In *Proceedings of the 35th International Conference on Intelligent Robots and Systems, 2022* (IROS 2022), Kyoto, Japan October 2022

Quantifying Changes in Kinematic Behavior of a Human-Exoskeleton Interactive System

Keya Ghonasgi[1], Reuth Mirsky[2,3], Adrian M. Haith[4], Peter Stone[2,5], Ashish D. Deshpande[1]

***Abstract*— While human-robot interaction studies are becoming more common, quantification of the effects of repeated interaction with an exoskeleton remains unexplored. We draw upon existing literature in human skill assessment and present extrinsic and intrinsic performance metrics that quantify how the human-exoskeleton system's behavior changes over time. Specifically, in this paper, we present a new performance metric that provides insight into the system's kinematics associated with 'successful' movements resulting in a richer characterization of changes in the system's behavior. A human subject study is carried out wherein participants learn to play a challenging and dynamic reaching game over multiple attempts, while donning an upper-body exoskeleton. The results demonstrate that repeated practice results in learning over time as identified through the improvement of extrinsic performance. Changes in the newly developed kinematics-based measure further illuminate how the participant's intrinsic behavior is altered over the training period. Thus, we are able to quantify the changes in the human-exoskeleton system's behavior observed in relation with learning.**

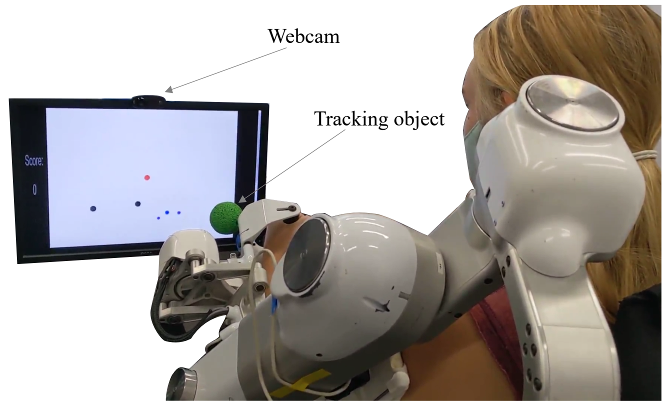

Fig. 1. Image of a participant at the start of a Reach Ninja game episode. The green ball attached to the exoskeleton handle is tracked by the webcam and represented as the a cursor on the screen. The participant is wearing the left arm of the Harmony Exoskeleton.

I. INTRODUCTION

Recent advances in the design and applications of human-friendly robots has led to an increased interest in characterizing human-robot interactions. Robots are being deployed to perform collaborative tasks with humans [1], augmenting human capabilities [2], for physical rehabilitation [3], and various other human-centric applications. While the majority of research on human-robot interaction focuses on the design and control of the robot and building collaborative behaviors with the human, not enough attention has been paid to the effect of the interaction itself on human motor behavior. We address this gap by drawing on previous work that characterizes the human motor system through the use of performance metrics [4] to similarly quantify the behavior of the combined human and robot interactive system.

Exoskeleton robots are unique in that they are designed to closely interact with the wearer at the joint level rather than just at the end effector. These devices thus have the potential to present rich environments for affecting change in the wearer's motor behavior. Such changes can be affected both by learning through repeated practice, and by modifying the robot's interaction control. Quantifying the changes in the human behavior and capabilities within this environment is crucial to ensuring that the human-robot system is safe, comfortable, and effective. The primary goal of this paper is to identify and evaluate performance metrics that elucidate how participants' behavior changes as they learn a new motor task over multiple attempts in an exoskeleton environment.

Quantification of human behaviors has been studied in the context of motor control and learning. From existing literature, we know that changes in motor behavior are often measured using task-space performance metrics [4]–[7]. These metrics, such as precision and accuracy, act as an *extrinsic measure* of a person's ability to successfully perform a given task. However, they do not provide a sense of the *intrinsic change* in the person's joint-level kinematic behavior. Without capturing how a participant might be changing their motor behavior as they learn new skills and/or adapt to a robot, our picture of human-robot interaction is incomplete. As exoskeleton robots are capable of direct interaction at the joint level, they provide an opportunity to not only assess intrinsic changes but also to study and affect the kinematic behavior of the human-exoskeleton system.

