Electric Wheelchair–Humanoid Robot Collaboration for Clothing Assistance of the Elderly

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***Abstract*—In rapidly aging societies, robotic solutions for clothing assistance can significantly improve the quality of life of the elderly while coping with the shortage of caregivers. Previously, we proposed a framework for the same by employing imitation learning from a human demonstration to a compliant dual-arm robot. As the robot has a limited workspace, this framework involves a manual movement of the wheeled chair by pushing it while coordinating with the robot to stay within the workspace of the robot [1]. To avoid the manual push and coordination, we facilitate the automatic movement of the chair based on the trajectory of the robot's dual arms. In this paper, we present an approach for the collaboration of an electric wheelchair and a humanoid robot to achieve the clothing assistance task. Our approach incorporates Manifold Relevance Determination (MRD) to learn an offline latent model from the simultaneous observations of the clothing assistance task as well as the movement of the wheelchair. We trained and tested the latent model on different human subjects by dressing a sleeveless T-shirt. Experimental results verify the plausibility of our approach. To the best of our knowledge, this is the first work addressing collaboration between wheelchair and robot to perform clothing assistance.**

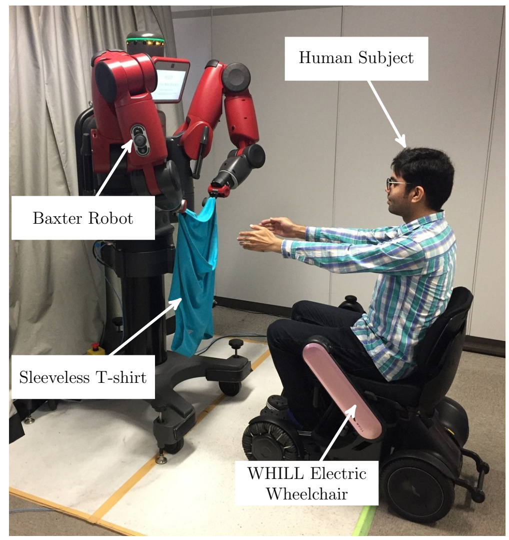

Fig. 1: Setup of the task.

I. INTRODUCTION

There has been a significant increase in the elderly population in developed countries in recent times. In such countries, the ratio of the elderly population to the overall population is predicted to increase further in forthcoming years. The population ratio for the elderly is the highest in Japan at 28.1 percent, followed by Italy at 23.3 percent, Portugal at 21.9 percent, and Germany at 21.7 percent [2]. This demographic trend has created a high demand for caregivers in nursing homes. There is thus a need for robotic assistance for elderly care in nursing homes.

Dressing is an essential and difficult ADL for the elderly, which is generally taken care of by caregivers. While coping with the shortage of caregivers, robotic clothing assistance can significantly improve the quality of life of the elderly. In our previous study, we had proposed a framework for the same by using imitation learning from a human demonstration to a compliant dual-arm robot [1]. As the robot has a limited workspace, this framework involves a manual movement of the wheeled chair so as to stay within the workspace of the robot. This manual movement requires pushing the chair while coordinating with the robot, which is difficult to perform by the elderly. Thus, we focus on automating the movement of the chair to make the dressing task much more comfortable for the subject.

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In robotic clothing assistance, the robot operates in close proximity to the person. Therefore, the robot needs to be aware of the presence of the person to ensure his safety. Not to mention that the posture of the person can vary while performing the task. Therefore, Gao *et al.* [3] used Gaussian mixture models to encode user-specific upper body movements. Also, Erickson *et al.* [4] tackled the problem of human pose tracking during the clothing assistance task by using proximity sensing. Zhang *et al.* [5] performed tracking of the user's movements to perform robotic clothing assistance. In these studies, authors have used a jacket or hospital gown as a clothing article. They limited their experiments by considering only one arm dressing.

