Robotic cloth manipulation for clothing assistance task using Dynamic Movement Primitives*

Ravi P. Joshi†
Institute for Clarity in Documentation
P.O. Box 1212
Dublin, Ohio 43017-6221
joshi-ravi-prakash@edu.brain.kyutech.ac.jp

Nishanth Koganti‡
Institute for Clarity in Documentation
P.O. Box 1212
Dublin, Ohio 43017-6221
nishanth-k@is.naist.jp

Tomohiro Shibata§
The Thørväld Group
1 Thørväld Circle
Hekla, Iceland
tom@brain.kyutech.ac.jp

ABSTRACT

The need of robotic clothing assistance in the field of assistive robotics is growing, as it is one of the most basic activities in daily life of elderly and disabled people. In this study, we are investigating the applicability of using Dynamic Movement Primitives (DMP) as a task parameterization model for performing clothing assistance tasks. The robotic cloth manipulation task deals with putting the cloth on both the arms. The robot should do cooperative manipulation by holding the cloth. Also, there can be many failure scenarios as clothes are highly non-rigid. DMP can represent nonlinear motion with a set of differential equations. These equations can be adapted to generate any movement trajectory just by changing the goal parameter. The system consists of Baxter humanoid robot and Microsoft Kinect RGBD sensor for tracking the posture of hands. To perform the task, a demonstration is recorded by moving the Baxter arms in the appropriate trajectory. The recorded trajectory is parameterized by using DMP. Once the system is trained, new postures are accommodated by DMP. The cloth manipulation is done by Baxter humanoid robot which follows the trajectory generated by DMP. We have performed the experiments on soft mannequin instead of human. The result shows that DMPs are able to generalize the movement trajectory for the modified posture.

CCS CONCEPTS

•**Computer systems organization** →**Embedded systems;** *Redundancy;* Robotics; •**Networks** →Network reliability;

*Produces the permission block, and copyright information
†Dr. Trovato insisted his name be first.
‡The secretary disavows any knowledge of this author's actions.
§This author is the one who did all the really hard work.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).
WOODSTOCK'97, El Paso, Texas USA
© 2016 Copyright held by the owner/author(s). 123-4567-24-567/08/06. . . $15.00
DOI: 10.475/123_4

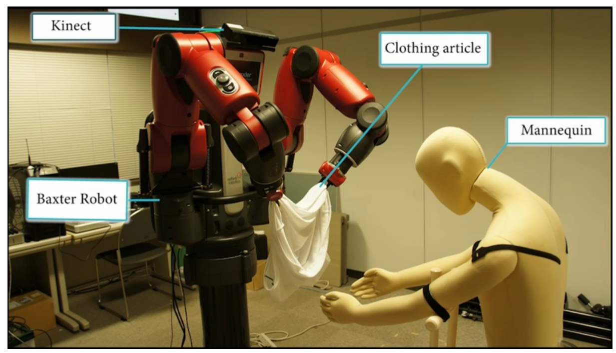

Figure 1: Setup of Robotic cloth manipulation task

KEYWORDS

Robotic Clothing Assistance, Dynamic Movement Primitives (DMP), Human-Robot Interaction, Learning and Adaptive Systems

ACM Reference format:
Ravi P. Joshi, Nishanth Koganti, and Tomohiro Shibata. 1997. Robotic cloth manipulation for clothing assistance task using Dynamic Movement Primitives. In *Proceedings of ACM Woodstock conference, El Paso, Texas USA, July 1997 (WOODSTOCK'97),* 6 pages.
DOI: 10.475/123_4

1 INTRODUCTION

Due to the demographic trend in developed countries, the robotic assistance in the filed of elderly care is in home environments growing [1]. Although there has been a significant number of research done in this field, robotic clothing assistance, one of the basic and important assistance activities in daily life of elderly as well as disabled people is yet an open field for research. While rigid object manipulation with robots has mainly relied on precise robot control, the deformable objects are rather require a complex control scheme. The clothing assistance is a challenging problem since robots must interact with non-rigid and highly deformable clothes, and with the assisted person whose posture can vary during the assistance.

In this study, we are investigating the applicability of using Dynamic Movement Primitives (DMP) as a task parameterization model for performing clothing assistance tasks. The robotic cloth manipulation task deals with putting the cloth on both the arms. The idea of using DMP is inspired from the fact that DMP can learn the complex task from the demonstration [6, 7, 14] and thus reduce the manual efforts to design the controller from scratch or to fine-tune the controller parameters. We choose the dual arm Baxter robot in this research as it is safe and flexible by the design [3].

