Estimating Human Teleoperator Posture Using Only a Haptic-Input Device

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Abstract—Ergonomic analysis of human posture plays a vital role in understanding long-term, work-related safety and health. Current analysis is often hindered due to difficulties in estimating human posture. We introduce a new approach to the problem of human posture estimation for teleoperation tasks which relies solely on a haptic-input device for generating observations. We model the human upper body using a redundant, partially observable dynamical system. This allows us to naturally formulate the estimation problem as probabilistic inference and solve the inference problem using a standard particle filter. We show that our approach accurately estimates the posture of different human users without knowing their specific segment lengths. We evaluate our posture estimation approach from a haptic-input device by comparing it with the human posture estimates from a commercial motion capture system. Our results show that the proposed algorithm successfully estimates human posture based only on the trajectory of the haptic-input device stylus. We additionally show that ergonomic risk estimates derived from our posture estimation approach are comparable to those estimates from gold-standard, motion-capture based pose estimates.

I. INTRODUCTION

Workplace injury is a concerning issue which affects millions of workers worldwide every year and costs businesses billions in revenue. Work-related musculoskeletal disorders (WMSDs) are the 2nd largest cause of disabilities worldwide [1]. Awkward postures are known to contribute to WMSDs, as such ergonomics of at risk workers should be examined to reduce the risk of WMSDs and improve efficiency over long periods of work.

Teleoperation is a well suited alternative for high-risk manual tasks (e.g. mining and construction). In telemanipulation the user interacts with a master robot or a haptic-input device to control a remote robot that does the real task in the target environment. A significant advantage of teleoperation is that remote workspaces can be designed ergonomically for both equipment and workstation design [2]. Moreover, teleoperation provides the potential to use the master robot for continuous monitoring of ergonomics risk factors through posture estimation in order to (1) raise an alert when the risk is high, and (2) help in designing the workplace ergonomically as an evaluation tool.

Collecting accurate and continuous posture data is a major challenge in ergonomics analysis. Ergonomists often perform risk assessments by taking measurements of human posture onsite or from recorded images and finding the worst posture during the task. However, it is tedious to determine a risk score for the entire task due to the complexity of the task and inadequate data. In most cases, it is impossible to perform a comprehensive risk assessment of all motions which often results in missing important events or only partially understanding the frequency and duration of awkward postures.

Early efforts to improve the efficiency of ergonomic assessments included using computer vision to estimate the posture1 and task parameters (e.g. frequency of the task or the time that the person maintains a posture). Recent approaches for posture estimation include two main categories: (1) marker-based approaches and (2) markerless approaches. In marker-based approaches, reflective markers are attached to the human body and a motion capture (mocap) system records the position of the markers and estimates the posture based on predefined skeleton models. Although they are fast (greater than 100Hz) and accurate in many applications, they require significant time and effort for set up [3]. Additionally, putting markers on human operators can be inconvenient. Markerless alternative techniques are more adaptable, minimally intrusive, and less expensive. However, they require vision systems or IMU sensors that need to be calibrated, in order to deal with errors and uncertainties from the sensors [4], [5]. The most minimally invasive, vision-based markerless methods rely purely on external RGB or RGB-D cameras. These approaches are easily perturbed by the magnitude of the light, background color and even the user’s clothes [6]. In teleoperation, using the robot in such close proximity increases occlusion and makes it even more difficult for existing vision-based methods to provide an accurate posture estimation. Instead, we propose an alternative approach to estimate human posture without using any additional sensor beyond the haptic-input device necessary for the operation of the remote robot.

1Different communities use different terms. We use “posture” because “pose” estimation could be misconstrued as a 6-DOF pose of a rigid body.
We envision an autonomous solution to ergonomics analysis in teleoperation that includes two main steps: (1) estimating the human operator’s posture, (2) analyzing the ergonomics and injury risk of the estimated posture. In this paper, we suggest a new approach to estimate posture of the human upper body in teleoperation using only the data observed from the haptic-input device. We additionally provide an algorithmic approach to assess the user’s risk of WMSDs using RULA [7], a standard measure in the ergonomics and safety community. Figure 1 shows the haptic-input device setup we examine.

