Folding Behavior Acquisition of A Shirt Placed on the Chest of a Dual-Arm Robot*

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***Abstract*— In this paper, we describe folding behavior acquisition of a shirt by a dual-arm robot. We focus on a way of folding that assumes to place a cloth product on a chest, as people often do. This method has the following advantages: (1) Because it uses the body part, a small workspace is sufficient and a work table is not needed, (2) Since the cloth product is unfolded in a state of suspending and the work is progressed therefrom, the recognition of shape change of the cloth product can be done to a certain extent easily. We divide the folding procedure into three phases, and focus on the operation to fold a sleeve by holding the shoulder part. In our approach, a basic folding motion is acquired by *teaching by showing* manner, and the action suitable for robots is acquired by reinforcement learning. We show that the folding work can be achieved by an actual dual-arm robot.**

***Index Terms*— Cloth manipulation, teaching by showing, reinforcement learning.**

I. Introduction

Cloth products are indispensable for people to have their daily lives. Therefore, it is necessary to frequently perform work related to cloth products such as washing and storage, and people repeat such unproductive work every day. One of the work is a folding of cloth products. This is a typical example of nonproductive work and there are many requests for automation. Based on such a background, research and development on the folding of cloth products has been proceeded.

In conventional study aimed at folding cloth products, basically, a horizontal table or the like which can place cloth products on is used in many cases. Thereby ensuring that the part not being manipulated remains stationary on the table. Then, it becomes easier to set a prospect for work. On the other hand, in this study, we focus on how to fold cloth products with putting on chest as folding methods that humans often do. Then, it aims to let the robot acquire necessary operation ability.

Figure 1 shows an example of this folding. When a person performs this folding method, the following procedure is taken. First unfold the cloth product and bring it on the chest. This prevents the cloth product from sliding down due to the frictional force between the cloth and the human body part. After that, the person folds the parts such as sleeves in order to proceed the folding work. In automating the folding of cloth products, the authors awared that this folding method has the following advantages.

Fig. 1. Shirt folding by a person

1) In order to use the body part, it is sufficient if there is a small work space. A structure such as a table is not needed.
2) Since the cloth product is unfolded in a state of hanging substantially vertically and the work is progressed therefrom, the recognition of shape change of the cloth product can be done to a certain extent easily.

In the approach proposed in this paper, item 2) is particularly important. Since cloth is flexible, it is generally difficult to generate an operation that makes a transition to a desired shape. For example, when trying to fold a T-shirt placed on a table, it is necessary to grip the cloth with multiple hands at the same time in some processes. On the other hand, in the above item 2), for example, when a shoulder portion of a shirt unfolded in front of the chest is moved to fold toward the trunk side, the waist portion of the shirt will also deform with a trajectory similar to the shoulder portion. That is, it is relatively easy to predict the shape, and it is suitable for automation.

In this study, by using a robot whose structure is close to that of human beings, the folding operation as described above is automated. The basic approach is as follows. First, let the robot observe how a person is actually folding a

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shirt. At this time, the person's and the shirt's motions are measured by a three-dimensional range image sensor. Then, using the sensor data, motion for the robot is decided. In this procedure, there can be an approach to faithfully reproduce human movements. Also, there can be another approach to reconstruct the movement of the robot according to the joint configuration of the robot itself. In this paper, we examine the folding issue from both aspects, then especially describe the proposed method and implementation for the latter approach.

The contributions of this paper are as follows:

- We focus on a novel task of clothing handling: folding a shirt while surmounting it on a body part. The task can be simplified because this folding method restricts the shape change of cloth.
- Based on the concept of *teaching by showing*, we show that folding work can be achieved with an approach to decide motion of robot from how person to manipulate.
- To absorve the differene between human's body structure and robot's in the folding behavior, we propose a reinforcement learning method suitable for cloth manipulation.

The structure of this paper is as follows. Section II presents related work. In Section III, we discuss the issues and approaches for our cloth manipulation. In Section IV, we explain our proposed methods. Section V introduces our experimental results and discussion, and Section VI presents out our conclusion and future work.