Prior research has presented a few approaches to quantifying kinematic changes in human motor behavior. It has been shown that during learning of a new motor task participants tend to opt for movements that result in more predictable changes to their environment [8] and selectively allow high variability in movement dimensions that do not affect task success [9]. These task-specific approaches to quantifying kinematic behavior still do not capture the inherent changes in the human-exoskeleton system over time or due to interaction. Researchers have also quantified movement behaviors

[1]Mechanical Engineering Department at The University of Texas at Austin keya.ghonasgi@utexas.edu, ashish.deshpande@austin.utexas.edu
[2]Computer Science Department at The University of Texas at Austin pstone, reuth@cs.utexas.edu
[3]Computer Science Department at Bar Ilan University
[4]Neuroscience Department at Johns Hopkins University adrian.haith@jhu.edu
[5]Sony AI

that are independent of the task, two of which are of particular interest in this work [4]. The first is exploration of the kinematic workspace, often measured via variability in joint velocities. The second is kinematic coordination between different joints towards more synergistic and smooth movements. Due to their task-independent nature and the ease of measuring them using the exoskeleton robot's sensors, these two metrics are chosen to represent the human-exoskeleton system's kinematic behaviors.

Characterizing and quantifying the changes in kinematic behavior of the human-exoskeleton system is significant for several reasons. For instance, identifying the changes in the system's kinematics over time gives a sense of the effect of repeated practice in the human's kinematics and their interaction with the robot. The kinematic metrics also allow for the identification of desirable behaviors that correspond with improved performance in task-specific kinematic metrics. Further, changes in these performance metrics provide a quantitative measure of the effect of the robot's interaction on the human's kinematics. For example, the effect of two different robot controllers on the human's behavior can be assessed by comparing the kinematic performance of the system under both conditions. Finally, the identification of an interaction controller's effects and desirable motor behaviors can together be used create an effective environment for human-robot interaction tailored to a variety of applications.

We have developed a challenging video game requiring dynamic upper-arm movement, called "Reach Ninja". Participants in a human-subject study practice this game while wearing the Harmony exoskeleton [6] and we use previously established extrinsic performance metrics to identify trends indicative of learning. In this paper, we present novel kinematic metrics of performance to quantify how the human-exoskeleton system's intrinsic behavior changes as a consequence of learning. Results from this study demonstrate the effect of repeated practice on both extrinsic and intrinsic metrics over time. The presented metrics and their interpretation are a crucial step in the design of robot controllers that responsively modulate the exoskeleton's interactions with the wearer. The contributions of this paper are thus two-fold: First, we present a new intrinsic evaluation metric that can be used to measure distances between joint space coordinations in a variety of motor tasks. Second, we present an empirical analysis of the changes in this kinematic metric, in conjunction with other extrinsic and intrinsic performance metrics, as participants train on a task in the exoskeleton environment. This quantification of behavioral changes can be used to monitor the effects of human-robot interaction over time. The characterization of human-exoskeleton behavior is thus better informed with the quantification of kinematic performance, validating the use of our proposed metrics.

II. MATERIALS AND BACKGROUND

The experimental setup of a participant playing a video game while wearing the exoskeleton can be seen in Fig. 1. We use the Harmony exoskeleton [10] as the robotic device in a human-subject study with the goal of identifying changes in the human-exoskeleton system over time. We use a task domain and experimental protocol that have previously been shown to elicit improvement in extrinsic performance metrics through repeated practice [6] in human subjects in the absence of an exoskeleton environment.