We formalize posture estimation as a probabilistic inference problem, in which we measure the haptic-input device stylus trajectory (pose and velocity) as the observation and infer the unobserved human posture (joint angles and angular velocities). We encode human factors and biomechanics knowledge into our partially observable dynamic model. We use the circle point analysis (CPA) [8] for segment length estimation of the human body and compare it with anthropometry models. We also impose physical limits on joint angles. We incorporate multiple observations over time enabling us to perform inference using a standard particle filter. We use the estimated posture over the course of the task to calculate the RULA score for the performed task. Finally, we find an overall RULA score based on these data points during the whole task. We conduct a human subject study to evaluate our method including 8 subjects.

Below, we summarize our main contributions:

1) We formulate the problem of human posture estimation as a partially observable dynamical system that uses only the robot’s stylus trajectory as observation.

2) We solve the partially observable problem of human posture estimation from the robot trajectory using a particle filter.

3) We provide a systematic RULA analysis and compare RULA scores from our estimated posture and the posture estimated with a mocap system.

4) We compare three different methods for human body segment length estimation: (1) manual measurement of segment length on subjects; (2) measuring the subject height and using an ANSUR II model to calculate the length of the rest of segments; and (3) circle point analysis (CPA) using collected data for each subject during calibration motion routines.

We structure the remainder of this paper as follows. In Section II, we review related work in posture estimation and its application in telerobotics, ergonomics, and risk assessment tools. We define the problem of posture estimation in teleoperation in Section III. Section IV introduces our approach including modeling human posture estimation as a partially observable dynamical system, our filter-based inference solution, and our algorithmic, ergonomic assessment procedure. We present our implementation and data collection procedure in Section V. Section VI covers the results and evaluation of our approach. We conclude the paper and in Section VII with some final remarks and directions for future work.

II. RELATED WORK

Human posture estimation has been the focus of research in various areas including biomechanics [9], gait analysis [10], behavior analysis [11], rehabilitation [12] and robotics [13]. Generally, posture estimation refers to the process of estimating the kinematic or skeletal configuration of the human body. Some recent studies add an analysis process after the human posture estimation to improve human-robot interaction performance. For instance, researchers have discussed ergonomics analysis and safety-based factors such as joint overloading [14], [15], the separation distance between the robot and human [16], and muscular fatigue [17].

For many years, mocap systems using reflective markers ([18], [19]) were the dominant approach for posture estimation. However, advances in computer vision have led to increases popularity in markerless posture estimation techniques [20], [21]. In marker-based methods, in markerless posture estimation, human posture is acquired through passive sensing systems and then processed into a kinematic configuration. Usually the passive sensing system is a 2D perspective view of the subject from multiple frames of a single video or multiple synchronized videos, and in some cases combined with IMU sensors attached on the subject’s body [22].

In physical human-robot interaction and teleoperation, different methods have been used by researchers to estimate the user’s posture, especially for hand gestures. Varholomeos et al. [23] explored the use of IMU sensors in a versatile movement sensing device that can be used to telemanipulate a soft robot arm as an assistive device for bathing. Buzzi et al. [24] estimated the posture of a human arm interacting with a 7-DOF haptic-input device using mocap data and solving the associated inverse kinematics problem using the OpenSim simulator as an offline process. They investigated how master robots with different kinematic structures and different task constraints influence users’ capabilities in exploiting arm redundancy. Martiencz et al. [25] propose a maximum-likelihood motion estimation algorithm to control the ROBONAUT. They used this algorithm to estimate the motion of the right arm of a human using a single monocular camera. In all of the approaches, vision system or IMU sensors were the key additional sensors used for posture estimation.

The application of particle filters in human posture estimation is extensively discussed in the literature [26]–[28]. The main feature of particle filters making them well suited to human posture estimation is their ability to handle the nonlinearities of human motion [29] due to its sampling basis. However, the high dimension of human motion requires a high number of particles to achieve accurate estimation.

