Quantitative Evaluation of Clothing Assistance using Whole-Body Robotic Simulator of the Elderly

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***Abstract*— The recent demographic trend across developed nations shows a dramatic increase in the aging population, fallen fertility rates and a shortage of caregivers. Robotic solutions to clothing assistance can significantly improve the Activity of Daily Living (ADL) for the elderly and disabled. We have developed a clothing assistance robot using dual arms and conducted many successful demonstrations with healthy people. It was, however, impossible to systematically evaluate its performance because human arms are not visible due to occlusion from a shirt and robot during dressing. To address this problem, we propose to use another robot, Whole-Body Robotic Simulator of the Elderly that can mimic the posture and movement of the elderly persons during the dressing task. The dressing task is accomplished by utilizing Dynamic Movement Primitives (DMP) wherein the control points of DMP are determined by applying forward kinematics on the robotic simulator. The experimental results show the plausibility of our approach.**

I. 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]. This dramatic increase in the aging population combined with fallen fertility rates are reaching up to an alarming situation. According to a survey focusing on difficulties in performing various Activity of Daily Living (ADL), the use of caregivers was seen as more common for clothing assistance tasks [2]. 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 [3].

Therefore, robotic solutions to clothing assistance can significantly improve ADL for the elderly and disabled [4], [5], [6]. Clothing assistance is a challenging problem since the robot is required to manage two difficulties: (a) robot must do cooperative manipulation by holding clothing article using both the arms while interacting with nonrigid and highly deformable clothing article and (b) maintain safe human-robot interaction with the assisted person whose posture can vary during assistance. To address these problems, we have been developing clothing assistance robot systems using a compliant dual-arm robot such as WAM arms (Barrett, Technology) [7] and Baxter (Rethink Robotics) [8], [9]. In both systems, the research key point was on human skill transfer to robots. In our approach, feasible arm trajectories were given by humans, and the arm trajectories were adaptively modified by employing reinforcement learning [7] and by Dynamic Movement Primitives (DMP) [10].

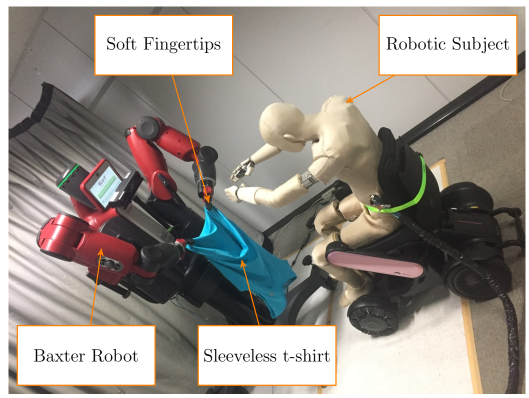

Fig. 1: Setup of the task

We have conducted many successful demonstrations mainly with healthy people [9]. It was, however, impossible to systematically evaluate its performance with a human subject because the posture of human arms can vary and also are invisible in a cloth during dressing. To address this problem in this paper, we propose to use another humanoid robot, Whole-Body Robotic Simulator of the Elderly [11], [12] that can simulate the pose and motion of the elderly persons during the dressing task (see Fig. 1). This robotic simulator is also referred as the robotic subject in this paper. The trajectory of Baxter arms required for the dressing task is parameterized by using DMP. To adapt to perturbations generated by the subject's arm, we need to modify control points of DMP on the fly. In other words, we need to track control points which are the fingertips and elbows of the robotic subject. A potential solution to perform this tracking is by employing optical markers. These markers can be attached on desired points and can be tracked by optical cameras. However, this approach has a severe drawback. During the dressing task, due to the occlusion from clothing article and robot arms, marker tracking fails miserably. In this paper, we apply forward kinematics on the robotic subject to determine the control points. Since the subject is a robotic mannequin, we are blessed with its capabilities. We can acquire all joints angles necessary for performing forward kinematics.

