Estimating 3D Hand Location for Clothing Assistance Initialization Using Dynamic Movement Primitives

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The need of robotic clothing assistance in the field of robotics is growing, as it is one of the most basic and essential activities in daily lives of elderly people. The robotic clothing assistance is comprised of several subtasks, and this study focuses on the initialization task in which a dual-arm robot puts a clothing article on both human arms. For adaptive and safe interaction, this paper proposes to apply Dynamic Movement Primitives (DMP) with its goal parameter set automatically by real-time estimation of the 3D hand location by a template matching algorithm. Results acquired in the experiments where the hand location was changed by changing the inclination of the shoulder show the plausibility of our approach.

Keywords— Robotic Clothing Assistance, Template Matching, Dynamic Movement Primitives, Human-Robot Interaction

1. Introduction

Robotic assistance in the field of elderly care in home environment is growing [1]. Although there has been a significant number of research done in this field, robotic clothing assistance is yet an open field for research. While rigid object manipulation with robots has mainly relied on precise robot control, deformable objects rather require complex control scheme. Clothing assistance is a challenging problem since robot is required to manage two difficulties: (a) robot must do cooperative manipulation by holding clothing article using both the arms while interacting with non-rigid and highly deformable clothing article and (b) maintain safe human-robot interaction with the assisted person whose posture can vary during assistance.

The robotic clothing assistance is comprised of several subtasks, and this study focuses on the initialization task in which a dual-arm robot puts a clothing article on both human arms. For adaptive and safe interaction, this paper proposes to apply Dynamic Movement Primitives (DMP) with its goal parameter set automatically by real-time estimation of the 3D hand location by a template matching algorithm.

2. Related Works

Many researchers have used vision information with combination of techniques such as motor skills learning using Reinforcement Learning in the field of robotic clothing assistance. Koganti et al. [3] 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 online tracking of human-cloth relationship using a depth sensor. They showed that shared GP-LVM is able to learn reliable motion models of the T-shirt state for clothing task. Representing cloth state in low-dimensional field by using topology coordinates is another impressive work by Tamei et al. [7]. They proposed Reinforcement Learning framework and demonstrated that robot quickly learns a suitable arm motion for putting T-shirt into the mannequin's head. Another exciting work was done by Monsó et al. [4], 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. Joshi et. al. [6] proposed a framework using Dynamic Movement Primitives (DMP) as a task parameterization model for performing clothing assistance task. Result shows that DMPs are able to generalize movement trajectory for modified posture.

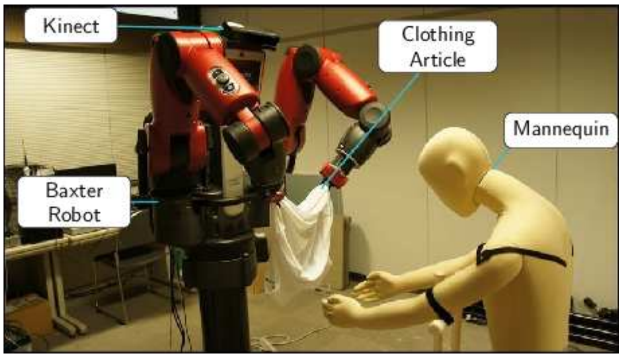


Fig.1: Setup of robotic cloth manipulation task

3. Method

Robotic cloth manipulation task deals with estimating hand location and putting a clothing article on both the arms (Figure 1).

3·1 Hand Location by Template Matching

To initialize the clothing assistance system using DMP, both the starting and goal parameters are needed. These parameters pertain to the hand location of the mannequin.

Fig.2: Workflow of robotic cloth manipulation task. Initially, a kinesthetic demonstration is performed with the robot controlled in gravity compensation mode. This demonstration is recorded and parameterized by DMP. Later on, posture of the mannequin is changed. Hand location is detected by Kinect sensor. Accordingly start and goal parameter of initial DMP are modified. Now, the modified DMP can accommodate new posture.

(a) (b) (c)

Fig.3: Sample templates used for 3D hand location

Hence, our solution to estimate this parameter leverages on three dimensional (3D) data from the depth sensor for extracting the hand of the mannequin at different poses. For the 3D visual information, a depth sensor is mounted on the top of the Baxter Robot as shown in Figure 1. The mannequin is placed beforehand in front of the sensor, so that the sensor can clearly see its hands. Point cloud data (PCD) is used and analyzed for detecting the hand location. Point clouds contain the xyz coordinate data of each point in reference to the viewpoint of the sensor. In template matching technique, we are matching previously recorded object templates with the new data and find the position of the object in new data [8].