Several studies show that evaluating ergonomics and improving the tasks and workplace using those tools on reducing the number of reported musculoskeletal injuries [30], [31]. Recently, new software has been developed for systematic risk assessment [32], [33] and researchers are focusing on perceiving ergonomic-related parameters of the task and human motion automatically from vision systems. Among all of the
risk assessment tools, RULA [7] and REBA [34] are relying on the human posture (i.e. joint angles) and they target the human upper body and whole body respectively. This makes the RULA more suitable for analyzing the tasks in which the motion relies mostly on the upper body (e.g. teleoperation). The state-of-the-art literature in risk assessment using computer vision, machine learning and artificial intelligence [35], [36] also use RULA or REBA as the assessment tool in their algorithms. In RULA, the posture is ranked based on regions in the range of motion of body segments. Each region receives a score and the final RULA score is calculated based on several look-up tables and modifications on the segment scores.

Our proposed approach uses the haptic-input devise as the only sensor for estimating the posture and it does not suffer from the drawbacks of marker-based and markerless approaches in teleoperation tasks. Without prior information on segment lengths, it provides a sufficiently accurate estimation for continuous monitoring of the posture and ergonomics analysis in order to reduce the risk of WMDs.

III. PROBLEM STATEMENT

We seek to solve the problem of estimating the human joint-space trajectory during teleoperation using only the observed task-space poses and velocities of the haptic-input device. We model the physical interaction between the human and the haptic-input device as an interaction point where the human kinematic chain makes contact with (i.e. grasps) the robot stylus as shown in Figure 1.

The joint-space state variables of the human include posture (joint angles) $q$ and angular velocities $\dot{q}$. They map into the task-space state variables of the grasped stylus through the kinematics and dynamics of the human model parameterized by the segment length parameter $\psi$. We estimate $\psi$ independently, prior to posture estimation. At each time step, the robot provides an observation in the form of task-space pose $z$ and velocity $\dot{z}$ of the stylus at the interaction point,

$$[z_t; \dot{z}_t] = h([q_t; \dot{q}_t], \psi)$$ (1)

Important this defines only a partial observation of the human pose, because of redundancy in the human posture and noisy measurement as the interaction point of the human on the stylus, which may change slightly during a task.

The goal is to estimate $\tau = [[q_t; \dot{q}_t], \ t = 1, ..., T]$ given the stylus trajectory $Z = [[z_t; \dot{z}_t], \ t = 1, ..., T]$ that results in the closest stylus pose to the observed stylus pose:

$$\tau^* = \arg \min_{\tau} \sum_{t=0}^{T} ||h([q_t; \dot{q}_t], \psi) - [z_t; \dot{z}_t]||^2 +$$ (2)

$$s.t. \ q_{min} \leq q \leq q_{max}$$

where $q_{min}$ and $q_{max}$ are the joint limits and $f$ defines the forward dynamics of the human. The high number of degree-of-freedom in human kinematics makes this problem a redundant problem with an infinite number of solutions. We seek the solution closest to the true posture of the human teleoperator.

IV. APPROACH

In this section, we provide an approximate solution for the partially observable posture estimation in teleoperation using a particle filter. First, we present a 10-DOF kinematic model of the human upper body with only one moving arm and develop the dynamic model of the system. Next, we discuss the observation model from the haptic-input-device and how to adopt a particle filter to solve the problem. Finally, we discuss the details of CPA for segment length estimation.

A. Human Dynamic Model

We use a 10-DOF kinematic model (Figure 2) to analyze the upper body motion of a human sitting on a chair and operating a haptic-input device. Our model includes the right hand, right forearm, right upper arm, shoulder, and torso. We assume the hip is fixed to the chair and that the chair does not move during operation. The parameters of this model ($\psi$) include the length of each segment in the upper body model. Measuring those for each person is a tedious job. Therefore, we compare 3 methods including: (1) Full measurement: measuring the segments lengths of subjects manually from anatomical landmarks on subject bodies [37], [38], (2) Height measurement: measuring the height of the subject and use the ANSUR II model ([39], [40]) to estimate the segment lengths fitting to 50-percentile populations, (3) CPA analysis in which each subject repeats 5 motion routines trajectories described in Section IV-D.