The remainder of the paper is organized as follows. First,

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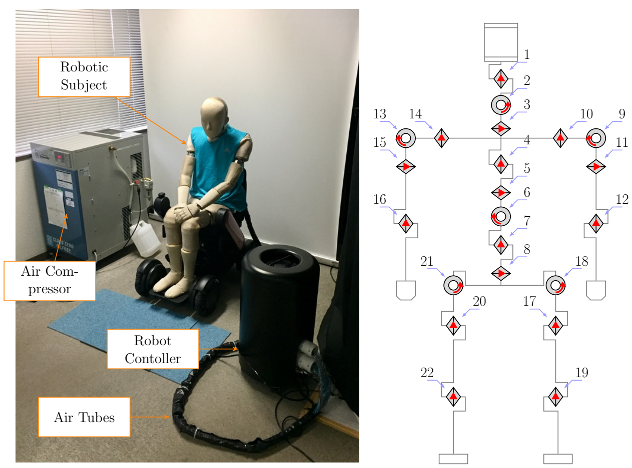
we briefly introduce the robotic simulator in Section II. Section III describes our method followed by the details of the experimental setup in Section III-A and the mathematical formulation of DMP in Section III-B. In Section IV, we evaluate the proposed framework on the robotic subject. The discussion along with the conclusion and future directions of the research is presented in Section V.

II. A ROBOTIC SIMULATOR FOR ELDERLY

In robotic devices of non-wearable transfer aids and toileting aids, their underlying mechanism, movement, mechanistic performance such as safety and usability were evaluated using the robotic simulator. Following are the specifications of this human simulator [11]:

- It can make arbitrary postures to fit various shapes of the assistive robotic devices.
- It can move joints to simulate the behavior of a person.



(a) Setup (b) Skeleton model

Fig. 2: The robotic subject. Fig. (a) shows all components of the system, Fig. (b) shows the skeleton model of the robotic subject that contains active and passive joints. However, only active joints are shown. All the joints are revolute joints.

The parameters of the robotic simulator are shown in Table I. The shape, weight, and length of each body segment was determined to simulate the body of an elderly male in his 60s based on "Japanese Body Dimension Data" [13]. The developed robotic simulator and the position of the degree of freedom are shown in Fig. 2b. The robotic simulator has 28 passive and 22 active joints that are controlled based on positional control. The actuator of an active joint is an air actuator, controlled using an air compressor (about 8 atmospheres) and valve units (22 channels), that are set outside the robotic simulator. To contact the complex surface for nursing care, the robotic simulator is covered with a soft material. The distribution pressure patterns of the robotic simulator, human, and crash test dummy on a bed were measured.

TABLE I: Parameters of the Robotic Simulator

Length	1650 mm
Weight	50 Kg
Number of active joints	22
Number of passive joints	28

III. METHOD

In this section, we are explaining our method used for the evaluation of clothing assistance. The framework of our method is shown in Fig. 3. Our method contains three stages named as "Demonstration," "Training" and "Testing." As per the formulation described in section III-B, DMP can learn from the demonstration. Therefore we start by performing a kinesthetic demonstration with the robot controlled in gravity compensation mode, which 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, the pose trajectory of end-effector is recorded using Baxter API and stored in a file. The term "pose" collectively refers to 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, the recorded trajectory is parameterized using DMP. 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 a 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." 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 Fig. 4. The control points of DMP are retrieved by applying rigid body forward kinematics on the robotic subject. Joint angles of the robotic subject are retrieved and then used to calculate the position of control points in a Cartesian coordinate system. These coordinates derived by applying forward kinematics are referenced in the robotic subject frame. However, the Baxter robot has a different frame of reference. Hence, a coordinate calibration is done to transform the robotic subject frame into the Baxter robot frame. We prepared two experimental conditions/movement trajectories for the robotic subject as shown in Fig. 5. During the "Testing Stage," these trajectories are applied to the robotic subject. At every timestamp, the control points are calculated and then set as the current start and goal parameters of DMP. Therefore, tracking of control points and rolling of DMPs are done at every timestamp. In this way, we have a DMP system, which can adapt accordingly while the arms of the robotic subject are in motion. To verify the adaptation, trajectories of Baxter and the robotic subject are recorded which are then analyzed in Sec. IV.

