Visual Perception of Limb Stiffness

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***Abstract*— For robotic systems to interact with or learn from the actions of surrounding humans, it is important that they can accurately interpret the intention driving human motor actions. Making such interpretations, however, requires the ability to perceive the relevant feature(s) from the observed human behavior. With visual sensing alone, robots are typically limited to perceiving only the human's overt motion in the form of joint angles and positions. Ideally, robots designed to interface with humans would also be able to infer information as to how the human is controlling itself from that overt motion. In this study, we investigated if and how humans might be able to visually sense changes in limb mechanical impedance of others. Results indicated that humans can visually perceive changes in joint stiffness from the motion of a two-link planar arm, suggesting that humans can extract information regarding how humans control limb impedance from kinematic information. These findings have important implications for applications where robots must interpret the motor actions of humans, such as during robot imitation learning and human-robot physical interaction.**

I. Introduction

Robotic systems are becoming increasingly autonomous and prevalent in everyday life. The success of their assimilation into human society, however, will critically depend on their ability to interact and coordinate with humans. To effectively operate with or in the vicinity of humans, robots need to perceive and interpret the actions of humans. To perform robustly in ever-changing human environments, it would be also advantageous for robots to learn not only from their own action and outcomes, but to also learn from observing actions and interactions of others, just as humans do [1]. Hence, the ability to interpret human action is a ubiquitous need for integrating robotic systems into human life.

Interpreting human control or intention from motion is still a challenge. This is because only the overt motion of the person can be visually perceived. The hidden features that actually generate the motion, such as muscle activation, or the neuromotor commands that control motion cannot be seen [2], [3]. This limitation presents a challenge for developing controllers for successful human-robot interaction, as well as for robot imitation learning. Only the features of human motor behavior that can be perceived or observed can be imitated. Due to this constraint, a robot learning from visual observation is often limited to matching the joint and end effector motion of the human demonstrator [3].

Interpreting the motor actions of others, and subsequently learning from them, is a critical process in human sensorimotor skill acquisition [4], [5], [6], [7] and motor development [8], [9]. Yet, our understanding of how humans learn to interpret and imitate the motor behavior of others is limited. The current challenges in robot imitation learning speak to this limited understanding. At present, robot systems are capable of mapping sensory information into motor actions through human-inspired learning techniques such as reinforcement learning [10]. When learning from human demonstration, however, it is unclear what aspects of the demonstrated motor action should be perceived and learned by the robot [3]. This major barrier in robotics research highlights a knowledge gap in our understanding of human observational learning. We have limited insight as to what perceptual information humans use to understand and learn from the motor behavior of others.

It has been proposed that humans use their own motor system to understand actions and identify biological motion [11]. Neuroimaging evidence [12], [13] suggests that humans have a mirror-neuron system, such that the same neural circuitry is active during both the execution and observation of a task. It is hypothesized that by mapping observed actions in the motor system, the observer gains knowledge of how those actions may be internally controlled [14]. On one hand, this might suggest that if the system being imitated has different "rigid body properties" than a human, imitation learning would have to occur via other processes. On the other hand, if the features that humans perceive and mimic are independent of the rigid body properties of demonstrator, then imitation learning and action understanding of human and non-human systems should be similar. Behavioral evidence suggests that infants [8], [9] and primates [15] can imitate motor behavior of adult humans, which would support the latter notion that humans may be able to understand and imitate motion despite large differences in rigid body properties. Identifying such features would point to new approaches for robot imitation learning as well as human-robot interaction.

One possibility is that humans can perceive the dynamic properties, or impedance, of the demonstrators limb. Not only is limb impedance a feature that is superimposed on the rigid body structure of the demonstrator, the control and regulation of limb impedance is an important process in human motor control and learning [16], [17], [18], [19], [20], [21], [22], [23]. Thus it is possible that humans can sense and utilize such information for understanding the actions of others. Prior studies have demonstrated that human stiffness

*This work was supported in part by the Eric P. and Evelyn E. Newman Fund, by NSF EAGER Grant 1548514 Fund, and by NIH Grant R01-HD087089.

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[28] and viscosity [29] can be perceived with proprioceptive information. It is untested, however, whether humans can also perceive such properties with vision alone.