We define the human’s state variables in our 10-DOF model as $q = [q_i, \ i = 1, ..., 10]$, $\dot{q} = [\dot{q}_i, \ i = 1, ..., 10]$ where $q_i$ represents the angle of joint $i$ (shown in Figure 2). We assume that the user’s hand stays attached to the haptic-input device stylus, as such we can calculate the pose of the stylus from by transferring the pose of the hand from the human’s coordinate frame to the robot’s coordinate frame.

From the dynamics of human motion, we find joint angles and velocities based on the previous step as follows:

$$\ddot{q}_k = \ddot{q}_{k-1} + \dot{q}_{k-1} dt$$ (3)

$$q_k = q_{k-1} + \dot{q}_k dt$$ (4)

Here, we model joint accelerations as unknown variables generated from a Gaussian distribution with zero mean and variance $\Sigma_v$ as:

$$\ddot{q}_{k-1} \sim N(0, \Sigma_v)$$ (5)
Fig. 3: Five motion routines for CPA segment length estimation.

Since \( dt \) is fixed, setting \( \Sigma_v = ˜\Sigma_v \cdot dt \) transforms Eq. 3 to:

\[
p(\hat{q}_k \mid \hat{q}_{k-1}) \sim \mathcal{N}(\hat{q}_{k-1}, \Sigma_v)
\]

(6)

B. Observation Model

We model the observation likelihood function by a Gaussian distribution over the hand’s pose and velocity as the end-effector of the human kinematic chain:

\[
p((\mathbf{z}_k, \mathbf{\dot{z}}_k) \mid \{\mathbf{q}_k, \mathbf{\dot{q}}_k\}) = \mathcal{N}(h(\mathbf{q}_k, \mathbf{\dot{q}}_k, \psi), \Sigma_K)
\]

(7)

In which \( \Sigma_K \) is the kinematic covariance matrix.

C. Particle Filter for Posture Estimation

We approximate the solution for the partially observable problem of posture estimation by using a particle filter presented in [41] (and discussed in the supplementary document) with two modifications. First, to generate a posture similar to those used during the telemanipulation tasks, we incorporate a prior in our particle filter, that encodes that the human starts the task in a static, neutral posture close to that shown in Figure 3. We initialize the particle from a truncated normal distribution, limited around a neutral posture and set the initial angular velocities to zero:

\[
\mathbf{q}_0^{[m]} \sim \mathcal{N}(\mathbf{q}_{\text{neutral}}, \Sigma_{\text{init}}), \quad m = 1, ..., M
\]

(8)

\[
\mathbf{\dot{q}}_0^{[m]} = 0, \quad m = 1, ..., M
\]

(9)

where \( \mathbf{q}_{\text{neutral}} \) is the neutral posture and we select the standard deviation \( \Sigma_{\text{init}} = 0.2 \times (q_{\text{max}} - q_{\text{min}}) \) for each joint. Second, we use human biomechanics [42] to define the range of motion constraints. Based on the type of the teleoperation tasks, we assume that the torso stays around the vertical position with a low deviation. We provide exact values of joint limits in the supplementary material. If the joint angle for any joint exceeds its range of motion, we select the corresponding joint limit as the joint angle.

D. Circle Point Analysis for Segment Length Estimation

We can estimate segment lengths \( \psi \) using the data collected through a calibration process with the user holding the robot. Starting from the neutral posture, the user performs some predefined motion patterns that only include motion in one of their joints. When following such a pattern, we can assume that the human hand will move on a circle. Finding the circle parameters gives us information on the placement of the active joint and the distance from the end-effector to that joint. We use this information to estimate the human segment lengths. This method is a variation of circle point analysis (CPA) [8].

Figure 3 presents the 5 motion patterns used in data generation for CPA: (1) wrist flexion/extension to estimate hand length; (2) upper arm external/internal rotation to estimate forearm length; (3) upper arm abduction/adduction to estimate upper arm length; (4) rotation from the hip to estimate shoulder length; and (5) lateral bending from the hip to estimate torso length. We note that in estimating the last two segments we use the previously estimated arm and hand segment lengths. We compare the deviation of estimated segment lengths from the different methods from mocap lengths among all subjects in Figure 4. The deviation for full measured lengths of hand from mocap is zero because the mocap could not provide a length for the hand, so we used the manually measured one instead of it. The last column of the figure shows that lengths from CPA deviate least from the mocap lengths. Actual length values and comparison of the segment lengths with the full-measured lengths are included in the supplementary document.

