

# Personalized Robot-assisted Dressing using User Modeling in Latent Spaces

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**Abstract**—Robots have the potential to provide tremendous support to disabled and elderly people in their everyday tasks, such as dressing. Many recent studies on robotic dressing assistance usually view dressing as a trajectory planning problem. However, the user movements during the dressing process are rarely taken into account, which often leads to the failures of the planned trajectory and may put the user at risk. The main difficulty of taking user movements into account is caused by severe occlusions created by the robot, the user, and the clothes during the dressing process, which prevent vision sensors from accurately detecting the postures of the user in real time. In this paper, we address this problem by introducing an approach that allows the robot to automatically adapt its motion according to the force applied on the robot’s gripper caused by user movements. There are two main contributions introduced in this paper: 1) the use of a hierarchical multi-task control strategy to automatically adapt the robot motion and minimize the force applied between the user and the robot caused by user movements; 2) the online update of the dressing trajectory based on the user movement limitations modeled with the Gaussian Process Latent Variable Model in a latent space, and the density information extracted from such latent space. The combination of these two contributions leads to a personalized dressing assistance that can cope with unpredicted user movements during the dressing while constantly minimizing the force that the robot may apply on the user. The experimental results demonstrate that the proposed method allows the Baxter humanoid robot to provide personalized dressing assistance for human users with simulated upper-body impairments.

## I. INTRODUCTION

Dressing is an essential aspect of the daily life in which many people require assistance due to impairments. Studies indicate that over 80% of people in skilled nursing facilities require assistance with dressing [1]. In this paper, we propose to address this problem by providing robotic dressing assistance for human users considering upper-body impairments and user movements.

Recent studies on robotic dressing assistance usually describe dressing as a trajectory planning problem [1]. A common approach to solve this problem is to recognize the postures of the user in real time and to adjust the robot’s trajectory accordingly [2-6]. However, severe occlusions occur when the robot arms, the clothes and the human body are in close contact [7], which lead to real-time human pose recognition failures during the dressing process. For instance, depth cameras, which are often used for human pose recognition, typically fail to extract the user’s skeleton because of the occlusions. As a result, the accurate arm

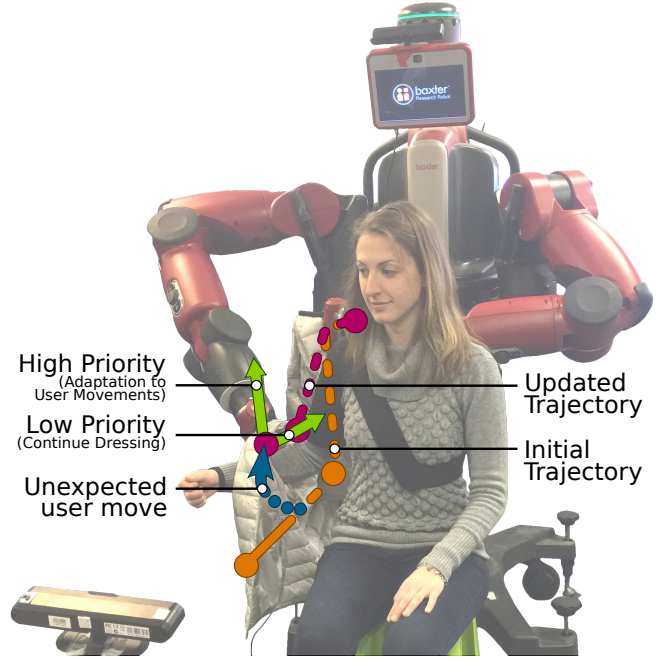


Fig. 1: The proposed method enables the Baxter humanoid robot to provide personalized dressing assistance, which can cope with unexpected user movements during the dressing process, for users with upper-body movement limitations (here, healthy users wearing braces that limit their movements). Assistive dressing is described as two hierarchical tasks. The high priority task is the robot motion adaptation to minimize the force applied between the gripper and the user caused by the human users movements. The low priority task is to complete the dressing trajectory such that the human is properly dressed. The upper-body movement limitations are projected into a latent space through GP-LVM for the online update of the dressing trajectory.

postures may not be obtained when the human user moves to perform other activities (*i.e.* grasping objects, or scratching himself) during the dressing process. Such movements may lead to the robot applying undesired force on the user, which may lower the comfort of the user, or even put the user at risk and lead to dressing failures. Ideally, the robot should not interfere with the user movements, while providing personalized dressing assistance by taking the user movement limitations into account.

In this paper, we propose an assistive dressing control strategy based on hierarchical multi-task control and upper-body movement modeling. The proposed method is implemented on the Baxter humanoid robot to provide personalized dressing assistance for human users with different upper-

body movement limitations (Fig. 1). The proposed approach represents the assistive dressing as two hierarchical tasks: 1) the high priority task is adapting robot motion to minimize the force applied between the user and the robot caused by human user movements, and 2) the low priority task is to complete the dressing trajectory such that the human is properly dressed. These two tasks are combined into a hybrid force/position controller for hierarchical multi-tasks control.