In literature, Deep Neural Networks (DNN) is well known for classification and regression problems. Clegg *et al.* [6] used Deep Reinforcement Learning (DRL) for hospital gown dressing by human-robot collaboration. They used a simulation environment to learn control policies for human and robot simultaneously. They employed a co-optimization approach to train two dense DNN and optimized it to maximize expected long-term rewards. DNN is very promising in classification and regression problems demands a massive amount of data to learn. Collecting a large dataset in robotics, especially in robotic clothing assistance, is highly challenging and time-consuming and hence discouraged by the research community in robotics. On the other hand, in DRL based methods, the agent needs to perform numerous interactions with a test environment [7]. The test/simulation environment contains limited knowledge about the environment. It can be extremely unfeasible to model a simulation environment for a real and complex environment. Manifold Relevance Determination (MRD) [8] adopts Bayesian treatment to learn from a little amount of data. It constructs a low dimensional latent space by determining a common representation among underlying high dimensional data.

The important feature of this study is human-robot and robot-robot collaboration in service robotics. In this study, we present an approach to collaborate between the wheelchair and the humanoid robot to perform the clothing assistance task. The setup of our system is shown in Fig. 1. A human subject is sitting in an electric wheelchair and facing his hands towards the robot. The robot's arms have a limited workspace and need to reach the torso of the subject to perform the dressing task. Hence the chair must move forward to stay within the workspace of the robot during the dressing task. Therefore, it is empirical that the joint angles of the robot and the movement of the chair share a common latent space. This is why we employed MRD to learn the latent space offline for the simultaneous observations from the clothing assistance task as well as the movement of the wheelchair. To the best of our knowledge, this is the first work addressing collaboration between wheelchair and robot to perform clothing assistance.

The rest of the paper is organized as follows. In Section II, we explain the proposed method, followed by an introduction of MRD. Section III deals with the various experiments performed. Results and discussion are provided in Section IV, followed by limitations of this study in Section IV-A. Finally, we conclude in Section V with future directions.

II. METHOD

Robotic clothing assistance supports the subject in getting him dressed up. In this study, we are using a sleeveless T-shirt as the clothing article. This task is performed using a compliant dual-arm Baxter robot while coordinating with WHILL, an electric wheelchair [9]. The cloth goes through the arms, then goes over the head, and finally reaches up to the torso of the subject. An overview of the proposed method is shown in Fig. 2. We define two observation spaces, i.e., Baxter joint angle space, and WHILL movement space. We perform a kinesthetic demonstration of the task while Baxter is controlled under gravity compensation mode. During the demonstration, an expert manipulates the arms of Baxter robot while a subject is sitting in the wheelchair, as shown in Fig. 3. At this stage, the wheelchair is controlled manually by using a joystick. Baxter joint angle space consists of the joint space trajectory of the robot, whereas the WHILL movement space consists of the movement given to the wheelchair during the demonstration. We apply MRD on both the observation spaces to discover shared dimensions in a 2D latent space. This latent space encodes the motor skills required to perform the clothing assistance tasks as well as to depict the wheelchair movement. During the inference, the mean trajectory is sampled from the latent space. This mean trajectory of the latent space is used to infer the joint space trajectory of the Baxter robot. We then use the joint angles of Baxter to predict the movement of the wheelchair in real-time using the learned MRD model.

In the following subsection, we present a brief mathematical formulation of MRD.

A. Manifold Relevance Determination (MRD)

MRD is a nonlinear dimensionality reduction technique proposed by Damianou *et al.* [8]. It is used to learn a shared latent space among multiple observation spaces. It involves the use of Bayesian inference as it was proposed as an extension to the Bayesian Gaussian Process Latent Variable Model (BGPLVM) proposed by Titsias *et al.* [10].

