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Human-Robot Deformation Manipulation Skill Transfer: Sequential Fabric Unfolding Method for Robots

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***Abstract*—Deformable object manipulation has been considered a challenging task for robots for its complex dynamics and the infinite dimensional configuration space. Fabric unfolding manipulation takes on critical significance in the textile industry and household services. Accordingly, enabling robots to possess the above-mentioned skill has been confirmed as a crucial and challenging task. In this study, a general framework is developed for transferring human skills to robots in fabric unfolding manipulation. The developed framework comprises two key components (i.e., behavior cloning to learn human unfolding policy and learning from demonstration to transfer unfolding actions). A mixture density network is introduced, with the aim of addressing the multimodality in human policy. Moreover, task parameter weighting is considered during action generalization to adapt to a wide variety of unfolding scenarios. As revealed by the experimental results of this study, the framework can successfully unfold fabrics of different colors and sizes, and its performance can be comparable to human-level operation. Furthermore, the framework also can be applied to garment unfolding, and experiments suggest that it exhibits generalization.**

***Index Terms*—Imitation Learning, learning from Demonstration, manipulation Planning.**

I. INTRODUCTION

ROBOTS have been extensively employed for the manipulation of rigid objects, whereas their capability of manipulating deformable objects remains at the research stage [1]. The handling of fabrics, especially fabric unfolding, has been confirmed as a specific task covering deformable manipulation [2] . Fabric unfolding takes on critical significance in areas (e.g., garment production and household services) for serving as a vital preparatory step. For several tasks (e.g., sewing, ironing, and folding), the fabric should be completely unfolded and free of wrinkles. Nevertheless, fabrics generally exist under highly deformed conditions (e.g., stacking and wrapping).

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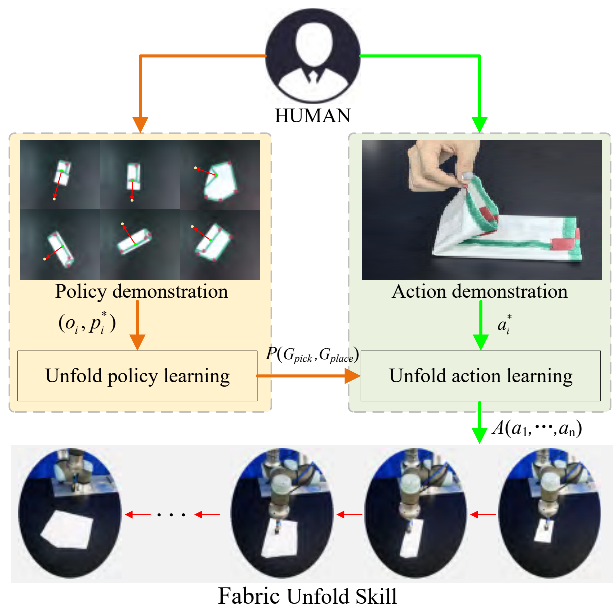

Fig. 1: Framework of human-robot deformable object manipulation skill transfer. The policy and action for fabric unfolding are determined through demonstrations. Policy demonstration involves human selection of grasp and placement points p_i^* under image o_i, while action demonstration refers to human-generated trajectory a^* for fabric unfolding. Lastly, combining the policy and action, the unfolding skill actions A is transferred to the robot for sequential unfolding of wrapped fabric.

The task investigated in this study refers to transforming the fabric from a highly wrapped initial structure into a flat configuration based on several grasping and unfolding actions. Two major difficulties are revealed by this manipulation in the sequential unfolding process of robots. The first difficulty refers to the grasping policy, comprising the selection of the grasp points and placement points. Not consistent with rigid objects, fabric lacks a clear posture representation, such that it is challenging to determine the appropriate grasp and placement points in accordance with the observed state of the fabric. Moreover, the placement point is significantly related to the grasping point, such that both points should be considered as pairs. The second difficulty is the trajectory planning for unfolding. Fabric is capable of easily deforming if inappropriate trajectories are selected for its nonlinear dynamic characteristics. Furthermore, the unfolding operation typically

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involves a lengthy sequence of intricate actions, such that it is difficult to carry out multi-step operation planning.

Addressing manipulating deformable objects using conventional methods (e.g., visual detection and trajectory planning) has been confirmed to be challenging [3]. However, humans exhibit an intuitive ability to manipulate fabric, and it is capable of unfolding it without requiring excessive information. Learning from demonstration (LfD) [4] is effective in transferring this ability to robots and overcome the aforementioned challenges [5]. However, the emphasis on learning from demonstrations is largely on the manipulation of rigid objects, whereas attention has been rarely given to transferring skills for manipulating deformable objects from humans.

