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FULL PAPER

A Framework for Robotic Clothing Assistance by Imitation Learning

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The recent demographic trend across developed nations shows a dramatic increase in the aging population, fallen fertility rates and a shortage of caregivers. Hence, the demand for service robots to assist with dressing which is an essential Activity of Daily Living (ADL), is increasing rapidly. Robotic Clothing Assistance is a challenging task since the robot has to deal with two demanding tasks simultaneously, (a) non-rigid and highly flexible cloth manipulation and (b) safe human-robot interaction while assisting humans whose posture may vary during the task. On the other hand, humans can deal with these tasks rather easily. In this paper, we propose a framework for robotic clothing assistance by imitation learning from a human demonstration to a compliant dual-arm robot. In this framework, we divide the dressing task into three phases, i.e., reaching phase, arm dressing phase, and body dressing phase. We model the arm dressing phase as a global trajectory modification using Dynamic Movement Primitives (DMP), while we model the body dressing phase toward a local trajectory modification applying Bayesian Gaussian Process Latent Variable Model (BGPLVM). We show that the proposed framework developed towards assisting the elderly is generalizable to various people and successfully performs a sleeveless shirt dressing task. We also present participants feedback on public demonstration at the International Robot Exhibition (iREX) 2017. To our knowledge, this is the first work performing a full dressing of a sleeveless shirt on a human subject with a humanoid robot.

Keywords: Robotic Clothing Assistance; Imitation Learning; Learning from Demonstration; DMP; BGPLVM; Service Robot.

1. Introduction

The world's population is rapidly aging. The number of people aged 60 years or older is expected to rise from 12% to 22% of the total global population between 2015 and 2050 [1]. Most of the developed countries across the globe have been aging for decades. With the aging population, life expectancy is raising beyond 80 years in countries such as Japan [2]. The number of elderly who need support for Activities of Daily Living (ADL) [3] in developing countries is forecast to quadruple by 2050 [1, 4]. This dramatic increase in the aging population combined with fallen fertility rates are reaching up to an alarming situation. It brings a growing need for long-term care including home nursing. Many initiatives address these issues including the European Commission and member states that have invested more than €1 billion to empower research and development for the welfare of the elderly [5]. Furthermore, according to a survey focusing on difficulties in performing various ADLs, the use of caregivers was seen more common for clothing assistance tasks. Only 3.7% of people were found using assistive technology whereas others rely on personal caregivers [6]. On the other hand, due to the rapidly growing demand,

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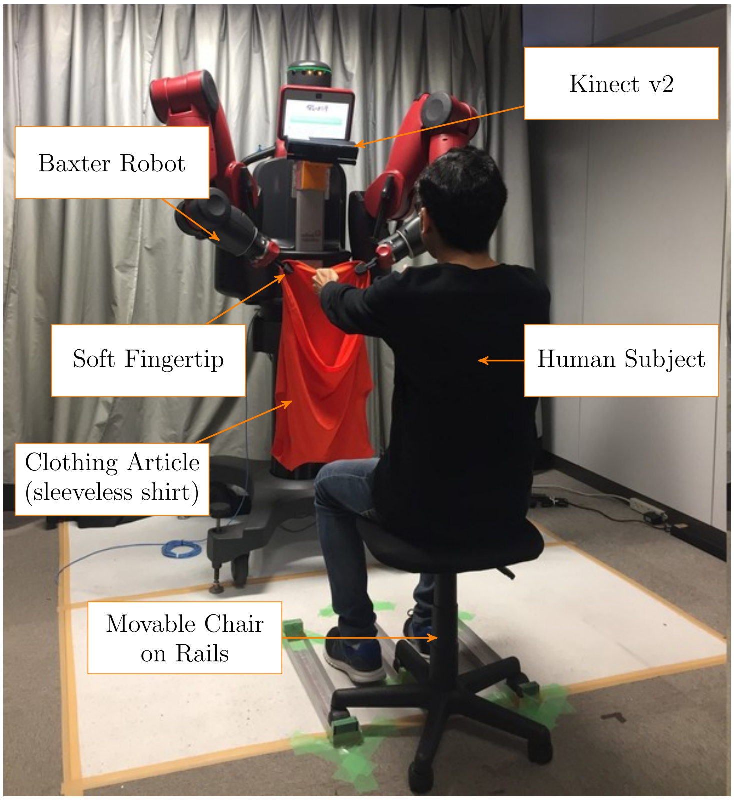
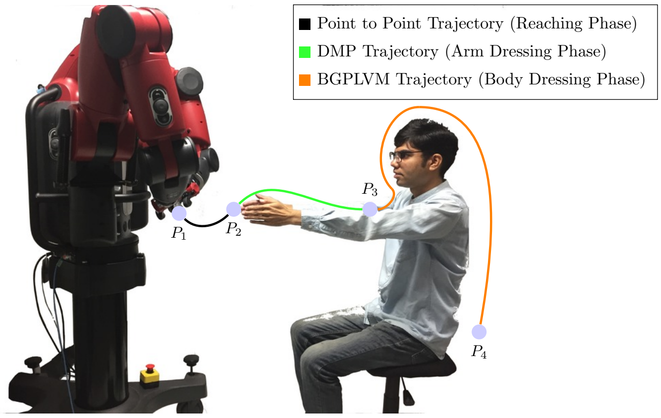


Figure 1. Setup of robotic clothing assistance task showing various components of the system.

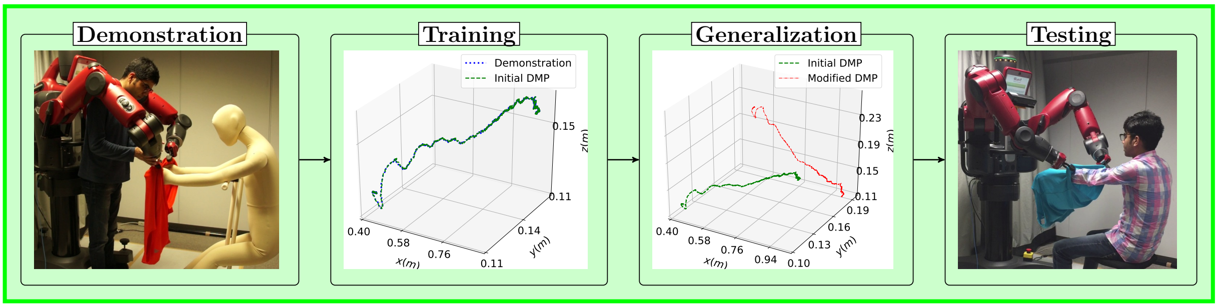
the nursing industry in Japan is facing a severe shortage of caregivers. As per the Japanese ministry's estimate, the nation will need 2.53 million caregivers in fiscal 2025, but the available caregivers will fall short of this number by 377,000 [7]. Under these circumstances, a robotic solution for assisting in dressing can significantly improve the quality of life of the elderly and disabled.

Robotic clothing assistance is hard to accomplish because of two significant difficulties, (a) cloth manipulation, (b) safe human-robot interaction. Clothes are non-rigid and highly flexible objects which make it difficult to manipulate. Unlike rigid object manipulation, which heavily relies on precise robot control, cloth manipulation requires adaptive control. The tight coupling between the human and the clothing article is difficult to model wherein the clothing article undergoes severe deformations. Concerning safety, the robot needs to take care of the human whose posture may vary while assisting.

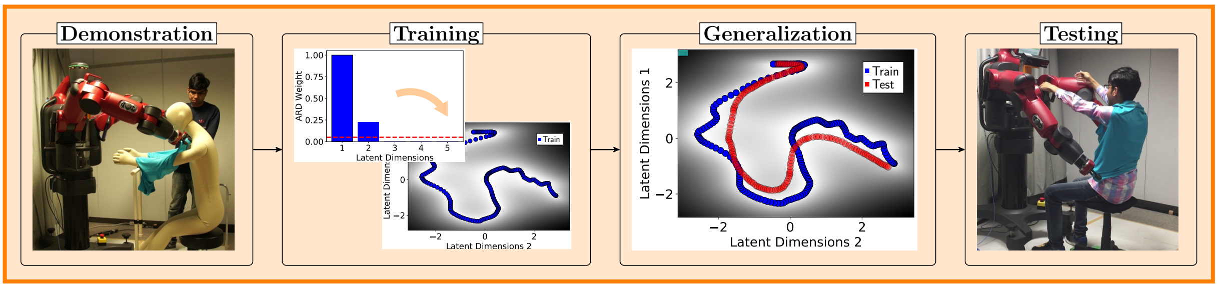
In this paper, we propose a framework for robotic clothing assistance by imitation learning from a human demonstration to a compliant dual-arm robot, since clothing assistance is generally not difficult for humans. In this framework, we divide the dressing task into three phases, i.e., reaching phase, arm dressing phase, and body dressing phase. The reaching phases can be achieved through point-to-point motion planning. We apply Dynamic Movement Primitives (DMP) for the arm dressing phase and Bayesian Gaussian Process Latent Variable Model (BGPLVM) for the body dressing phase. The arm dressing phase is considerably a trajectory planning problem, and it is taken care of by DMP. In the body dressing phase, the robot operates close to the subject. We employ BGPLVM in the body dressing phase. DMP by formulation provides adaptive control of the robot. DMP parameterizes the robot trajectory acquired from the kinesthetic demonstration by a human. By changing the start and goal parameters of DMP, the generated trajectory can be modified globally. Hence, we can say that DMP is goal-directed since a change in the goal affects the entire trajectory. On the other hand, the latent space generated by BGPLVM provides local modification. We assume that performing a dressing task requires a consistent set of motor skills. These motor-skills can be acquired from the robot trajectory by constraining it to a



(a) Setup of the task showing trajectories consisting of points P_1, P_2, P_3 and P_4 corresponding to three phases



(b) Arm dressing phase. The trajectory starts from the fingertip (i.e., point P_2) and ends at the elbow position (i.e., point P_3). It is achieved using DMP.