II. Related work

Attempts to deform fabric products into desired shapes by robots have been ongoing continuously. Maitin-Sphepard et al. [1] achieved a folding task of several cloth products by a mobile dual-arm robot. The robot picked up a cloth product one by one, and then folded them in order. Besides that, recently we have results such as Li et al. [3] and Xiong et al. [4]. In the study of Li et al., the trajectory of folding was learned using a physics simulator for clothes placed on a desk, thereby achieving efficient sleeve folding. Our group also worked on the task of unfolding rectangular cloth fabrics placed on a table [6]. We adopted "pinch-and-slide" motion proposed by Shibata et al. [7], and used POMDP for behavior selection for efficient unfolding.

There are also studies that attempt to achieve some objectives by manipulating cloth products in a suspended state. Osawa et al. [12] and Abbeel et al. [11] succeeded in identifying the type of a cloth product by a robot observing the contour and the position of the lower end point while operating the cloth product. Kita et al. [10] proposed a method of matching a deformable model with a 3D point cloud obtained from a trinocular stereo camera. Doumanoglou et al. [5] succeeded in unfolding and classification of fabric products while changing hanging state. Compared with the results of Osawa's work, Doumanoglou's work is progressive to be able to select grasping portion other than the lowest end point.

In the above-mentioned studies, recognition methods and operation procedures necessary for folding are provided in advance. What does the robot do is to pick up an appropriate operation method from the pre-defined choices. On the other hand, in this study, we aim to extract the information necessary for the operation from the manipulation of human beings and make it possible to reproduce it as the behavior of robots. This reduces the burden on developers.

III. Problem setting and approach

A. Problem setting

As a cloth product to be folded, we use a short sleeve shirt. A human demonstrator folds the shirt as an example, and a robot observes the situation with a sensor and extracts data necessary for its own motion generation. The flow of folding is as follows. The demonstrator picks up the portion of both shoulders first and unfolds the shirt. After that, put the shirt on the chest in that state, so that the shirt does not slide down due to friction between the chest and the shirt. Then, as shown in the rightmost picture of Fig.1, fold one sleeve, then finally fold the other side.

This problem setting is considered to be a kind of *teaching by showing*[13] or *programming by demonstration*[14]. Conventionally, most of the manipulation targeting in such a framework are rigid objects[15]. However, it is difficult to predict deformation caused by operation when soft objects are to be manipulated. Although there is room for question whether the deformability is the reason, there are few cases where soft objects are targeted for such a framework. Even though we can find related work[16][17], e.g. folding a towel in two, it is simpler than the folding of a shirt. On the other hand, according to the procedure described above, it is possible to approximate the shape change of the shirt to the property of the simple articulated body with respect to the work of folding. That is, it is possible to make a premise that it is easy to predict the shape change of the cloth product accompanying the operation. This makes it easy to acquire operations.

B. Our approach: Recognition of the folding work

We utilize a dual-arm robot whose upper body has similar structure with human. A 3D range image sensor is used as a sensor for observing the folding operation. The sensor is placed against a demonstrator and at a position where the whole part of the shirt is always captured within the field of view. A color image and a depth image are acquired while the demonstrator performs the folding work and used for recognizing the state of the cloth or the demonstrator. Also, in the verification experiment after the robot have generated motion sequence, the 3D range image sensor is made to face

TABLE I

IMPORTANCE OF OPERATOR BEHAVIOR

	1st phase	2nd phase	3rd phase
Arm Motion	low	low	low
Hand Trajectory	medium	**high**	**high**
Final Pose	**high**	low	low

the robot in the same positional relationship as the teaching, and it is used for recognizing the state of the shirt.

In order to assist recognition of the shape state of the cloth, we affixed different color markers to the front and the back of the shirt, respectively. As mentioned before, the position of the markers to be pasted was the positions of both waist hem of the front and back, both shoulders position in the front, and the center of the collar on the back. These were chosen from the positions that are invisible and newly visible as the folding procedure progresses. Conversely, if such a position can be recognized, it is possible to grasp the shape of the shirt necessary for the folding work.