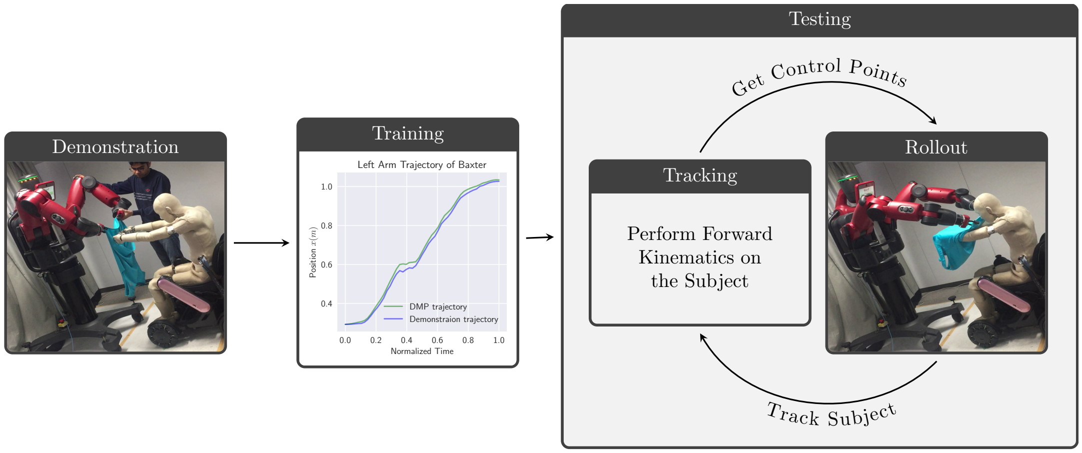


Fig. 3: The framework for our method. It consists of three stages named as “Demonstration”, “Training” and “Testing.”

A. 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 Fig. 1. We are using an in-house developed robotic simulator to simulate the pose and motion of the elderly person during the dressing task. The robotic system is treated here as a subject for the evaluation of clothing assistance. We have used two finger electric gripper provided by Baxter. We designed soft fingertips that were plugged into these fingers tightly. These soft fingertips allow firm gripping by providing sufficient traction to hold the cloth. These soft fingertips are necessary for firm gripping of flexible clothing articles hence provides better cloth manipulation. These fingertips hold the clothing article. The cloth is put in the arms of the Baxter robot manually by a human assistant.

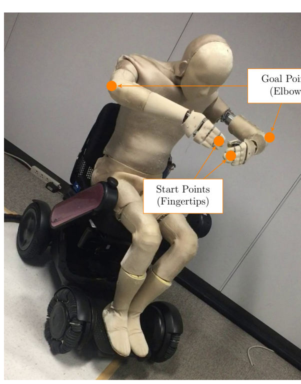


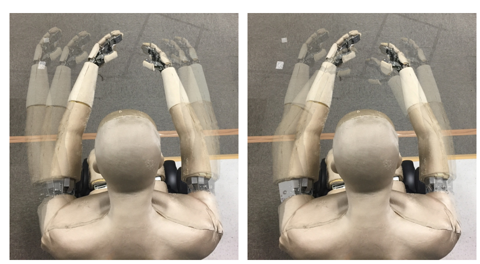
Fig. 4: Control points for arm dressing task showing start and goal points of DMP system colored as orange.

B. Dynamic Movement Primitives

DMP aims at designing a controller for learning and generalization of motor skills by learning from demonstration [10]. 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 [14]. 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 [15]. Originally, for a one-dimensional system, DMP is defined by a linear spring model combined with an external force as follows.

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

where $\tau \dot{x} = v$. The term x and v are position and velocity of the system respectively, x_0 and x_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. The nonlinear function f, which is also called the forcing term is a nonlinear function to be learned to allow complex movements. 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.* [14] in which Eqn. 1 was redefined as follows.



(a) The first type of movement

(b) The second type of movement

Fig. 5: Movements defined for the arms of the robotic subject.