A. Harmony Exoskeleton

The Harmony exoskeleton is a bi-manual upper-limb robot. Each arm of the exoskeleton has seven degrees of freedom: shoulder elevation/depression (θ_1), shoulder protraction/retraction (θ_2), shoulder abduction/adduction (θ_3), shoulder internal/external rotation (θ_4), shoulder flexion/extension (θ_5), elbow flexion/extension (θ_6), and forearm pronation/supination (θ_7). The torque sensors at each joint are used to control the robot using impedance control [11]. In the gravity-assist mode, also referred to as the transparent mode, the motors compensate for the weight of the robot's links without compensating for its inertia. The robot passively follows the wearer's movements, and the resulting environment gives the wearer a sense of mild resistance (similar to moving their arm in water). During run-time, we measure joint angles, joint velocities and joint torques at each of the seven degrees of freedom. A soft cuff is strapped to the wearer's upper arm and attached to the robot's upper arm. The wearer holds the exoskeleton handle at the hand. This physical human robot interaction setup allows for good agreement between the movement of the wearer and the robot end effector and joint angles [11], [12].

B. Reach Ninja

We have developed a dynamic task domain, called Reach Ninja, a video game environment that was found to be engaging and challenging enough to elicit learning over time [6]. The task is therefore suitable for the study of motor learning and the corresponding changes in motor behavior. The game tracks an object held in the participant's hand using a webcam and this motion is displayed on screen as a red cursor. Participants play the game by reaching to moving blue and black markers to maximize their score. Participants are able to improve task performance over time, which is indicative of motor learning. The task begins when the participant brings the red cursor tracking their hand movement to the center of the screen and holds this position thus restricting the starting configuration. 3 blue and 2 black markers act as moving targets and when these markers disappear, either off-screen or by coming in contact with the player's cursor, the task ends. This episodic version is short and of variable duration. A demonstration of the game can be found in the supplementary video.

The task difficulty is modulated by two additional interventions: (i) Partial Feedback: the red cursor showing the motion of the tracked object on screen fades away in the first second and remains invisible until the end of the episode. (ii) Magnetic Field: a virtual magnetic field is introduced such that the positive blue markers are repelled by the red cursor while the negative black markers are attracted. These interventions are combined to create a challenging target task to be learned through training. A mirror intervention task, where the lateral movement of the arm cursor is inverted, is used for familiarization.

III. Methods

A. Protocol

A total of 16 participants (aged 24.38 $\pm$ 3.03, 6 female, 10 male) are randomly assigned to one of two groups similar to our prior work [6]. For the 'targeted practice' group, training consists of repetitive practice of the target task, whereas for the 'ordered practice' group, tasks of varying difficulty level are practiced with the goal of improving performance on the same target. These two groups are chosen to test for effects of varying the task environment on the overall learning curve. All subjects are right-handed and performed the task with their non-dominant (left) arm. Prior to its use, the Harmony exoskeleton's link sizes are adjusted to match robot and body joint location. At the start of the experiment, each participant dons the Harmony exoskeleton and the tracking object is attached to the end of the exoskeleton handle (Fig. 1).

The participant first completes four episodes of a mirrored familiarization task to get accustomed to the robot and game environment. The participant then completes eight episodes of the target task referred to as the pre-training episodes. Next, the participant performs 308 training episodes. For the ordered practice group, these episodes are ordered as 100 partial feedback source task (PFST) episodes, 4 probe task episodes, 100 magnetic field source task (MFST) episodes, 4 probe task episodes, and 100 target task episodes. Participants in the targeted practice group practice the same target task for all of the 308 training episodes. Following training, the participant repeats 8 episodes of the target task, referred to as the post-training episodes. To facilitate comparison before and after training, the marker initializations are matched for pre-training and post-training episodes, i.e. the first pre-training is the same as the first post-training episode and so on. These seeds are randomly selected for each subject before the start of the experiment. This experiment protocol has been approved by the Institutional Review Board at The University of Texas at Austin (STUDY 1215).