In order to personalize the robot dressing motion according to different upper-body movement limitations, we use the Gaussian Process Latent Variable Model (GP-LVM) to project the upper-body movements into a 2-Dimensional latent space. Kernel Density Estimation (KDE) is then used to compute the density plot in the latent space that shows how frequently each upper-body posture is adopted by the user. Such information is used to perform an online update of the robot dressing trajectory.

## II. RELATED WORK

Several approaches have been proposed for assistive dressing by humanoid robots in home environments. For example, reinforcement learning has been successfully used to enable a robot to wrap a scarf [2] and to dress a T-shirt on human mannequins with different head and shoulder inclinations [3, 4, 8]. The topological relationships between the mannequin and the item of clothing have been studied to optimize the trajectory of the robot through reinforcement learning [5, 6]. These methods usually do not consider the user movements that may impact the dressing task. For instance, in many cases soft mannequins are used for experiments. However, the user's arm may move during the dressing process, which complicates the task and often leads to dressing difficulties when such methods are applied to real users.

In order to take the user postures into account during the dressing process, vision information is usually used to recognize the human poses. In [3], a motion capture system has been successfully used to detect the markers attached on the mannequin and the T-shirt. While that approach leads to successful dressing behaviors, the posture of the mannequin is assumed to not change during the dressing sequence. However, as described in Section I, the occlusions created by the clothes, the robot and the user's body, make the real-time tracking of the user postures particularly challenging. To compensate for the disadvantages of using vision information only, force information has been successfully used in [1] to infer if the user's forearm can successfully enter the sleeve. In [9] and our previous research [7], the force resistance between the robot gripper and the body has been used to adjust the robot motion with a pure position controller. Although these methods can update the robot motion based on the detected force, this is not achieved in real-time and the delay induced by robot position update may let the robot in an uncomfortable or even dangerous state for the user.

Moreover, human movements vary significantly according to the different upper-body movement limitations they may suffer from. To provide personalized assistance, one

typical approach is human movement modeling. Multivariate Gaussian distributions has been successfully used to model the planar hand motion for robotic rehabilitation [10, 11]. To model the upper-body movements in 3D coordinates, Gaussian Mixture Models (GMMs) have been used in our previous research [12] to model the movement space of each upper-body joint of the user (hand, elbow and shoulder) separately. However, the movements of the upper-body joints are correlated. For instance, the movements of the hand are affected by the movements of the elbow and the shoulder. The model introduced in [12] does not capture this relationship. In general, the high dimensionality and non-linearity features of human behaviors make them particularly challenging to study [13]. In order to address these problems, dimensionality reduction algorithms have been used in [13, 14] to model human movements in latent spaces. In this paper, we will use a related approach to model the user movement limitations and to update the robot trajectory after the robot has recorded a significant perturbation caused by user movements.

## III. HIERARCHICAL MULTI-TASK CONTROL FOR ASSISTIVE DRESSING

In this section, we present a hierarchical multi-task control for assistive dressing. The main idea is that the low priority task should not interfere with high priority one. In our case, the high-priority task requires the robot to adapt its motion to constantly minimize the force that the robot applies on the user, while the low-priority task is to complete the dressing trajectory which should not interfere with this high-priority task. We use a velocity-input hybrid force/position control schemes to combine these two hierarchical tasks.

### A. Task Priorities for Assistive Dressing

Recent studies usually describe dressing as a trajectory planning task. However, as described in Section I, the arms of the users may move to perform other tasks, like grasping objects or scratching, during the dressing process. Because of the severe occlusions, the postures of the arm may not be obtained accurately when the user moves during the dressing process. Such unpredicted movements can make the robot apply large force on the user.

To solve this problem, in this paper, we propose to model the dressing process as two hierarchically organised tasks: 1) the high priority task is the robot motion adaptation to minimize the force applied between the robot and the user, using a force controller, and 2) the low priority task is to execute the dressing trajectory to allow the human to get properly dressed with a motion controller. This high priority task ensures that the robot will compensate the human movements allowing the user to perform other activities, like grasping objects and scratching, during the dressing process without lowering user's comfort and security. The low priority task ensures that progress are made on the dressing task.

Here, we adopt a strict hierarchy of tasks, where a hierarchical ordering of the tasks is predefined. The task with the

high priority is systematically fulfilled, and the low-priority tasks are solved in the null-space of the higher priority tasks [15]. The two tasks are expressed in terms of velocity-control tasks and combined according to this equation:

$$\dot{\mathbf{q}} = \mathbf{J}_c^\dagger \dot{\mathbf{t}} + (\mathbf{I} - \mathbf{J}_c^\dagger \mathbf{J}_c) \dot{\mathbf{q}}_0 \quad (1)$$

where  $\dot{\mathbf{q}}$  denotes the joint velocity,  $\dot{\mathbf{t}}$  denotes the desired end-effector velocity of the high-priority task, and  $\dot{\mathbf{q}}_0$  denotes the desired joint velocity of the low-priority task. The matrix  $\mathbf{J}_c$  is obtained by projecting the geometric Jacobian Matrix  $\mathbf{J}$  along the end effector force direction,  $\mathbf{J}_c^\dagger$  is the pseudoinverse of  $\mathbf{J}_c$ , and  $(\mathbf{I} - \mathbf{J}_c^\dagger \mathbf{J}_c)$  represents the orthogonal projection matrix in the null-space of  $\mathbf{J}_c$ .