Recent research in robotic tele-operation demonstrates how sensing and replicating human-like impedance control can improve robot control. Howard et al. [24] identified imitating variable impedance control of humans as a promising approach to allow robots to be compliant, yet precise. Moreover, they demonstrated that feature-based tracking and imitation of human impedance (e.g., equilibrium position and stiffness) can be effective for online, interactive control of a robotic arm. Ajoudani et al. [25] have also proposed a similar method for imitating human motor actions by estimating the equilibrium positions and impedance profiles of human arm motion and using these parameters in the teleoperation of a robot arm. Both of these studies, however, used electromyography (EMG) to estimate limb impedance of the human controller. For robots to interpret and learn from human motion in real world applications, it would be advantageous to sense limb impedance without additional sensors placed on the human.

In this study, we address the novel question of whether humans can visually perceive changes in joint stiffness from the multi-joint motion of a simulated arm. The results of this study significantly contribute to our understanding of how humans visually perceive and interpret the actions of other humans and even other robots. Thus, these results also suggest important considerations for any autonomous robot system that learns from or interacts with humans. The remainder of the paper is organized as follows. Section II describes two human experiments in which we tested the prediction that humans perceive changes in the stiffness properties of a simulated moving arm. Section III presents the group and individual results from these two experiments. Section IV discusses our interpretation of the experimental results and their important implications for robotic imitation learning and human-robot interaction.

II. Approach

We conducted two experiments in which we asked subjects to watch simulated motions of a 2 link planar arm and rate the stiffness of the arm on a numeric scale. Note that the known challenges in estimating individual joint stiffness from human motion motivated our use of a simulated arm in the this study. In Experiment 1, the stiffness of the elbow joint was varied across simulations, and in Experiment 2, the stiffness of the shoulder joint was varied. For both experiments, we hypothesized that there would be a positive linear relationship between the respective joint stiffness values used in simulation and the arm stiffness rated by the subject.

A. Participants

A total of ten subjects participated in the experiments (3 males and 7 females with a mean age of 23.56 $\pm$ 4.72 years). Subjects had a variety of educational backgrounds, including engineering, computer science, material science, and biology. Five subjects participated in Experiment 1, and five subjects participated in Experiment 2. Each subject participated in only one experiment, and none had any prior experience with the experimental task. All subjects gave informed written consent before the experiment. The experimental protocol was reviewed and approved by the Institutional Review Board of the Massachusetts Institute of Technology.

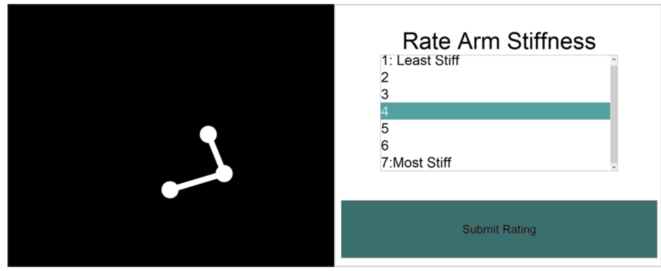

Fig. 1. In each of the trials, subjects viewed a two-link planar arm moving in periodic fashion for 20 seconds (left). After watching the simulated motion, a new screen appeared asking subjects to rate the "arm stiffness" during that motion on a Likert scale from 1 to 7 (right).

B. Experimental Task

Subjects sat in front of a computer monitor which displayed a custom graphical user interface developed in MATLAB (The Mathworks, Natick, MA). With this interface, subjects viewed and subsequently rated the stiffness of the simulated arm motions in the two experiments (Figure 1).

In each trial, subjects watched a simulated two-link arm rhythmically move its endpoint along an orbital path for twenty seconds. Directly following the simulated motion, subjects rated the "arm stiffness" on a Likert scale from 1 to 7 for that trial. A rating of 1 indicated that the arm was "least stiff", and a rating of 7 indicated that the arm was "most stiff". In the event that a subject was unsure of what the term stiffness meant, s/he received the following definition: *"Stiffness is the extent to which an object resists deformation or deflection in response to an applied force. A stiffer object has higher resistance to deflections than a less stiff object."* Subjects then clicked on a button to initiate the next trial.