In this study, a general framework is presented to transfer deformable manipulation skills between humans and robots, with the aim of addressing the issue of how robots can possess fabric unfolding skills from human demonstrations. Fig. 1 illustrates the task of unfolding a highly wrapped piece of fabric into a target configuration. The contributions of this study are outlined as follows:

- For unfolding policy learning, a mixture density networks-based behavior cloning method is proposed, which is capable of addressing the issue of inconsistent correspondence between fabric states and selection policy.
- For unfolding action learning, a task parameter-weighted unfolding trajectory learning and generalization method is proposed to avoid fabric deformation in the unfolding process, such that adaptive trajectory planning can be achieved in different states.
- For experiments, a carefully designed and executed data collection process was employed, and it was demonstrated that the learned skills are effective in performing the tasks of unfolding fabrics, while these skills can be generalized to fabrics that are not applied in the training.

II. RELATED WORK

The manipulation of fabrics has been a persistent challenge in robotics, with a specific focus on the unfolding of fabric garnering significant attention. Two main methods have been proposed for robot fabric unfolding [6]. One method refers to grasping specific points of the fabric and suspending it in the air, leveraging gravity to unfold the fabric [7], [8] or achieve a partially folded simple state [9], [10]. The other method involves unfolding the fabric on a workbench surface through sequential interactions [11]. Both methods comprise the selection of grasping and placing policies and the design and planning of unfolding actions. Accordingly, the focus of this study is placed on the robotic unfolding of fabric from the perspectives of unfolding strategies and unfolding actions.

A. Unfolding Policy

The selection of appropriate grasping and placing points has been confirmed a vital step in successfully unfolding fabric. Research on the robotic unfolding policies can fall into two aspects (i.e., heuristic-based methods and learning-based methods) [12]. The former places a focus on recognizing operational features (e.g., fabric edges, corners, and folds) and formulating fabric unfolding policies based on geometric models. For instance, Willimon et al. identified corners from depth images using the Harris corner detector. Furthermore, they proposed an interactive unfolding strategy using eight fixed angles [13]. Sun et al. performed effective fabric smoothing by estimating the angle bisectors of folds in the fabric [14]. However, the above-mentioned methods are subjected to challenges in detecting features and generalizing policies in situations involving self-occlusion and fabric deformation. Learning-based methods focus on directly learning the end-to-end correlation between fabric shapes and policies. Tanaka et al. developed an encoding-operation-decoding network directly connecting fabric manipulation with changes in fabric shape [15]. Tsurumine et al. combined the properties of smooth strategy updates with the automatic feature extraction capabilities of deep neural networks for T-shirt folding [16]. Learning-based methods are capable of avoiding explicit fabric state modeling, whereas they require considerable training data, and interactive learning is inefficient for efficiency. In fact, besides heuristic and self-learning methods, learning unfolding policy from human demonstrations is capable of effectively reducing the analytical and computational burden of addressing the high-dimensional state of fabric [17]. Moreover, as revealed by experience, combining human-selected grasping points with analytical placing performs well in fabric unrolling. This method has been applied by some researchers to fabric manipulation. Seita et al. applied deep imitation learning to achieve smooth manipulation of unordered fabric through dragging [11]. Furthermore, Hoque et al. proposed LazyDAgger [18], [19], an extension of interactive imitation learning for robot folding of fabric. In comparison, this study place a greater focus on unfolding wrapped fabric, instead of smooth dragging.

B. Unfolding Action

Since folding and unfolding share similarities in motion, research in both areas is considered. In general, currently proposed methods for path design can fall into three types [20]. The first type applies geometric algorithms to the unfolding process using simple paths (e.g., triangles [21], circles [22]). The above-described methods have the advantage of low computational cost, whereas material parameters are not considered, thus triggering wrinkles. Another method is through modeling and simulation in software environments (e.g., Maya [23]), where paths are planned in accordance with theories (e.g., Euler-Bernoulli [24] and Kirchhoff-Love shell [25]). The above-mentioned method is capable of generating paths that produce the desired effects, whereas it is computationally expensive and requires prior knowledge of material properties. The third type is to dynamically adjust the trajectory through visual servoing. In [26], a visual servoing controller for collaborative fabric flattening was proposed, extracting fold features from images and mapping them to robot actions. In [6], a depth image combined with an SVM classifier is employed at predefined decision points to assess whether a readjustment of the unfolding path is required. Dynamic real-time adjustments can increase the robustness of the trajectory but may also