The projection of the geometric Jacobian Matrix  $\mathbf{J}$  along the end-effector force direction is used to impose the rank of  $\mathbf{J}_c$  to be equal to one (or zero when the force is null), which prevents the dimension of its null-space to be zero. This implies that the robot is allowed to move in directions that are orthogonal to the direction of the force to fulfill the low-priority task, while moving according to the direction of the force to fulfill the high-priority task.

### B. High Priority Task

In this section, we present the force controller employed to fulfill the high priority task. Note that we do not have force sensors at the wrist of the robot. In this paper, we estimate the external force and torque applied at the end effector of the Baxter robot from the measured joint torques as proposed in [16]. Indeed, the Baxter robot is built using series elastic actuators that can sense the torque being applied by the motor via a spring connected directly to the actuator. The end-effector force can be estimated using this equation:

$$\mathbf{h}_{ext} = (\mathbf{J}^T)^\dagger f_{dz}(\boldsymbol{\tau} - \mathbf{g}(\mathbf{q})) \quad (2)$$

where  $\mathbf{h}_{ext}$  denotes the estimated force at the end effector,  $\boldsymbol{\tau}$  is the joint torque, the function  $f_{dz}(\cdot)$  is a deadband added to counter the effect of measurement noise, and  $\mathbf{g}(\mathbf{q})$  is the estimated gravity compensation torques for the joint configuration  $\mathbf{q}$ .

The measured force is then mapped into desired velocity for the end effector using the standard generalized damper approach [17]

$$\dot{\mathbf{t}} = \mathbf{D} \mathbf{h}_{ext} \quad (3)$$

where  $\mathbf{D}$  is a damping constant,  $\dot{\mathbf{t}}$  denotes the desired end-effector velocity according to the high-priority task as shown in equation (1).

### C. Low Priority Task

A position controller is used to fulfill the low priority task which consists in achieving the dressing trajectory such that the user gets properly dressed. The trajectory is defined as a sequence of waypoints associated to the user's hand, forearm, elbow, upper-arm and shoulder (more details are given in the Section IV-A). Given the initial and target positions of the end-effector and a predefined time interval, the joint

velocities  $\dot{\mathbf{q}}_0$  used to drive the robot at a particular end-effector velocity are calculated using the Jacobian damped-least-squares controller:

$$\dot{\mathbf{q}}_0 = \mathbf{J}^\dagger \frac{([\mathbf{P}_t, \mathbf{R}]^T - [\mathbf{P}_i, \mathbf{R}]^T)}{t_d} \quad (4)$$

where  $\mathbf{J}^\dagger$  is the pseudoinverse of  $\mathbf{J}$ ,  $\mathbf{R}$  is the orientation of the end-effector,  $t_d$  is the time interval,  $\dot{\mathbf{q}}_0$  denotes the desired joint velocity of the low priority task as shown in equation (1),  $\mathbf{P}_t, \mathbf{P}_i$  are the target and initial positions of the robot in 3-D coordinates respectively, which are the waypoints of the dressing sequence. In this work, the orientation of the robot gripper is fixed during the whole dressing process.

## IV. PERSONALIZED ASSISTIVE DRESSING

In this section, we introduce a control strategy for personalized dressing assistance, based on the hierarchical multi-task controller described in Section III. We detail how this approach takes user upper-body movement limitations into account to provide personalized assistance.

### A. Control Strategy for Personalized Assistive Dressing

Inspired by real scenarios where a human assistant helps another person to get dressed, in this work, we propose to use the humanoid robot to dress a user's forearm first, and then the upper arm. Therefore, the dressing sequence is: hand, forearm, elbow, upper arm, and shoulder.

In order to take the different upper-body movement limitations into account, a model of the user is constructed before the dressing. This is achieved by asking the user to move his arm randomly prior to the dressing scenario. We record the arm posture data and project such data onto a low-dimensional latent space with the Gaussian Process Latent Variable Model (GP-LVM) [18]. Then, we compute the density plot of the latent space representation using the Kernel Density Estimation (KDE) [19]. This modeling method is detailed in Section IV-B.

During the initialization, the user's hand, elbow and shoulder positions detected by the depth camera are defined as the waypoints of the initial dressing trajectory. Then the robot gripper moves the clothes from the initial hand position to the initial elbow position. This motion is designed based on the multi-task controller presented in Section III-A: the joint velocity  $\dot{\mathbf{q}}$  has been described in equation (1). The joint velocity of the low-priority task  $\dot{\mathbf{q}}_0$  in equation (1) is calculated through equation (4). In equation (4), the initial hand position is used as  $\mathbf{P}_i$ , the initial elbow position is used as  $\mathbf{P}_t$ . The end-effector velocity of the high-priority task  $\dot{\mathbf{t}}$  in equation (1) is calculated through equation (2) and (3).