B. Extrinsic Performance Metrics

The human-exoskeleton system's extrinsic performance is measured using the following outcome metrics [6]:

- Mean Speed (confidence, pixel/sec): expected to increase as training progresses as an indicator of increased confidence.
- Final Score Percentage (accuracy, percentage): learning is expected to result in increased normalized scores from pre- to post-training.
- Capture Target Percentage (precision, percentage): an increase in percentage of positive markers captured indicates improved precision.
- Score Per Capture (strategy, percentage): strategic selection of optimal markers maximizes score per target capture ratio.

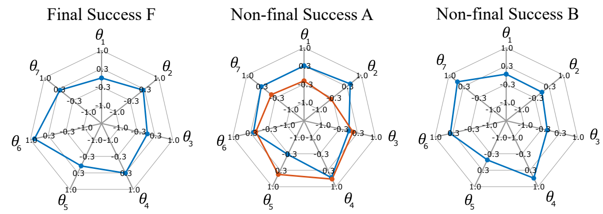

Fig. 2. Linear coordination of the exoskeleton's joints to the principal successful movement coordinations for a representative subject for three separate successful movements. Final success F shows the coordination in the final successful movement, whereas successes A and B are two other successful movements. These figures serve as an example of the observed coordinations and their similarities for a given subject.

C. Kinematic Performance Metrics

The Harmony exoskeleton records the human-exoskeleton system's kinematic data in addition to the extrinsic performance metrics. Sensors on the exoskeleton provide joint angle measurements, the corresponding joint velocities, and joint torque measurements along each of the seven degrees of freedom. Prior work has used various methods to assess kinematic performance through the observation of joint angle, velocity, and torque data [13]–[15]. Based on this literature, we discuss two metrics which we use to characterize the kinematic behavior of the system.

1) Joint Velocities: In a reaching task, as upper-limb motion may be unconstrained and dependent on the direction of the target, joint angles may provide biased information depending on the specific task episode. On the other hand, joint velocities provide a good comparison across different task configurations and the Harmony exoskeleton's sensor precision allows for reliable measurement of these velocities [10]. To ensure appropriate weighting of the joint velocities, for each subject we determine the mean absolute joint velocity for a given joint across the pre-training episodes [4]. This initial absolute velocity is used to normalize the absolute joint velocities at each timestep so they can be compared across joints, episodes, and subjects. Two metrics are derived from these normalized joint velocities for each episode:

1) Mean joint velocities: The mean absolute normalized joint velocity is calculated across all joints after normalization. An increase in this metric would indicate faster movements on average in any given joint.
2) Standard deviation of joint velocities: the standard deviation of the absolute normalized joint velocity averaged across all joints after normalization is calculated for a given episode. An increase in this metric indicates exploration in the joint velocity space.

While these measures provide valuable information about the system's kinematics, they do not provide a fine measure of movement behaviors related to task success.

2) Principal Kinematic Coordination Distance: As the reach ninja task is stochastic in nature and can require abrupt changes in movement behavior, each episode of the task needs to be broken down further before analysis. The moment when a participant reaches a blue target, resulting in a score increase, is identified. Visual inspection of the movement data reveals that a time window of 0.5s centered around this moment captures the movement leading up to the success and the follow-through. This 0.5s window around the success contact is referred to as an instance of “successful kinematic behavior”.

Kinematic data from the robot is collected at each of the seven joints of the robot, while the motion performed by the participant is translated to a 2D screen. To best identify movement behaviors that are correlated with successful movements, a dimensionality reduction method is used to identify dominant kinematic behaviors. Principal component analysis (PCA) is a dimensionality reduction method used to analyze multivariate data [16]. Following its success in elucidating kinematic coordinations [17]–[20], this method is chosen to reduce dimensionality. We identify the principal orthogonal components of the data using singular value decomposition. Next, the percentage of variance in the data that is captured by each principal component is quantified and the components are ordered in decreasing order of variance explained. The first n principal components that describe a total majority of the variance (say 90%) are considered to be the primary components and the remaining are discarded. The contributions of each principal component gives a sense of linear coordination between the robot's joints. We refer to these principal components as the principal kinematic coordinations. Further, when these components are identified for successful movements, they are referred to as successful principal kinematic coordinations. Fig. 2 shows a few examples of successful kinematic coordinations for subject S13. Note that the final successful movement F and success B both reduce to a single principal component describing over 90% of the movement, while success A reduces to two principal components.