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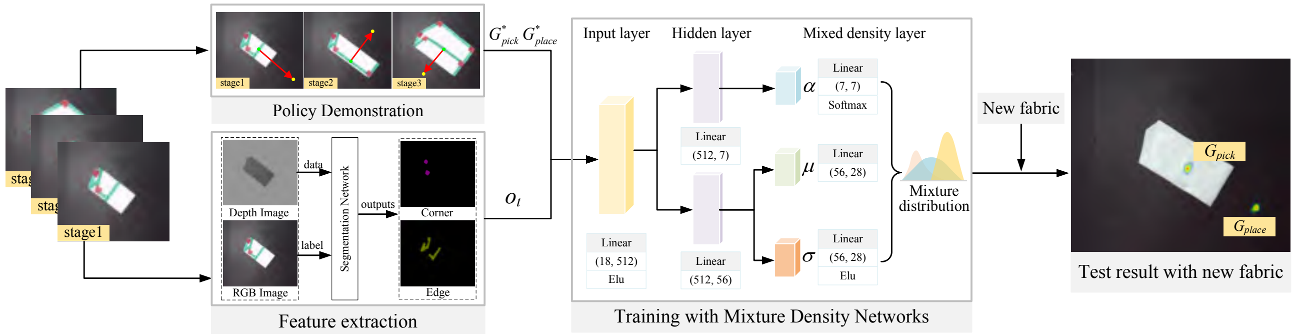

Fig. 2: An overview of the method for learning sequential fabric unfolding policy from demonstrations. The mixture density network takes an 18-dimensional vector as input, including the pixel centre coordinates and depth of the five corners and all edges of the fabric, denoted as the fabric feature O_t. The grasping point G^*_{pick} and placing point G^*_{place} demonstrated by humans serve as training labels for the network. The network outputs the probability distribution of grasp point G_{pick} and placing point G_{place}. The network comprises 45,295 parameters and was initialized using the He initialization method.

reduce task execution efficiency. Compared with path design methods, demonstration-based methods learning the action trajectories of human fabric unfolding are capable of avoiding complex parameter modeling and reducing the difficulty of trajectory planning. The above-mentioned methods are likely to achieve better performance in achieving flexibility and efficiency in manipulating deformable objects.

III. METHODOLOGY

A. Problem Statement

In this section, the task formulation for unfolding wrapped fabric is presented. Before performing the testing task, the fabric is wrapped and randomly placed in the workspace. The task of manipulating the fabric from its initial state is considered to maximize its coverage in a planar through a series of actions. We address the problem via learning from demonstration. We denote the demonstration by $D = \{(o_t, p_t, a_t)\}_{t=1}^N$, Let $o_t \in O$ be the RGB-D image observation of fabric at time t, where O represents the space of images. $p_i \in P$ denotes the possible grasping policy that the robot may adopt from the set of policies P. $a_t \in A$ denotes the action that the robot can perform from the set of actions. The task performance is measured by coverage $C(o_t)$,

$$C(o_t) = s(o_t)/s_{\max}, \tag{1}$$

where $s(o_t)$ is a function which represents area of o_t in pixels and $s_{\max}$ is an area of the manipulated fabric in pixels.

The problem goal is to learn a skill π that maps an observation O to a policy P and an action A, denoted by $\pi : O \rightarrow (P,A)$.

B. Unfolding Policy and Action

The unfolding policy comprises two parts: the grasping point $G_{pick} = [u_s, v_s]$ and the placing point $G_{place} = [u_e, v_e]$ on the image. The unfolding policy can be defined as:

$$p_t = (G_{pick}, G_{place}) = ([u_s, v_s], [u_e, v_e]). \tag{2}$$

The unfolding action refers to the complex and continuous motion trajectory performed by the robot's end-effector, starting from the grasping point (x_s, y_s, z_s) and ending at the placing point (x_e, y_e, z_e), which can be represented as a collection of sequence points.

$$a_t = \{(x_s, y_s, z_s), \ldots, (x_e, y_e, z_e)\}. \tag{3}$$

What sets it apart from previous "pick and place" work is that we take into account the influence of trajectories on the fabric unfolding process, aiming to minimize deformation of the fabric during unfolding, which is difficult to achieve using simple trajectories. The grasping and placing points are obtained by mapping the unfolding policy $[u_s, v_s], [u_e, v_e]$ through hand-eye calibration. Considering that human unfolding the fabric does not involve fingertip rotation, the motion trajectory only considers positional degrees of freedom.