When the user movements cause an external force  $\mathbf{h}_{ext}$ , the robot will adapt its motion to not interfere with the user movements, based on equation (1). Then, when the user stops moving and no external force  $\mathbf{h}_{ext}$  is detected, the robot will also stop the current execution. As described in Section I, real-time human pose recognition is challenging because of the severe occlusions. As a result, the accurate positions of the hand and the elbow may not be obtained when the

human arm moves during the dressing process. In this paper, we propose to choose the next target position for the robot gripper based on the latent space data (detailed in Section IV-B) and the current gripper position  $\mathbf{P}_g$ . In Section IV-C, we will detail the selection of the next target position. This proposed method enables the robot to put the clothes in a position that can be reached without difficulty by the user by taking the user's movement limitations into account.

Then, the robot gripper will move from the current position  $\mathbf{P}_g$  to the chosen target position based on the multi-task controller in equation (1). Here in equation (4), the current gripper position  $\mathbf{P}_g$  is used as  $\mathbf{P}_i$ , the chosen target position is used as  $\mathbf{P}_t$ . This process is repeated until the forearm is dressed, and then the robot dresses the upper-arm using the same method. If no external force  $\mathbf{h}_{ext}$  is detected during the dressing process, the gripper will then move from the initial human hand position, to the initial elbow position, and then to the initial shoulder position.

Meanwhile, the motion of the other gripper is designed to cooperate with the dressing motion. For instance, if the robot is dressing the right impaired arm, the left robot gripper will hold the clothes at the user's right shoulder. After the robot finishes dressing the right arm, the left robot gripper will move the clothes to the user's left area so that the user can wear the left part of the clothes without reaching difficulty. Here in this paper, restricted by the workspace when the robot arm manipulating the clothes, we assume that only one arm suffers from movement limitations.

### B. Upper-body Movement Modeling

Human behaviors are particularly challenging to study because of their inherent high-dimensionality and non-linearity [14]. For this reason, linear dimensionality reduction approaches (e.g., Principal Component Analysis [20]) often fail to accurately model human movements. Conversely, it has been shown that Gaussian Process Latent Variable Model (GP-LVM) [18] can efficiently embed human actions into a 2-D latent space while preserving most stylistic information [21]. These features make GP-LVM attractive for modeling the upper-body movements for assistive dressing.

GP-LVM creates a Gaussian Process (GP) that maps a high dimensional dataset  $\mathbf{Y} = [\mathbf{y}_1, \dots, \mathbf{y}_N]^T$  to a low dimensional latent space represented by a dataset  $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_N]^T$ , such that:

$$\mathbf{y}_i = f(\mathbf{x}_i) + \epsilon, \epsilon \sim \mathcal{N}(\mathbf{0}, \beta^{-1} \mathbf{I})$$

where  $\mathbf{y}_i \in \mathbb{R}^D$ ,  $\mathbf{x}_i \in \mathbb{R}^Q$ ,  $Q$  and  $D$  are the dimensionality of the corresponding dataset respectively,  $N$  is the number of samples,  $f$  denotes the GP mapping.

The marginal likelihood for the observed data, given the latent coordinates is defined by

$$p(\mathbf{Y}|\mathbf{X}, \boldsymbol{\theta}) = \frac{1}{\sqrt{(2\pi)^{ND} |\mathbf{K}|^D}} \exp\left(-\frac{1}{2} \text{tr}(\mathbf{K}^{-1}) \mathbf{Y} \mathbf{Y}^T\right)$$

where  $\boldsymbol{\theta}$  is the kernel hyperparameter,  $\mathbf{K}$  is the kernel matrix constructed from  $\mathbf{X}$  and  $\boldsymbol{\theta}$ . GP-LVM aims to find the values

of  $\mathbf{X}$  and  $\boldsymbol{\theta}$  that maximize the likelihood of the predictions of the model given the dataset  $\mathbf{Y}$ .

In this work, we use GP-LVM to map the high dimensional upper-body movements into a 2-D latent space. The observed dataset for our model is therefore

$$\mathbf{Y} \equiv \{\mathbf{y}_i = [\mathbf{P}_{h[i]} \ \mathbf{P}_{e[i]} \ \mathbf{P}_{s[i]}]\}_{i=1,2,\dots,N} \quad (5)$$

where  $\mathbf{P}_h, \mathbf{P}_e, \mathbf{P}_s$  are the positions of human hand, elbow and shoulder joint in 3-D robot coordinates respectively, that correspond to the 9-dimensional arm posture. The resulting projections of the 9-D arm posture data in a 2-D latent space produced with GP-LVM will be detailed in Section V-B and Fig. 3.