C. Our approach: Segmentation of work process and analysis

The general flow of folding work was divided into three steps as shown in the lower part of Fig. 1.

1) From the state where the shirt is unfolded with both hands, until the shirt is put on the chest
2) The behavior of folding one sleeve
3) The behavior of folding the other sleeve

In these steps, the shape change of the shirt is relatively well coordinated with the movement of the demonstrator's hand. That is, even in a portion away from the gripping position, such as the waist portion of the shirt, it moves corresponding to the movement of the hand. This means that the operation of the cloth product can be simplified as compared with the case of operating the cloth product placed on the table.

Table I summarizes the importance of folding work for each process. From this result, it is possible to judge whether emphasis should be placed on reproducing the movement of a person, or whether to emphasize the shift or reaching position of a part of the cloth. In phase 1, from the situation where the shirt is unfolded with both hands, move both hands in parallel and apply it to the chest part. Although there are some issues, such as searching for a position to be applied, we do not focus on this phase since the manipulation in itself is rather simple.

On the other hand, in phase 2, large deformation occurs on the cloth. However, the movements of the human hand and the movement of the cloth are relatively linked. Therefore, there can be both a method of mimicking the motion of a human hand as it is and a method of automatically acquiring an manipulation trajectory by a robot. The same is true for phase 3.

D. Method selection

In accordance with the basic policy described in the previous subsections, we select an approach to mapping human motion directly to the movement of a robot, and introduce a method for adjusting motion that is suitable for the robot. Based on the summary shown in Table I, especially focusing on the boldface part, we propose a method for phase 2 and 3.

It is necessary to fold a cloth product into an appropriate shape. To achieve this task, we can use the position shift of color markers pasted on the cloth. This can be regarded as a search problem in which the final state is explicitly defined by the marker positions. In this study, PILCO[22] is used. It is possible to efficiently acquire the movement of the arm up to the target marker position.

In this study, the feasibility by other methods is also examined. We tried to use Q-learning[21] for phase 2 and examined which one is easier to use compared with PILCO. Details are described in the Section V-B. From the next section, we will explain details of the motion acquisition method.

IV. FOLDING MOTION ACQUISITION

When a robot folds one of the sleeves of a shirt, it can be considered that the movements of the hand and the movement of the waist marker of the shirt are interlocked. Therefore, it can be considered that the dynamics model of the waist marker is determined by the movement of the hand, which means that the movement of the waist marker is somewhat predictable. For the above reason, the problem is possible to drop to a basic problem for hand trajectory acquisition and it becomes possible to apply existing efficient model-based reinforcement learning method.

PILCO is a practical, data-efficient model-based policy search method, which is able to reduce model bias and conduct policy search in closed form using state-of-the-art approximate inference. By using PILCO, we can sample from learning trial and build the dynamics model to acquire the policy efficiently. The algorithm of PILCO is shown in Algorithm 1.

As an example, in the situation of phase 2, we consider a dynamics system

$$\mathbf{x}_t = f(\mathbf{x}_{t-1}, \mathbf{u}_{t-1}), \tag{1}$$

where $\mathbf{x} \in \mathbb{R}^D$ denotes a continuous valued state, $\mathbf{u} \in \mathbb{R}^F$ denotes a control signal, and f is unknown transition dynamics. In PILCO, the objective is to find a deterministic policy $\pi : \mathbf{x} \mapsto \pi(\mathbf{x}) = \mathbf{u}$, which minimizes the cost of the entire episode of learning. In the case of phase 2, The states and the control signals at each time step t are defined as following:

$$\mathbf{x}_t = [x_r, y_r, z_r, wd_m, \dot{x_r}, \dot{y_r}, \dot{z_r}, \theta]^\top, \tag{2}$$