All subjects performed five blocks of six trials, for a total of thirty trials. Each trial within a block displayed a different simulated arm motion. In Experiment 1, the arm motion was simulated with different values rotational stiffness at the elbow joint (0, 10, 20, 30, 40, and 50 Nm/rad). The range of elbow stiffness values used are similar to those reported in human studies [26], [27]. For simplicity, we did not mimic the observation that human joint stiffness changes with posture and during movement [20], [26]. In Experiment 2, the arm motion was simulated with different values of rotational stiffness at the shoulder joint (0, 10, 20, 30, 40, and 50 Nm/rad). As we were unable to identify estimates of human shoulder stiffness from the literature, we used the same stiffness values in the Experiment 1 for consistency. The order of the trials within each block was randomized.

After finishing the experiment, which lasted approximately 20 minutes, subjects were asked to qualitatively describe the

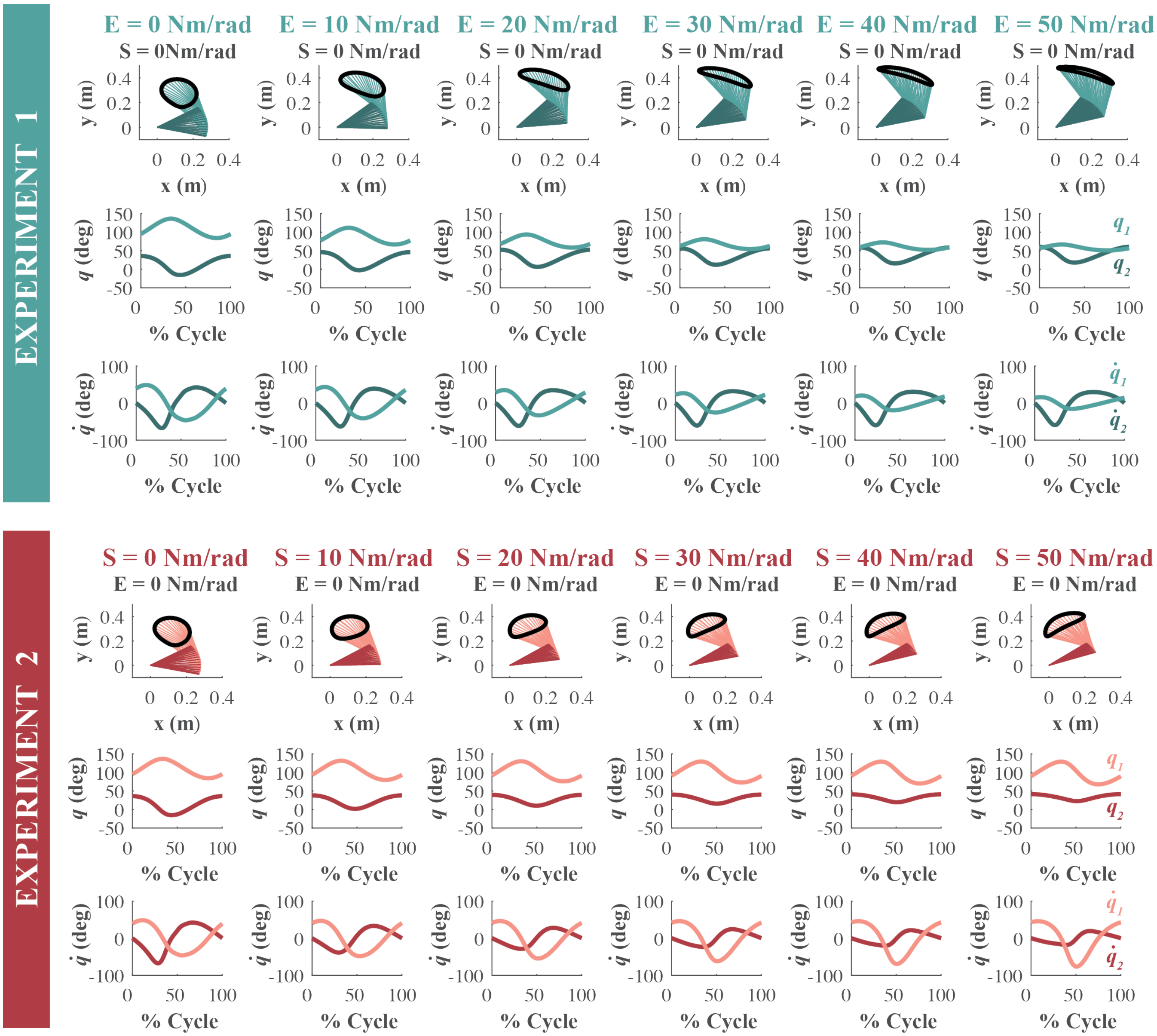

Fig. 2. In each experiment, subjects rated arm stiffness of 6 arm motions shown 5 times in randomized order. The value of elbow stiffness, E, was changed to generate the arm motions shown in Experiment 1 (top panel). The value of shoulder stiffness, S, was changed to generate the arm motions shown in Experiment 2 (bottom panel). Changing the joint stiffness values altered the endpoint and joint motion of the arm as shown.

strategy they used to determine their arm stiffness rating.

TABLE I
PARAMETERS OF THE SIMULATED ARM

	Link 1	Link 2
Length (m)	0.2817	0.2689
Center of Mass (m)	0.1326	0.1434
Mass (kg)	2.0438	1.1749
Moment of Inertia (kgm^2)	0.0039	0.0013

C. *Simulating Arm Motion*

The simulated arm was modelled as a two-link planar manipulator moving in the vertical plane. The dynamics of this model were described as

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = \tau \tag{1}$$

where

- $q = \begin{bmatrix} q_1 & q_2 \end{bmatrix}^{\mathrm{T}}$ are the joint angular positions,
- $\dot{q}, \ddot{q} \in \mathbb{R}^2$ are the joint angular velocities and accelerations, respectively,
- $M(q) \in \mathbb{R}^{2\times 2}$ is the inertia matrix,