To get a better understanding of the latent space, we compute its density plot. For this purpose, we use the Kernel Density Estimation (KDE) to calculate the density distribution. Let the latent space dataset  $(\mathbf{x}_1, \dots, \mathbf{x}_N)$  be sampled from an unknown density  $\hat{f}_d$ , then estimating the shape of this function can be done with its kernel density estimator [19]

$$\hat{f}_d(\mathbf{x}_r) = \frac{1}{N} \sum_{i=1}^N K_d\left(\frac{\mathbf{x}_r - \mathbf{x}_i}{h}\right) \quad (6)$$

where  $K_d$  is the kernel function,  $h$  is a smoothing parameter called bandwidth,  $\mathbf{x}_r$  is a random variable, in our case the 2-D latent space data.

The density plot extracted from the latent space shows how frequently each upper-body posture is adopted by the human user. The more dense locations in the density plot represent the upper-body postures which are more frequently adopted by users. The density plots will be detailed in Section V-B and Fig. 4.

### C. Trajectory Updating Algorithm

As described in Section IV-A, due to the severe occlusions, a new target position needs to be defined after the robot has recorded a significant perturbation caused by user movements during the dressing process. In order to do so, we use the density plot of the 2-D latent space data (as described in Section IV-B), which contains information about the postures that are most frequently adopted by the user, to choose the next target position and thus update the dressing trajectory, given the current robot gripper position. This is achieved by discretizing the latent space representation into  $M$  points ( $\hat{\mathbf{X}} = [\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_M]^T$ ) and using the associated density values  $\hat{f}_d(\hat{\mathbf{x}}_k)$  in equation (6) to find the 2-D location in the latent space where the density is higher, and its corresponding reconstructed high dimensional arm posture. This can be formulated as a constrained optimization problem:

$$\hat{\mathbf{y}}_k^* = \underset{\hat{\mathbf{x}}_k}{\operatorname{argmax}} \hat{f}_d(\hat{\mathbf{x}}_k) \quad (7)$$

subject to

$$d_r < d < d_l \quad (8)$$

where  $d$  denotes the distance between the current gripper position  $\mathbf{P}_g$  and the reconstructed high dimensional postures

$\hat{\mathbf{y}}_k$ ,  $d_r$  denotes the radius of the human arm,  $d_l$  is an artificial distance, detailed in the following paragraphs.

Here, we assume that the current gripper position can be treated as the latest contact point between the gripper and the current arm posture because the controller is designed to stop its motion as soon as no external force is detected anymore.

Equation (8) represents the constraints of the optimization problem. We assume that the distance  $d$  between the current gripper position and the reconstructed high dimensional posture should be larger than the radius of the human arm. We also assume that the distance  $d$  between the current gripper position and the reconstructed high dimensional posture should be smaller than an artificial distance  $d_l$ . As described before, the current gripper position can be treated as a contact point on the current arm posture. The human user can move the arm randomly during the dressing process which may not be within the dense region of the latent space. Therefore,  $d_l$  here ensures that the robot will not put the clothes too far from the current arm posture when choosing the optimal posture  $\hat{\mathbf{y}}_k^*$  based on the density plot of the latent space.

As shown in equation (7) and (8), we propose to choose the most frequently adopted arm posture by the human user which satisfies the constraints in equation (8). If the robot is dressing the users forearm, the elbow position  $\hat{\mathbf{P}}_{e[k]}^*$  of the chosen posture  $\hat{\mathbf{y}}_k^*$  is defined as the target position for the gripper; if the robot is dressing the users upper arm, the shoulder position  $\hat{\mathbf{P}}_{s[k]}^*$  of the chosen posture  $\hat{\mathbf{y}}_k^*$  is defined as the target position for the gripper. The target position chosen by the robot ensures that the user can reach the clothes without difficulty by taking movement limitations into account.

## V. EXPERIMENTS AND RESULTS

We conduct experiments to investigate: 1) how the movement modeling captures different upper-body limitations (the Movement Modeling Evaluation), 2) how the hierarchical multi-task control method takes user movements into account (the Multi-task Hierarchical Control Evaluation), and 3) the generalizability of our proposed method (the Generalizability Evaluation).

### A. Experimental Setup

We implement the proposed method on the Baxter humanoid robot. We use an ASUS Xtion Pro camera which provides RGB and depth images at the frame rate of 30Hz and frame resolutions of  $640 \times 480$ . The camera is set in front of the robot and users for human posture recognition with the OpenNI skeleton tracker during the initialization of the dressing sequence, which can provide hand, elbow, and shoulder positions (Fig. 2a). The coordinate transformation between the camera and the robot has been determined before the experiments.

We define scenarios in which our users have limitations with their right arm movements. Thus their right arms are



Fig. 2: The experiment environment set up. Four different healthy users (ages 23-32, mean:28, std:2.19) wear braces to simulate 6 scenarios including elbow, shoulder, and elbow-shoulder movement limitations.

supposed to receive help from the Baxter robot while dressing a sleeveless jacket. Three scenarios of right arm movement limitations are represented: 1) the shoulder movement limitation (Fig. 2b); 2) the elbow movement limitation (Fig. 2c); 3) both the elbow and the shoulder movement limitations (Fig. 2d). In order to simulate the movement limitations, our healthy participants wear elbow and shoulder braces that are used to limit the movements of the elbow and the shoulder respectively. Overall four healthy users participated in the experiments (Fig. 2).