Algorithm 1 PILCO

init: Sample controller parameters $\theta \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$. Apply random control signals and record data.
repeat
  Learn probabilistic (GP) dynamics model, using all data.
  Model-based policy search.
  repeat
    Approximate inference for policy evaluation, get $J^{\pi}(\theta)$.
    Gradient-based policy improvement, get $dJ^{\pi}(\theta)/d\theta$.
    Update parameters θ.
  until convergence;
  return θ^*
  Set $\pi^* \leftarrow \pi(\theta^*)$.
  Apply π^* to system (single trial/episode) and record data.
until task learned

$$\mathbf{u}_t = [\dot{x_r}, \dot{y_r}, \dot{z_r}, \theta]^{\top}, \tag{3}$$

where vector (x_r, y_r, z_r) is the position of the right hand of the robot, vector $(\dot{x_r}, \dot{y_r}, \dot{z_r})$ is the velocity of the right hand. d_m is the distance from the position of the left waist marker to the goal position of this phase. $w \in [0, 1]$ is the weight of d_m, and θ is the signal which sets the yaw axis of robot right hand holding or moving to 0 or $-\pi/2$. In the case of phase 2, the goal position is acquired from the position of the left waist marker when a demonstrator folds the shirt. For the supposition that the waist part deforms with a trajectory similar to the shoulder portion, d_m in the states can be defined as follows:

$$d_m = g(x_r, y_r, z_r, \theta), \tag{4}$$

where g is a unknown function. This ensures that d_m can be predicted by a dynamcis model with the samplings of the right hand status if the target of marker is known.

In phase 2, the goal position of right hand can be conjectured by the marker on the waist of the shirt, shown as Fig. 2. Therefore, the goal states $\mathbf{x}_{target}$ can be calculated from an image sequence that the demonstrator folds the shirt which recorded in advance. So the cost function of being in state $\mathbf{x}$ at time step t can be defined as follows:

$$c(\mathbf{x}_t) = 1 - \exp(-\|\mathbf{x} - \mathbf{x}_{target}\|^2). \tag{5}$$

The long-term cost of the entire episode is defined as

$$J^{\pi}(\theta) = \sum_{t=0}^{T} \mathbb{E}_{\mathbf{x}_t}[c(\mathbf{x}_t)], \mathbf{x}_0 \sim \mathcal{N}(\mu_0, \mathbf{\Sigma}_0). \tag{6}$$

In order to minimize $J^{\pi}(\theta)$ efficiently, a dynamics model should be established to predict the state evolution. In PILCO,

Fig. 2. The goal position of right hand is conjectured by the goal position of the left waist marker.

the probabilistic dynamics model is defined as a Gaussian Process(GP). As the states and the control signals are defined as $\mathbf{x}_t \in \mathbb{R}^8$ and $\mathbf{u}_t \in \mathbb{R}^4$, the model is trained by the input tuples $(\mathbf{x}_{t-1}, \mathbf{u}_{t-1}) \in \mathbb{R}^{12}$. The training target is defined as the differences $\mathbf{\Delta}_t = \mathbf{x}_t - \mathbf{x}_{t-1} + \varepsilon \in \mathbb{R}^8$, where $\varepsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_{\varepsilon}), \mathbf{\Sigma}_{\varepsilon} = \mathrm{diag}([\sigma_{\varepsilon 1}, ..., \sigma_{\varepsilon D}])$. Then the one-step prediction can be yielded by the GP, where

$$p(\mathbf{x}_t|\mathbf{x}_{t-1}, \mathbf{u}_{t-1}) = \mathcal{N}(\mathbf{x}_t|\mu_t, \mathbf{\Sigma}_t), \tag{7}$$

$$\boldsymbol{\mu}_t = \mathbf{x}_{t-1} + \mathbb{E}_f[\mathbf{\Delta}_t], \tag{8}$$

$$\mathbf{\Sigma}_t = \mathrm{var}_f[\mathbf{\Delta}_t]. \tag{9}$$

To obtain all states of each time step during the entire episode of learning, PILCO approximates $p(\Delta_t)$ by a Gaussian distribution using exact moment matching, which means $p(\Delta_t) \sim \mathcal{N}(\mathbf{\Delta}_t|\mu_{\Delta}, \mathbf{\Sigma}_{\Delta})$. Then one-step prediction has been cascaded and a Gaussian approximation to the desired distribution $p(\mathbf{x}_t)$ is given by PILCO as $p(\mathbf{x}_t) \sim \mathcal{N}(\mathbf{x}_t|\mu_t, \mathbf{\Sigma}_t)$, where

