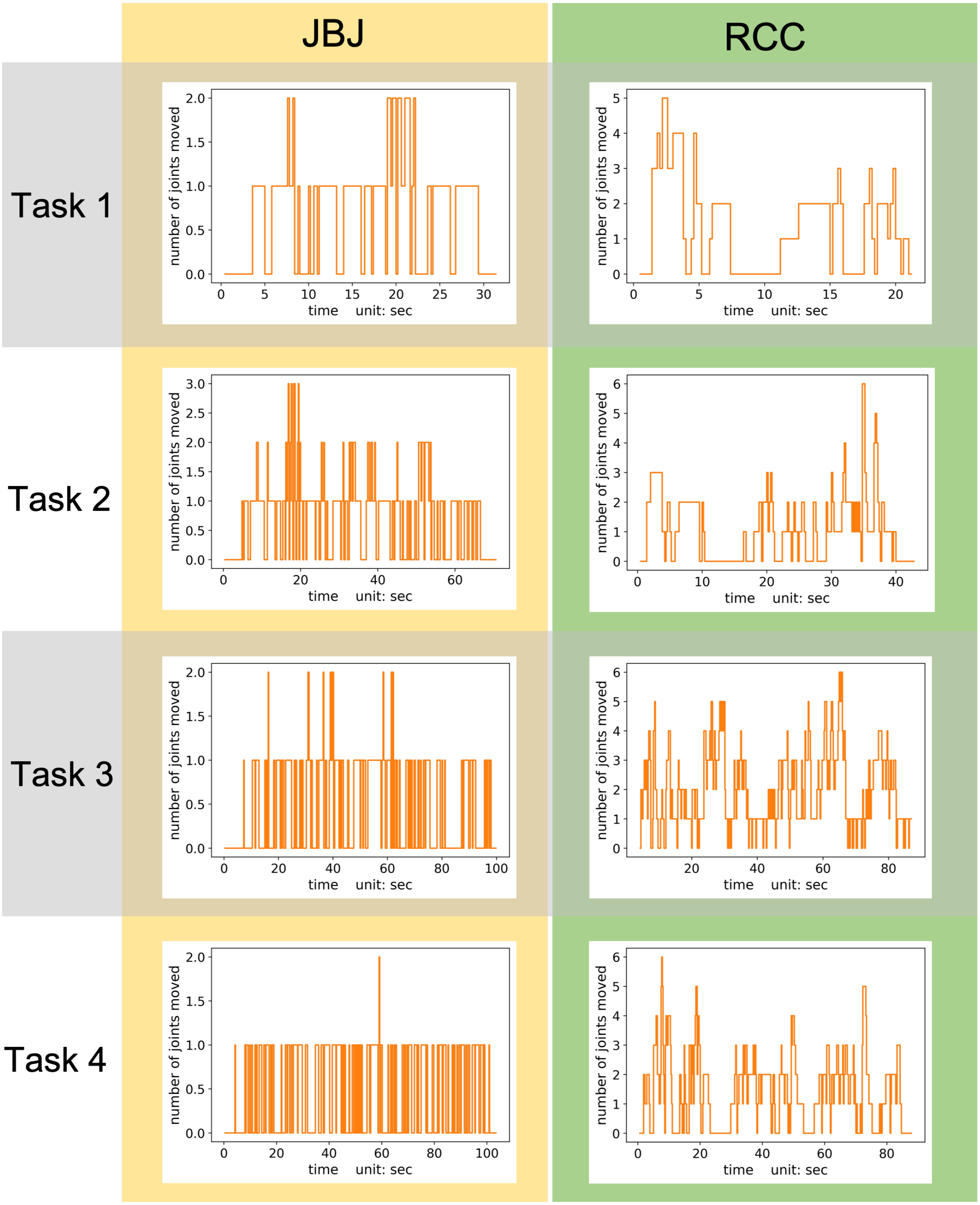

Figure 5: The graphs in this figure plot the number of joints moving with respect to time, with the JBJ method on the left and the RCC method on the right, during all four tasks. A general trend through these plots is that the JBJ plots typically range between zero and one joints moving at any given time whereas the RCC plots range between zero and six. Task 2 exhibits more of an uncommon occurrence of three joints moving at once for JBJ, but RCC still far outperforms in terms of the number of joints moving at a given point in time. Another interesting attribute to note is that the RCC graph very rarely stays at zero joints moving, and is constantly bouncing off of the "floor" of the graph (no joints moving) whereas the the JBJ graph tends to stay at zero joints moving for longer time periods than RCC.