The rest of the paper is organized as follows. Section 2, gives a brief overview about the related literature in this field. Section 3 introduces the mathematical formulation about Dynamic Movement Primitives. In Section 4, we describe our system and various components used in the experiments. Section 5 deals with the details about experiments performed. Section 6 shows the experimental results. Finally we conclude in Section 7 with some future directions.

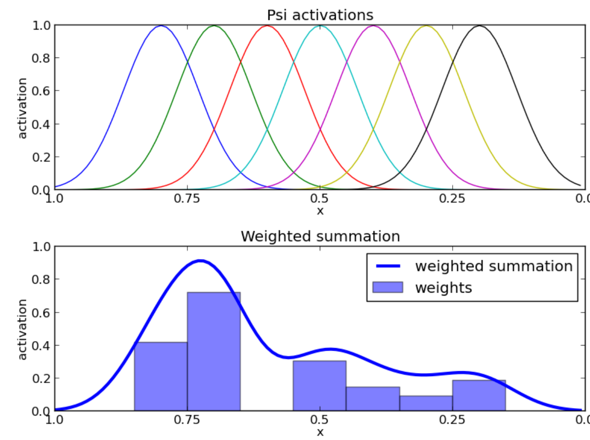

Figure 2: ψ activations and weighted summation of Gaussians

2 RELATED WORKS

In this section, we provide brief overview of the related literature in this field. There has been significant number of research done in the field of Robotic Clothing Assistance. Colomé et al. [2] proposed a framework for Reinforcement Learning of Robotic Tasks in non-rigid environments. They performed the task of wrapping a scarf around the neck of a mannequin and used color based segmentation to distinguish mannequin, scarf and a mark placed on the nose of mannequin. The main focus of their work is to incorporate friction based model while performing clothing task. Gao et al. [4, 5] has focused on user upper-body modeling for personalized dressing by using top-view depth camera. Randomised decision forests was used to estimate user pose and proposed an online iterative path optimisation method to enable Baxter humanoid robot to assist human to wear a sleeveless jacket. Another interesting work by Kapusta et al. [9] is focused towards designing a controller inspired from data-driven haptic perception. They classified the forces measured at robot's end effector by using hidden Markov models and performed the clothing task on hospital gown. Their focus was to classify force data for haptic perception with high accuracy. Klee et al. [10] worked on personalized assistance for dressing a user, where they used vision module to monitor the human's motion. The robot request to user to move towards robot, monitors motion and puts hat on the user once users is rechable by the robot. Koganti et al. [11] proposed a framework for offline learning of cloth dynamics model using Gaussian Process Latent Variable Models (GP-LVM) by incorporating motion capture data and applying this model for the online tracking of human-cloth relationship using a depth sensor. They showed that the shared GP-LVM is able to learn reliable motion models of the T-shirt state for robotic clothing assistance tasks. Representing cloth state in low-dimensional field by using topology coordinates is another impressive work done by Tamei et al. [15]. They proposed Reinforcement Learning framework and demonstrated that the robot quickly learns a suitable arm motion for putting T-shirt into the mannequin's head. Yamazaki et al. [18, 19] worked on bottom dressing by a Life-sized humanoid robot, where they recognize the cloth state by using optical flow on the images acquired from single camera. They showed that the robot can pull a bottom clothing item along the subject's legs.

Another related filed of research is Motor-skills Learning for Cloth Handling, in which Yamakawa et al. [17] proposed a new strategy for dynamic manipulation of sheet-like flexible objects by a high-speed robot system. The system consists of two high-speed multi-fingered hands mounted on two sliders and a high-speed vision system. The proposed system learns the necessary motor skills from the demonstration performed by a human subject. They validated the robot trajectory obtained from the motion planning method was with simulation results. Another exciting work done by Monsó et al. [12], where they proposed a probabilistic planner, based on Partially Observable Markov Decision Process (POMDP) approach, for reducing the inherent uncertainty of cloth sorting (isolation/extraction) task. Their approach relaxes the precision requirements of robot vision and manipulation.