C. Unfolding Policy Transfer

The unfolding policy is collected through a point-and-click interaction. Due to the non-unique correspondence between fabric state and unfolding behavior when humans select the picking and placement points, conventional behavior cloning has limitations in addressing multiple uncertain outputs. Accordingly, a mixture density network is introduced, such that the inherent multimodal issues in human unfolding policies can be effectively addressed. The overall procedure of the method is illustrated in the Fig. 2. The input consists of fabric feature samples $O = (o_1 \ldots o_n)$, with corresponding human demonstration strategy target values $P = (p_1 \ldots p_n)$. The mapping output function of the fully connected network is denoted as $h(\cdot)$. The output layer generates the weight, mean values, and standard deviations for M Gaussian distributions, respectively. The probability density function of the j-th sample's mixture Gaussian distribution is expressed as:

$$f(p_j | o_j) = \sum_{i=1}^{m} \alpha_i(o_j) \frac{1}{\sqrt{2\pi}\sigma_i o_j} \exp\{-\frac{\left\| p_j - \mu_i(o_j) \right\|^2}{2\sigma_i^2(o_j)}\} \tag{4}$$

where $\mu_i(o_j)$ and $\sigma_i(o_j)$ represent the mean and standard deviation of the i-th Gaussian kernel, which are obtained through the output of fully connected layers:

$$\mu_i(o_j) = h_i(o_j) \tag{5}$$

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$$\sigma_i(o_j) = \exp(h_i(o_j)) \tag{6}$$

$\alpha_i(o_j)$ denotes the weight of the i-th Gaussian distribution, satisfying the constraint $0 \le \alpha_i(o_j) \le 1$, $\sum_{i=1}^{m} \alpha_i(o_j) = 1$, which is expressed as follows:

$$\alpha_i(o_j) = \frac{\exp(h_i(o_j))}{\sum_{i=1}^{m} \exp(h_i(o_j))}. \tag{7}$$

Under the assumption of maximum likelihood estimation, the likelihood function is defined to maximize the probability value of the output distribution at the target value P, which can be expressed as:

$$L(\theta) = \frac{1}{N} \prod_{j=1}^{N} f(p_j | o_j). \tag{8}$$

Accordingly, the loss function of the mixture density network can be expressed using the logarithm of the likelihood function as:

$$Loss = -\ln(L(\theta)) = -\frac{1}{N} \sum_{j=1}^{N} \ln(f(p_j | o_j)). \tag{9}$$

The network is trained using the gradient descent algorithm to minimize the loss function and obtain the optimal network parameters.

D. Unfolding Action Transfer

The grasping and placing points are obtained through the unfolding policy, but achieving the complete unfolding skill requires further obtaining the trajectory between the two points through demonstrations. The main issue in trajectory-based demonstration learning for skill transfer is how to represent skills [27]. The dynamic motion primitive (DMP) [28] model is an algorithm that can mimic various types of motion trajectories. It is characterized by high efficiency, generation of continuous trajectories, and ease of generalization. Currently, it is widely applied. Therefore, this study employs the DMP algorithm to learn the unfolding actions. Specifically, during the model training phase, human-demonstrated trajectories are input into the DMP model. According to the paper [28], with given DMP model parameters $\alpha_a = 25$, $\beta_a = \alpha_a/4$, $\alpha_x = 1.0$, $\tau = 1.0$, the forcing term $f(x)$ is calculated. The similar manipulation trajectory to the human demonstrate is output by combining a_0(grasp point G_{pick}), g(placing point G_place), and $f(x)$.

We consider the unfolding distance (the distance between the grasping and placing points) as a parameter of the fabric unfolding task. When changing the unfolding distance, the trajectory shape of fabric unfolding typically undergoes corresponding changes, such as in height and direction. However, the trajectories generalized by the DMP model can only maintain similar variations in direction to the demonstrated trajectories (input to the model), which is insufficient for fabric unfolding tasks. Accordingly, a task parameter weighting-based manipulation generalization method is proposed in accordance with the provided grasp and placement points following the unfolding policy to enhance the generalization performance of the DMP model. The specific process is illustrated in the Fig. 3. First, N demonstration trajectories were collected under different task parameters, which are represented using the DMP model, separately, where the task parameter d denotes the distance between the grasp point and the placement point. The trajectory under the new task parameters d^* can be considered the weighted superposition of these N existing task trajectories. The task parameter weights k_i is judged by the task similarity and k_i are set as

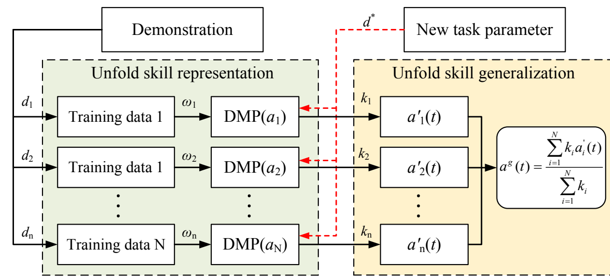

Fig. 3: The method for learning fabric unfolding actions from demonstrations.