Visual inspection of different successful movements reveals that certain kinematic coordinations might be preferred over others as learning progresses. Bockemuhl et al. [17] similarly use PCA to identify joint angle synergies in catching movements performed by healthy humans. To further compare the principal component subspaces from different movements, the authors define a distance metric that measures the amount of rotation required to go from one principal component subspace to the other. However, this metric [17] is only applicable to comparisons between two subspaces with the same number of principal components. Instead, the goal in the current paper is to identify the *minimum rotation required to align at least one axis of the two subspaces being compared*. Thus, we perform a pairwise comparison of each principal component from two different principal component subspaces (matrices U and V) using their dot product to get the sine of the angle (ϕ) between them. This results in a distance matrix of size $m \times n$ where m and n are the number of principal components in the first and second subspace respectively. The minimum value in this matrix is calculated as

$$D_{P_F,P_X} = min_{i,j} sin(\phi_{i,j}) = min_{i,j}\sqrt{(1-(u_i \cdot v_i)^2} \qquad (1)$$

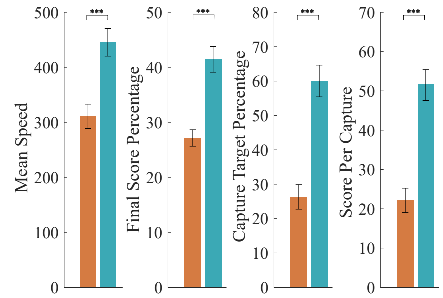

Fig. 3. Outcome metrics across all subjects, pre-training versus post-training (***: p<0.001).

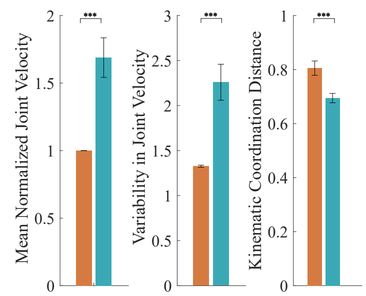

Fig. 4. Kinematic performance metrics across all subjects, pre-training versus post-training (***: p<0.001).

where $i \in (1,m), j \in (1,n)$. D_{P_F,P_X}, referred to as the principal kinematic coordination distance, represents the minimum distance between any pair of vectors between the two subspaces P_F and P_X. As the principal vectors are orthonormal, two different vectors in U that are equidistant from V, must necessarily be at a distance of $sin(45^o)$ from V. The distance of the final successful coordination P_F from other coordinations P_A and P_B in Fig. 2 as measured by Eq. 1 is 0.67 and 0.78 respectively.

IV. RESULTS

We now present the results of the human subject experiment described in section III-A. Two factor repeated measures ANOVA is used to determine statistical significance of the results. The two factors are training group (between) and measurement time (within). In Fig. 3–5, the overall average pre-training performance is shown in orange and post-training performance is shown in blue. Standard error bars are shown to give a sense of variability in the metrics across subjects. Significance of results is demarcated by the number of * symbols (refer to captions).

A. Extrinsic Performance Metrics

Each of the four outcome metrics are measured and averaged across the pre-training and post-training episodes for all subjects. The overall results are shown in Fig. 3. All four metrics increase from pre-training to post-training in both the targeted practice and ordered practice group participants ($p < 0.001$ for all metrics). This result indicates that the participants learned to perform the task in the exoskeleton environment (just as they did outside the robot in the past [6]). To understand if this learning resulted in