(c) Body dressing phase. The trajectory starts from the elbow position (i.e., point P_3) and finishes at the torso position (i.e., point P_4). It is achieved using BGPLVM.

Figure 2. Overview of the framework. The complete task is divided into three phases. The first phase, i.e., reaching phase, is a point-to-point trajectory. The remaining two phases are arm dressing and body dressing phase for which four stages such as demonstration, training, generalization, and testing are defined.

lower dimensional latent space using BGPLVM. The body dressing phase requires a complicated trajectory as compared to the arm dressing phase. Hence, we apply BGPLVM to encode these complicated motor-skills. We have shown that generated latent space by BGPLVM provides safe human-robot interaction during the body dressing phase wherein a tight coupling between the human and the cloth happens.

Clothing assistance is difficult to tackle using reinforcement learning as it takes a long time which is undesirable in dressing tasks, to find the optimal policy. This difficulty can be resolved by using imitation learning as a form of prior knowledge. The prior knowledge is incorporated by using Learning from Demonstration (LfD) frameworks to avoid the complexity and uncertainty associated with the modeling of the clothing assistance environment which consists of the human, robot and clothing article. We evaluated the proposed framework on human subjects by dressing a sleeveless shirt using the Baxter robot. Our approach is focused on assisting the elderly and disabled having limited upper arm movement. Hence while assisting, the robot cooperates with the subject and expects minimal upper arm movement to provide a relaxed experience. The robot used in this research meets the international ANSI RIA R15.06-2012 and ISO 10218-1:2006 safety standards [8] and hence suitable for our research.

The remainder of the paper is organized as follows. First, we briefly introduce some of the related works in Section 2. Later, in Section 3 we provide an overview of the framework followed by the mathematical formulation of DMP and BGPLVM. In Section 4, we evaluate the proposed framework by showing our results. The discussion about the research is presented in Section 5. Finally, we conclude in Section 6 with some future directions.

2. Related Works

The state of the art research related to cloth manipulation is mainly implemented for cloth folding tasks. In order to understand the challenges involved in robotic clothing assistance, first, we need to look at the sophisticated research related to the cloth manipulation. In the subsequent section, we will summarize the related works in the field of cloth manipulation followed by the actual robotic clothing assistance task.

2.1 *Robotic Manipulation of Clothes*

In order to deal with tedious and complex cloth modeling, Monsó *et al.* [9] proposed a probabilistic planner based on Partially Observable Markov Decision Process (POMDP). The planner was applied to perform clothes sorting task from a pile of laundry. Yamazaki *et al.* [10] exploited optical flow on image sequences for cloth state estimation in trouser dressing tasks. They propose a method to recognize the cloth state by matching the optical flow with the training dataset. Yamakawa *et al.* [11] proposed visual feedback control for dynamic manipulation of sheet-like flexible objects by a high-speed robotic system that learns necessary motor-skills from demonstration performed by a human subject. Kita *et al.* [12] applied a model-driven strategy to recognize the shape of the clothing article based on observations during manipulation. They used a humanoid robot and provided a three-dimensional view to pick up an arbitrarily placed clothing article on a desk and spread it open by holding the cloth at specific locations.

Willimon *et al.* [13] performed classification of clothing article lying in a pile of laundry by comparing against a dataset of known items. A robot equipped with an overhead stereo and side-facing cameras was used to interact with the pile to isolate each item one at a time. Graph-based segmentation algorithm and nearest neighbor algorithm (K-NN) on a dataset labeled in a supervised manner were used. Li *et al.* [14] worked on cloth folding by finding an optimal trajectory to move robotic arm given start and end folding position. A quadratic objective function defined using material properties of the garment and frictional force was trained offline in a simulation environment, which was later executed on a real robotic arm. Towner *et al.* [15] tackled the problem of identifying clothing articles from an unknown configuration and bringing it to the desired configuration. They used Hidden Markov model (HMM) for estimating the identity of the clothing article. Miller *et al.* [16] performed a shape-based classification by examining the best-parametrized model fit for recognizing the configuration of clothing articles spread in a pile of laundry. Ono *et al.* [17] developed a two finger hand for cloth handling which can separate a clothing article from the pile of clothes. The thickness of clothing articles was found proportional to the output of the strain gauge of the hand. Doumanoglou *et al.* [18] presented a pipeline for folding a pile of clothes using a dual-arm robot. Cloth spreading was done by detecting deformations of the cloth contours, and grasping points were detected using Active Random Forests.

Studies such as Kita *et al.* [12], Willimon *et al.* [13], Li *et al.* [14] and Towner *et al.* [15] heavily rely on offline simulation of the environment wherein no human intervention is considered. The clothing articles are spread out on a flat surface in Towner *et al.* [15] and Miller *et al.* [16], and polygon mesh models are used to approximate clothing articles. These assumptions together with slow manipulation of clothing articles such as Doumanoglou *et al.* [18] can produce inaccurate results during the dressing process since clothing article goes through severe deformations while dressing on a human body.

2.2 *Robotic Clothing Assistance*

Some studies that tackle the problem of robotic clothing assistance. Researchers have used vision information with a combination of techniques such as motor skills learning and proprioceptive sensory information. Tamei *et al.* [19] formulated the task of putting the sleeveless shirt into the mannequin's head as a reinforcement learning system. They proposed to use topology coordinates [20] to represent the human-cloth relationship in a low-dimensional state. Yamazaki *et al.* [21] exploited visual and force sensory information for trouser dressing using a humanoid robot. Dressing state estimation was done by computing optical flow from two consecutive images [10]. A three-dimensional range camera was used to estimate the shape of the legs. A set of trajectory segments corresponding to standard leg size was also created in advance. Colomé *et al.* [22] performed the task of placing a scarf on a mannequin by incorporating a friction-model based controller using reinforcement learning. A combination of kinematic, dynamic and visual feedback was used to design the cost function for the learning agent. Klee *et al.* [23] proposed a framework to coordinate with the human subject to complete the task of putting a hat on the subject. They emphasize human's motion tracking using a vision system.

Koganti *et al.* [24, 25] proposed a framework for offline learning of cloth dynamics using GPLVM by incorporating motion capture data and applying this model for online tracking of the human-cloth relationship using a depth sensor. They showed that generated latent space could learn reliable motion models of the sleeveless shirt state for dressing tasks. Gao *et al.* [26, 27] have focused on user upper-body modeling for personalized dressing by using randomized decision forests for estimating user pose. They proposed an online iterative path optimization method to enable the robot to assist a human in dressing a sleeveless jacket. Kapusta *et al.* [28] proposed a haptic-based perception to estimate the human-cloth relationship. They used HMM with force information to classify success in the task of pulling a hospital gown onto the subject's arm. This task was later formulated as a deep recurrent model by Erickson *et al.* [29] using haptic and kinematic data. A physics-based simulation was used to train the model. Chance *et al.* [30, 31] proposed strategies using way-points and error handling through force sensory information in robotic clothing assistance tasks. They used a motion capture system to determine the arms of the mannequin and also proposed a simple fixed vocabulary for human-robot interaction using speech.

Most of the studies presented above have various limitations. In studies such as Tamei *et al.* [19] and Koganti *et al.* [24, 25], the experiments were limited to tests with a static mannequin, without the involvement of human subjects which suffers from lack of human-robot interaction. In Gao *et al.* [26] preprocessing of the user-specific dataset for personalized dressing such as collecting a large dataset of images and manual labeling is tedious and time-consuming. Studies such as Colomé *et al.* [22] and Klee *et al.* [23], deals with putting a scarf/hat on the subject do not provide enough interaction between the clothing article and the human subject. Some studies such as Gao *et al.* [27] require much cooperation from the subject concerning arms movement during the dressing process. It should be noted that most of the elderly have limited upper arm movement, and it can be painful to move arm beyond a limited range [32]. The robot must adapt and expect less cooperation from the subject to provide much-relaxed experience during the aid. In some studies such as Tamei *et al.* [19] and Koganti *et al.* [24, 25], it was assumed that the clothing article, i.e., the sleeveless shirt is already in the arms of the mannequin. This assumption simplifies the dressing process as they do not need to tackle the problem of dressing arm, wherein the clothing article can get stuck on the fingers. Hence, in this study, we are trying

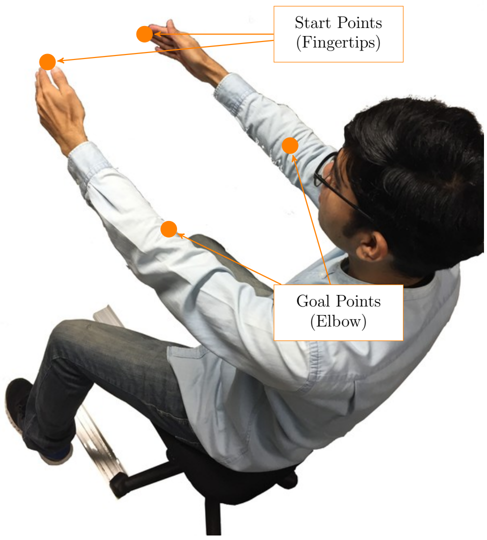


Figure 3. Control points for arm dressing phase showing start and goal points of DMP system colored as orange. Fingertips and elbow positions are chosen as start points and goal points respectively.

to overcome these limitations, wherein we are using human subject while focusing on the elderly subjects having limited upper arm movement. This research is an extension of our previous work [33]. We are using a dual-arm compliant Baxter robot to ensure the safety of the human subject and proposing a framework to dress a sleeveless shirt to human subjects.