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

Notice the term $K(x_g - x_0)s$ which is necessary for avoiding a sudden jump at the beginning of a movement. The forcing term f is now defined as a function of variable s as shown

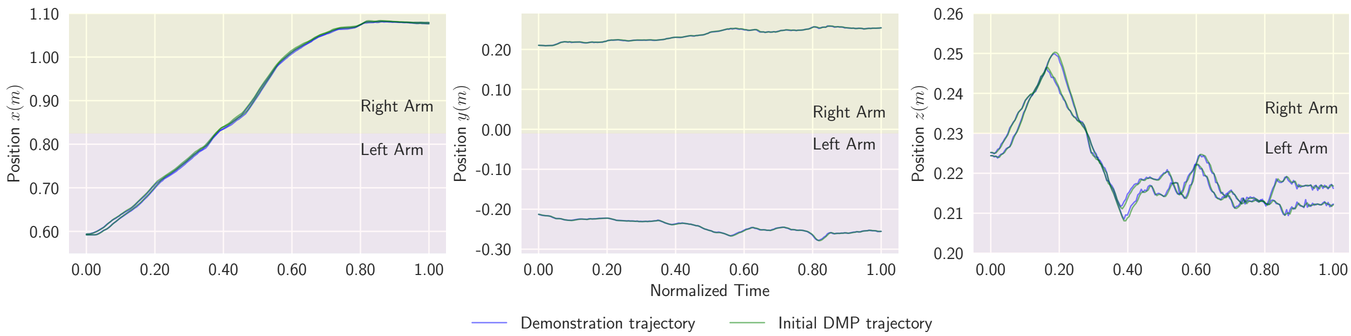


Fig. 6: Baxter's arms trajectories for both the arms which are parameterized by using DMP. The time is normalized to [0, 1] range. The figure shows the DMPs are well capable of learning the complex Baxter trajectories.

below.

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

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. The variable s is called the phase variable which starts from 1 and monotonically decreases to 0. It is defined by the equation $\tau \dot{s} = -\alpha s$, where α is a positive gain term.

Our goal is to design a forcing term that can learn from demonstration and allows us to scale the movement defined by start and goal state, i.e., x_0 and x_g respectively. So that the system can follow a specified path. The forcing term can be redefined as follows

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

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

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

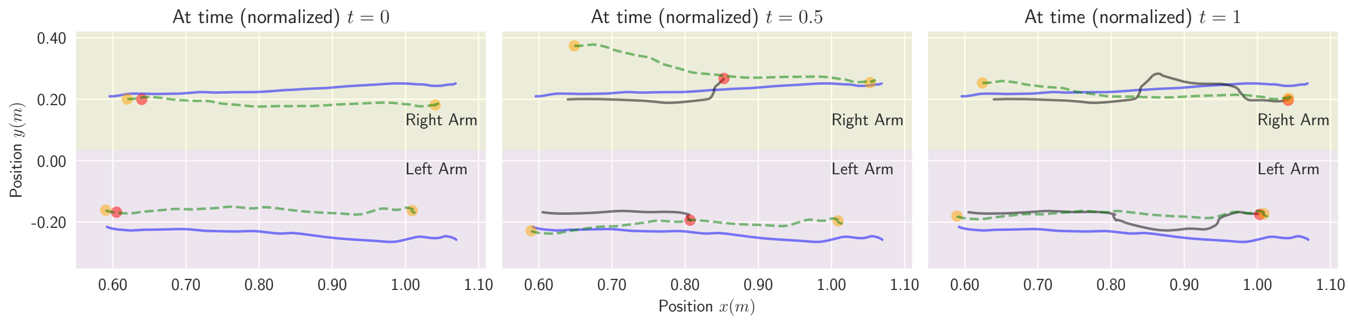
The forcing term in Eqn. 3 is comprised of the weighted summation of Gaussians that are going to be activated as a system converges to the goal. We want that forcing term matches the desired trajectory, i.e., f_{target} should be as close as possible to f. Mathematically, we can formulate it as an optimization problem such as $J = \sum_s \left(f_{target}(s) - f(s)\right)^2$. Finally, to calculate weight parameters across Gaussians, optimization methods such as Locally Weighted Regression (LWR) [15] can be used. So that the forcing term matches the desired trajectory. In this way, DMP can be made to imitate the desired path [14].