V. IMPLEMENTATION & EXPERIMENT PROTOCOL

In this section, we describe our experimental procedure in evaluating our approach. We conduct a human subject experiment in which subjects are interacting with a Quanser HD2 haptic-input device (see Figure 1). We collect human motion using an Optitrack mocap system with 12 cameras to compare with our approach.

We use a fixed rigid-body transformation \( R_{wc} \) for wrist joints to correct the hand pose in the posture from mocap to be as the link between the wrist and the robot interaction point at the stylus as it is shown in Figure 5. Mocap data includes three segments for the torso (hip, abdomen and chest) as our model only uses one segment. For the sake of comparison of angles with our approach, we make a virtual torso segment from the beginning of hip to the end of chest in mocap and compare the orientation of this virtual torso with the estimated torso orientation from our approach.

We collect data from 8 human subjects including 4 female and 4 male subjects, with ages ranging from 25 to 33 and heights in the range of \((1.50m, 1.92m)\). In our experiments, each subject performs 4 tasks visualized in Figure 6: (1) following a straight line in the X direction, (2) Following a straight line in the Y direction, (3) following an elliptical path, (4) pick and place with free motion and high range of wrist rotation. We provide a printed guide path on the table for the
first three tasks, to guide the subjects track the path visually. The goal is to provide different types of motion for analysis; the subjects are not required to follow the path accurately. The robot does not exert any force and it is only collecting data.

As neither marker-based nor markerless posture estimation techniques provide ground truth posture, we additionally provide qualitative analysis by overlaying the estimated posture on synchronized video frames, showing the posture inferred by our approach aligns well with mocap estimates. While other possible approaches exist (e.g. hand-labeling image points [43]), these approaches are error prone and extremely time-consuming, so we do not perform them.

We use a fixed number of particles (M=500), as this appears to work well across a large number of tasks in the experimental trials. Deriving the kinematic covariance matrix is included in the supplementary document.

In running the the RULA risk assessment on both the estimated postures from our approach and mocap, we consider

2The human subject experiment is approved by the IRB with reference number:IRB_00094626

the prior information on the task including: the human is sitting on a chair, minimal intermittent force/load (<2.0Kg), muscle use occurrence less than 4x per minute, untwisted and vertical position for neck and trunk, and supported legs and feet.

VI. RESULTS & DISCUSSION

This section presents results from our human subject experiments. We discuss the performance of the proposed approach comparing with posture estimated from mocap in real-world studies. We also compare the estimated risk assessment results.

A. Posture Estimation

Figure 7 shows the effect of initializing the particles using a Gaussian distribution centered at the human’s neutral posture with covariance $\Sigma_K$. We see this quickly resolves the redundancy issue, converging to a single mode in the particle filter. All the particles for each time step are plotted as well as their mean and standard deviation of their distributions. On the top, we initialize particles from a uniform distribution over joint limits and use high values of kinematic covariance (0.1 for position, 0.5 for orientation). In this case, particles from multiple modes are kept for almost 40 steps, then they converge into a single mode. On the bottom, we initialize particles from a normal distribution around neutral posture and we use the kinematic covariance matrix (as described in the supplementary document). The particles converge quickly to a correct mode and track the posture.

To show a qualitative performance of our proposed approach, Figure 8 illustrate video frames of a subject doing the task with circular motion with overlaid reconstructed skeletons from mocap (green) and our approach (red). We see that the estimated posture aligns well with the observed posture of the operator at different times during the task.

Figure 9 compares the quantitative deviation\(^3\) of estimated posture from the haptic-input device using three segment length estimation methods, from the estimated posture by the mocap system for a subject performing the circular task. It shows that the proposed approach using CPA has the lowest deviation from the mocap posture. We see that the deviation is very low for torso orientation ($q_1, q_2, q_3$) since they are limited to a low range of motion. The deviations increase in the shoulder joints ($q_4, q_5, q_6$) and we see higher deviations in the elbow joint ($q_7$), especially with full measurement and height measurement methods. This deviation is mainly due to the deviation in forearm and upper arm lengths which cause the particle filter to increase or decrease the elbow flexion angle to keep the hand attached to the stylus. We also see deviation in wrist flexion ($q_{10}$) which can be caused by the error in the fixed rigid-body transformation that we used to correct the hand pose in the mocap data.