$$k_i = \frac{1}{\|d^* - d\| + \varepsilon} \tag{10}$$

ε denotes a minimal positive value to avoid numerical problems during calculations. Lastly, the new unfolding trajectory $a^g(t)$ is written as:

$$a^g(t) = \sum_{i=1}^{N} k_i a_k(t) / \sum_{i=1}^{N} k_i. \tag{11}$$

E. Data Collection

For the collection of training data for unfolding policy, the 2000 RGB-D images of fabric in various states were collected, with fabric corners and edges first marked with different colors. In these images, the edge and corner pixels were extracted based on color to serve as training labels for the segmentation network, while the depth images were used as training data for the segmentation network. Subsequently, an additional 300 fabric images under different packaging sequences were collected. For each image, the grasp and placement points were labeled using the human-machine interaction interface provided by [19], with their pixel coordinates serving as training labels for the mixture density network. The center values of pixel regions containing fabric edge and corner pixels were used as training data for the mixture density network. To enhance the network's generalization, we applied data augmentation techniques such as rotation, scaling, and deformation to the training data.

For the collection of training data for unfolding actions, a reflective marker sphere was affixed to the thumb, the position of the reflective ball was captured using an NDI camera at a capture rate of 120 frames per second, and the motion trajectory was recorded. To mitigate the randomness of individual demonstration trajectories, five sets of motion trajectories were collected for different unfolding distances. To mitigate the randomness of individual demonstration trajectories, multiple

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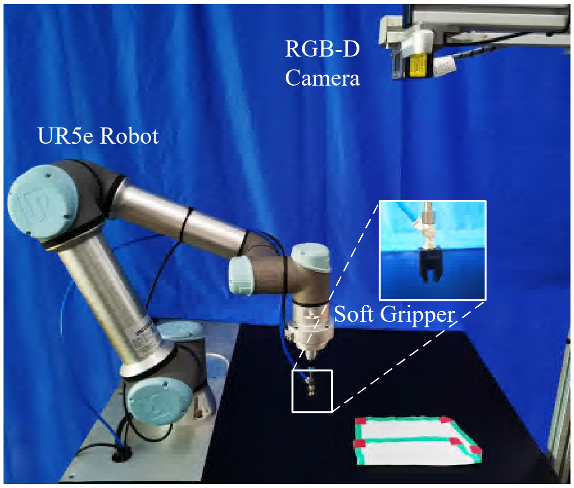


Fig. 4: Fabric Unfolding Experimental Test Platform.

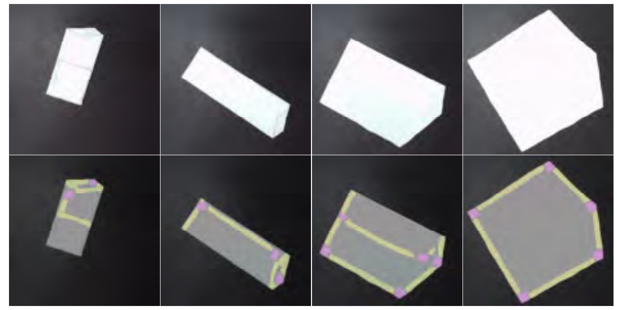
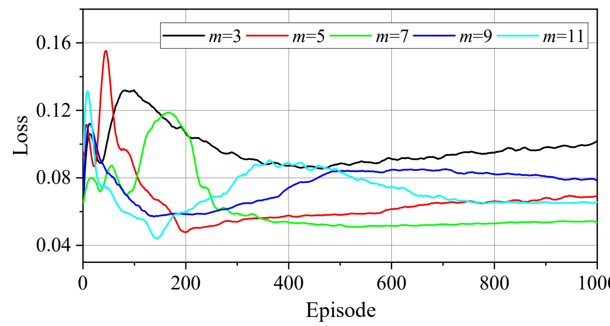
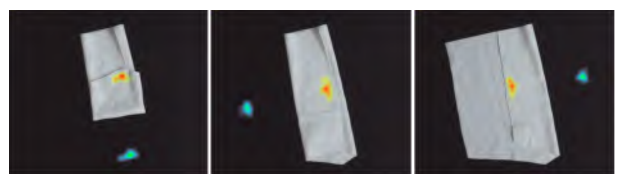


Fig. 5: Visualization of the key feature points. The predicted corners are colored pink, the edges are yellow.



(a) Hyperparameter selection in the mixture density network: We varied the number of Gaussian distributions and computed the network's loss function to find parameters that resulted in good model performance.



(b) Pick and placement points predictions on the test set. Bright red and yellow regions correspond to high probability pick points. Cool green and blue regions correspond to high probability placement points.

Fig. 6: Parameters selection and visualization of unfolding policy.

sets of demonstration trajectories were collected. A Gaussian Mixture Model (GMM) was then used to model and encode all trajectories, followed by the utilization of Gaussian Mixture Regression (GMR) to calculate the average trajectory as the final training data.