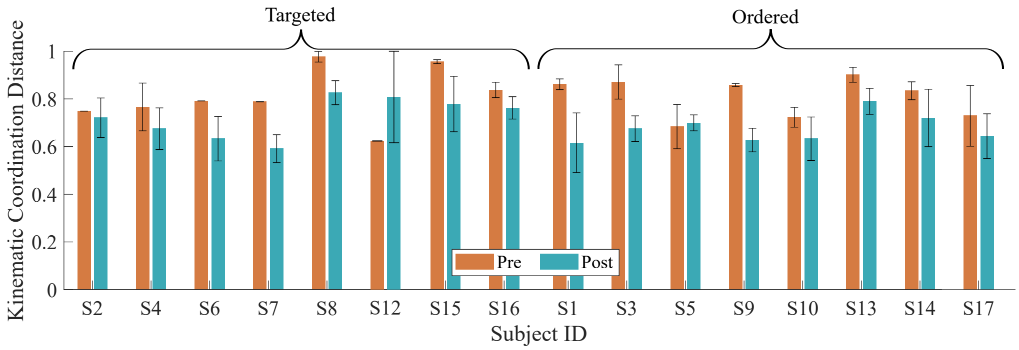

Fig. 5. Subject-wise successful kinematic coordination distance from final successful coordination in joint angles.

consistent changes in the kinematic behavior of the human-exoskeleton system, we turn to the kinematic metrics relating to joint space exploration and joint coordination.

B. *Kinematic Metrics*

We first consider the mean and standard deviations of the normalized joint velocities averaged across all seven degrees of freedom (Fig. 4). We observe that, on average, across all the joints, the mean joint velocity increases from pre-training to post-training regardless of the training group. The change from pre-training to post-training is statistically significant ($p < 0.001$) and there is no evidence of an interaction effect. Similarly, the standard deviation of the joint velocities increases as well ($p < 0.001$) with no evidence of an interaction effect for either group.

Next, we assess the kinematic joint angle coordinations for successful movements measured across different episodes of the experiment. Specifically, we identify the last successful attempt in the post-training episodes which is expected to represent the most learned or preferred coordination behavior. This principal kinematic coordination distance to the final successful coordinations is evaluated for each successful movement and averaged across pre-training and post-training successes. Note that the final success in the post-training episodes is omitted in this calculation to avoid biasing the average distance to be artificially lower in the post-training subjects. The overall average results are shown in Fig. 4, and the subject-wise results are shown in Fig. 5. Overall, we observe a reduction in this average distance to the final successful movement going from pre-training to post-training performance ($p < 0.001$), with no interaction effect of the training group. The trend was observed in 14 of 16 total subjects (Fig. 5). Two subjects, one in the targeted group (S12) and one in the ordered group (S5), showed an opposite trend where the kinematic coordination distance increased in the post-training episodes. However, comparison with other participants' trends shows that these two participants are likely to be outliers.

V. DISCUSSION

Our overarching goal is to quantify changes occurring in the kinematic behavior of a participant during multi-session interactions with an upper-limb exoskeleton. Specifically, we consider the effects of repeated practice with an exoskeleton and assess them in the context of motor learning. We carried out human subject testing with 16 participants who completed a task involving repeated 3D arm movements over multiple sessions. The task was presented in the form of playing the Reach Ninja game while donning the Harmony exoskeleton. We observe positive changes in *both* the extrinsic performance metrics, indicative of learning [6], and in the newly developed kinematics-based intrinsic metrics. The kinematic metrics thus allow for the quantification of intrinsic changes in the human-exoskeleton system as caused by training on a given task.

The extrinsic performance metrics showed increasing trends going from pre-training to post-training performance, similar to changes observed in our previous study without the robot [6]. We thus conclude that the human-exoskeleton system did not negatively affect participant's ability to make progress in the task. The mean and standard deviation of the normalized joint velocities averaged across all joint angles also show an increase going from pre-training to post-training performance in participants regardless of their practice group. This increase suggests that, as in the case of the mean speed measured in the extrinsic metrics, there was an overall increase in the joint speeds employed by the participants as they train. The increase in standard deviation of the normalized joint velocities further indicates an increase in joint-space exploration by the participants. However, this result is still only indicative of an overall kinematic behavior across a whole episode as opposed to success-specific behaviors which are expected to improve as learning occurs. The highly stochastic nature of the Reach Ninja task makes it difficult to identify how this result translates to an improvement in overall task performance.