- $C(q,\dot{q}) \in \mathbb{R}^2$ are centrifugal and Coriolis force terms,
- $g(q) \in \mathbb{R}^2$ are the gravitational force terms, and
- $\tau \in \mathbb{R}^2$ are commanded joint torques.

The length, mass, center of mass, and moment of inertia parameters for the two links were chosen to match the forearm and upper arm of an average, male human as described in [30] (Table 1). In anatomical terms, q_1 is considered the shoulder joint angle, and q_2 is considered the elbow joint angle relative to the orientation of the upper arm.

The commanded joint torques were determined by

$$\begin{aligned}\tau = J(q)^{\mathrm{T}} K_x (x^d - x) - J(q)^{\mathrm{T}} K_v (v^d - J(q)\dot{q}) \\ + K_q (q^d - q)\end{aligned} \tag{2}$$

where

- $J(q) \in \mathbb{R}^{2\times 2}$ is the Jacobian matrix,
- $x, x^d, v^d, q^d \in \mathbb{R}^2$ are the end effector positions, desired end effector positions, end effector velocities, and joint angular positions, respectively, and
- $K_x, K_v, K_q \in \mathbb{R}^{2\times 2}$ are the feedback gains for the end effector positions, end effector velocities, and joint angular positions, respectively.

For this study, this controller aimed to move the end effector of the arm in a desired circular motion $x^d(t) = \begin{bmatrix} 0.1\cos(\frac{2t}{0.3}) & 0.1\sin(\frac{2t}{0.3}) \end{bmatrix}^{\mathrm{T}}$ with a feedback gain of $K_x = \begin{bmatrix} 500 & 0; & 0 & 500 \end{bmatrix}^{\mathrm{T}}$ with a desired velocity of the end effector set to $v^d = \begin{bmatrix} 0 & 0 \end{bmatrix}^{\mathrm{T}}$ with a feedback gain of $K_v = \begin{bmatrix} 10 & 0; & 0 & 10 \end{bmatrix}^{\mathrm{T}}$. At the same time, a desired joint configuration of $q^d = \begin{bmatrix} \frac{\pi}{4} \frac{\pi}{4} \end{bmatrix}^{\mathrm{T}}$ was imposed on the arm with a feedback gain of $K_q = \begin{bmatrix} S & 0; & 0 & E \end{bmatrix}^{\mathrm{T}}$. The shoulder rotational stiffness, S, was set to 0 Nm/rad in Experiment 1 and set to either 0, 10, 20, 30, 40, or 50 Nm/rad in Experiment 2. The elbow rotational stiffness, E, was set to either 0, 10, 20, 30, 40, or 50 Nm/rad in Experiment 1 and set to 0 Nm/rad in Experiment 2.