F. System Framework

The robot acquires an RGB-D image from the camera and employs a segmentation network, as outlined in [29], to identify fabric edges and corners. Following this, the detected set of corners and edges serves as input to a neural network, which generates mixture density parameters, including Gaussian model means, standard deviations, and relative weights. Utilizing this mixture of Gaussians, the system calculates pick and place points. Finally, the pick-and-place points determined by the network are fed into the dynamic motion primitive model to generate the ultimate unfolding trajectory.

IV. EXPERIMENTAL EVALUATION

The collaborative robot UR5e developed by Universal Robots was employed in the experimental study here. A RGB-D depth camera (FS820-E1) developed by Percipio.XYZ was adopted to capture images of the fabric's state. A soft gripper designed specifically for unfolding and handling multiple layers of fabric was used. A highly wrapped pentagon-shaped fabric unfolding task was illustrated to verify the effectiveness of the proposed framework. The platform is illustrated in Fig. 4.

A. Unfolding Policy Experiments

A white fabric was employed to assess the feature extraction performance of the segmentation network, the results are presented in Fig. 5. In order to select optimal mixture density network parameters, we experimented with the hyperparameters of the mixture density network. As indicated by the results (Fig. 6(a)), the network with 7 Gaussian distributions yielded the optimal performance in testing. Using the network with the above-mentioned parameters, heatmaps corresponding to the probability density were generated on the test set (Fig. 6(b)). The generated heatmaps are capable of capturing the multimodality in human actions.

B. Unfolding Action Experiments

1) Unfolding Action Reproduction: Considering the size of the selected fabric (35cm * 35cm), We collected five demonstration trajectories each at short distance (17.5cm), medium distance (26.25cm), and long distance (35cm), respectively. (Fig. 7(a)-(c)). Then, the data was processed using GMM and GMR, and the results are presented in Fig.8(a)-(c). The motion trajectories are presented in the camera coordinate system. In actual control, the trajectories can be transformed to the robotic arm coordinate system through hand-eye calibration. Based on the smoothed trajectory obtained from GMR fitting, DMP was employed for trajectory learning. As depicted in Fig.7(d)-(e), the reproduction trajectories enable the robot to successfully unfolding the fabric, such that, the basic unfolding

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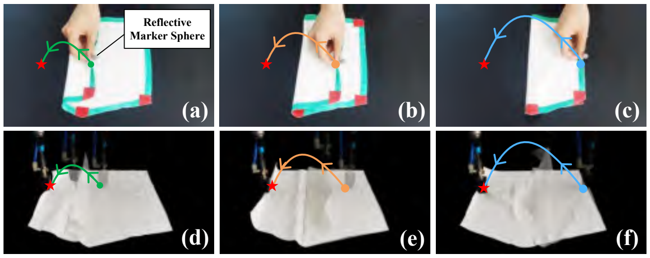

Fig. 7: Demonstration and reproduction of unfolding actions. The demonstrations at short distance, medium distance, and long distance are presented in (a), (b) and (c). The corresponding robot task reproductions are depicted in (d), (e) and (f).

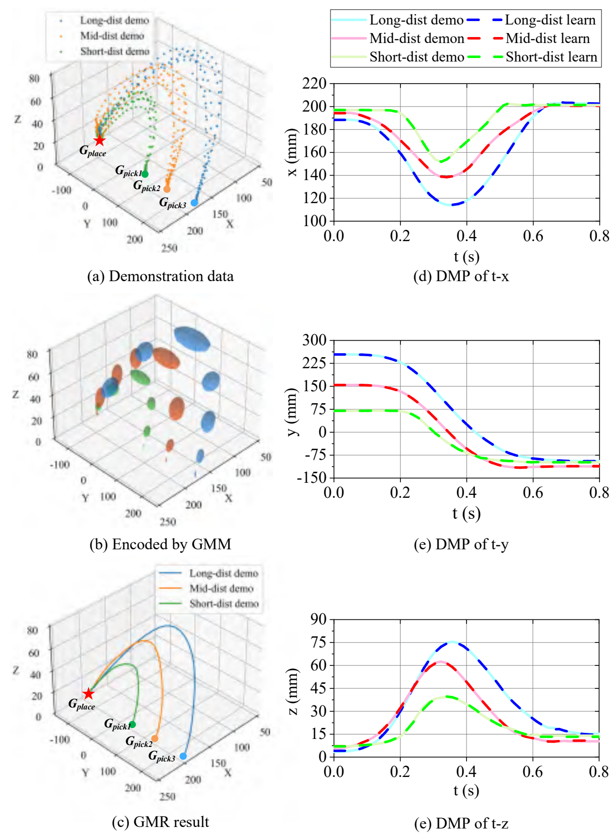

Fig. 8: The result of unfolding action reproduction.

skill can be confirmed to be transferred successfully from human to the robot.