To better quantify changes in learned kinematic behavior this paper introduces a kinematic metric that only considers movement behaviors associated with "success" instead of overall movements. Further, we assume that as the learner is expected to improve through training, the final successful movement is representative of the most learned behavior. The proposed metric calculates the distance between this learned behavior and other successful movements in pre-training and post-training episodes. As learning progresses, this distance is observed to reduce across most participants regardless of their training group. Thus, as participants learn to perform the task over time, they also learn to control the human-exoskeleton system through similar kinematic coordinations.

These results demonstrating change in intrinsic performance of the human-robot system taken together with an improvement in the extrinsic metrics lead to two significant conclusions. First, quantifying the changes in intrinsic behavior of the human-robot system allows for a more complete representation of changes in the system's behavior over time than using the extrinsic performance metrics alone. Second, the consistent reduction in the principal kinematic coordination distance from the final successful coordination demonstrates a trend towards desirable kinematic behaviors associated with success. These desirable coordinations are of particular interest in the context of motor training design and rehabilitation.

In prior work [21], researchers have used robotic interventions to train subjects to use desired movement coordinations. Similarly, robots have been proposed as a solution to train participants to avoid undesirable coordinations [19], such as flexion synergy post stroke. We note two limitations of the work presented here. First, the designed task is highly stochastic making it difficult to use the kinematic coordination distance metric to its full potential. Second, we use visual inspection to segment the task, resulting in a subjective analysis. We thus plan to further validate the proposed metric with other more controlled motor tasks and to automate the segmentation process to ensure accuracy. Our next steps are to extend this analysis to different exoskeleton interaction controllers and to design training protocols that adaptively modulate the interaction to encourage the human-exoskeleton system towards known desirable behaviors.

ACKNOWLEDGMENT

This work was carried out jointly by the ReNeu Robotics Lab and Learning Agents Research Group (LARG) at UT Austin. Effort in the ReNeu Lab is supported, in part, by NSF (1941260, 2019704) and Facebook. LARG research is supported in part by NSF (CPS-1739964, IIS-1724157, NRI-1925082, CMMI-2019704), ONR (N00014-18-2243), FLI (RFP2-000), ARO (W911NF-19-2-0333), DARPA, Lockheed Martin, GM, and Bosch. Peter Stone serves as the Executive Director of Sony AI America and receives financial compensation. Ashish Deshpande serves as the Chief Research Officer for and has equity shares in Harmonic Bionics. The terms of these arrangements have been reviewed and approved by The University of Texas at Austin in accordance with its policy on objectivity in research.

REFERENCES

[1] D. Rodríguez-Guerra, G. Sorrosal, I. Cabanes, and C. Calleja, "Human-robot interaction review: Challenges and solutions for modern industrial environments," *IEEE Access*, vol. 9, pp. 108 557–108 578, 2021.

[2] B. Yang, J. Huang, X. Chen, C. Xiong, and Y. Hasegawa, "Supernumerary robotic limbs: A review and future outlook," *IEEE Transactions on Medical Robotics and Bionics*, 2021.

[3] T. Proietti, V. Crocher, A. Roby-Brami, and N. Jarrasse, "Upper-limb robotic exoskeletons for neurorehabilitation: a review on control strategies," *IEEE reviews in biomedical engineering*, vol. 9, pp. 4–14, 2016.

[4] R. A. Schmidt, T. D. Lee, C. Winstein, G. Wulf, and H. N. Zelaznik, *Motor control and learning: A behavioral emphasis*. Human kinetics, 2018.

[5] R. Magill and D. Anderson, *Motor learning and control*. McGraw-Hill Publishing New York, 2010.

[6] K. Ghonasgi, R. Mirsky, S. Narvekar, B. Masetty, A. M. Haith, P. Stone, and A. D. Deshpande, "Capturing skill state in curriculum learning for human skill acquisition," in *2021 IEEE International Conference of Intellingent Robotics and Systems (IROS)*. IEEE, 2021.