3 DYNAMIC MOVEMENT PRIMITIVES

Dynamic Movement Primitives (DMP) aims at designing contoller for learning and generalization of Motor Skills by learning from demonstration [6]. The controllers are based on nonlinear dynamical systems, and use locally weighted regression techniques to learn complex, discrete or rhythmic, movements demonstrated by a human subject [8]. These controllers can be considered to be discrete or rhythmic pattern generators which can replay and modulate the learned movements, while being robust against perturbations.

The basic idea behind DMP formulation is to use an analytically well-understood dynamical system and add a nonlinear terms, so that it produces the desired behavior [7]. Formally, the system is defined by a damped spring model as below:

$$\ddot{y} = \alpha_y(\beta_y(g - y) - \dot{y}) + f \tag{1}$$

The term α_y and β_y are positive gain terms. y is the system state and g represents goal state. The nonlinear function f, which is also called as forcing term is defined over time, making the problem a well defined structure that can be solved in a straight-forward way. This system is termed as canonical dynamical system, denoted by x and has very simple dynamics:

$$\dot{x} = -\alpha_x x \tag{2}$$

The forcing function f is chosen as a function of canonical system:

$$f(x, g) = \frac{\Sigma_{i=1}^{N} \psi_i w_i}{\Sigma_{i=1}^{N} \psi_i} x(g - y_0) \tag{3}$$

with N exponential basis functions ψ_i and y_0 is the initial position of the system,

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

where h_i and c_i are constants that determine, respectively, the width and centers of the basis functions. In this way, the forcing function f is comprised of weighted summation of Gaussians, that are going to be activated as system converges to the goal as shown in figure 2.

Our goal is to design the forcing function that can learn from the demonstration and allows us to scale the movement defined by goal state g. In other words, we want to setup the system which can follow a specified path. The forcing term can be redefined as:

$$\mathbf{f}_d = \ddot{\mathbf{y}}_d - \alpha_y(\beta_y(g - \mathbf{y}) - \dot{\mathbf{y}}) \tag{5}$$

where desired acceleration $\ddot{\mathbf{y}}_d$ can be calculated by double differentiating the position data as:

$$\ddot{\mathbf{y}}_d = \frac{\partial}{\partial t}\dot{\mathbf{y}}_d = \frac{\partial}{\partial t}\frac{\partial}{\partial t}\mathbf{y}_d$$

This ends by calculating the weight parameters across Gaussians. Optimization methods such as locally weighted regression can be used, so that the forcing function matches the desired trajectory. In other words equation can be rewritten as-

$$\Sigma_t \psi_i(t)(f_d(t) - w_i(x(t)(g - y_0)))^2 \tag{6}$$

The solution[16] is given by:

$$w_i = \frac{\mathbf{s}^T \boldsymbol{\psi}_i \mathbf{f}_d}{\mathbf{s}^T \boldsymbol{\psi}_i \mathbf{s}} \tag{7}$$

where

$$\mathbf{s} = \begin{pmatrix} x_{t_0}(g - y_0) \\ \vdots \\ x_{t_N}(g - y_0) \end{pmatrix}, \quad \boldsymbol{\psi}_i = \begin{pmatrix} \psi_i(t_0) & \dots & 0 \\ 0 & \ddots & 0 \\ 0 & \dots & \psi_i(t_n) \end{pmatrix}$$

This way the DMP can be made to imitate the desired path. However, this formulation of DMP suffers from critical issues when used in practical application, such as when the scaling term of f, $g - x_0$ if close to zero, a small change in g may lead to huge acceleration and thus it may break the limits of robot. We used the improved version of DMP [13] in this research.

4 OVERVIEW OF THE SYSTEM

Robotic cloth manipulation task contains a dual arm humanoid robot Baxter. The complete setup is shown in figure 1. We choose soft mannequin instead of a human for this preliminary experiment. Both the arms of mannequin are open and given the support by a metallic stand, to avoid falling down the arms. The mannequin is positioned in such a way, so that it resides within the limits of work space of the Baxter robot. Also both the arms of mannequin are facing towards robot. A kinect v2 sensor is mounted on the LCD display of Baxter root. Kinect sensor can see the mannequin and clothing article. Before starting the experiment, the clothing article is put in arms of the baxter robot manually.

The Baxter robot is connected to a computer directly using Ethernet cable. It is controlled using Robot Operating System (ROS), one of the widely used tool by the researchers in robotics community. We used Baxter robot's API, which are available and supported by ROS to command the robot. The Kinect sensor is also controlled by Open source Kinect API for ROS.