### B. Movement Modeling Evaluation

In this experiment, we simulate the three scenarios of right arm movement limitations with one healthy user (Fig. 2a-c). In each simulated limitation scenario, the user moves the arm randomly and the corresponding arm posture data is recorded as the dataset of GP-LVM shown in equation (5). The movements of the user without limitations (*i.e.*, without the braces) have also been recorded to provide reference data. Overall, 9565 healthy arm postures, 9001 elbow-limited arm postures, 8434 shoulder-limited arm postures, and 8403 arm postures when both elbow and shoulder are limited, have been recorded.

To investigate how the upper-body movement modeling captures the specificities of users with different movement limitations which can be used to personalize the dressing assistance, we project all the data together into a 2-D latent space with GP-LVM. Fig. 3 represents the resulting projections. The different colored subspaces represent the range of

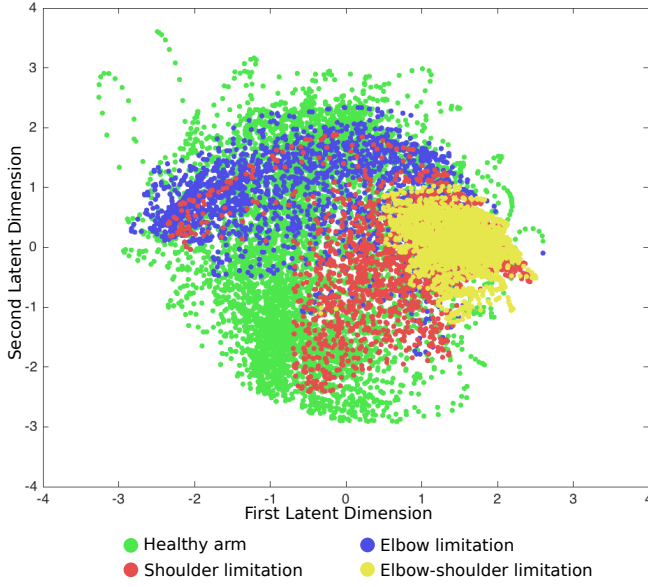


Fig. 3: The latent space representation of the 9-D arm posture data in a 2-D space produced with GP-LVM. The different colored subspaces denote the arm movements with different impairments.

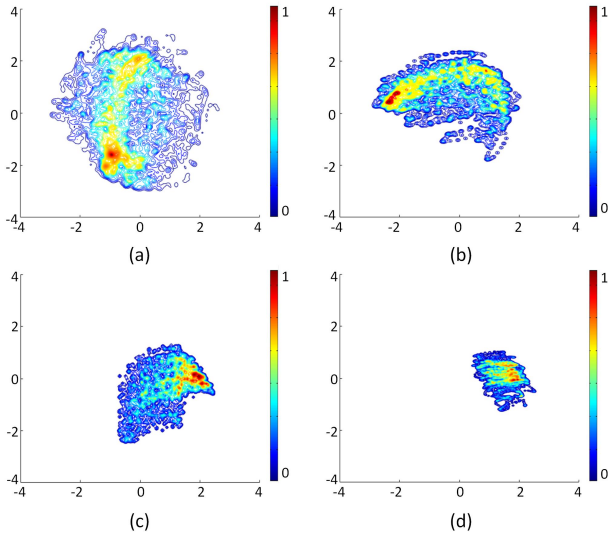


Fig. 4: The density plot of the latent space. Warmer colors denote the postures that more frequently adopted by the user.

arm movements with different limitations respectively. Two immediate observations can be made from this graph: 1) The elbow-limited arm movement subspace (blue), shoulder-limited arm movement subspace (red), and elbow-shoulder-limited arm movement subspace (yellow) are parts of the healthy arm movement subspace (green) respectively; 2) The elbow-shoulder-limited arm movement subspace (yellow) is at the overlap space of the elbow-limited arm movement subspace (blue) and the shoulder-limited arm movement subspace (red).

We further compute the density distribution of each latent subspace separately with KDE, as described in Section IV-B. The density plots are shown in Fig. 4a-d. Colors denote the

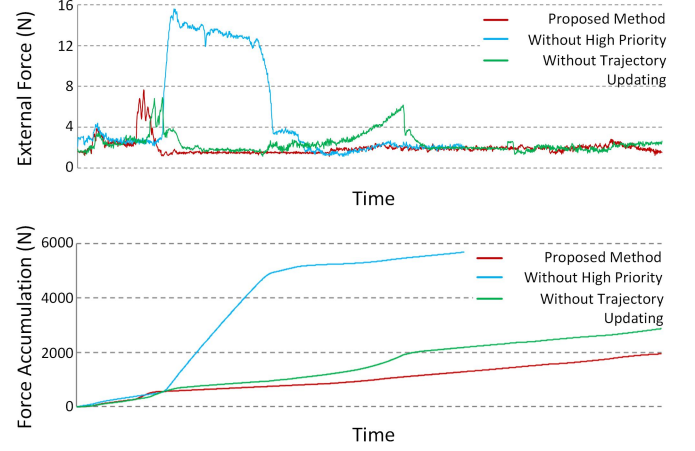


Fig. 5: The results of the evaluation of the hierarchical multi-task control. (Top) This panel presents the external force recorded by the robot during the dressing process. (Bottom) This panel shows the accumulation of the external force over the time.