Figure 10 shows the deviation between the posture from our approach and the posture from mocap for all the subjects, tasks, and trials across the joints. Overall, the approaches

\(^3\)The word ‘deviation’ is used here since the mocap posture is not the ground truth posture and the difference of the estimated posture from mocap posture does not necessarily means to be ‘error’.

![Fig. 5: Hand pose correction from mocap in grasping the stylus using a fixed rigid-body transformation.](image)

![Fig. 6: Tasks for human subject experiments: (a) following a straight line in the X direction, (b) following a straight line in the Y direction, (c) following a circular path, (d) pick and place with free motion.](image)

![Fig. 7: Behaviour of particles through time for the joint 4 of subject 1 doing task 3. (top) Particles initialized from a uniform distribution over joint limits and with higher diagonal values of $\Sigma_K$. (bottom) Particles initialized from a normal distribution over the neutral posture and with lower diagonal values of $\Sigma_K$.](image)
from the most probable particle which is the output of a filter itself and we do not want to suppress information. A better solution for the posture estimation would be using smoothing instead of filtering and for the jumps in risk assessment, we suggest to first develop a continuous risk assessment model based on RULA that has more resolution.

Figure 13 shows that the maximum RULA score in a task (the one that matters in ergonomics) for our approach. Our proposed posture estimation approach was successful in raising an alert in all the cases where the RULA score was higher than 2 that occurred in all 32 trials. The experiment resulted the same interpretation of RULA score in 28 trials (87.5%) and the same RULA score in 16 trials (50%). Our approach estimates the same RULA score (not the maximum value for task) for all the time steps of tasks done by different subjects with median accuracy of more than 85% for task 1 and 2, and more than 77% for task 3 and 4. More info is provided in the supplementary document.

Overall, the results show that the proposed approach that estimates the posture solely from the trajectory of the haptic-input device has the potential to be used for continuous monitoring of posture and ergonomics during teleoperation. Our approach is also accurate enough to provide alerts when further ergonomics investigation is required.

VII. CONCLUSION

In this paper, we addressed an increasing concern in teleoperation: human posture estimation and ergonomic analysis from a haptic-input device without any additional sensors. Our solution is based only on the data recorded from a haptic-input device end-effector, something already necessary to perform the teleoperation task. We defined the problem as a partially observable dynamical system and use a particle filter to estimate the posture of a 10-DOF upper body model. We use CPA to estimate human segment lengths. Then, we ran the RULA risk assessment over the estimated motion. The proposed approach is robust to differences in anthropometry.

B. Risk Assessment

We demonstrate the discrete behavior of RULA as a risk assessment tool over estimated posture of human during different tasks in Figure 12. It shows that RULA score is only sensitive to the moments that the posture passes between regions in joint limits, and does not change if the posture moves within the same region. It results in jumpy risk scores during a task.

A low-pass filter could help to smooth the jumps in Figure 12 and Figure 9 and also in the overlaid video. However, we note that in all of them, the output of our approach comes generally agree with a median deviation less than 0.19 rad (less than 11 deg) and upper quartile less than 0.26 rad (less than 15 deg) considering the observation solely from stylus trajectory and having no extra sensors. The same discussions for higher deviation observed in elbow and wrist joints hold here too.

We also show the deviation from mocap for all trials among tasks in Figure 11. It shows a similar performance of our proposed approach in different tasks and the upper quartiles are around 0.2 rad (less than 12 deg). However, using CPA segment lengths, we see that the deviation increases as the tasks get harder and include more wrist motion.

The results show that the accuracy of our approach is sufficient enough to be used to continuously monitor human posture. In the next section, we evaluate if it is enough to produce hazard scores that provide alerts when further ergonomics investigation is required.