5 EXPERIMENTS

As per the formulation 1, the DMP can learn by the demonstration. Hence we starts by performing a demonstration by holding the robot arm and move accordingly. During the demonstration, pose of the end-effector is recorded. The term pose collectively refers to position and orientation. Once the demonstration is finished, DMP is initialized using the recorded trajectory. Three DMP trajectories one for each coordinate axis are initialized for one arm. In this way, we have totally six DMP trajectories, which can control both the arms of Baxter robot. We performed following two experiments by using these trajectory- (a) Clothing task using position DMP (b) Failure detection using end-effector forces.

5.1 Clothing task using position DMP

The aim of this experiment is to put the clothing article on both the arms of mannequin by using DMP system. We use the position data to initialize the DMP trajectories, which are being used in this task. The posture of mannequin is changed by lifting the arms up or down. At this point, we use Kinect Sensor to get the 3D coordinates of the arm. Now we change the goal of DMP trajectories by using this information. The modified DMP can be acquired as described in section 3.

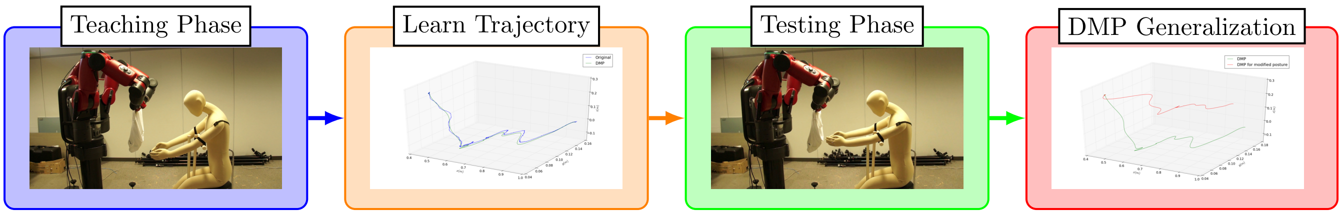

Figure 3: Work flow of Robotic cloth manipulation task. Initially a demonstration is performed by moving the Baxter arms in the appropriate trajectory. The demonstration is recorded and parameterized by DMP. Later posture of the mannequin is changed and accordingly the goal posture of DMP is modified. Now, the modified DMP can accommodate new posture.

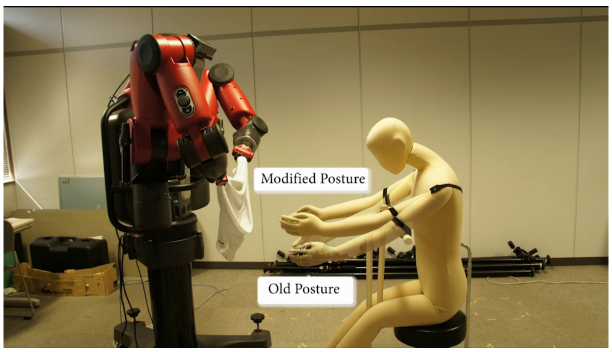

Figure 4: Various postures used in Clothing task

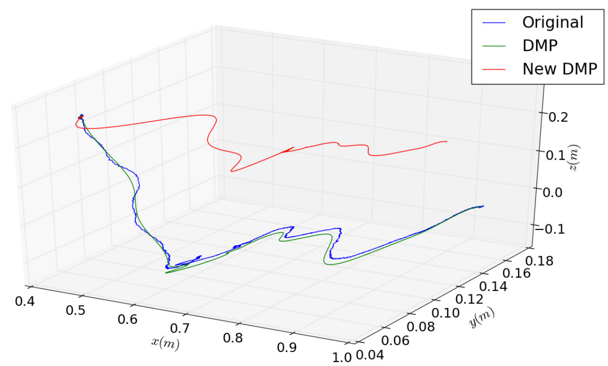

Figure 5: Left arm trajectory of Baxter

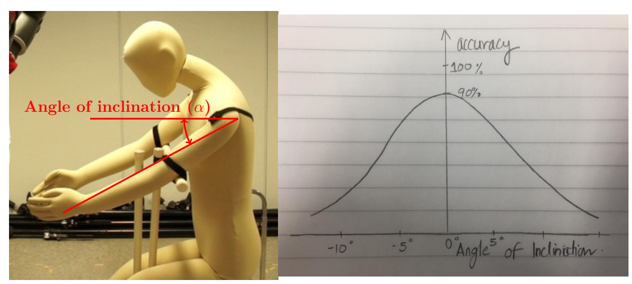

Figure 6: Accuracy measurement

5.2 Failure detection using end-effector forces

This experiment is designed to deal with failure cases. There can be many failure cases during the clothing task, such as the clothing article gets stuck into the fingers. In this experiment, we are using forces being applied on the end-effector of Baxter robot to detect the failure scenario. Appropriate action can be taken once the failure is detected.