value of the density function at each latent point as described in equation (6), which have been normalized between  $[0, 1]$ . Warmer colors denote the postures more frequently adopted by the user. Note that different users have different density distributions according to the specificities of their arm movements.

### C. Hierarchical Multi-task Control Evaluation

This experiment investigates how our proposed hierarchical multi-task control method enables the robot to provide dressing assistance which does not interfere with the user movements during the dressing process. In this experiment, one healthy user simulates to suffer from the shoulder movement limitation (Fig. 2b).

In this experiment, the user is asked to suddenly move his arm to a fixed position, so that he will push the robot gripper and thus perturb its dressing sequence. This scenario is used to simulate the user executing another action during the dressing sequence (e.g., grasping a bottle, or scratching). We compare our proposed method with: 1) the same approach but without the high-priority task; 2) the same approach but without the online update of the dressing trajectory.

The method without the high-priority task is equivalent to a method using only a motion planning algorithm to fulfill the dressing task (as commonly considered in the literature). In this context, the gripper cannot respond to the external force caused by human movements. The mechanical compliance of the Baxter robot allows the physical interaction between the user and the robot, but does not minimize the discomfort of the user. For the method without the online update of the dressing trajectory, the robot still reacts according to the external force based on equation (1), but when human stops moving and that the robot stops the current execution, the gripper will continue to move to the initial elbow position instead of choosing a new target position based on equation (7).

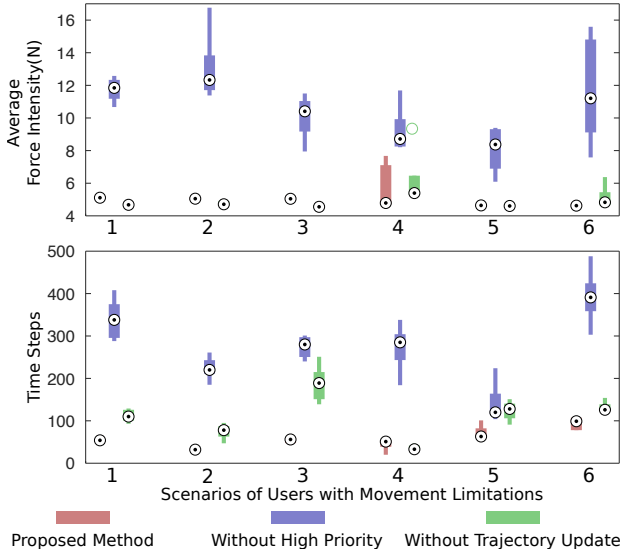


Fig. 6: The boxplots pictures the data from the six scenarios replicated five times each. (Top) Boxplot of the averaged intensity of the force perceived by the robot during the dressing process (when the force is larger than 4N). (Bottom) This boxplot represents the number of time steps during which the perceived force is larger than 4N. The central dot corresponds to the median value of the five replications, while the sides of the box refer to the first and third quartiles of the data. The whiskers extend to the most extreme data points that are not considered as outliers, which are displayed as individual circles. When only the central dot is visible, this means that the variance of the data is too small to be displayed.

Fig. 5-top presents the external force  $h_{ext}$  in equation (2), but without the deadband function  $f_{dz}(\cdot)$ , during the dressing process with the three methods. Fig. 5-bottom shows the accumulation of the external force during the dressing process with the three methods. We start to record the force when the gripper starts to move from the hand position. We stop recording when the right arm is dressed. Two conclusions can be drawn from this figure: 1) the proposed approach (red) shows the smallest external force compared to the two other approaches, while the approach without the high-priority (i.e., the robot motion adaptation and force minimization) shows the largest force. This result is expected and illustrates that hybrid force/position control is an effective approach to accomplish the dressing task, while minimizing the force applied between the robot and the user; 2) the approach without the online update of the dressing trajectory (green) presents two peaks, which means that the robot has been twice in significant collision with the user. One collision occurs when the user suddenly moves the arm. The other collision occurs when the robot gripper moves to the initial elbow position after the perturbation, while the arm posture has changed. Conversely, our proposed approach does not show the similar results. This demonstrates that the approach to update the robot dressing trajectory after a significant perturbation caused by user movements is an effective way to personalize the control of the robot according to the user modeling in the latent space.