IV. EVALUATION

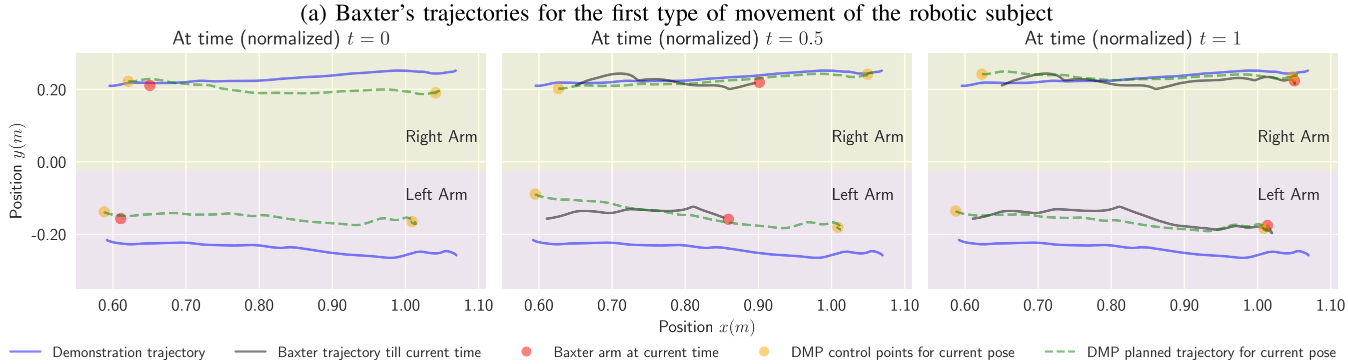
We use Robot Operating System (ROS) to implement our framework in Ubuntu OS. Baxter robot is connected to the Ubuntu computer using an Ethernet cable. We used Ubuntu 14.04 LTS 64 Bit OS having 8 GB RAM on Intel Core i7, 3.40 GHz x 8 CPU for training and testing our framework. The clothing articles used in this study is 100% polyester (size L) sleeveless t-shirt. We have defined two types of movements for the arms of the robotic subject as shown in Fig. 5. These movements belong to day-to-day arm stretching movements and are defined empirically. More precisely, in these two movements, both the arms move in a horizontal plane. In the first motion, only the shoulder joint rotates. However, in the second motion, the elbow joint rotates primarily. The control points of DMP are set based on these movement trajectories.

The DMP system accomplished the arm dressing task. We defined a DMP for each coordinate axis and each arm. Hence we have a total of 6 DMPs, 3 for each arm. The demonstrated trajectory is parameterized using these DMPs. Fig. 6 shows the DMPs are well capable of learning the complex Baxter trajectories. We can see that DMPs are following the demonstrated trajectory.

Initial DMP is modified to accommodate new posture by changing start and goal parameters acquired from the forward kinematics of the robotic subject. The robot is commanded at each timestamp while setting the control points on the fly. During the movements of arms of the robotic subject, the robot adapts as shown in Fig. 7a. This figure corresponds to the first type of arm movement as shown in Fig. 5a. Baxter robot starts from the fingertips of the robotic subject. The time (t) is normalized to [0, 1] range for easier visualization. At $t = 0$, the fingertips of the robotic subject are parallel to the elbow of the robotic subject. As per the defined movement, the fingertips of the robotic subject start moving apart from each other. At $t = 0.5$, we can see that both the arms of the Baxter robot are adopting this change and moving away from each other. Baxter's end-effector corresponds to the left arm of the robotic subject is moving downwards whereas Baxter's end-effector corresponds to the right arm of the robotic subject is moving upwards. This motion is desired since Baxter needs to put the clothing article. Hence, it needs to expand the cloth in this situation. At $t = 1$, Baxter arms are approaching elbows of the robotic subject. The same behavior can be observed in Fig. 7b. This figure corresponds to the second type of arm movement as shown in Fig. 5b. At $t = 0.5$, we can see that the fingertips of the robotic subject