3. Method

Our framework is shown in Figure 2. We have divided the trajectory into the following three phases

(1) Reaching phase, which refers to the trajectory that starts from the home position of the robot, i.e., P_1 and ends at the fingers of the subject, i.e., P_2.
(2) Arm dressing phase, which refers to the trajectory that starts from fingers of the subject, i.e., P_2 and reaches up to the elbow, i.e., P_3.
(3) Body dressing phase, which refers to the trajectory that starts from the elbow, i.e., P_3 of the subject goes over the head and reaches up to the torso of the subject, i.e., P_4.

The reaching phase is a point-to-point trajectory, performed using a simple position based controller, but for the rest of the phases, we need an efficient controller which can learn required motor skills from the demonstration and can generalize to various people. The arm dressing phase is reasonably a trajectory planning problem, and DMP takes it to care. DMP can be generalized to various postures of the subject's arm by changing the start, and goal parameters thus enable adaptive control of the robot. More information is provided in Section 3.1. In body dressing phase, the robot operates close to the subject. Hence to address safe human-robot interaction, we propose to use BGPLVM wherein tight coupling between the human and the clothing item occurs. We assume that performing a dressing task requires a consistent set of motor skills. The robot trajectory can be constrained to a lower dimensional latent space using BGPLVM. Both DMP and BGPLVM being data-efficient can learn even from a single demonstration thus suitable for our task. In the subsequent sections, we are explaining two phases of dressing task and the mathematical formulation of them.

3.1 *Arm Dressing Phase*

In this section, we are going to incorporate DMP for putting the clothing article on the arms of a subject. As per the formulation described in section 3.1.1, DMP can learn from the demonstration. Therefore we start by performing a kinesthetic demonstration with the robot controlled in gravity compensation mode as shown in Figure 2. This is referred to as "Demonstration Stage" since, in this stage, an expert provides a demonstration of the dressing task while the robot is under gravity compensation. During the demonstration, pose trajectory of end-effector is recorded using Baxter API and stored in a file. The term pose collectively refers to as position in Cartesian space $p = (p_x, p_y, p_z) \in \mathbb{R}^3$ and orientation. The orientation is defined in terms of quaternion $q = (q_x, q_y, q_z, q_w) \in \mathbb{R}^4$. Once the demonstration is finished, DMP is parameterized using the recorded trajectory file. This is termed as "Training Stage". The parameterized DMP can represent all the characteristics of the original trajectory. Here, three DMP systems, one for each coordinate axis, i.e., x, y, and z are initialized for one arm. In this way, we have totally six DMP systems, which can control both the arms of the Baxter robot. The orientation of the end-effector is not considered as a part of the DMP system and kept the same as it was at the time of "Demonstration Stage". It should be noted that the expert demonstrations were performed on a mannequin as it can be time-consuming for a human subject to sit while recording demonstrations. After training the DMP system, it can generalize to various arm postures. Now, we need to set the control points which are start and goal parameters of DMP as fingertip and elbow positions of the subject respectively shown in Figure 3. The control points of DMP are retrieved by using a Kinect v2 sensor. More information is given in Section 4.1. In this way, we have modified DMP system, which can adapt modified posture referred to as "Generalization Stage". The adaptation is verified by executing the generated trajectory during "Testing Stage".

3.1.1 DMP Formulation

DMP aims at designing a controller for learning and generalization of motor skills by learning from demonstration [34, 35]. The controller is based on a nonlinear dynamical system and uses Locally Weighted Regression (LWR) to learn complex, discrete or rhythmic movements demonstrated by a human subject [36]. The basic idea behind DMP formulation is to use an analytically well-understood dynamical system and add a nonlinear term so that it produces the desired behavior [37]. Originally, for a one-dimensional system, DMP is defined by a linear spring model combined with an external force as follows

$$\tau \dot{v} = K(g - x) - Dv + (g - x_0)f \tag{1}$$

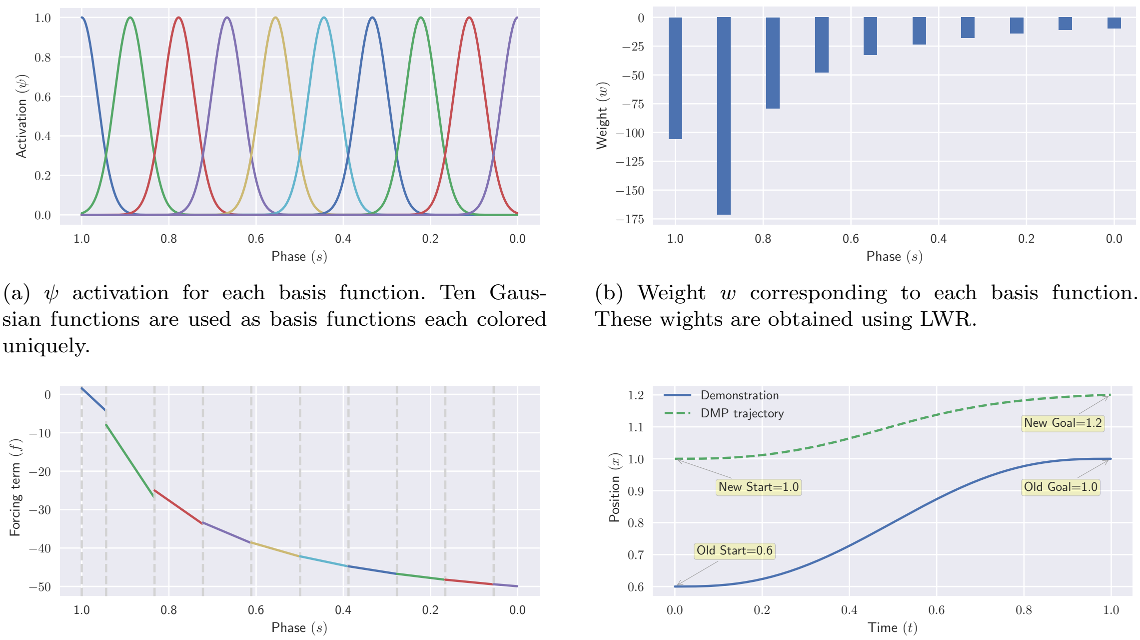
where

$$\tau \dot{x} = v$$

The term x and v are position and velocity of the system respectively, x_0 and g are start and goal position respectively, τ is the temporal scaling term, K acts like spring constant and D is damping factor chosen in a way such that system is critically damped. However, the above formulation of DMP suffers from stability issues such as high accelerations for special cases. Hence, a new formulation was proposed by Pastor *et al.* [38] in which Eqn. 1 was redefined as follows

$$\tau \dot{v} = K(g - x) - Dv - K(g - x_0)s + Kf(s) \tag{2}$$

where s is called phase variable. Phase variable s starts from 1 and monotonically decreases to



(a) ψ activation for each basis function. Ten Gaussian functions are used as basis functions each colored uniquely.

(b) Weight w corresponding to each basis function. These wights are obtained using LWR.

(c) Forcing term f corresponding to each basis function and colored uniquely. For each Gaussian, function f gets activated for a certain time period as shown by the gray colored dashed vertical lines.

(d) Learning a trajectory using DMP. Start and goal points of a demonstrated trajectory are modified to generate a DMP trajectory.

Figure 4. Brief overview of a one-dimensional discrete DMP system.

0, defined by following equation $\tau \dot{s} = -\alpha s$, where α is a positive gain term. In Eqn. 2, notice the term $K(g - x_0)s$ which is necessary for avoiding a sudden jump at the beginning of a movement. The nonlinear function f, which is also called the forcing term is a non-linear function to be learned to allow complex movements. The forcing function f is chosen as

$$f(s) = \frac{\Sigma_i w_i \psi_i(s)}{\Sigma_i \psi_i(s)} s \tag{3}$$

where ψ_i is defined as Gaussian basis function as

$$\psi_i = \exp\left(-h_i\left(s - c_i\right)^2\right) \tag{4}$$

where h_i and c_i are constants that determine, respectively, width and centers of basis functions. w_i represents weight defined for each Gaussian. Forcing function f depends on phase variable s. Our goal is to design a forcing function that can learn from demonstration and allows us to scale the movement defined by start and goal state, i.e., x_0 and g respectively. So that the system can follow a specified path. The forcing term can be redefined as

$$f_{target}(s) = \frac{Dv + \tau \dot{v}}{K} - (g - x) + (g - x_0)s \tag{5}$$

where desired acceleration $\dot{v}(t)$ can be calculated by taking the second derivative of the positional data recorded from demonstration as

$$\dot{v}(t) = \frac{\partial v}{\partial t} = \frac{\partial^2 x}{\partial t^2} \tag{6}$$

The forcing function in Eqn. 3 is comprised of the weighted summation of Gaussians that are going to be activated as system converges to goal as shown in Figure 4. We want that forcing function matches the desired trajectory, i.e., f_{target} should be as close as possible to f. Mathematically, we can formulate it as an optimization problem such as

$$J = \sum_s (f_{target}(s) - f(s))^2 \tag{7}$$

This ends by calculating weight parameters across Gaussians. Optimization methods such as Locally Weighted Regression (LWR) [39] can be used, so that forcing function matches the desired trajectory. In this way, DMP can be made to imitate the desired path [38].

3.2 *Body Dressing Phase*

In this section, we provide the details for generating the latent space using BGPLVM described in section 3.2.1. BGPLVM is used to dress the body part of the subject. Similar to DMP; we start by performing a kinesthetic demonstration with the robot controlled in gravity compensation mode as shown in Figure 2. We record joint angle trajectories of Baxter's arms using Baxter API and use them for modeling BGPLVM.

3.2.1 BGPLVM Formulation

BGPLVM is an extension of GPLVM [40] in which inputs are unobserved, treated as latent variables and outputs are observed using multiple output Gaussian Process (GP) regression model as shown in Figure 5.