MRD aims to relate two observation spaces $\mathbf{Y} \in \mathbb{R}^{N \times D_Y}$ and $\mathbf{Z} \in \mathbb{R}^{N \times D_Z}$ within a single model. Here, N represents the number of observations. D_Y and D_Z represent the dimensionality of each observation, i.e., $\mathbf{Y}$ and $\mathbf{Z}$ respectively. The two observations spaces are assumed to be generated from a low-dimensional latent space $\mathbf{X} \in \mathbb{R}^{N \times L}$ such that $L \ll D$ (to account for the dimensionality reduction) and corrupted by Gaussian noise:

$$\begin{aligned} \mathbf{y}_n &= f^Y(\mathbf{x}_n) + \epsilon_n^Y,\ \epsilon_n^Y \in \mathcal{N}(\mathbf{0}, \beta_Y^{-1}\mathbf{I}), \\ \mathbf{z}_n &= f^Z(\mathbf{x}_n) + \epsilon_n^Z,\ \epsilon_n^Z \in \mathcal{N}(\mathbf{0}, \beta_Z^{-1}\mathbf{I}) \end{aligned} \tag{1}$$

where β_Y, β_Z denote the inverse variance parameters for the noise random variables ϵ_n^Y, ϵ_n^Z. A Gaussian Process (GP) prior is placed on the mapping function f, $f(\mathbf{x}) \sim \mathcal{GP}(\mathbf{0}, k(\mathbf{x}, \mathbf{x}\prime))$, where $k(\mathbf{x}, \mathbf{x}\prime)$ is the covariance function, which is defined by the automatic relevance determination (ARD) kernel.

The likelihood under the model is denoted by, $\mathsf{P}(\mathbf{Y}, \mathbf{Z} | \mathbf{X}, \boldsymbol{\theta})$ where $\boldsymbol{\theta} = \{\boldsymbol{\theta}^Y, \boldsymbol{\theta}^Z\}$ collectively denotes the parameters of the mapping functions and the noise variances β_Y, β_Z.

The selection of the latent space dimensionality is performed automatically using the ARD kernel,

$$k_Y(\mathbf{x}_i, \mathbf{x}_j) = \sigma_Y^2\ \exp\left(-\frac{1}{2}\sum_{l=1}^{L} \alpha_l^Y (x_{i,l} - x_{j,l})^2\right) \tag{2}$$

and similarly for the $\mathbf{Z}$ observation space. The relevance of each latent dimension is determined by its ARD weight α_l, and the scale of the GP mapping function is determined by σ.

The ARD weights α_l^Y, α_l^Z also help in partitioning the latent space into shared $(\mathbf{X}_S)$ and private spaces $(\mathbf{X}_Y, \mathbf{X}_Z)$. This is done by using a threshold δ which is set heuristically on the normalized ARD weights to determine the relevance of