$$\mu_t = \mu_{t-1} + \mu_{\mathbf{\Delta}}, \tag{10}$$

$$\mathbf{\Sigma}_t = \mathbf{\Sigma}_{t-1} + \mathbf{\Sigma}_{\mathbf{\Delta}} + \mathrm{cov}[\mathbf{x}_{t-1}, \mathbf{\Delta}_t] + \mathrm{cov}[\mathbf{\Delta}_t, \mathbf{x}_{t-1}]. \tag{11}$$

Therefore, to evaluate the expected long-term cost $J^{\pi}(\theta)$ in Eq.(6), it only remains to compute the expected values

$$\mathbb{E}_{\mathbf{x}_t}[c(\mathbf{x}_t)] = \int c(\mathbf{x}_t)\mathcal{N}(\mathbf{x}_t|\mu_t, \mathbf{\Sigma}_t)d\mathbf{x}_t, \tag{12}$$

where $t = 1, ..., T$ is the time step in the entire episode of learning.

Since a distribution $p(\mathbf{x}_t)$ depends on the moment of $p(\mathbf{x}_{t-1})$ and controller parameters θ through $\mathbf{u}_{t-1}$, a derivative $dJ^{\pi}/d\theta$ can be obtained by repeating application of

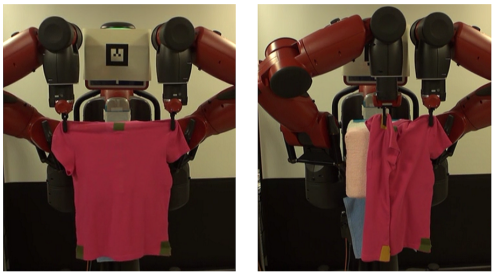

Fig. 3. Left: Initial situation of experiment. Right: Folded one sleeve in success.

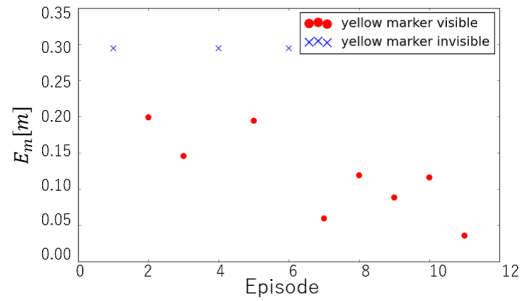

Fig. 4. Result of learning in phase 2

the chain-rule. The calculation of μ_Δ, $\mathbf{\Sigma}_\Delta$ and the cross-covariance $\mathrm{cov}[\mathbf{x}_{t-1}, \mathbf{\Delta}_t]$ in Eq.(10), Eq.(11) and $dJ^\pi/d\theta$ is detailed by [22]. Therefore, standard gradient-based non-convex optimization methods are available to acquire the optimized policy parameters θ^*, and it is much more efficient than the approach that sampling $J^\pi(\theta)$ from an actual manipulation.

V. Experiment

A. Experimental settings

Experiments for motion acquisition was performed for the phase 2 and phase 3 by the methods described in Section IV. The robot used for the experiment was Baxter made by Rethink Robotics. This robot has 7 degrees of freedom in one arm and one degree of freedom in the neck. To the chest part of the robot, a fabric was pasted: the purpose is to make it easier for the shirts to stay and also to make resemble the situation when humans fold a shirt. The cloth product to be folded was a half-length shirt with 100% cotton. As a color marker, colored cloth tape was cut into rectangles, and it was affixed to neck, both sides of shoulder, and both sides of waist.

Xtion Pro Live manufactured by ASUS was used as a three-dimensional range image sensor. This sensor was placed in a position facing a human demonstrator. First, the operator demonstrated a folding motion in front of the sensor. A color image sequence and a depth image sequence obtained from the sensor were given to the robot as reference data. Then, for acquiring the folding manipulation, the robot was placed on the same position with the operator and made to acquire appropriate folding motion by using sensor data obtained online.