Fig. 9: Deviation of the posture estimated by the proposed approach from mocap on the circular task, performed by subject 1.
and can fit different populations of users with different body segment lengths.

We evaluated our posture estimation approach by comparing it with the human posture data from a mocap system. Our results show that the proposed algorithm can successfully estimate the posture based solely on the haptic-input device stylus trajectory with a low deviation from mocap. Furthermore, the results from the RULA risk assessment show that within 32 trials, our proposed approach resulted in the same interpretation of the RULA score in 28 trials (87.5%) and the same RULA score in 16 trials (50%).

We note that it would be straightforward to combine our proposed approach with other sensing modalities (e.g. vision or mocap) when available in a specific application context by integrating these additional observations into the particle filter weighting scheme. We evaluated our method in teleoperation, which has high prevalence of musculoskeletal injuries. However, it is possible to extend it to other physical human-robot interaction tasks such as programming by demonstration and human-robot co-manipulation.

Future work will focus on improving the performance of our approach by increasing the complexity of the human model and encoding more accurate priors and constraints based on human biomechanics of motion. For example, we can build a prior based on muscle activation at different postures and prefer postures using less energy or lower overall muscle activation. Additionally, we are examining substituting the particle filter with an incremental smoothing method [44] in order to improve estimation results and decrease runtime. Finally, we wish to examine how our approach works in bimanual teleoperation using two haptic-input devices.

In terms of risk assessment, based on the structure of the RULA scoring approach, we are planning to develop a continuous scoring function. This will improve the resolution of our risk assessment tool and determination of optimal ergonomic posture correction in the future.

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I. PARTICLE FILTER FOR POSTURE ESTIMATION

In this paper, we follow the particle filter algorithm presented in [7]. Here we discuss the algorithm in details. The pseudocode of our algorithm for human posture estimation is presented in Algorithm 1. We define the particles as a set of joint angles and joint velocities:

\[ p[m] := [q[m], \dot{q}[m]], \quad m = 1, ..., M \]  

(1)

where \( M \) is the total number of particles.

Each particle is propagated in time based on the dynamics of human motions (lines 3-7). The particles are weighted based on the observation likelihood function (line 6) defined as the innovation error between the estimated pose of the stylus and the observed pose from the haptic device. We use Equation 7 from the paper and the definition of multivariate Gaussian distribution for defining the likelihood weighting function.

\[
w_k^m = \det(2\pi\Sigma_K)^{-\frac{1}{2}} \times \exp\left\{ -\frac{1}{2} (\begin{bmatrix} z_k, \dot{z}_k \end{bmatrix} - f(q_k, \dot{q}_k, \psi))^T \Sigma_K^{-1} (\begin{bmatrix} z_k, \dot{z}_k \end{bmatrix} - f(q_k, \dot{q}_k, \psi)) \right\}
\]  

(2)

After normalizing the weights (line 8), we record the maximum a posteriori particle into the set \( P^* \) (lines 9-10). Using these weights we sample a new belief distribution of particles (lines 11). These procedure repeats for every observed time step. Once given the last observation, the algorithm returns the set of estimated human postures along the entire trajectory, \( P^* \).

We use human biomechanics ([?]) to define the range of motion constraints in the filtering algorithm. Based on the type of the teleoperation tasks, we assume that the torso stays around the vertical position with a low deviation. Table I shows the joint limits we used with the reference to the T-pose as the zero-angle configuration.

For the kinematic covariance matrix, we use a diagonal covariance matrix as:

\[
\Sigma_K = 0.01 \cdot \text{diag}(0.001, 0.001, 0.001, 0.05, 0.05, 0.05, 1.0, 1.0, 1.0, 1.0, 10, 10, 10)
\]  

(3)

and define the acceleration covariance as:

\[
\Sigma_a = 0.01 \cdot \text{diag}(0.01, 0.01, 0.01, 0.01, 0.05, 0.05, 0.05).
\]  

(4)

These parameters have been tuned based in one subject and used for all subjects without any modification.