2) Unfolding Action Generalization: First, ablation experiments were performed to examine the performance of the proposed method based on task parameter-weighted generalization. The task of unfolding was tested at a distance of 30cm, 20cm and 15cm, using the multi-task parameter-weighted method and the original single-task parameter DMP method. As depicted in Fig. 9, the trajectory generalized from the original single-task parameter DMP model cannot flatten the fabric. As indicated by the above result, the DMP model, which relies solely on a single demonstration trajectory, is insufficient to fulfill the demands of all unfolding tasks. In normal circumstances, even with different unfolding distances, the unfolding process should maintain a similar direction to ensure the shape of the fabric remains unchanged. The

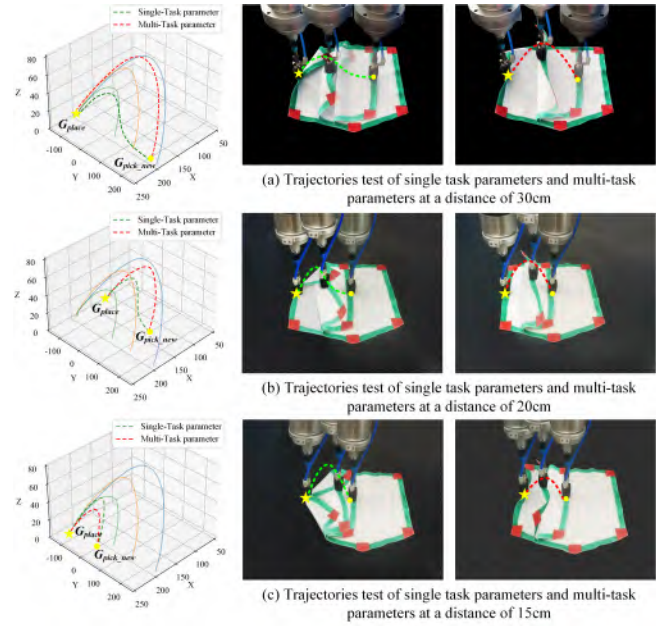

Fig. 9: The result of unfolding action generalization.

proposed multi-task parameter-weighted method is capable of allocating trajectory weights based on task similarity, such that a similar direction can be ensured, and the task can be completed.

Furthermore, the flexibility of the proposed method in generalization was tested. Similarly, as depicted in Fig. 9, the proposed method allows the robot to flexibly adjust the unfolding actions based on the novel grasping and placing points by simultaneously changing the grasping and placing points.

C. The Results of Unfolding Tests and Comparative Analysis.

The unfolding policy is combined with the unfolding action and performed unfolding tasks on wrapped fabric of different sizes and colors. On that basis, the generalization ability of the proposed skill transfer framework across various unfolding tasks is examined. On the one hand, fabrics of different materials were used in three colors, i.e., white, purple, and yellow. On the other hand, we used fabrics of the identical material with three different shapes (i.e., big, normal, and small, scaled proportionally). The respective stage can be broken into a sequence: take a photo to get the grab placement point, grasp the pick point, action towards the place point, then release and return to the ready position. Five sets of experiments were performed with fabrics of different colors and sizes. The results of 20 experiments were summarized for the respective group. The unfolding results are listed in TABLE I where two conditions should be met for successful unfolding: (1) The unfolding strategy at the respective stage is correct; (2) The final coverage of the fabric should exceed 95%. Fig. 10 presents the examples of unfolding fabrics of different sizes. As indicated by the experimental results, the framework is capable of executing sequential unfolding manipulation. Moreover, the unfolding framework exhibits a prominent generalization ability for fabric with a range of colors and sizes. Furthermore, the identical pipeline was applied

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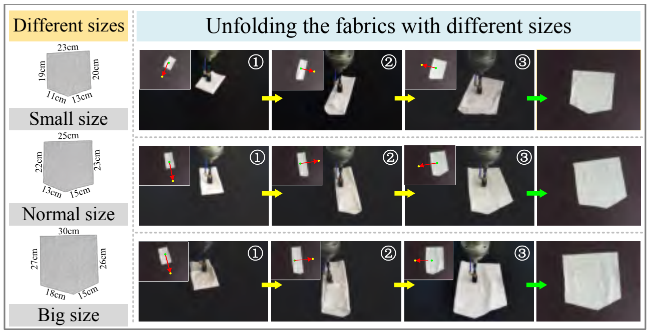

Fig. 10: Results of the experiments for unfolding the fabrics with different sizes.

TABLE I: EXPERIMENTS RESULTS OF UNFOLDING FABRICS

Color	Size	Success
Purple	Normal	20/20
Yellow	Normal	19/20
White	Normal	20/20
White	Small	20/20
White	Big	19/20

to the skill transfer of garment unfolding, and experiments were performed on a small white T-shirt. Fig. 11 presents the experimental results, such that the proposed method is confirmed to be a versatile framework.