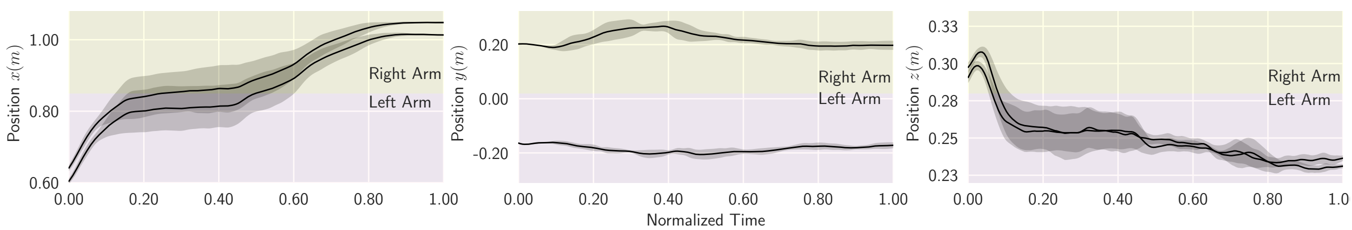


(a) Baxter's trajectories for the first type of movement of the robotic subject

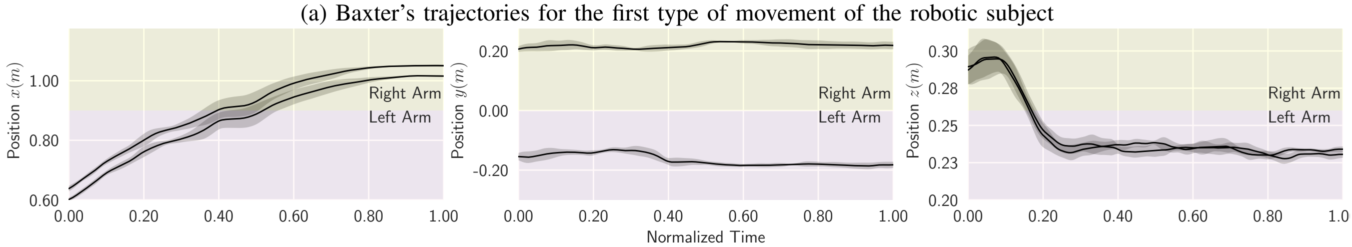


(b) Baxter's trajectories for the second type of movement of the robotic subject

Fig. 7: The trajectories of Baxter's arms while performing arm dressing task. The orange colored points showing control points of DMP, are moving as per the defined motion. The robot successfully adopts to the fast motions of the arms.



(a) Baxter's trajectories for the first type of movement of the robotic subject



(b) Baxter's trajectories for the second type of movement of the robotic subject

Fig. 8: The trajectories of Baxter's arms for the motions of the robotic subject. Baxter is run ten times for each type of movement. The time is normalized to [0, 1] range. For each trajectory, the mean position is plotted with the black color, and the region $\mu \pm \sigma$ along the mean position is filled with the gray color.

are moving closer to each other. Hence Baxter immediately starts moving closer to the arms of the robotic subject. We can also see that even though the demonstrated trajectory is quite simple but Baxter trajectory turned out to be a complex one.

We ran the arm dressing task ten times for each type of arm movements and visualized the robot trajectory during the task. The visualization is shown in Fig. 8. The time is normalized to [0, 1] range. For each trajectory, the mean position is plotted with the black color, and the region $\mu \pm \sigma$ along the mean position is filled with the gray color. Even though, from the setup of our system, it appears that both the arms of the robotic subject are in symmetry. However, after looking at the y and z coordinate axis of Baxter's trajectories, it can be said that the arms are indeed not in symmetry. The z coordinate is in the vertical direction and corresponds to the height of arms of the subject. Moreover, the difference in z coordinate validates the unsymmetrical position of the arms.

V. CONCLUSIONS

In recent years, assistive robotic devices for nursing care have been developed and commercialized for such purposes. To make such devices accessible in the care facilities, we need to systematically evaluate the performance and the effects of the devices on the care receivers and caregivers.

We have developed a clothing assistance robot using Baxter and conducted many successful demonstrations mainly with healthy people. It was, however, impossible to systematically evaluate its performance with a human subject because the posture of human arms is invisible due to the cloth over them during dressing. To address this problem, we have proposed to use another humanoid robot, Whole-Body Robotic Simulator of the Elderly [11], [12] that can mimic the posture and movements of the elderly persons during the dressing task. In this study, we specifically evaluated our clothing assistance framework employing DMP for the arm dressing tasks with the robotic subject. The control points of DMP are determined by applying forward kinematics on the robotic simulator. We have performed a quantitative evaluation of arm dressing task by using forward kinematics for calculating the arm positions of the robotic simulator. We have shown the plausibility of our approach through the experiments where we defined two different arm movements, which were supposed to be disturbances, of the robotic subject during the arm dressing task.