By using the information of point cloud, we recorded dataset of the mannequin and get point clouds of the hand at several orientations manually. These PCD on each hand are saved and set as input templates to the extraction algorithm. For our experiment we used 5 different hand templates for each left and right arm which created from five different pose of the hand. Template samples can be seen in Figure 3. The technique takes these templates one by one and patches each iteration to the target point cloud, search through the whole data and find where the templates match. And then, we stored the matching results so that later on will be used to locate the coordinate position of the hand within the matched region.

The technique starts by setting a given template as the source cloud of Sample Consensus Initial Alignment(SAC-IA) algorithm, and then aligning these input templates to the target [8]. SAC-IA is an implementation of matching various overlapping 3D point cloud data views into a complete model, also known as 3D registration [5][8]. During the alignment of each input template, fitness scores are produced on each template and the best one is selected. After finding the best matched template, the method also calculates rotational, translational matrices, including the region's centroid. The complete framework is shown in Figure 4.

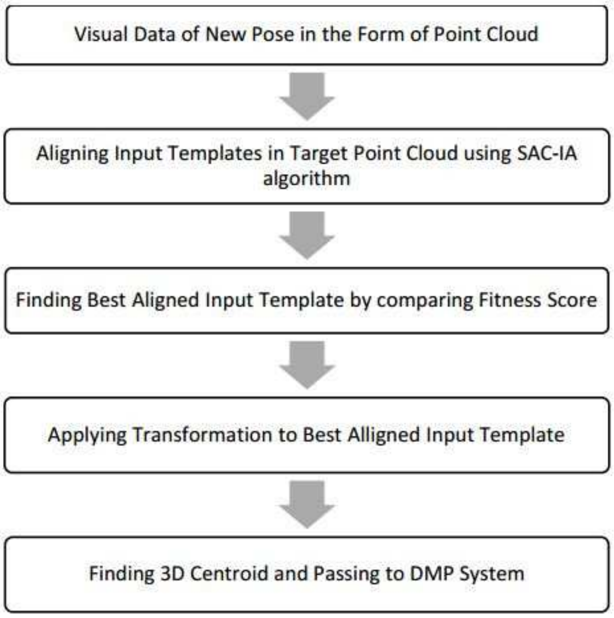


Fig.4: Flow of algorithm for estimating hand location using template matching

3·2 Dynamic Movement Primitives

Dynamic Movement Primitives (DMP) aims at designing controller for learning and generalization of motor skills by learning from demonstration [2]. The controller is based on nonlinear dynamical system and uses Locally Weighted Regression (LWR) techniques to learn complex, discrete or rhythmic movements demonstrated by a human subject. The controller can be considered to be discrete or rhythmic pattern generator 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 term, so that it produces the desired behavior [6]. Formally, it is defined by a damped spring model as below:

$$\tau \dot{v} = K(g - x) - Dv - K(g - x_0)s + Kf(s) \quad (1)$$

$$\tau \dot{x} = v \quad (2)$$

The term x and v are position and velocity of the system respectively, x_0 and g are start and goal position, τ is a scaling term, K acts like spring constant and D is damping factor chosen in a way such that system is critically damped. The term $K(g - x_0)s$ is necessary for avoiding sudden jump at the beginning of a movement. The nonlinear function f, which is also called as forcing term is a non-linear function to be learned to allow complex movements. The forcing function f is chosen as

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

where ψ_i is defined as Gaussian basis function as

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

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. Phase variable s starts from 1 and monotonically decreases to 0. Our goal is to design a forcing function that can learn from demonstration and allows us to scale the movement defined by goal state g. So that the system can follow a specified path. The forcing term can be redefined as:

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

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

The forcing function in eq. (3) is comprised of weighted summation of Gaussian that are going to be activated as system converges to goal. We want that forcing function matches the desired trajectory. In other words, we want f_{target} to be as close as possible of f as written below:

$$J = \sum_s \left(f_{target}(s) - f(s)\right)^2 \quad (6)$$

This ends by calculating weight parameters across Gaussians.

3·3 Robotic cloth manipulation using DMP

In this section, we provide brief overview of our system. As per the formulation described in section 3·2, DMP can learn from 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 as "Teaching Phase", since in this phase, we are teaching skills to robot to perform the task. During the demonstration, pose trajectory of end-effector is recorded using Baxter API and stored in a file. Once the demonstration is finished, DMP is parameterized using recorded trajectory file. This is termed as "Learn Trajectory" phase. The parameterized DMP can represent all the characteristics of 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 total six DMP systems, which can control both the arms of Baxter robot. The orientation of the end-effector is not considered as a part of DMP system and kept same as it was at the time of "Teaching Phase". In "Testing Phase", we change the posture of mannequin by changing the angle of inclination of hand w.r.t horizontal line in 2D space. At this point, we use the results of hand location estimated by Kinect sensor to get its 3D coordinates of mannequin described in the section 3·1. We change start and goal parameter of DMP system by using this information. In this way, we have modified DMP system, which can adapt modified posture referred as "DMP Generalization". For Kinect-Baxter calibration 3D coordinates are translated from Kinect space to Baxter space.We collect a dataset of points observed by Baxter and Kinect. Then we use absolute orientation calibration to align the frames of reference.