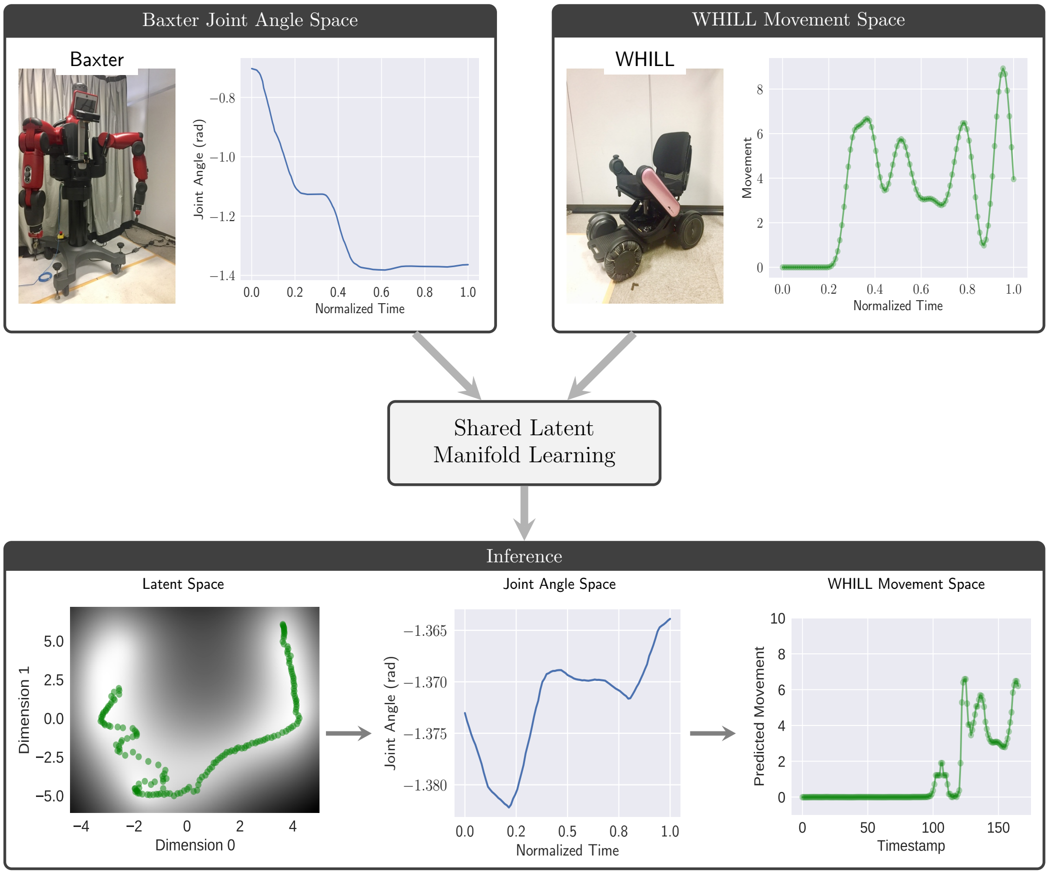


Fig. 2: An overview of the proposed method for the collaboration between Baxter and WHILL. We defined two observation spaces, i.e., Baxter joint angle space (only 1 of the 14 joint angles of the robot is indicated in the graphs here) and WHILL movement space, and learned a shared latent space by employing MRD.

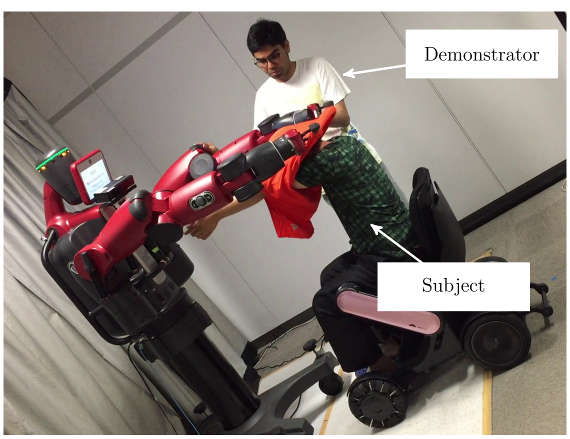


Fig. 3: Demonstration of the task

a latent dimension in reconstructing each observation space. The shared and private spaces are defined as follows:

$$\begin{aligned}
\mathbf{X}_S &= \{\mathbf{x}_l\}_{l=1}^{L} : \mathbf{x}_l \in \mathbf{X},\ \alpha^Y > \delta,\ \alpha^Z > \delta \\
\mathbf{X}_Y &= \{\mathbf{x}_l\}_{l=1}^{L} : \mathbf{x}_l \in \mathbf{X},\ \alpha^Y > \delta,\ \alpha^Z < \delta \\
\mathbf{X}_Z &= \{\mathbf{x}_l\}_{l=1}^{L} : \mathbf{x}_l \in \mathbf{X},\ \alpha^Y < \delta,\ \alpha^Z > \delta
\end{aligned} \tag{3}$$

Now, we briefly explain the inference process in MRD. Given a set of observed test points $\mathbf{Y}^\star \in \mathbb{R}^{N^\star \times D_Y}$, we aim to generate a new set of outputs $\mathbf{Z}^\star \in \mathbb{R}^{N^\star \times D_Z}$. This is done in the following three steps:

1) We predict the set of latent points $\mathbf{X}_Y^\star$, $\mathbf{X}_S^\star$ which is most likely to have generated $\mathbf{Y}^\star$.
2) The shared latent space $\mathbf{X}_S^\star$ is then used to find the nearest neighbors among the latent points corresponding to the training data and obtain the information on the private dimension of $\mathbf{Z}$, $\mathbf{X}_Z^{NN}$.
3) We use the full latent state $\mathbf{X}_S^\star$, $\mathbf{X}_Z^{NN}$ to infer the outputs $\mathbf{Z}^\star$.