Three comparative baseline policies and two ablation policies are proposed, referring to [19], to compare the performance of unfolding manipulation skill transferred by human demonstrations, which are elucidated as follows.

(1) *Random Selection (Random)*: As a simple baseline, a random picking and placing strategy is implemented. Corners or edges on the identified features of the fabric are randomly and uniformly selected as a pick point, and then locations outside the fabric but within the camera's field of view are selected randomly and uniformly as a placement points.
(2) *Human Teleoperation (HUMAN)*: A human selects pick and place points for unfolding through a point-and-click interface.
(3) *Learning Keypoints (KP)*: The five corners of the fabric are classified, the final flattened state serves as a predefined flattening template, and then corners are randomly selected based on the current state for unfolding manipulation, such that the corners are iteratively moving to their target positions on the template.
(4) *Ours without MDN (Our\mdn)*: To assess the influence of our Mixture Density Network (MDN) component, we have conducted experiments with a single Gaussian mixture component, effectively rendering the MDN network ineffective in modeling multimodal distributions. This allows us to compare the performance of our method with and without the MDN.
(5) *Ours without DMP (Our\dmp)*: In this experiment, we have replaced human-demonstrated trajectories learned through Dynamic Movement Primitives (DMP) with simple grasp-move-place encoded trajectories. This evaluation helps us understand the influence of DMP on the effectiveness of our method.

TABLE II: EXPERIMENTS RESULTS OF UNFOLDING FABRICS WITH DIFFERENT POLICY

Policy	Coverage(%)	Actions
Rand	57.0±7.0	20±0
HUMAN	**98.2±1.5**	**5±2**
KP	74.8±8.7	20±0
Ours\mdn	79.4±7.3	20±0
Ours\dmp	91.6±4.7	13±7
Ours	**97.8±2.5**	**7±4**

The methods all start from the initial wrapped state, with an initial coverage rate of around 40%, i.e., the percentage of pixel coverage compared to the fully flattened fabric. A total of 20 experiments were performed on all unfolding methods, allowing a maximum of 20 actions per experiment. However, termination is triggered prematurely if the coverage threshold (maximum flattening of 95%) is reached. The results are listed in TABLE II where averages and standard deviation of the 20 experiments are calculated. Our experimental findings demonstrate that Human teleoperation serves as the performance upper bound, and our proposed method consistently outperforms other algorithms. It achieves performance levels that are comparable to human manipulation within a limited number of actions. Importantly, our experiments confirm that both the MDN and DMP components significantly contribute to the improved performance of our method.

However, the current method also has some limitations. When there are issues with camera depth information or when the detection network's performance is inadequate, it can lead to incorrect fabric feature detection, resulting in erroneous unfolding policy and, consequently, the failure of the unfolding task. Moreover, fabric types are not considered in this study, and different fabric types may have multiple layers of fabric adhesion in the unfolding process, such that the unfolding actions deviate from expectations. In future research, an attempt will be made to optimize the instance segmentation network model, with the aim of improving the accuracy and robustness of feature detection. Furthermore, the unfolding of different material fabrics will be considered, and dynamic manipulation will be applied to the unfolding process.

V. CONCLUSION

In this study, the sequential robotic manipulation for unfolding wrapped fabric is investigated. A framework for human-robot transfer of deformation object manipulation skills is proposed, such that skill learning of unfolding policy and action can be achieved through human demonstrations. Experimental results confirm the effectiveness and practicality of the proposed framework for fabric unfolding tasks, such that the unfolding of fabrics with different colors and sizes can be successfully achieved, and high generalization performance can be achieved. It outperforms other methods in comparison. Furthermore, the proposed framework is a general framework

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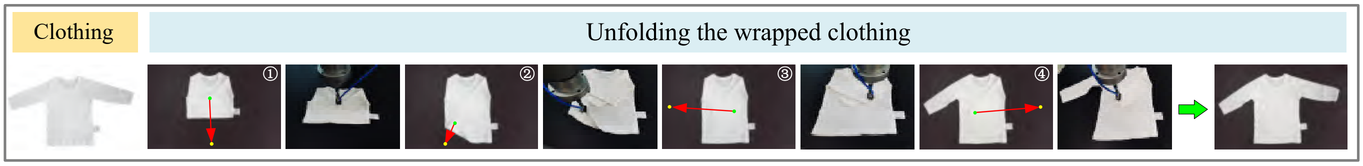

Fig. 11: The proposed framework also applies to sequential garment unfolding.

that can be applied to fabric unfolding and tasks (e.g., flattening and folding garments).

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