B. The experimental result

The experimental result on phase 2 is reported as example. According to the method described in Section IV, the experiment was conducted to acquire an end-effector trajectory of the right hand of the robot. The initial situation of phase 2 was the situation that the shirt was placed on the chest, and the goal situation was that the robot folded one of the sleeves and then the state of the shirt was similar to the state that a demonstrator folded. The two situations are is shown in Fig. 3.

In our experiment, d_m was calculated from a yellow marker on the left side of the waist. If the yellow marker was visible, d_m was calculated. Otherwise, d_m was calculated from the position of a green marker pasted on the back side to the yellow marker, and -0.1 was added to d_m to notify that the left sleeve of the shirt is not flipping over. At the end of each episode, E_m which indicates the distance from marker positions to the goal position was used to evaluate the episode. If E_m is lower than 0.15 in five consecutive episodes of learning, it is determined that the learning is successful and the learning is terminated.

Learning trials were carried out 11 times, and in each episode, the right hand of the robot moved 10 times in 3D space, and rotated 10 times along the yaw axis. That is, there were 20 times movements in total. E_m of each episode is shown in Fig. 4. After 11 episodes of learning, the robot could fold the shirt that the marker moved whitin the allowable range.

C. Discussion

In this study, we took an approach to obtaining robot motion from the motion of human demonstrator. The folding operation was divided into three phases, and we focus on two phases to fold shoulder part of a shirt. Although we selected PILCO to acquire hand trajectory, it is not unique ways that achieve the folding task.

We also conducted an experiment using Q-learning. Fig. 5 shows the final state of the shirt of each approach. and Table II shows the comparison in the case of phase 2, Here, E_m indicates the distance from the marker to the goal position, and N is the number of episodes needed at learning. From the table we can see that if we removed d_m from the state input, the learning process becomes faster as shown in the middle row. However, the result of folding clothes was less accurate since E_m is getting larger. On the other hand, if Q-learning was applied, E_m was whitin the allowable range but the time required for learning was increased. From these

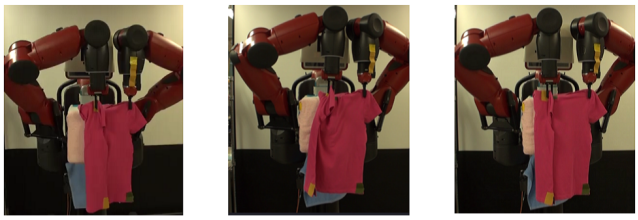

Fig. 5. (1): Final state of the shirt using approach described in the section IV. (2): Final state of the shirt using approach using PILCO that removed d_m input. (3): Final state of the shirt using approach using Q-learning.

TABLE II

COMPARISON OF DIFFERENT METHODS

	The proposed PILCO (with marker evaluation)	PILCO without marker evaluation	Q-learning
E_m	0.0358	0.2058	0.1328
N	11	7	200

results, we can draw a conclusion that our method performs well in the learning of phase 2 and phase 3.

In addition to these, a method to recreate the demonstrator's hand trajectory acquired by OpenPose[23] was examined. However, it was difficult to accurately estimate the orientation of human hands, so the folding of the shirt did not come as expected. That is, even if the hand trajectory could be reproduced roughly, it was impossible to appropriately mimic the deformation of the shirt. Also, because the joint structure of the robot and the human being are different, it was difficult to reproduce human motion while avoiding collision. In other words, when imitating the trajectory of a human hand, collision between both hands or between the hand and the body occurred.

VI. CONCLUSION

In this paper, we proposed a method of folding behavior acquisition of a shirt. We utilized a robot whose structure is close to that of human and focused on a novel task: folding a shirt while surmounting it on a body part. We decided to use the concept of *teaching by showing* partly and to let the robot acquire the manipulation method from the observation when a demonstrator folds a shirt. We divided the task into three phases and selected suitable operation methods based on the characteristic of folding motion for each phase. We confirmed that a short-sleeved shirt can be folded with actions that are suitable for robot's body structure.

Future work includes to achieve folding of various kinds of clothing. We will also systematize the proposed approach.

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