Although, it appears from the setup of our task that both arms of the subject are required to be in symmetry. However, separate DMPs are employed to take care of each arm. During the task, arms are constrained due to the t-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.

Using three-dimensional arm movements, and head and torso movements during the dressing tasks are our near future work. We have tested our approach on healthy human subjects [9], wherein Baxter was used to perform a full dressing of a sleeveless shirt. However a much rigorous evaluation on elderly is planned as a future work. We will also consider safely issues in the future.

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REFERENCES

[1] World Health Organization, "Facts about ageing," http://www.who.int/ageing/about/facts/en/, 2014, [Online] Accessed: 2018-03-21.

[2] B. J. Dudgeon, J. M. Hoffman, M. A. Ciol, A. Shumway-Cook, K. M. Yorkston, and L. Chan, "Managing activity difficulties at home: a survey of Medicare beneficiaries," *Archives of physical medicine and rehabilitation*, vol. 89, no. 7, pp. 1256–1261, 2008.

[3] The Japan Times, "Nursing care workers hard to find but in demand in aging Japan," https://www.japantimes.co.jp/news/2016/06/27/reference/nursing-care-workers-hard-to-find-but-in-demand-in-aging-japan, 2016, [Online] Accessed: 2019-02-28.

[4] A. Jevtić, A. F. Valle, G. Alenyà, G. Chance, P. Caleb-Solly, S. Dogramadzi, and C. Torras, "Personalized robot assistant for support in dressing," *IEEE Transactions on Cognitive and Developmental Systems*, 2018.

[5] Z. Erickson, M. Collier, A. Kapusta, and C. C. Kemp, "Tracking human pose during robot-assisted dressing using single-axis capacitive proximity sensing," *IEEE Robotics and Automation Letters*, vol. 3, no. 3, pp. 2245–2252, 2018.

[6] G. Chance, A. Jevtić, P. Caleb-Solly, and S. Dogramadzi, "A quantitative analysis of dressing dynamics for robotic dressing assistance," *Frontiers in Robotics and AI*, vol. 4, p. 13, 2017.

[7] T. Tamei, T. Matsubara, A. Rai, and T. Shibata, "Reinforcement learning of clothing assistance with a dual-arm robot," in *2011 11th IEEE-RAS International Conference on Humanoid Robots*. IEEE, 2011, pp. 733–738.

[8] R. P. Joshi, N. Koganti, and T. Shibata, "Robotic cloth manipulation for clothing assistance task using dynamic movement primitives," in *Proceedings of the Advances in Robotics*. ACM, 2017, p. 14.

[9] ——, "A Framework for Robotic Clothing Assistance by Imitation Learning," *Advanced Robotics*, vol. 0, no. 0, pp. 1–19, 2019. [Online]. Available: https://doi.org/10.1080/01691864.2019.1636715

[10] S. Schaal, "Dynamic movement primitives-a framework for motor control in humans and humanoid robotics," in *Adaptive motion of animals and machines*. Springer, 2006, pp. 261–280.

[11] K. Ogata, Y. Matsumoto, I. Kajitani, K. Homma, and Y. Wakita, "Whole-body robotic simulator of the elderly for evaluating robotic devices for nursing care," in *International Conference on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management*. Springer, 2018, pp. 478–487.

[12] Y. Matsumoto, K. Ogata, I. Kajitani, K. Homma, and Y. Wakita, "Evaluating robotic devices of non-wearable transferring aids using whole-body robotic simulator of the elderly," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2018, pp. 1–9.

[13] AIST Digital Human Research Group, "Japanese Body Dimension Data," https://unit.aist.go.jp/hiri/dhrg/ja/dhdb/97-98/index_e.html, 2001, [Online] Accessed: 2019-02-26.

[14] P. Pastor, H. Hoffmann, T. Asfour, and S. Schaal, "Learning and generalization of motor skills by learning from demonstration," in *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on*. IEEE, 2009, pp. 763–768.

[15] S. Vijayakumar and S. Schaal, "Locally weighted projection regression: An O(n) algorithm for incremental real time learning in high dimensional space," in *Proceedings of the Seventeenth International Conference on Machine Learning (ICML 2000)*, vol. 1, 2000, pp. 288–293.