#### D. Generalizability Evaluation

In order to investigate the generalizability of the proposed method, we ask three other users to simulate different movement limitations respectively. Overall, six scenarios of movement limitations have been simulated by four healthy users (Fig. 2a-f). For each simulated limitation scenario, an individual movement model needs to be built in the latent space with GP-LVM. For each of the six scenarios, we test the three methods as described in Section V-C. For each method, five trials have been carried out.

Over all the trials, the robot successfully dresses the right arm of the user. Fig. 6-top shows the average of the external force recorded by the robot during the dressing process with the three methods. To counter the effect of measurement noise, we consider the data after using the deadband filter of the function  $f_{dz}(\cdot)$  in equation (2) filtering all the noise below 4N (as described in Fig. 5). We calculate the average of the external force, when it is larger than 4N in each trial and report the result in the boxplots. Fig. 6-bottom reports the numbers of time steps in which the force is larger than 4N in each trial.

We can see from this figure that the same conclusion as the previous experiment can be drawn independently from the user: our proposed approach minimizes the force applied between the robot and the user and avoids to interfere with the user a second time after the first collision. More precisely, the difference between the average force intensity observed with the proposed method and the method without the online trajectory update is not significantly different (ranksum p-value=0.17 when all the trials are considered), while the difference with the variant without the high-priority task is statistically significant (p-value=4.5e-11). This result is expected because the force minimization is governed by the high-priority task. With respect to the number of time steps in which a force larger than 4N is perceived, the proposed method also outperforms the other approaches with a statistically significant difference (p-value=3.7e-11 when compared to the variant without the high-priority task and 5.6e-5 when compared to the variant without the trajectory update). We can also note some variations between the users, for instance, the scenario number 5 shows the smallest difference between the different approaches, while the scenario number 6 the largest. This could be explained by different confidence levels on the robotic setup from the users. However, we can observe that the general trend described above remains valid for all the users when considered individually.

Fig. 7 shows an example of the dressing sequence when the robot provides dressing assistance for a user with elbow movement limitation (Fig. 2a). This dressing sequence shows the robot motion adaptation when human user moves suddenly during the dressing process and the online update of the dressing trajectory after the significant perturbation.

The above statistics and observations suggest that our proposed method based on hierarchical multi-task control and upper-body movement modeling is capable of generalizing to users with different movement limitations while maintaining

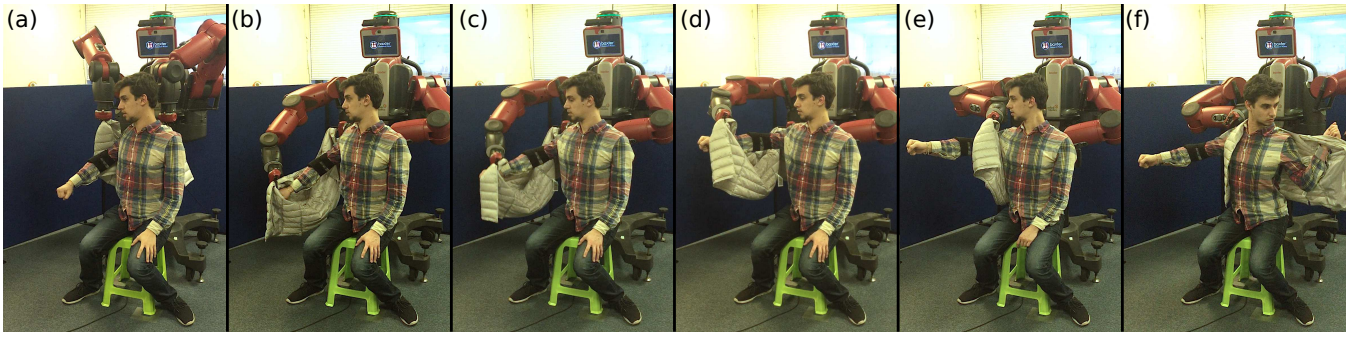


Fig. 7: Snapshots of the assistive dressing process with a user suffering from elbow movement limitation. (a) Initialization of the dressing sequence. (b) The robot reaches the initial hand position and starts the dressing trajectory. (c) The user moves his arm suddenly. (d) the robot adapts its motion accordingly and updates its trajectory. (e) The robot finishes dressing the right arm. (f) End of the dressing process.

better performance against other methods.

## VI. CONCLUSIONS AND FUTURE WORK

In this paper, we have presented a method for personalized dressing assistance based on hierarchical multi-task control and the upper-body movement modeling. The force applied between the robot and the user caused by arm movements are considered in the high priority task, while the low priority task ensures that the human can be properly dressed. The upper-body movement modeling takes different upper-body movement limitations into account. The experimental results have demonstrated that the proposed method is capable of allowing the Baxter humanoid robot to help users with different arm movement limitations to wear a sleeveless jacket.

Real-time human pose recognition during the dressing process is challenging because of the severe occlusions. We have investigated the recognition of human postures in real time with Motion Capture Systems, which still yielded failures because of the occlusions. In future work, we aim to combine multi-modal information, including gripper positions, force information and depth images, into a probabilistic framework to obtain real-time estimate of the arm pose during the dressing process.

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