Let $\mathbf{Y} \in \mathbb{R}^{N \times D}$ be the observed data where N is the number of observations, and D is the dimensionality of each observation. In Latent Variable Model (LVM) methodology, we assume that these observations are generated from an unobserved space also known as latent space $\mathbf{X} \in \mathbb{R}^{N \times Q}$ such that $Q \ll D$. We start by defining a generative mapping from latent space to observation space as

$$\mathbf{y}_n = f(\mathbf{x}_n) + \epsilon_n \; \forall \; \epsilon_n \sim \mathcal{N}(\mathbf{0}, \beta^{-1}\mathbf{I}) \tag{8}$$

where $\mathbf{y}_n, \; \mathbf{x}_n$ represents n^{th} row of $\mathbf{Y}, \mathbf{X}$ respectively. The random noise variable ϵ is derived from a Gaussian distribution with mean zero and covariance $\beta^{-1}\mathbf{I}$. It should be noted that the above mapping is governed by GP[41] wherein GPs are taken to be independent across the features. Hence conditional likelihood is written as

$$\begin{aligned} p(\mathbf{Y}|\mathbf{X}) &= \prod_{d=1}^{D} p(\mathbf{y}_d|\mathbf{X}) \\ &= \prod_{d=1}^{D} \mathcal{N}(\mathbf{y}_d|\mathbf{0}, K_{NN} + \beta^{-1} I_N) \end{aligned} \tag{9}$$

In the above equation, Gaussian distribution has zero mean and covariance $K_{NN} + \beta^{-1}I_N$. Term K_{NN} is $N \times N$ covariance matrix composed by kernel function $k(\mathbf{x}, \mathbf{x\prime})$, which is defined

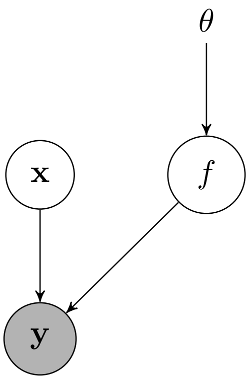


Figure 5. Graphical representation of BGPLVM. Gray circle represents the observed variable whereas the white circle shows the latent variable.

by Automatic Relevance Detection (ARD) kernel [41, 42]. ARD kernel solves model selection problem by determining the dimensionality of latent space and is written as

$$k(\mathbf{x}, \mathbf{x}\prime) = \sigma^2_{ARD} \exp\left(-\frac{1}{2}\sum_{q=1}^{Q} \alpha_q (x_q - x\prime_q)^2\right) \tag{10}$$

ARD kernel consists of weight parameters $\{\alpha_q\}_{q=1}^{Q}$ which describe the relevance of each dimension. Term σ_{ARD} describes the scale of GP mapping function [25].

The model consists of hyperparameters $\theta = (\beta, \sigma^2_{ARD}, \{\alpha_q\}_{q=1}^{Q})$. The objective is to infer latent variable $\mathbf{X}$. We can assign a Gaussian prior into it as follows

$$p(\mathbf{X}) = \prod_{n=1}^{N} \mathcal{N}(\mathbf{x}_n | \mathbf{0}, I_Q) \tag{11}$$

The joint probability of the model can be defined as

$$p(\mathbf{Y}, \mathbf{X}) = p(\mathbf{Y}|\mathbf{X})p(\mathbf{X}) \tag{12}$$

Here, we use a variational Bayesian approach for the marginalization of the latent variable $\mathbf{X}$, which allows optimizing resulting lower bound on marginal likelihood w.r.t. the hyperparameters θ [43]. The marginal likelihood of the data is written as

$$p(\mathbf{Y}) = \int p(\mathbf{Y}|\mathbf{X})p(\mathbf{X})d\mathbf{X} \tag{13}$$

To compute the above equation, we need to use $p(\mathbf{Y}|\mathbf{X})$ from Eqn. 9. Eqn. 9 contains $\mathbf{X}$ nonlinearly inside $K_{NN} + \beta^{-1}I_N$ as shown in Eqn. 10, which makes it intractable. Here, we make use of variational inference to approximate posterior distribution $p(\mathbf{X}|\mathbf{Y})$ by introducing a variational distribution $q(\mathbf{X})$ written as

$$q(\mathbf{X}) = \prod_{n=1}^{N} \mathcal{N}(\mathbf{x}_n | \mu_n, S_n) \tag{14}$$

where $\{\mu_n, S_n\}_{n=1}^{N}$ are variational parameters. The idea behind variational inference is to use Kullback-Leibler (KL) divergence as a measure of distance between $p(\mathbf{X}|\mathbf{Y})$ and $q(\mathbf{X})$. It allows computing Jensen's lower bound on marginal likelihood as follows

$$\begin{aligned}\log p(\mathbf{Y}) &\geq F(q) \\ &= \int q(\mathbf{X}) \log p(\mathbf{Y}|\mathbf{X}) d\mathbf{X} - \int q(\mathbf{X}) \log \frac{q(\mathbf{X})}{p(\mathbf{X})} d\mathbf{X} \\ &= \tilde{F}(q) - \mathrm{KL}(q \| p)\end{aligned} \tag{15}$$

The hyperparameters θ are dropped for notation clarity. Term $\tilde{F}(q)$ can be computed by using Eqn. 9 and by breaking it down to separate computation at each dimension of observation as follows

$$\begin{aligned}\tilde{F}(q) &= \sum_{d=1}^{D} \int q(\mathbf{X}) \log p(\mathbf{y}_d|\mathbf{X}) d\mathbf{X} \\ &= \sum_{d=1}^{D} \tilde{F}_d(q)\end{aligned} \tag{16}$$

The term $\tilde{F}_d(q)$ contains an intractable integration because conditional likelihood term $p(\mathbf{y}_d|\mathbf{X})$ contains $\mathbf{X}$ nonlinearly inside the inverse of covariance matrix, i.e., $K_{NN} + \beta^{-1} I_N$. In order to derive a closed-from lower bound for $\tilde{F}_d(q)$, variational sparse GP regression [44] was used in which auxiliary variables were introduced in an augmented probability model [43]. The augmented model defines $\mathbf{f}_d \in \mathbb{R}^N$ associated with $\mathbf{y}_d$ as follows

$$\begin{aligned}p(\mathbf{y}_d|\mathbf{f}_d) &= \mathcal{N}(\mathbf{y}_d|\mathbf{f}_d, \beta^{-1} I_N) \\ p(\mathbf{f}_d|\mathbf{X}) &= \mathcal{N}(\mathbf{f}_d|\mathbf{0}, K_{NN})\end{aligned} \tag{17}$$

M auxiliary variables also known as inducing variables, i.e., $\mathbf{u}_d \in \mathbb{R}^M$ are defined in pseudo input locations $\hat{\mathbf{X}} \in \mathbb{R}^{M \times Q}$. The augmented joint probability of the model is given by following

$$p(\mathbf{y}_d, \mathbf{f}_d, \mathbf{u}_d|\mathbf{X}, \hat{\mathbf{X}}) = p(\mathbf{y}_d|\mathbf{f}_d) p(\mathbf{f}_d|\mathbf{u}_d, \mathbf{X}, \hat{\mathbf{X}}) p(\mathbf{u}_d|\hat{\mathbf{X}}) \tag{18}$$

GP prior evaluated at input $\mathbf{X}$ and $\hat{\mathbf{X}}$ factorizes as $p(\mathbf{f}_d, \mathbf{u}_d|\mathbf{X}, \hat{\mathbf{X}}) = p(\mathbf{f}_d|\mathbf{u}_d, \mathbf{X}, \hat{\mathbf{X}}) p(\mathbf{u}_d|\hat{\mathbf{X}})$ gives following

$$p(\mathbf{f}_d, \mathbf{u}_d|\mathbf{X}, \hat{\mathbf{X}}) = \mathcal{N}(\mathbf{f}_d|\alpha_d, K_{NN} - K_{NM}^{-1} K_{MN}) \tag{19}$$

where $\alpha_d = K_{NM} K_{MM}^{-1} \mathbf{u}_d$ and marginal GP prior over inducing variables is given by $p(\mathbf{u}_d|\hat{\mathbf{X}}) = \mathcal{N}(\mathbf{u}_d|\mathbf{0}, K_{MM})$.

Above calculations leads to an interpretation which says that unlike $\mathbf{X}$, inducing inputs $\hat{\mathbf{X}}$ are neither random variables nor model hyperparameters. They are treated as variational parameters [45]. Variational distribution over inducing variables was found independent of $\mathbf{X}$. The model leads to tractable Jensen's lower bound $\tilde{F}_d(q)$ by using mean field approach which forces independent distribution from the input variable $\mathbf{X}$ thereby making the approximation tractable. Detailed derivation of the model is further explained in [43].

In order to make predictions $p(y_*|\mathbf{Y})$ in unseen data $y_* \in \mathbb{R}^D$, latent variables $\mathbf{X}$ and new test latent variables x_* are introduced, and the ratio of two marginal likelihoods is calculated as follows

$$\begin{aligned} p(y_*|\mathbf{Y}) &= \frac{p(y_*, \mathbf{Y})}{p(\mathbf{Y})} \\ &= \frac{\int\int p(y_*, \mathbf{Y}|\mathbf{X}, x_*)p(\mathbf{X}, x_*)dXdx_*}{\int p(\mathbf{Y}|\mathbf{X})p(\mathbf{X})d\mathbf{X}} \end{aligned} \tag{20}$$

The term $\int p(\mathbf{Y}|\mathbf{X})p(\mathbf{X})d\mathbf{X}$ gives variational distribution $q(\mathbf{X})$ and is fixed during test time. $\int\int p(y_*, \mathbf{Y}|\mathbf{X}, x_*)p(\mathbf{X}, x_*)dXdx_*$ is approximated by the ratio of lower bounds as follows

$$\begin{aligned} p(y_*|\mathbf{Y}) &\approx q(y_*|\mathbf{Y}) \\ &= \exp\left(F(q(\mathbf{X}, x_*) - F(q(\mathbf{X}))\right) \end{aligned} \tag{21}$$

Detailed steps of the prediction process are further explained in [43].