[7] C. G. Rose, F. Sergi, Y. Yun, K. Madden, A. D. Deshpande, and M. K. O'Malley, "Characterization of a hand-wrist exoskeleton, READAPT, via kinematic analysis of redundant pointing tasks," in *International Conference on Rehabilitation Robotics (ICORR)*. IEEE, 2015, pp. 205–210.

[8] S. Bazzi and D. Sternad, "Human control of complex objects: towards more dexterous robots," *Advanced Robotics*, vol. 34, no. 17, pp. 1137–1155, 2020.

[9] M. Reiser, H. Maurer, K. Fiehler, and H. Müller, "Equifinal throwing movements–computational approach, mechanical implementation, and learning intervention," in *BIO Web of Conferences*, vol. 1. EDP Sciences, 2011, p. 00073.

[10] B. Kim and A. D. Deshpande, "An upper-body rehabilitation exoskeleton Harmony with an anatomical shoulder mechanism: Design, modeling, control, and performance evaluation," *The International Journal of Robotics Research*, vol. 36, no. 4, pp. 414–435, 2017.

[11] A. C. De Oliveira, J. S. Sulzer, and A. D. Deshpande, "Assessment of upper-extremity joint angles using harmony exoskeleton," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 916–925, 2021.

[12] K. Ghonasgi, C. G. Rose, A. C. De Oliveira, R. J. Varghese, and A. D. Deshpande, "Design and validation of a novel exoskeleton hand interface: The eminence grip," in *2021 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2021.

[13] L. Dipietro, H. I. Krebs, S. E. Fasoli, B. T. Volpe, J. Stein, C. Bever, and N. Hogan, "Changing motor synergies in chronic stroke," *Journal of neurophysiology*, vol. 98, no. 2, pp. 757–768, 2007.

[14] J. W. Krakauer, M. F. Ghilardi, and C. Ghez, "Independent learning of internal models for kinematic and dynamic control of reaching," *Nature Neuroscience*, vol. 2, no. 11, pp. 1026–1031, 1999.

[15] H. Ogihara, E. Tsushima, T. Kamo, T. Sato, A. Matsushima, Y. Niioka, R. Asahi, and M. Azami, "Kinematic gait asymmetry assessment using joint angle data in patients with chronic stroke—a normalized cross-correlation approach," *Gait & Posture*, vol. 80, pp. 168–173, 2020.

[16] A. Daffertshofer, C. J. Lamoth, O. G. Meijer, and P. J. Beek, "PCA in studying coordination and variability: a tutorial," *Clinical biomechanics*, vol. 19, no. 4, pp. 415–428, 2004.

[17] T. Bockemühl, N. F. Troje, and V. Dürr, "Inter-joint coupling and joint angle synergies of human catching movements," *Human Movement Science*, vol. 29, no. 1, pp. 73–93, 2010.

[18] K. Witte, N. Ganter, C. Baumgart, and C. Peham, "Applying a principal component analysis to movement coordination in sport," *Mathematical and Computer Modelling of Dynamical Systems*, vol. 16, no. 5, pp. 477–488, 2010.

[19] T. Proietti, E. Guigon, A. Roby-Brami, and N. Jarrassé, "Modifying upper-limb inter-joint coordination in healthy subjects by training with a robotic exoskeleton," *Journal of neuroengineering and rehabilitation*, vol. 14, no. 1, pp. 1–19, 2017.

[20] S. Tang, L. Chen, M. Barsotti, L. Hu, Y. Li, X. Wu, L. Bai, A. Frisoli, and W. Hou, "Kinematic synergy of multi-dof movement in upper limb and its application for rehabilitation exoskeleton motion planning," *Frontiers in Neurorobotics*, vol. 13, p. 99, 2019.

[21] Y. Xu, V. Crocher, J. Fong, Y. Tan, and D. Oetomo, "Moving the goal posts in movement pattern modification using a robotic force field," 2020.