Detailed explanation of MRD is given in [8].

III. EXPERIMENTS

A. Experimental Setup

The experimental setup contains a compliant dual-arm humanoid Baxter robot and an electric wheelchair WHILL [9]. The Baxter robot has 7 degrees of freedom (DOF) in each arm, adding up to a total of 14 joint angles required to define a specific configuration of the robot. The Baxter robot is controlled using the Robot Operating System (ROS) in Ubuntu

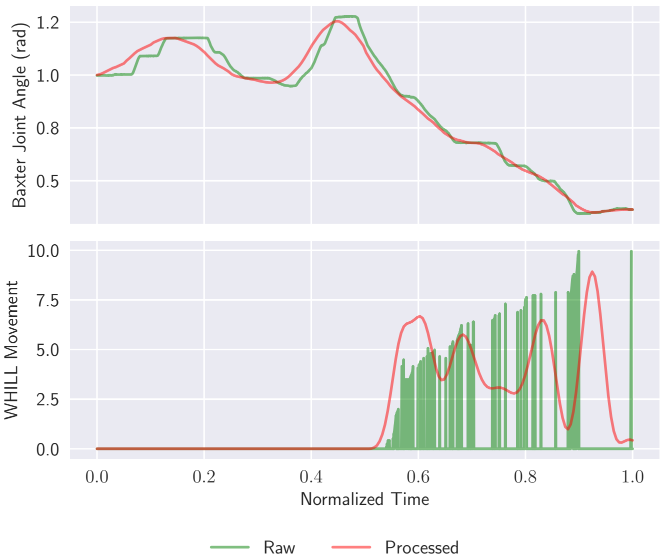


Fig. 4: Preprocessing of the collected data. We use the median filter and cubic interpolation to preprocess the collected data. We are showing only one joint angle of the Baxter robot. The WHILL movement refers to the forward tilt of the joystick.

PC. It is connected to the PC using an Ethernet cable. We command the robot using the Baxter API, which is supported by ROS.

The WHILL wheelchair is also controlled using ROS, and our in-house developed API is used to command the movement [11]. The movement of the wheelchair refers to the tilt of the joystick and comprises of two parameters, forward tilt and sidewise tilt. The forward and sidewise tilt causes the forward and turn movement, respectively. The default joystick value is a tuple of forward and sidewise tilt, and it is (0, 0). The range of forward and sidewise tilt is [-100, +100]. Note that if the forward tilt is negative, i.e., the joystick is tilted backward, the wheelchair moves in the backward direction. In this study, we focus only on the forward movement of the wheelchair and keep the sidewise tilt to 0 always.

The wheelchair is kept approximately a meter away from the robot. To dress the sleeveless T-shirt, the subject needs to keep his hands stretched outwards and facing the robot. We used a sleeveless polyester T-shirt during the experiment. We used Ubuntu 14.04 LTS 64-bit Operating System having 8GB RAM on Intel Core i7, 3.40 GHz x 8 CPU for training and testing our method.[1]

B. Shared Latent Manifold Learning for Automated Wheelchair Movement

For training the MRD model, we collected data of joint angles of the Baxter robot and the corresponding wheelchair movement by performing a kinesthetic demonstration of the task on a subject. The collected data comprises the joint space trajectory of the Baxter robot and corresponding wheelchair

[1]The source code used in experiments is available at https://github.com/ravijo/HSI2020