4. Evaluation

4.1 *Experimental Setup*

The experimental setup contains a compliant dual-arm humanoid robot Baxter. Each arm of the Baxter robot has 7 degrees of freedom (DOF). The setup of our system is shown in Figure 1. A Kinect v2 [46] depth sensor is mounted below the LCD on the chest of Baxter by a custom designed mount. We have used two finger electric gripper provided by Baxter. We designed soft fingertips which were plugged into these fingers tightly as shown in Figure 7. These soft fingertips 3D printed using soft-material, are necessary for firm gripping of flexible clothing article hence provides better cloth manipulation. The clothing article is held by these fingertips, and it is put in the arms of Baxter robot manually by a human assistant. A chair is provided to the subject to sit on during the dressing task and face the Baxter. The robot puts the clothing article on the human subject. During the process clothing article goes over the arms of the human subject. Hence it is essential for the subject to keep his arms straight and to face towards the robot. It should be noted that Baxter's arms have limited workspace and it cannot reach the torso of the subject while arms of the subject are extended. Therefore we propose to use a portable chair wherein the movement of the chair is restricted by keeping it on rails. This arrangement of the chair provides sufficient movement required for performing a dressing assistance task.

We use Robot Operating System (ROS) [47] to implement our framework in Ubuntu OS. Baxter robot is connected to this computer using an Ethernet cable. For human pose tracking, official Kinect APIs were used in a separate Windows OS which is also connected to Ubuntu OS. The skeleton tracking data is transferred from Windows OS to Ubuntu OS in real-time using ZeroMQ [48], a high performance distributed asynchronous messaging library. We used Ubuntu 14.04 LTS 64 Bit OS having 8GB RAM on Intel Core i7, 3.40 GHz x 8 CPU for training and testing our framework. The clothing articles used in this study are Adidas and Avail sleeveless 100% polyester (size L) sleeveless shirt as shown in Figure 6.

Figure 6. Clothing articles used in dressing task. All are 100% polyester sleeveless shirts. The size of all shirts is L.

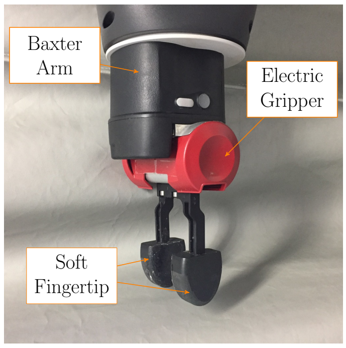
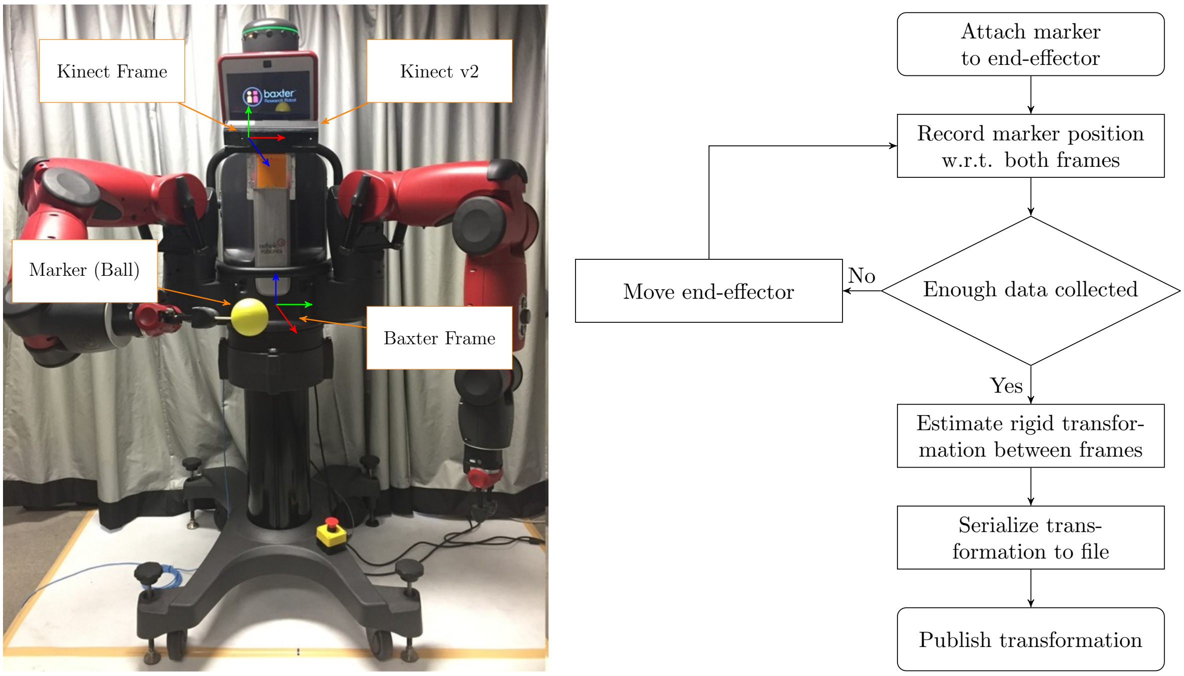


Figure 7. Soft fingertips mounted on fingers of the electric gripper of Baxter robot



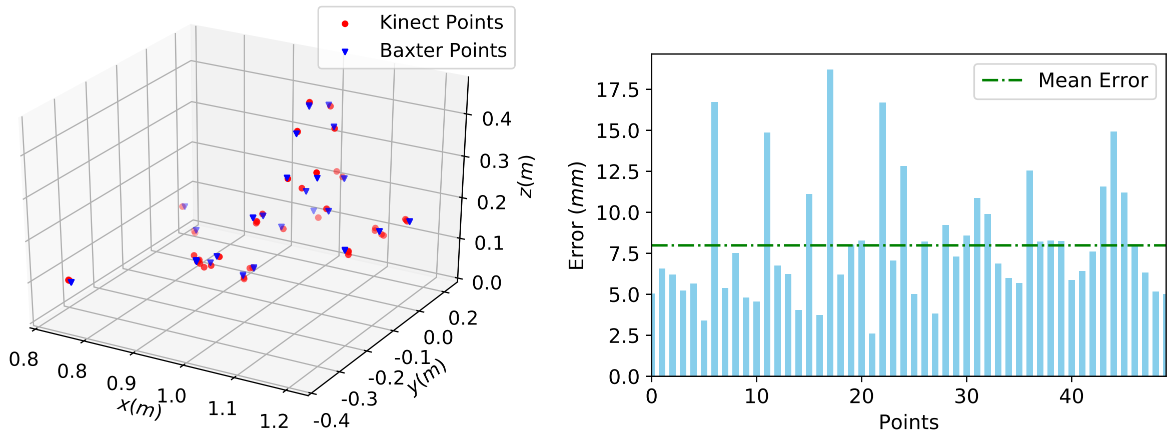
(a) Experimental setup for calibration showing robot and camera frames in three-dimensional space

(b) Flowchart of the calibration procedure

Figure 8. Robot Camera Calibration

4.2 *Robot Camera Calibration*

Our experimental setup of robotic clothing assistance contains a Kinect v2 depth sensor that is used for human pose tracking. We need to calibrate Kinect camera w.r.t. Baxter robot so that observations can be transformed into Baxter reference frame. To perform this calibration, we need to hold a marker in one arm of Baxter as shown in Figure 8(a). The idea behind the calibration technique is to record the position of the marker as observed from both the frames, i.e., Baxter and Kinect. In our experiment, we use a rubber ball as a marker. We start the calibration process by recording marker position w.r.t. both frames. It should be noted that an additional transformation on Baxter's end-effector was incorporated while recording marker position w.r.t. Baxter. Now, we moved the end-effector and recorded the position again. We recorded the data for several ($\approx$ 50) positions and created a dataset of points. The calibration process is automatic and finished in a few ($\approx$ 5) minutes. Later, we estimated a rigid transformation between two point sets by computing Singular-Value Decomposition (SVD) proposed by Umeyama [49]. This transformation is serialized to a file for later use in ROS. A flowchart representing the calibration



(a) Result of the calibration procedure showing transformed source points, i.e., Kinect corresponding to target points, i.e., Baxter

(b) Calibration error showing mean error as the green colored dotted line

Figure 9. Calibration Results

process is shown in Figure 8(b).

Figure 9(a) is showing the result of our calibration procedure, wherein we plotted the transformed source frame, i.e., Kinect frame along with the target frame, i.e., Baxter. The plot shows that the above calibration procedure finds a transformation that leads to match source and target point set. The mean error in the estimation of transformation is 8.0 mm as shown in Figure 9(b).

4.3 *Generalized DMP System for the Arm Dressing Phase*

The arm dressing phase was accomplished by the DMP system. Initial DMP was modified to accommodate a new posture by changing start and goal parameters. The generated trajectory from the modified DMP system was then run on Baxter robot as shown in Figure 10. The initial DMP trajectory (shown in green color) is parametrized and able to represent all characteristics of the demonstration trajectory (shown in blue color). The modified DMP trajectory (shown in red color) was found well suited as it is capable of performing the task. Since the DMP trained on a mannequin and tested on human subjects, we can notice the difference in control points of DMPs.