\begin{table}
\begin{tabular}{|c|c|c|c|}
\hline
Joint Name & Description & Min (deg) & Max (deg) \\
\hline
q1 & Torso flexion & -2 & 15 \\
q2 & Torso lateral bending & -5 & 5 \\
q3 & Torso rotation & -10 & 10 \\
q4 & Shoulder abduction & -90 & 135 \\
q5 & Shoulder vertical flexion & -90 & 90 \\
q6 & Shoulder horizontal flexion & -45 & 135 \\
q7 & Elbow flexion & 0 & 150 \\
q8 & Elbow supination & -180 & 90 \\
q9 & Hand radial deviation & -30 & 20 \\
q10 & Hand flexion & -45 & 45 \\
\hline
\end{tabular}
\end{table}

Algorithm 1: Human posture estimation algorithm

Result: \( P^* \)

1. initialize \( P_0 \); 
2. for \( k \leftarrow 1 \) to \( K \) do 
3. for \( m \leftarrow 1 \) to \( M \) do 
4. Sample \( q[m] \) from Eq. ??; 
5. Calculate \( q_k[m] \) from Eq. ??; 
6. \( w_k^m \leftarrow p(z_k, z_k) | [q_k[m], q_k[m]] \) 
7. end 
8. Normalize \( w_k \); 
9. \( n \leftarrow \arg \max_m w_k^m \); 
10. Add \([q_k[n], \dot{q}[n]]\) to \( P^* \); 
11. \( P_k \sim p(P_{k-1}) \); 
12. end 
13. return \( P^* \);

II. SEGMENT LENGTH ESTIMATION

Estimated and measured segment lengths for all the subjects are provided in II. We compare the deviation of estimated segment lengths from the different methods from the manually measured lengths among all subjects in Figure 1. The deviation for lengths of hand estimated by motion capture from the fully-
TABLE II: Subject information in the human subject experiment.

| Segments/Data | Estimation Type | Subject Number |
|---------------|----------------|----------------|
|               |                | 1  2  3  4  5  6  7  8 |
| Age (year)    |                | -   29  30  32  26  29  25  31  33 |
| Height (mm)   | Full-Measure  | 1720 1680 1500 1920 1530 1570 1690 1690 |
|               | CPA           | 475 479 595 497 396 390 424 478 |
|               | Full-Measure | 476 412 411 480 371 390 406 466 |
|               | CPA           | 476 412 411 480 371 390 406 466 |
|               | Full-Measure | 476 412 411 480 371 390 406 466 |
|               | Mocap         | 576 530 483 565 472 570 500 580 |
| Torso (mm)    | CPA           | 368 380 566 394 298 310 340 401 |
|               | Full-Measure | 352 334 510 416 284 324 354 346 |
|               | Height-Measure| 442 420 375 493 382 392 433 434 |
|               | Mocap         | 305 309 386 374 282 296 294 368 |
| Shoulder (mm) | CPA           | 331 308 263 308 284 273 297 304 |
|               | Full-Measure | 330 293 257 310 304 294 314 318 |
|               | Height-Measure| 333 320 286 372 292 299 327 327 |
|               | Mocap         | 329 315 256 328 284 287 304 303 |
| Upper Arm (mm)| CPA           | 256 241 216 272 221 210 217 226 |
|               | Full-Measure | 259 257 211 280 221 234 232 269 |
|               | Height-Measure| 263 245 219 293 223 229 258 258 |
|               | Mocap         | 218 204 185 227 193 193 202 220 |
| Forearm (mm)  | CPA           | 66 69 70 77 62 73 94 68 |
|               | Full-Measure | 66 67 65 75 61 68 80 64 |
|               | Height-Measure| 66 67 65 75 61 68 80 64 |
|               | Mocap         | 66 67 65 75 61 68 80 64 |

Fig. 2: Accuracy of our approach in risk assessment using versus using motion capture for all the trials.

measured lengths is zero because the mocap could not provide a length for the hand, so we used the manually measured one instead of it. The last column of the figure shows that lengths from CPA deviate less from the measured lengths.

III. RESULTS & DISCUSSION

In addition to the results shown in the paper, we present the accuracy of risk assessment based on our posture estimation approach for all the time instances of all the trials in Fig. 2. The median of accuracy is more than 85% for tasks 1 and 2 and 77% for tasks 3 and 4.