6 RESULTS

A soft mannequin was used in order to perform the clothing task. A sleeveless tee shirt was used during the experiment and the task was to put the clothing article on both the arms as shown in figure 4. Following subsections explains the results of the two experiments described above.

6.1 Clothing task using position DMP

In this experiment, the initialized DMP was modified to accommodate the new posture by changing the goal state of the DMP. The generated trajectory was then run on the Baxter robot as shown in figure 5. The newly generated DMP trajectory (shown in red color) was not only found well suited and capable of performing clothing task but also smooth compared to the original trajectory (shown in blue color). A video demonstartion of this experiment can be seen at YouTube[1].

To eventuate this experiment, we performed it many times for various postures by keeping the arms at different-different height. During the experiment, we monitored the trajectory generated by DMP system. The accuracy measurement is shown in figure 6.

6.2 Failure detection using end-effector forces

The clothing task has to deal with complex dynamics including manipulation of clothing article. The clothes are non-rigid, flexible and highly deformable objects, making the

[1] http://youtu.be/Rb2JePazJjk

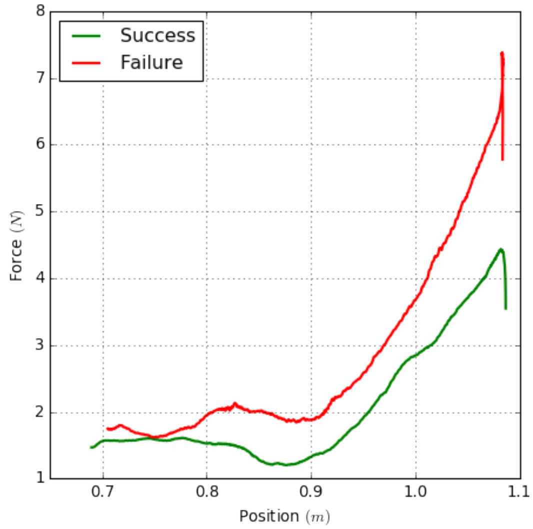

Figure 7: Failure detection using end-effector forces

task more difficult to perform. During the clothing task, we observed the forces being applied at both the end-effector of Baxter robot. The trajectories were monitored and categorized into two *success* and *failure*. The mean of these two category is calculated and plotted as shown in figure 7.

It is clearly visible from the figure 7 that the applied forces are very different in nature in both the cases. Both of these applied forces are increasing from the beginning however the applied forces in case of *failure* are much more higher than that of *success*. Hence one can easily differentiate and detect the failure by using this information.

7 CONCLUSIONS

This paper presents an approach for robotic cloth manipulation for clothing assistance task using Dynamic Movement Primitives. A dual arm Baxter robot, soft mannequin and very thin sleeveless tee shirt were used in the task. The authors have also presented an approach for failure detection using forces being applied on the end-effector of the robot. Authors have used the Baxter APIs in order to get the forces, which are calculated by Baxter Dynamics Module. Though raw forces were very noisy in nature, but after applying median filter most of the noise was eliminated properly.

We plan to extend our research to make the approach more robust by adding visual information and force information with DMP system in the future. Also there is a need of designing an adaptive controller for real time tracking to adapt and detect various failure scenarios. Therefore, in the future, a combination of robot vision and force data can provide the better estimation of cloth state.

ACKNOWLEDGMENTS

The authors would also like to thank the anonymous referees for their valuable comments and helpful suggestions. The work is supported by the National Natural Science Foundation of China under Grant No.: 61273304 and Young Scientsts' Support Program (http://www.nnsf.cn/youngscientsts).

REFERENCES

[1] Joost Broekens, Marcel Heerink, and Henk Rosendal. 2009. Assistive social robots in elderly care: a review. *Gerontechnology* 8, 2 (2009), 94–103.