To further investigate our DMP System, we performed arm dressing task on ten subjects. For each subject, we repeated the experiment ten times. During the experiment, the end-effector trajectory generated by the DMP system is recorded. We have plotted the mean and along with the standard deviation for all subjects as shown in Figure 11. Three sub-plots are showing x, y and z coordinates of end-effector w.r.t. time. The time is normalized to [0, 1] range. The largest range of coordinates is noticed across x-axis which reflect the length of the human's arm starting from the fingertip up to elbow. The y- and z-axis corresponds to the bending and height of the human's arm respectively. The different height of the human's arm is induced from the fact that many (ten to be precise) subjects having different body dimensions were involved in the evaluation of the experiment. The trajectory starts from the fingertip of the subject and reaches up to the elbow of the subject. The standard deviation is higher at the beginning, and it decreases as time passes. The beginning and the ending represent the fingertip and the elbow position of the subject respectively. For every subject at each trial, the fingertip position changes substantially higher compared to the elbow position. Hence the standard deviation is high at the beginning.

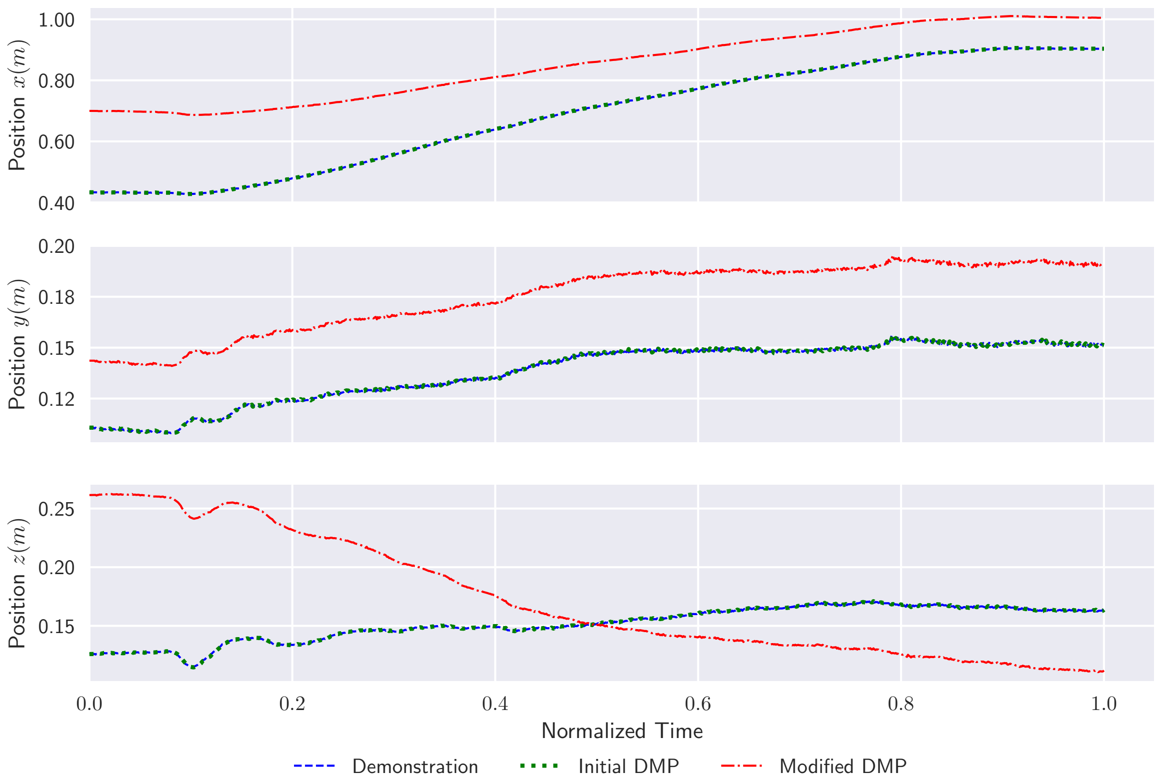


Figure 10. DMP trajectory corresponding to the left-arm of Baxter while performing arm dressing on a subject. The modified DMP is acquired by changing control points of initial DMP, which is modeled by parameterizing demonstration trajectory using DMP. The time is normalized to [0, 1] range.

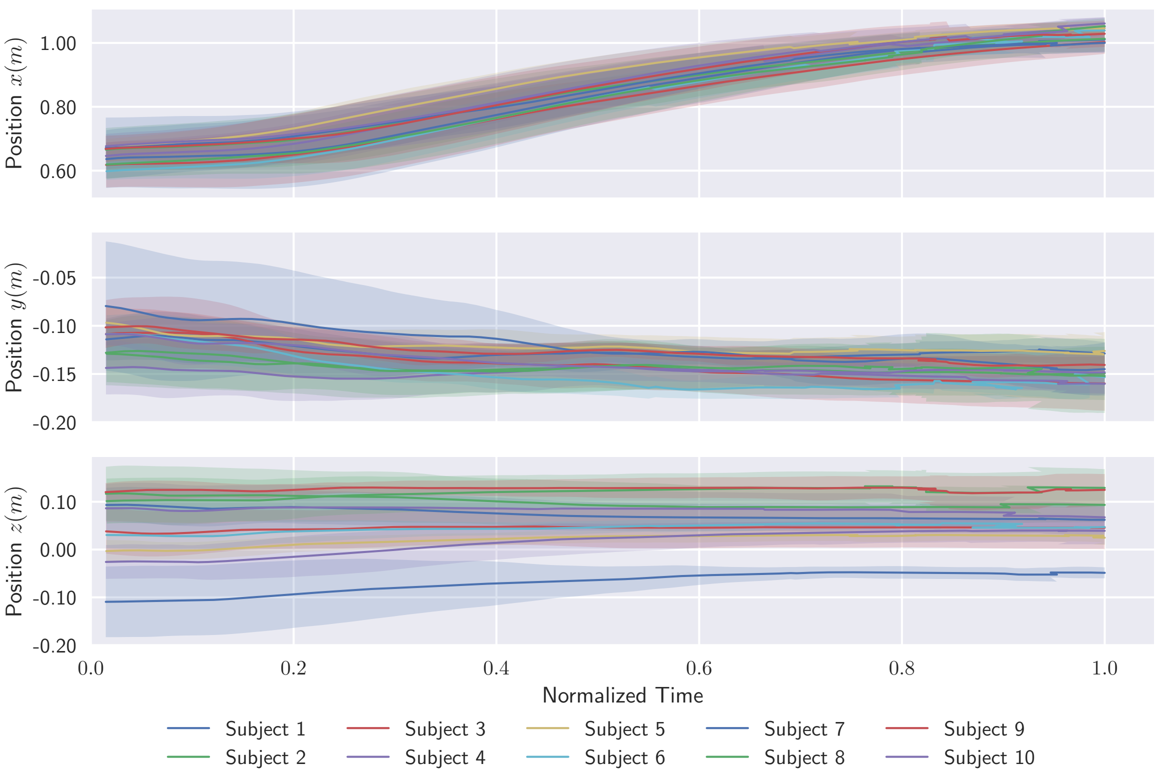
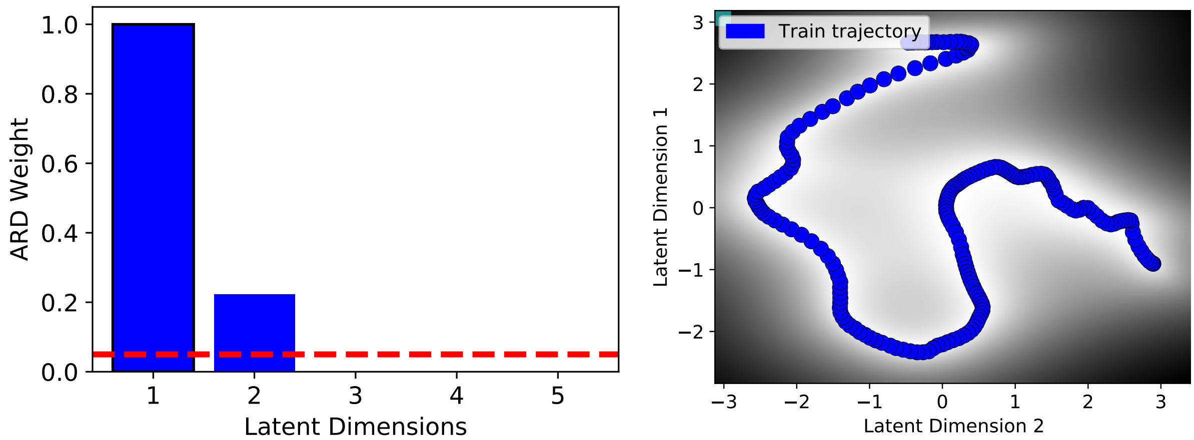


Figure 11. Right-arm trajectory of Baxter while performing arm dressing on multiple subjects. The time is normalized to [0, 1] range. For each subject, the mean position is plotted with a dark color and the region $\mu \pm \sigma$ along mean position is filled with a light color. The x, y and z-axis corresponds to the length (from fingertip up to elbow), bending and height of the human's arm respectively.

4.4 *Latent Space for the Body Dressing Phase*

Due to the strong human-cloth coupling during the body dressing phase, BGPLVM was utilized. It was implemented using GPy python library [50]. The input variable **X** was initialized using PCA from demonstration data as the first step for GPy library. ARD kernel and 100 inducing input points were supplied to BGPLVM model. The training of the model was done in two steps. Firstly, the signal-to-noise ratio (SNR) which was fixed to 10, was used to constrain the variance of model parameters. In this configuration, the model was optimized for 20 iterations. Secondly, we trained the model without any constraints and optimized for 500 iterations. Generated latent space with the relevance of each latent dimension is shown in Figure 12(a). The model can find two latent dimensions which are having the maximum contribution in defining the data.



(a) Relevance of each latent dimension. Dotted red colored line is showing weight threshold for relevance.