The values of rotational joint stiffness affect (1) the resulting motion of the end effector, (2) the relative range of motion between the joints, and (3) the relative range of angular velocities between the joints as shown in Figure 2.

D. Dependent Measures

The arm stiffness rating on the Likert scale [31] served as the primary dependent measure. Note that asking subjects to rate arm stiffness on this scale introduces a mapping error. This mapping error is analogous to the error resulting from representing a continuous analog signal with discrete, stepped digital data, known as quantization error [32]. For our experiments, the estimated quantization error in the Likert scale can be modelled as uniformly distributed noise with a mean of zero and a variance of 0.69 when subjects utilize the full range of the scale. The variance of the quantization error, σ^2_{qe}, was determined by

$$\sigma^2_{qe} = \frac{(s_{max} - s_{min})(r_{max} - r_{min})}{12(n-1)^2} \tag{3}$$

where

- s_{max}, s_{min} are the maximum and minimum values of the joint stiffness conditions, respectively,
- r_{max}, r_{min} are the maximum and minimum values of the Likert rating scale, respectively, and
- n is the number of equidistant units in the Likert rating scale.

E. Statistical Analysis

For each experiment, we tested the prediction that arm stiffness rating increases with the simulated joint stiffness. To test this prediction, we conducted a 6 (Simulated Joint Stiffness) x 4 (Block) repeated-measures analysis of variance (ANOVA) on the arm stiffness rating for both experiments [33]. Because it was difficult for subjects to gauge relative stiffness ratings in the beginning of the experiment, their arm stiffness ratings from the first block of trials were excluded from all statistical analyses.

Posthoc polynomial contrasts tested the linear trend in arm stiffness rating across the simulated joint stiffness levels. If linear trends were significant in each experiment, the slopes of the linear relationship between simulated joint stiffness and arm stiffness rating were calculated for each subject. A Student's t-test was then conducted to test for group differences in these slopes.

In all statistical tests, the significance level was set to $p < 0.05$. Statistical analyses were performed using SPSS Statistics for Windows, Version 24.0 (IBM Corporation, Armonk, NY).

III. Results

A. Experiment 1

The ANOVA of arm stiffness rating revealed a significant main effect of simulated joint stiffness on arm stiffness rating, $F(5,20) = 26.21, p < 0.001$. As predicted, subjects increased their arm stiffness rating as the simulated elbow stiffness increased (Figure 3). There was no significant effect of block, $F(3,12) = 0.07, p = 0.98$, nor an interaction, $F(15,60) = 1.02, p = 0.45$. These results indicate that subjects did not "learn" or significantly change their rating pattern as the experiment progressed.

Posthoc polynomial contrasts revealed a significant linear trend in arm stiffness rating across the levels of arm stiffness as predicted, $F(1,4) = 66.03, p = .001$.

B. Experiment 2

As in the previous experiment, the ANOVA of arm stiffness rating revealed a significant main effect of simulated joint stiffness on arm stiffness rating, $F(5,20) = 8.64, p < 0.001$. Again, subjects had higher arm stiffness ratings for arm motions simulated with higher shoulder stiffness values as predicted (Figure 3). There was no significant effect of block, $F(3,12) = 0.30, p = 0.82$, nor an interaction, $F(15,60) = 0.59, p = 0.88$.

Posthoc polynomial contrasts revealed a significant linear trend in arm stiffness rating across the levels of shoulder stiffness as predicted, $F(1,4) = 11.57, p = .027$.

The result of the t-test further revealed that there was no significant difference in how subjects rated arm stiffness when elbow stiffness changed compared to how subjects rated arm stiffness when the shoulder stiffness chaged, $t(8) = 1.59, p = 0.15$.