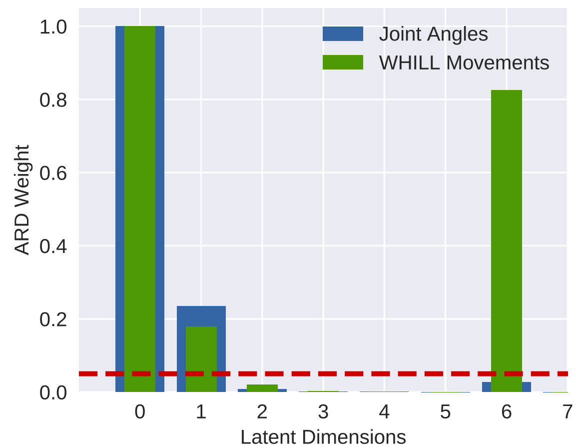


Fig. 5: ARD weights of each latent dimension

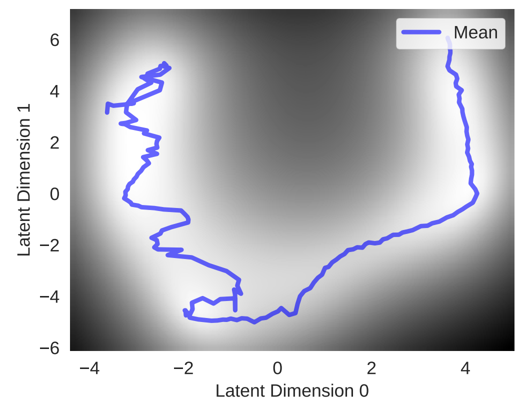
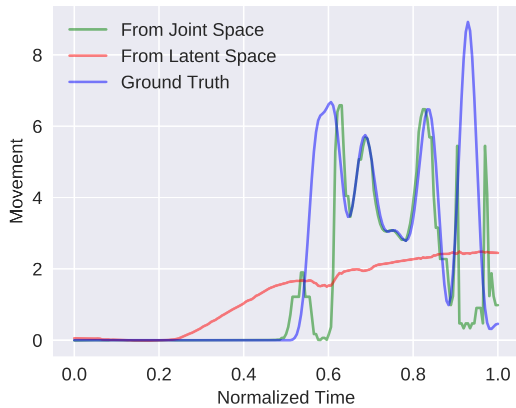


Fig. 6: Latent Space generated using first two latent dimensions

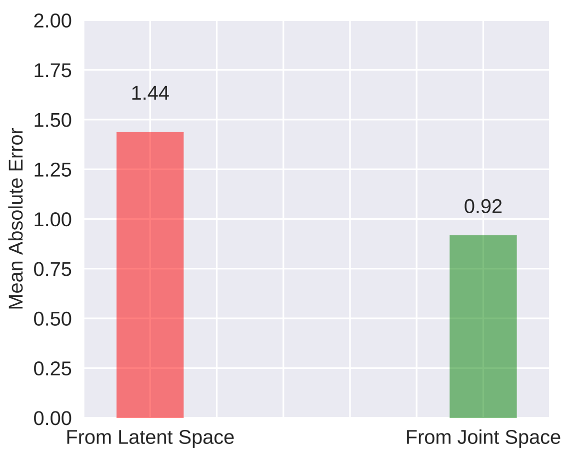
movement throughout the clothing task. The data were preprocessed before being used for training the MRD model, as shown in Fig. 4. We used the median filter and cubic interpolation to preprocess the collected data. The WHILL movement refers to the forward tilt of the joystick as we have not considered sidewise tilt by keeping it 0 always.

We aim to learn a single latent space for the two observation spaces, i.e., joint angles of the Baxter robot $\left(\mathbf{Y} \in \mathbb{R}^{N\times 14}\right)$ and forward movement of the wheelchair $\left(\mathbf{Z} \in \mathbb{R}^{N\times 1}\right)$. Therefore, we train a MRD model using these two observation spaces. The MRD model was implemented using the GPy python library [12]. The latent variable $\mathbf{X}$ was initialized using Principal Component Analysis (PCA) from the preprocessed data. We have used 8 latent dimensions in this experiment, with 6 latent dimensions allocated for the joint angles of the Baxter robot and 2 latent dimensions for the movement of the wheelchair. ARD kernel and 100 inducing points were used to learn the MRD model. The model was trained in the following 3 steps:

1) For both observation spaces, the signal-to-noise ratio



(a) Predicted WHILL movements. The WHILL movement refers to the forward tilt of the joystick.



(b) Comparison of the Mean Absolute Error (MAE)

Fig. 7: Comparison of the predictions for WHILL movement

(SNR) was fixed to constrain the variance of Gaussian noise and Radial Basis Function (RBF) kernel. In this configuration, the model was optimized for ten iterations.