(b) Two-dimensional latent space generated by BG-PLVM

Figure 12. BGPLVM Model

To show what the latent space encoded, we explored the latent space by choosing four points on latent space. At each point, we sampled and inferred the configuration of the robot as shown in Figure 14. Blue colored trajectory shows the training trajectory whereas sampled test trajectory is shown in red color. During the exploration of latent space, the robot along with its end-effector trajectories was visualized. The end-effector trajectories are shown in yellow color. The exploration confirms that the generated two-dimensional latent space is restricted to perform dressing tasks only and hence provides safe human-robot interaction, which is also shown in Figure 13. This figure plots forces acting on the end-effector recorded during the body dressing phase. End-effector forces are noisy; however, they all are following a similar trend, which indicates that our controller with the BGPLVM model achieved safe human-robot interaction..

4.5 *Complete Robotic Clothing Assistance*

We performed the dressing experiment on ten healthy people and observed the task. If the robot is able to dress sleeveless shirt such that sleeveless shirt reaches up to the torso, we labeled it as a successful dressing; otherwise, it is treated as failure dressing. Sometimes failure occurred due to the clothing article get slipped from the fingers while pulling it. The overall results are shown in Table 1. Overall, 93% of the trials of the dressing task were found successful. The complete dressing task took 45 seconds approximately. The dressing task at various timestamps is shown in Figure 15. After finishing the task, the robot arm is moved to its home position. This movement time is also included in dressing time shown in Table 1. The dressing time varies due to the different body dimensions of each subject. Intuitively, for thin subjects, the robot exerts less force while pulling the sleeveless shirt and hence dressing is quicker than others.

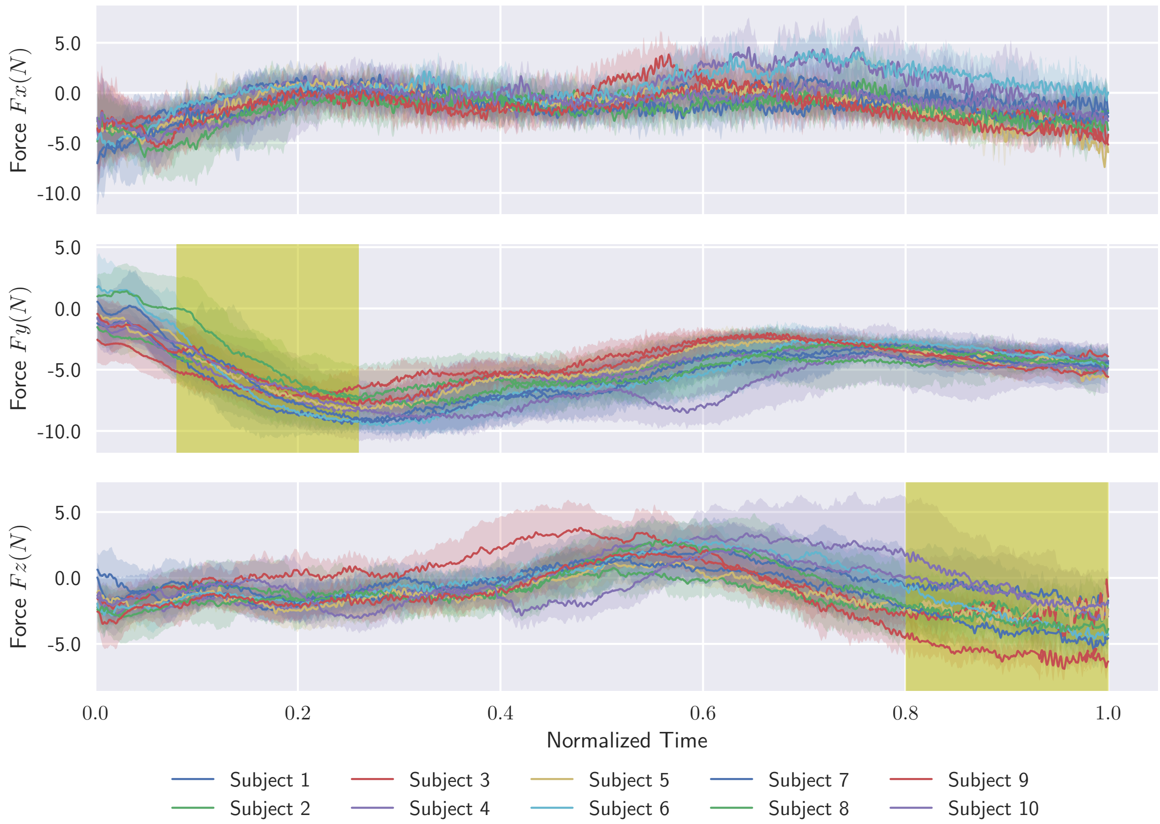


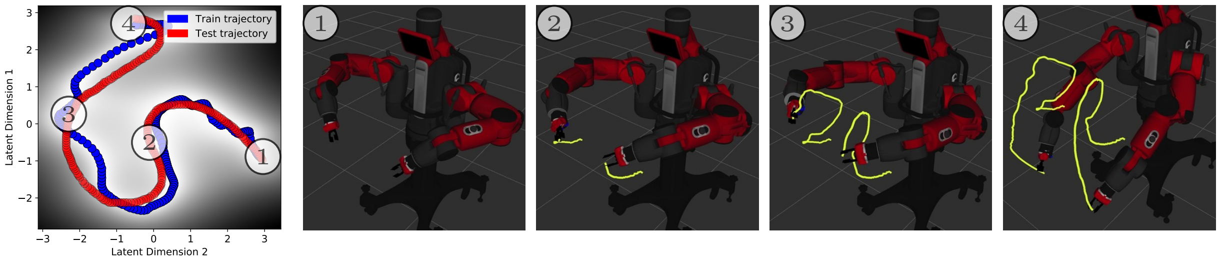
Figure 13. Forces acting on the right arm of Baxter while performing body dressing on multiple subjects. The time is normalized to [0, 1] range. For each subject, the mean force is plotted with a dark color and the region $\mu \pm \sigma$ along mean force is filled with a light color. The highlighted region in F_y shows increasing force while stretching out the clothing article to expand so that it can pass by the head and neck of the subject. On the other hand, the highlighted region in F_z shows increasing force while pulling down the clothing article to reach up to the torso of the subject.

Table 1. Results of Complete Robotic Clothing Assistance

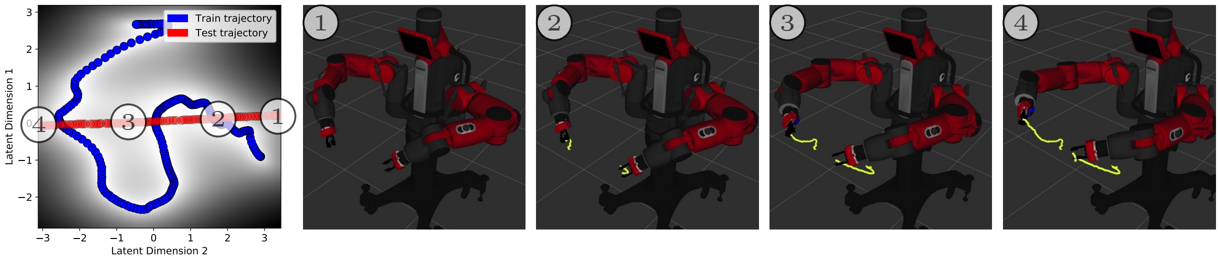
Subject No.	Trials	Dressing Successful	Failed	Dressing Time (sec) Average	Standard Deviation
1	10	9	1	47	5
2	10	10	0	46	4
3	10	10	0	40	4
4	10	10	0	48	2
5	10	9	1	41	4
6	10	10	0	42	3
7	10	8	2	52	4
8	10	9	1	43	3
9	10	9	1	44	3
10	10	9	1	51	3
Total	100	93	7		

5. Discussion

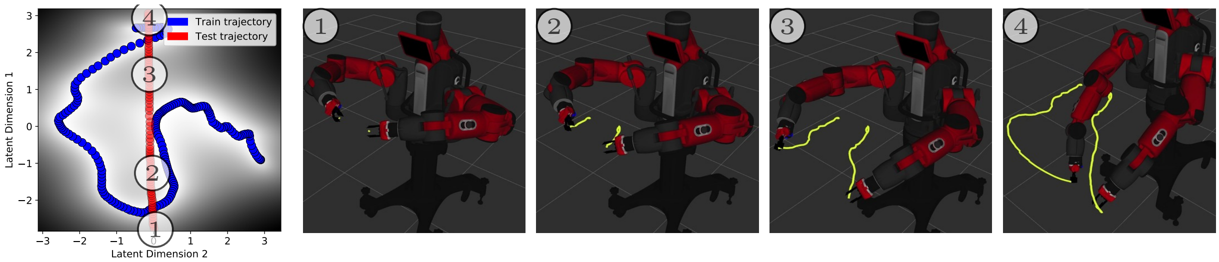
The robotic clothing assistance task deals with the manipulation of the clothing article, which contains complex dynamics due to the inherent non-rigid and flexible nature of clothes. Not to mention that a robot needs to perform the task close to humans, which further makes it complicated. In our experiment, Baxter's left and right arm trajectory depend on the posture of the person being assisted. During the arm dressing phase, it usually mirrors each other due to the symmetry of the posture of the subject's arms. In principle, we have employed separate DMPs for each arm. In the subsequent sections, we describe some of the problems faced in the experiment which can be considered as failure scenarios and public demonstration of the experiment at an international level robot exhibition followed by limitations of our current work.



(a) Dressing task trajectory



(b) Horizontal exploration



(c) Vertical exploration

Figure 14. Latent space exploration, showing robot configurations corresponding to four points on latent space inside a visualizer. Latent space contains the training trajectory (blue) and the exploration trajectory (red). The robot trajectories are shown inside the visualizer (yellow).