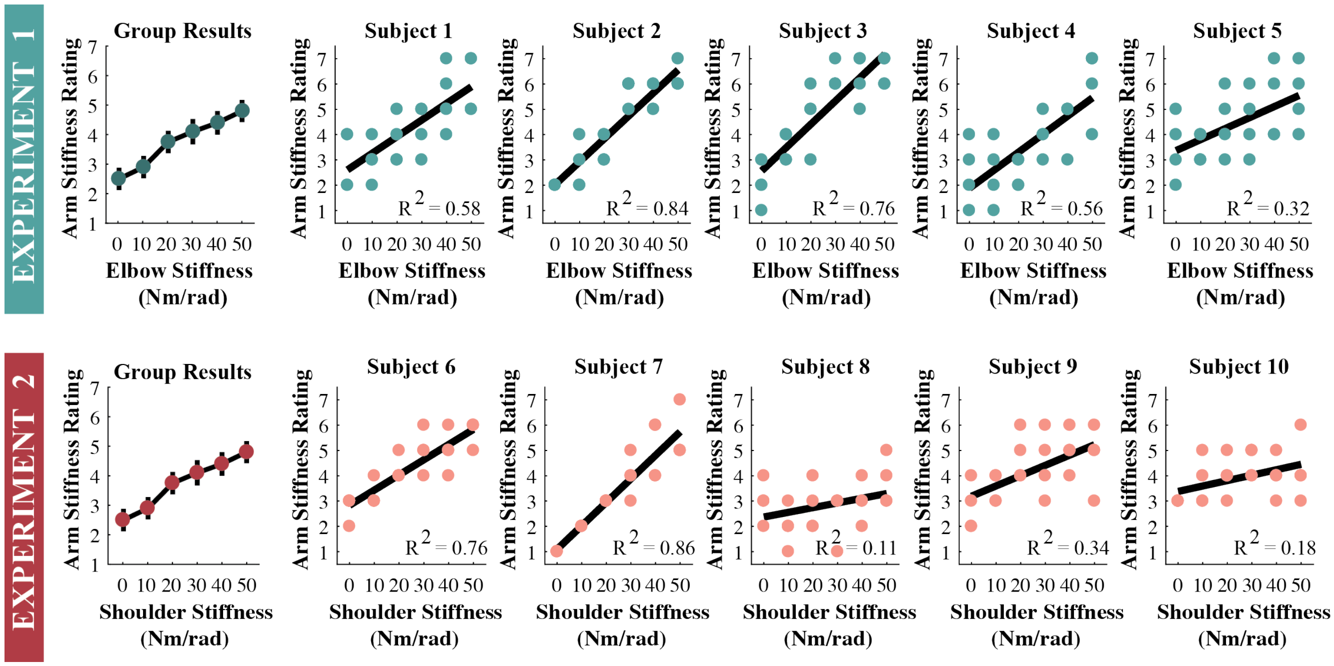

Fig. 3. In both experiments, there was a significant, positive linear effect of simulated joint stiffness level on the arm ratings made by subjects. In the group results, the circles represent the group means and the error bars represent $\pm$ one standard error of the mean. For the subject results, each circle represents a minimum of four ratings for each level of joint stiffness. Identical ratings are overlaid, this one circle may represent multiples of four ratings. The black line represents the linear fit of each subject's data. The R^2 value of the linear fit is reported in the bottom corner of the corresponding plot.

IV. Discussion

Prior research suggests that humans tune the dynamic properties of their limbs to stabilize and control their movements. It is has been proposed that modulating limb impedance allows humans to coordinate complex, multi-joint movements [20], [34]. Controlling impedance is also important for maintaining stability during physical interactions and tool use [35]. Thus, extracting such control-relevant information as how to humans modulate impedance during a task would be informative for robot imitation learning and human-robot interaction. However, limb impedance is modulated through muscle activation, which cannot be directly observed with vision. Hence prior work aimed at imitating human impedance profiles during motion relied on signalling from EMG [24], [25].

In this study, we investigated if humans can perceive changes in joint stiffness strictly from overt motion. If humans can perceive joint stiffness and we can understand how they are perceiving stiffness changes, then this form of perception could be replicated and used in the control of robotic systems. As predicted, the results of two experiments demonstrated that humans can visually perceive changes in both elbow and shoulder stiffness. Not only was there an effect of joint stiffness on the arm stiffness rating, the effect was positive and linear as predicted. The majority of subjects had very strong linear relationships between simulated joint stiffness level and arm stiffness rating (Figure 3).