2) Each observation space, i.e., $\mathbf{Y}$ and $\mathbf{Z}$, was optimized individually for 200 iterations.
3) The model was trained without any constraints and optimized for 200 iterations.

IV. RESULTS AND DISCUSSION

After training the MRD model, the ARD weights for each latent dimension are computed. We observed that there were two shared latent dimensions between the two observation spaces, namely latent dimensions 0 and 1. The ARD weights for each latent dimension are shown in Fig. 5. The latent dimensions 0 and 1 are following our intuition that the joint angles of the Baxter robot and the movement of the wheelchair share common latent dimensions. These two latent dimensions constitute the shared latent space $(\mathbf{X}_S)$. The 2D latent space generated using the first two latent dimensions is shown in Fig. 6.

TABLE I: Body physique information of the subjects

	Subject for Training	Subject for Testing
Height (cm)	166	173
Age	30	29
Shoulder Width (cm)	45	46
Waist Size (cm)	92	86

The latent space shown in Fig. 6 is used to infer the joint angles of Baxter. The corresponding WHILL movement is predicted in real-time from the joint angles of the Baxter robot using the learned MRD model through the inference process explained in Section II. Alternatively, we can predict both the observation spaces directly from the latent space itself. However, we observe that the latent dimension 6 encodes the second-highest amount of information about the WHILL movement as can be observed from the ARD weights shown in Fig. 5. This latent dimension constitutes the private latent space of the WHILL movement, $\mathbf{X}_Z$. Hence, the prediction of both the observation spaces from the latent space shown in Fig. 6 would lead to a poor prediction of the WHILL movement as this latent space is generated from latent dimensions 0 and 1 and does not consider the information of the movement of the wheelchair encoded by latent dimension 6. Therefore, we predict the WHILL movement from the joint angles of Baxter using MRD inference.

To calculate the prediction accuracy of WHILL movements, we computed the Mean Absolute Error (MAE) by comparing the predicted movements with the ground truth. The ground truth is obtained by preprocessing the collected WHILL movement data. MAEs are computed for WHILL movement prediction from joint space and latent space. The predicted WHILL movements are shown in Fig. 7a and the corresponding MAEs are shown in Fig. 7b.

The predictions from joint space are close to the ground truth, which can be verified by observing the corresponding MAE. We used the learned MRD model to perform the complete dressing of a sleeveless T-shirt. The robot starts moving from the home position. During the clothing assistance task, the Baxter robot collaborates with WHILL to successfully achieve the task. The dressing task at various timestamps is shown in Fig. 8. The complete task took 40 seconds to dress a sleeveless T-shirt. The body physique information of the subjects is given in Table I.[2]

A. Limitations

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

- We have only considered the forward movement of the wheelchair and ignored the sidewise rotation.
- In this study, wheelchair movement is defined by the tilt of the joystick, which is analogous to velocity control