5.1 *Failure Scenarios*

The task of clothing assistance inherits complex dynamics due to the presence of flexible clothing articles along with the human subject being assisted. Hence there can be various failure scenarios. At present, official API's of Kinect v2 depth sensor is being used for human pose estimation. The pose estimation is not robust to this environment as it fails during occlusion with Baxter arm and other objects such as clothing article. Another significant failure is caused by the clothing article. During the task, the clothing article undergoes severe deformations, and the shape of the clothing article keeps on changing, which affects the task settings. Therefore, a trajectory that was able to perform the task successfully once isn't guaranteed to work always. We noticed that there could be many other failure scenarios such as clothing article getting stuck to the fingers, clothing article not reaching up to the torso and clothing article getting slipped by end-effectors.

5.2 *Demonstration at iREX 2017*

To examine the performance of the proposed framework, we demonstrated it to the public in iREX (International Robot Exhibition) 2017 held in Tokyo (Japan). People from academia, industry, healthcare and government officials visited, and saw the demonstration. We requested them to be a subject, and then we performed a clothing assistance task. After completing the task, we had conversations with them during that we asked them to provide feedback about their experience by filling a paper-based questionnaire. Unfortunately, due to the immense visitors during the exhibition, it was difficult to take feedback from each participant. Nevertheless,

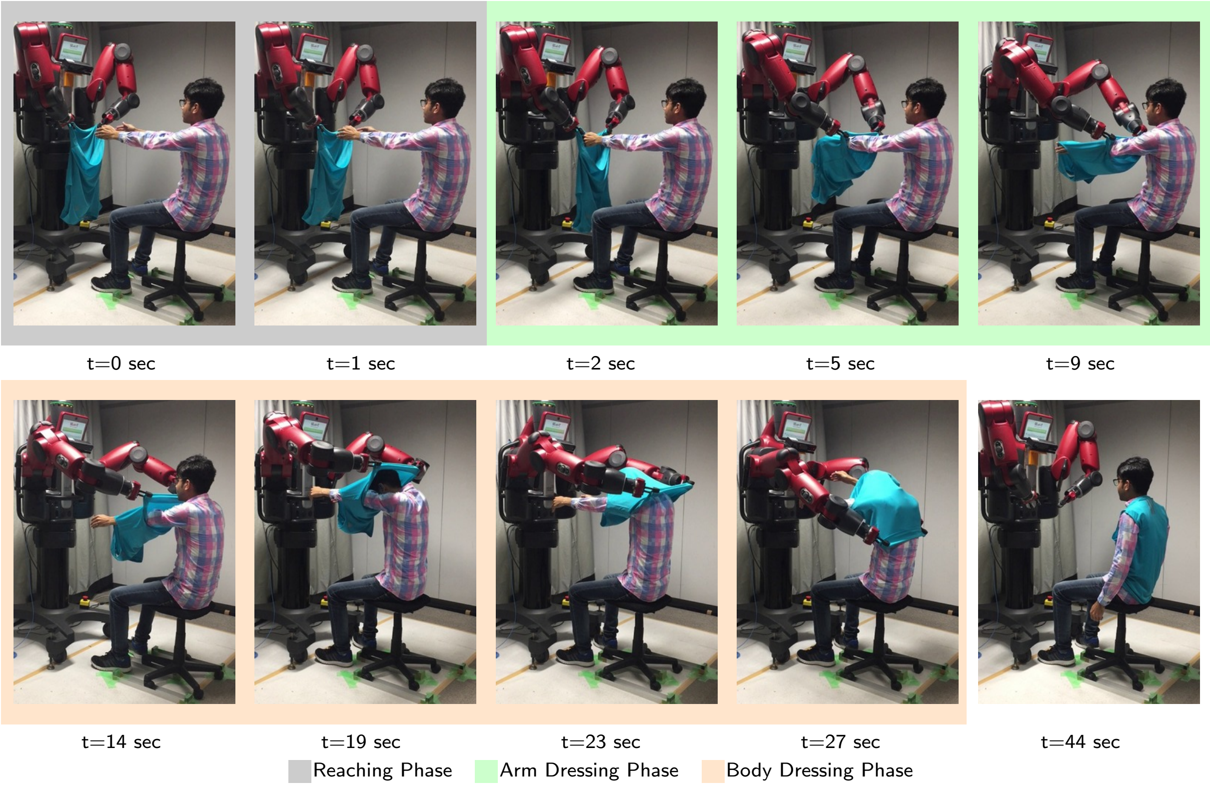


Figure 15. Robotic clothing assistance task shown at various timestamps. The clothing article, i.e., a sleeveless shirt which was initially held by the robot, is shown fully dressed on a human subject.

we managed to collect feedback from 35 participants. The feedback was mostly positive and encouraging. The comprehensive data is shown in Figure 16.

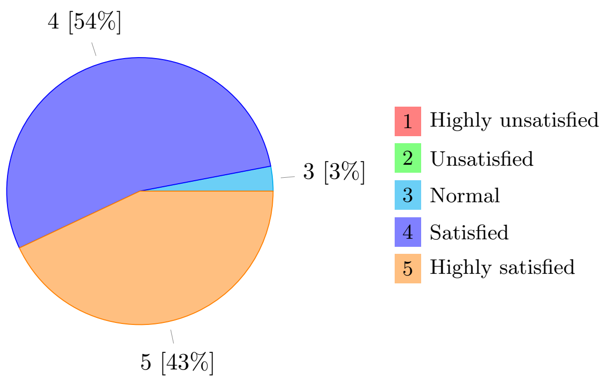


Figure 16. Feedback received from 35 participants during the public demonstration at iREX 2017. Most of the subjects were found excited and satisfied.

5.3 *Limitations*

At present, there are certain limitations of our work as listed below.

- The experiment is performed on healthy adults. Although we do have demonstrated this system to a few elderly at various exhibitions, a complete evaluation is yet to be done.
- During the arm dressing phase, arms are constrained due to the shirt over them. In this situation, the arms cannot be moved beyond a limited range. Hence, both the arms are restricted to be parallel even though separate DMPs are employed for both arms.

- Kinect v2 Sensor using Windows SDK is employed for human body recognition and tracking. All 26 joints defined by Kinect v2 are tracked. However, our algorithm uses only fingertips and elbow positions for both arms of the subject.
- The arm dressing phase is initialized by fingertips and elbow positions. Although, as per DMP formulation, it is possible to keep updating the fingertips and elbow positions during the dressing. Unfortunately, it is difficult to track these joints during the dressing due to the occlusion from cloth and robot arm. Hence, during the arm dressing phase, human arms are assumed to be stationary.
- During body dressing phase, due to the limited Baxter's workspace, the subject is requested to move towards the robot while sitting on the chair. This movement is difficult to achieve by using a mannequin. Hence, even though we performed the demonstration on a mannequin but we couldn't conduct the task on a mannequin.
- We have shown the dressing of a sleeveless shirt. However, our approach can be extended to other clothing articles such as pants, jackets and so on. Pant dressing can be incorporated from arm dressing. For each type of clothing articles, separate demonstration and training should be essential. However, in this work, our experiment is limited to the dressing of a sleeveless shirt.

6. Conclusion

Robotic clothing assistance can contribute to improving the quality of life of the elderly substantially and significantly reduce the burden on caregivers. Due to the inherent properties of clothes such as non-rigidity and flexibility, cloth manipulation is still limited to much simpler applications such as cloth folding tasks. Due to close cloth interaction with the human during dressing, robotic clothing assistance is still a challenging and open problem. We have presented a framework for robotic clothing assistance consisting of DMP and BGPLVM. We have shown that by dividing the entire trajectory into multiple parts, generalize using DMP and BGPLVM; robotic clothing assistance can be performed. Our framework is trained by imitation learning from a human demonstration on a single demonstration which intuitively makes it data-efficient. It has been developed focusing on assisting the elderly hence expects minimal cooperation from the human subject concerning body movement. The robot was programmed to move slowly compared to its default speed so that any collision has minimal inertia and impact. Although our paper has been focused only on sleeveless shirt dressing, our framework could enable robotic assistance in other dressing tasks such as the jacket, pant dressing, and undressing as well.

The proposed framework does not depend on robot hence can easily be applied to any dual-arm robot. Baxter robot has a narrow workspace. That is why a portable chair was used. It should be noted that a larger workspace and/or movable dual-arm robot should be preferred to perform the task. Few subjects have complained that the robot is scary due to the noise, shape, and size. The robot also lacks communication ability such as speaking. We think that adding this ability may improve its chance of social acceptance. Cloth handling requires dexterous operations. However, at present two finger grippers are used. This can be one of the future works towards rich cloth handling by using multiple fingers. The latent space generated by BGPLVM is constrained in task space and provides safe interaction with the human subject. At present, the latent space is generated from a single demonstration. Hence it suffers from limited generalizability. However, in the future, this latent space can be redesigned by providing multiple trajectories to accumulate the variability in human body shapes. Our framework provides a proper initialization for applying reinforcement learning. The generated latent space can be treated as a search space of learning agent for policy search so that the robot can adapt to various failure scenarios in real-time due to constrained two-dimensional search space, which will be one of our future works. We plan to consider training on differently sized mannequins for better generalization to different sized humans as one of the future works. We can achieve it by learning from a database of primitives.

At present, the experiment is performed on humans. Since the subject is a human being, even if it is an improper operation, the subject may be adjusted and dressed well. Therefore, in the future, we would like to perform the dressing experiment on a mannequin to evaluate whether the same performance can be obtained while using a mannequin. We would also like to perform detailed user evaluation in particular for acceptance and perceived the safety of elderly persons in the future. We want to demonstrate this system on the elderly not only to examine it but also to understand their experience in connection with psychology in the future.

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