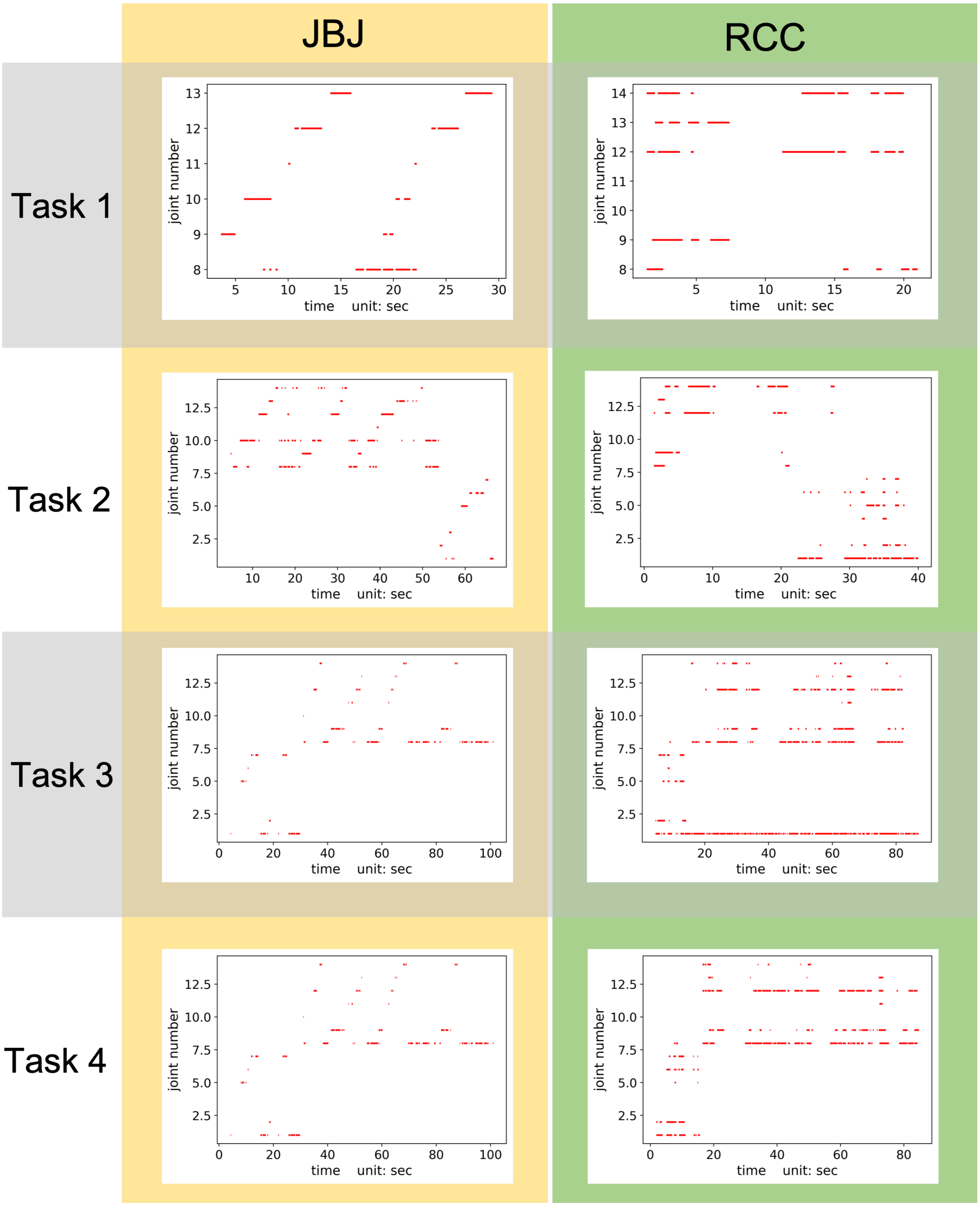

Figure 6: The graphs in this figure plot which specific joints are moving with respect to time, with the JBJ method on the left and the RCC method on the right, during all four tasks. An important distinction to make is that the JBJ graph resembles a type of step graph with a horizontal bar either jumping up or down. On the contrary, the RCC graph possesses several joints moving at one time, denoted by parallel red lines. Also, the horizontal lines of the RCC method are very frequently broken up into smaller segments. This resembles several little tweaks and adjustments to the motion of the limb as opposed to the straight, unbroken lines of JBJ which suggest more rigid movement.