[2] A short video of this study can be watched at https://youtu.be/yWj-UO8yGQE

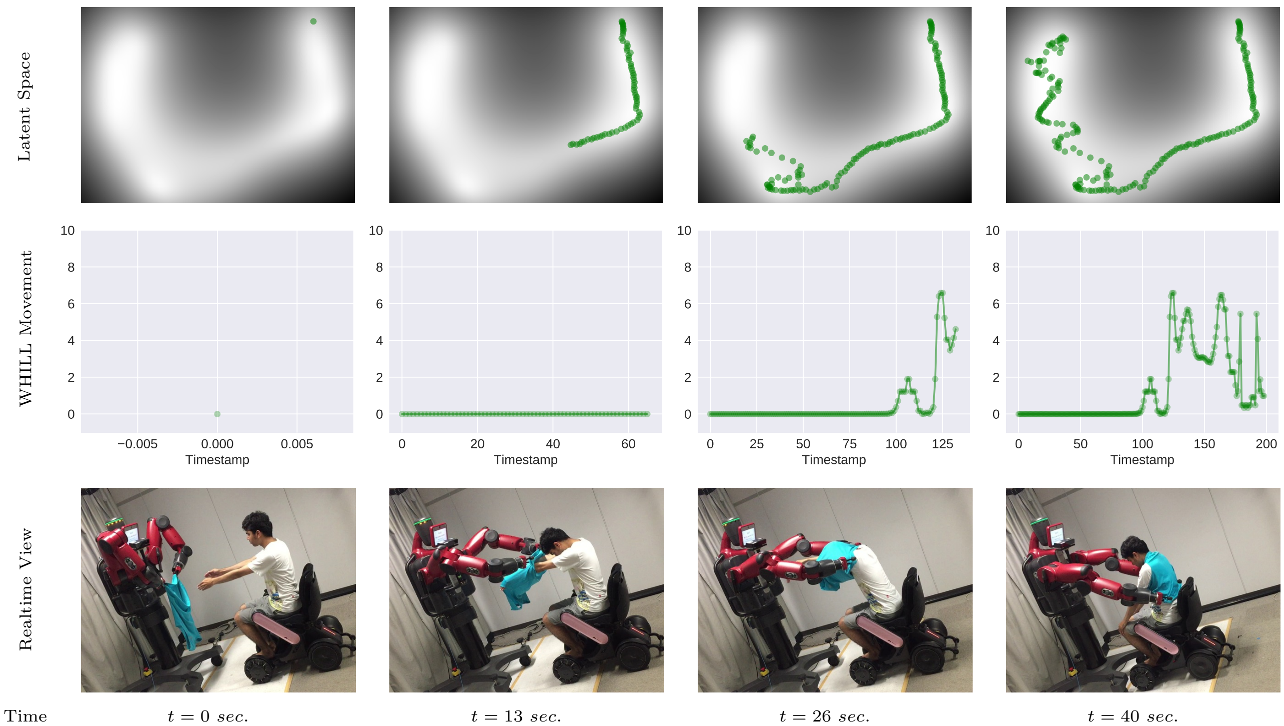


Fig. 8: The clothing assistance task with Baxter and WHILL shown at various timestamps. The mean trajectory in latent space is sampled and shown in Green color in the latent space.

of the wheelchair. Thus, the current system needs proper synchronization with the wheelchair to prevent overshooting the boundaries and causing a collision with the robot base. Due to this limitation, we have used a fixed starting position for the wheelchair.

- We assume that there are no obstacles in front of the wheelchair, as the current system does not have any obstacle avoidance mechanism.
- As this is a preliminary study, the current system is trained and tested only on healthy young subjects. An evaluation using elderly subjects is yet to be done.
- We have used a sleeveless T-shirt and shown successful dressing of it using the proposed method. Dressing using other types of clothes, such as pajamas and a hospital gown, is yet to be done.
- The MRD model is trained using one demonstration trajectory only. Empirically, it makes the proposed method data-efficient. However, in practice, the generalization capability of the model is limited. To tackle this issue, we can use multiple demonstrations to train the model in the future.

V. CONCLUSIONS

Robotic clothing assistance has the immense potential to improve the quality of life of the elderly while reducing the burden on caregivers considerably. It can cope with the shortage of caregivers in the care-house. In this paper, we have presented an approach for the collaboration of an electric wheelchair and a humanoid robot to achieve the clothing assistance task. We have shown that the coordinated movement of the wheelchair and the humanoid robot is viable by employing MRD. Furthermore, we learned an offline shared latent space which predicts the required movement for the wheelchair based on the current joint angles of the Baxter robot. We trained and tested our approach on different human subjects. We believe that the study reported in this paper should contribute to the advancement in the field of human-robot and robot-robot collaboration for service robotics.

In the future, instead of commanding movement as defined by the tilt of the joystick, it is more practical to command absolute positions to the wheelchair to ensure robust and safe control. Therefore, we plan to implement a position controller for the wheelchair in the future. We also plan to improve wheelchair control by applying SLAM based navigation into it. It will provide a safer control of the wheelchair by preventing collisions with other objects. In the future, we aim to make the whole system more robust and automatic by incorporating visual RGB-D observation in our model. We will perform detailed experiments with the elderly to evaluate the safety and acceptance of the system.

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