There were, however, a small number of subjects who appeared to be less successful at perceiving changes in joint stiffness. One potential reason for this could be variations in measurement noise caused by rating on a Likert scale. If subjects used only a subset of rating values as opposed to using the whole range of the Likert scale, there would be more noise in their rating responses. For example, Subject 10 limited their responses to between 3 and 6 on the rating scale, which means that the noise in their rating signal had a variance of 1.39 from Eq. (3). This is a two-fold increase in noise variance compared to the subjects who used the full range of the rating scale. This increased variance in the measurement noise could have caused poorer linear fits for some subjects.

Besides increased measurement noise, another possible reason is that subjects may have used different strategies to determine their ratings of arm stiffness. As previously mentioned, changing the values of rotational joint stiffness affected the resulting motion of the end effector, along with range of motion and velocity of the joints. It is possible that rating arm stiffness from certain features yielded more reliable rating responses than others.

For this study, we purposely kept the definition of "arm stiffness" vague for subjects rather than directing subjects attention to specific joints. We also chose not to show subjects examples of the different stiffness conditions before they performed the experiment. While this left the term "arm stiffness" up to the interpretation of each subject, it also allowed us to further examine how humans naturally perceive these changes without the influence of instruction. For implementing such perception capabilities on a robotic system, identifying the specific features of motion that give the most reliable estimates of joint stiffness is critical.

After performing the experiment, subjects reported a variety of strategies used to rate arm stiffness. Although it should be noted that many subjects could only describe their strategy in vague terms, the majority of subjects reported using the change in elbow and shoulder range of motion to make their ratings. The change in angular velocity of each joints was also reported as a strategy. At face value, it may seem obvious that subjects used range of joint motion to detect joint stiffness, but subjects were not informed that joint stiffness would change, let alone which joint stiffness would change across trials. When the elbow stiffness was increased in Experiment 1, the range of motion of both joints decreased. Thus, subjects could have used the change in range of motion of either joint for determining their ratings. When the shoulder stiffness was increased in Experiment 2, however, the range of motion in the shoulder joint decreased and the range of motion in the elbow joint increased (Figure 2). And yet, subjects in Experiment 2 were still able to correctly perceive changes in stiffness. In fact, subjects in both experiments always had a positive relationship between joint stiffness level and their arm stiffness rating. These results suggest that subjects are not necessarily relying on information from a single joint, but rather they are integrating information about the motions of both joints to perceive changes in joint stiffness.

Interestingly, none of the subjects mentioned the term "endpoint" or "hand position" when describing their rating strategy. Note that subjects were not informed of the desired motion of the end effector in the simulation. While subjects did not explicitly report using the changing shape of endpoint motion as their criterion for rating stiffness, it is still possible that they used this knowledge unknowingly [1]. Future experiments with a redundant simulated arm will allow us to determine if humans can still perceive changes in joint stiffness, even if the endpoint motion is the same. Future research will also test how the results of this study generalize to other desired endpoint actions, including those involving physical interaction.

Ultimately, the results of this study show that subjects can perceive changes in joint stiffness, which suggests that limb stiffness is another observable feature of human motor behavior. Moreover, it can be sensed without invasive or obtrusive equipment on the human demonstrator and without the need to perturb their motion. Further research is still needed to have a complete understanding how of limb impedance can be visually perceived, especially for cases where high degree-of-freedom limbs are performing complex actions with physical interaction. Additionally, it is still an open question whether humans can similarly perceive changes in other impedance properties such as inertia and damping from visual information. Nonetheless, the results of experiments presented here provide valuable first insights into how humans perceive changes in joint stiffness. This ability to estimate limb stiffness through vision, especially from only kinematic information, is especially desirable for robot imitation learning and teleoperation [24], [25], and human-robot interaction [36].

Typically in robot imitation learning, both the joint angles and end effector position of the human demonstrator are imitated by the humanoid robot in order to make the robot motion appear more human-like [37]. The premise is that if the robot motion is human-like, it will be more legible or predictable to humans [38]. The problem is that the "hardware" of humans and robots is different, especially in terms of kinematic structure, actuators, sensors, etc. While the limb motion of the robot might be human-like, its dynamic response to perturbations or physical contacts during motion may not be human-like. Instead of matching joint angles, an alternative approach may be to match limb impedance. This approach may allow for safer interaction between robots and their environment as well as humans and robots, which is important when robots are deployed for use in novel and ever-changing environments such as a home or factory setting.

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