[2] Adria Colomé, Antoni Planells, and Carme Torras. 2015. A friction-model-based framework for reinforcement learning of robotic tasks in non-rigid environments. In *Robotics and Automation (ICRA), 2015 IEEE International Conference on.* IEEE, 5649–5654.

[3] Cliff Fitzgerald. 2013. Developing baxter. In *Technologies for Practical Robot Applications (TePRA), 2013 IEEE International Conference on.* IEEE, 1–6.

[4] Yixing Gao, Hyung Jin Chang, and Yiannis Demiris. 2015. User modelling for personalised dressing assistance by humanoid robots. In *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on.* IEEE, 1840–1845.

[5] Yixing Gao, Hyung Jin Chang, and Yiannis Demiris. 2016. Iterative path optimisation for personalised dressing assistance using vision and force information. In *Intelligent Robots and Systems (IROS), 2016 IEEE/RSJ International Conference on.* IEEE, 4398–4403.

[6] AJ Ijspeert, Jun Nakanishi, and Stefan Schaal. 2003. Learning control policies for movement imitation and movement recognition. In *Neural information processing system*, Vol. 15. 1547–1554.

[7] Auke Jan Ijspeert, Jun Nakanishi, Heiko Hoffmann, Peter Pastor, and Stefan Schaal. 2013. Dynamical movement primitives: learning attractor models for motor behaviors. *Neural computation* 25, 2 (2013), 328–373.

[8] Auke Jan Ijspeert, Jun Nakanishi, and Stefan Schaal. 2002. Movement imitation with nonlinear dynamical systems in humanoid robots. In *Robotics and Automation, 2002. Proceedings. ICRA'02. IEEE International Conference on*, Vol. 2. IEEE, 1398–1403.

[9] Ariel Kapusta, Wenhao Yu, Tapomayukh Bhattacharjee, C Karen Liu, Greg Turk, and Charles C Kemp. 2016. Data-driven haptic perception for robot-assisted dressing. In *Robot and Human Interactive Communication (RO-MAN), 2016 25th IEEE International Symposium on.* IEEE, 451–458.

[10] Steven D Klee, Beatriz Quintino Ferreira, Rui Silva, Joao Paulo Costeira, Francisco S Melo, and Manuela Veloso. 2015. Personalized assistance for dressing users. In *International Conference on Social Robotics.* Springer, 359–369.

[11] Nishanth Koganti, Jimson Gelbolingo Ngeo, Tamei Tomoya, Kazushi Ikeda, and Tomohiro Shibata. 2015. Cloth dynamics modeling in latent spaces and its application to robotic clothing assistance. In *Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on.* IEEE, 3464–3469.

[12] Pol Monsó, Guillem Alenyà, and Carme Torras. 2012. Pomdp approach to robotized clothes separation. In *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on.* IEEE, 1324–1329.

[13] Peter Pastor, Heiko Hoffmann, Tamim Asfour, and Stefan Schaal. 2009. Learning and generalization of motor skills by learning from demonstration. In *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on.* IEEE, 763–768.

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

[15] Tomoya Tamei, Takamitsu Matsubara, Akshara Rai, and Tomohiro Shibata. 2011. Reinforcement learning of clothing assistance with a dual-arm robot. In *Humanoid Robots (Humanoids), 2011 11th IEEE-RAS International Conference on.* IEEE, 733–738.

[16] Sethu Vijayakumar and Stefan Schaal. 2000. 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. 288–293.

[17] Yuji Yamakawa, Akio Namiki, and Masatoshi Ishikawa. 2011. Dynamic manipulation of a cloth by high-speed robot system using high-speed visual feedback. *IFAC Proceedings Volumes* 44, 1 (2011), 8076–8081.

[18] Kimitoshi Yamazaki, Ryosuke Oya, Kotaro Nagahama, and Masayuki Inaba. 2013. A method of state recognition of dressing clothes based on dynamic state matching. In *System Integration (SII), 2013 IEEE/SICE International Symposium on*. IEEE, 406–411.

[19] Kimitoshi Yamazaki, Ryosuke Oya, Kotaro Nagahama, Kei Okada, and Masayuki Inaba. 2014. Bottom dressing by a life-sized humanoid robot provided failure detection and recovery functions. In *System Integration (SII), 2014 IEEE/SICE International Symposium on*. IEEE, 564–570.