We have divided the complete trajectory into two parts: (a) The reaching part, which refers to the trajectory starts from home position of robot and ends till fingers of mannequin (b) the clothing part, which refers to the trajectory starts from fingers of mannequin and reaches up to shoulder nearly. The reaching part can be performed through simple position based controller but for the clothing part, we need to use DMP system since this part changes drastically between postures and can be prone to failures.

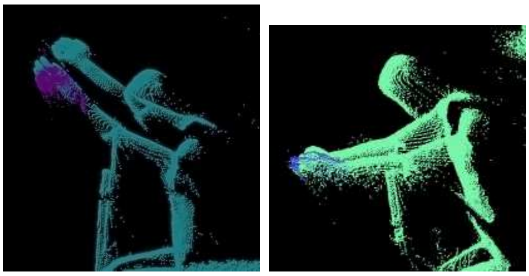
4. Experiments

4·1 Hand Location Estimation

The Kinect sensor was mounted on the top of the Baxter Robot as shown in the Figure 1 so that the sensor could easily see the mannequin's hands. Then, the posture of mannequin was changed from the previous state by changing the shoulder elevation. The template matching algorithm was applied for the new 3D point cloud captured by Kinect sensor. We experimented this method for six different hand positions by changing the angle of inclination of the hand w.r.t to horizontal line in 2D space. The template matching method was able to locate the hand smoothly in every posture and able to represent its position with extracted 3D centroid coordinates as shown in Figure 5.

4·2 Clothing task using position DMP

The aim of this experiment is to put sleeveless T-shirt on both the arms of mannequin by using DMP



(a) (b)

Fig.5: Locating the left hand from PCD with two different poses. Located hand is shown in another color.

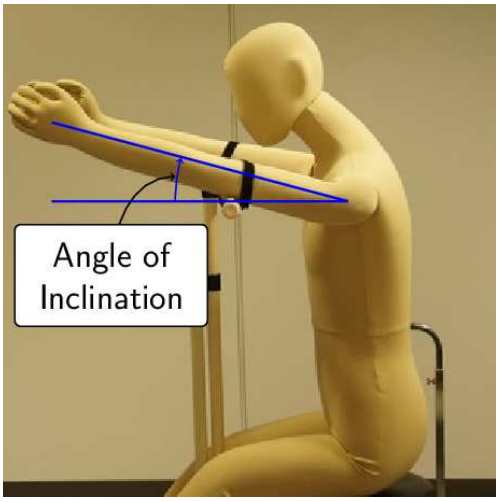


Fig.6: Angle of Inclination

system. By using the hand location information from Kinect sensor, we change the initial and the goal parameters of DMP system. Modified DMP can be acquired by rolling out initial DMP system as described in section 3·2. Newly generated DMP trajectory was not only found well suited and capable of performing clothing task but also smoother compared to demonstrated trajectory. A video demonstration of this experiment can be seen at YouTube[1].

We also assessed the success rate in nine trials for six different shoulder inclination. Figure 6 shows the definition of the angle of shoulder inclination, and Figure 7 presents the success rate to the angle of shoulder inclination.

5. Conclusions

This paper presents an approach for robotic cloth manipulation for clothing assistance task using visual information from Kinect sensor in the form of point cloud and Dynamic Movement Primitives. A dual arm Baxter robot, Kinect sensor, soft mannequin, and very thin sleeveless T-shirt were used in the task. We have demonstrated the feasibility of estimating the 3D

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

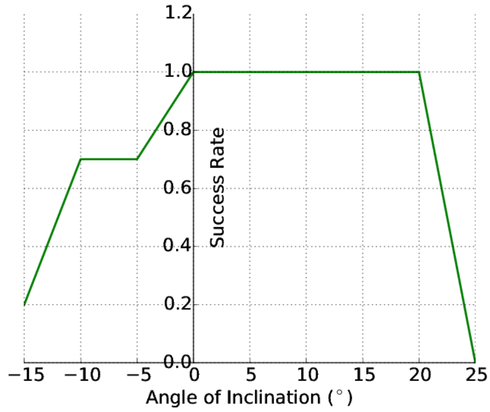


Fig.7: Accuracy Assessment

hand location and its features as initialization for the goal parameter of the DMP system.

This work will extend to design an adaptive controller for real-time tracking of the mannequin to adapt and detect various failure scenarios. DMP system also needs to be improved to incorporate orientation information of end-effector.

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