

# FabricFolding: Learning Efficient Fabric Folding without Expert Demonstrations

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**Abstract**— Autonomous fabric manipulation is a challenging task due to complex dynamics and self-occlusion during fabric handling. An intuitive method of fabric folding manipulation involves obtaining a smooth and unfolded fabric configuration before the folding process begins. To achieve this goal, we propose an efficient dual-arm manipulation system that combines quasi-static (including pick & place and pick & drag) and dynamic fling actions to flexibly manipulate fabrics into unfolded and smooth structures. Once this is done, keypoints of the fabric are detected, enabling autonomous folding. We evaluate the effectiveness of our proposed system in real-world settings, where it consistently and reliably unfolds and folds various types of fabrics, including challenging situations such as long-sleeved T-shirts with most parts of sleeves tucked inside the garment. Our method exhibits high efficiency in fabric manipulation, even for complex fabric configurations. Our method achieves a coverage rate of 0.822 and a success rate of 0.88 for long-sleeved T-shirts folding.

## I. INTRODUCTION

In recent years, significant progress has been made in the field of robotic manipulation, especially in the handling of rigid objects, and breakthroughs have been made in multiple aspects, such as the re-grasping of complex objects and manipulation in cluttered environments. However, the autonomous manipulation of fabrics still faces significant challenges compared with rigid objects. This is mainly attributed to two key factors: the complex dynamic model of the fabric and the persistent self-occlusion problem during fabric manipulation. Therefore, further research is necessary to overcome these challenges and unlock the full potential of fabric manipulation for robotic applications.

Early fabric manipulation research aims to develop heuristic methods for quasi-static manipulations with a single robotic arm to accomplish tasks such as fabric unfolding [1], smoothing [2], and folding [3]. However, these methods have some inherent limitations, including strong assumptions

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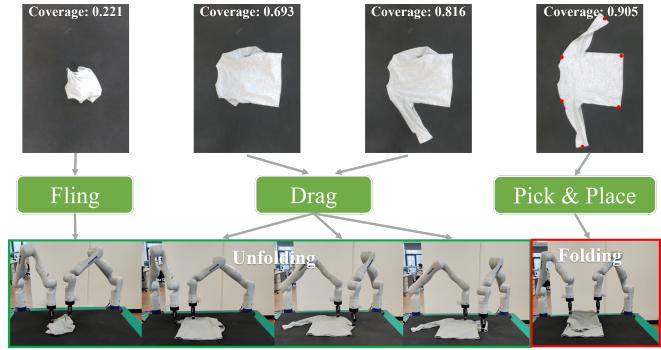


Fig. 1. FabricFold divides the task of fabric folding into two stages for any given initial configuration. The first stage aims to achieve a relatively smooth fabric by dynamically selecting and executing actions (dynamic or quasi-static) based on the current state of the fabric. The second stage commences once the fabric is sufficiently unfolded, and involves performing the folding task by detecting the keypoints of the fabric.

about the initial state and fabric type. Recently, there has been a surge in the development of deep learning techniques for fabric manipulation, where researchers introduce self-supervised learning to replace the need for expert demonstrations [4]. By learning goal-conditioned [5] strategies, it is now possible to effectively fold a single square fabric. However, this quasi-static method requires numerous iterations to obtain relatively smooth fabric. Ha *et al.* [6] propose a dynamic fling method to achieve fabric unfolding, but it cannot be generalized to other tasks. Some researchers have attempted to combine supervised learning from expert demonstrations to realize fabric folding and unfolding [7], but these methods require extensive human annotations, which are time-consuming and error-prone.

In this paper, we propose FabricFolding, a system that efficiently implements fabric folding tasks of arbitrary initial configurations without expert demonstrations. The system comprises two components: fabric unfolding and folding. The first component employs a self-supervised network to learn a set of grasping points from an RGBD input image to smoothen and unfold the fabric from its initial wrinkled state. The second component uses a keypoint detection network to detect the keypoints of the unfolded fabric, enabling the following fabric folding. Fig. 1 shows the FabricFolding work example. The contributions of this paper are summarized as:

- A system that efficiently implements the tasks of fabric unfolding and fabric folding with arbitrary initial configurations without expert demonstrations.
- We propose a self-supervised learning unfolding strat-

egy with a multi-manipulation policy that can choose between dynamic fling and quasi-static (including pick & place and pick & drag) actions to efficiently unfold the fabric, even when partial sleeves of long-sleeved T-shirts are tucked inside the garment.

- To improve the accuracy of fabric keypoint detection, we collect real-world images of different fabric types and develop a keypoint detection dataset for fabric folding.
- Our method has been evaluated on various fabrics using real robotic arms, achieving 0.822 coverage and 0.88 folding success on long-sleeved T-shirts.

Our experiments demonstrate that using both quasi-static (including pick & place and pick & drag) and dynamic fling policies can efficiently enhance the effectiveness of fabric unfolding and streamline subsequent folding tasks. Moreover, the design of our fabric keypoints network eliminates the need for expert demonstrations and provides critical assistance during the fabric's unfolding stage.

The following of this paper is organized as follows. Section II reviews the related work. We present the FabricFolding method in Section III. The corresponding experiments are reported and analyzed in Section IV. Finally, we conclude this work and discuss some future work in Section V.

## II. RELATED WORK

**Fabric unfolding** mainly changes the fabric from an arbitrary crumpled configuration to a fully unfolded configuration. The prior fabric unfolding is based on heuristics and the extraction of some geometric features of the fabric, such as the corners and edges of the fabric [1], [2], [8], [9]. Then these features are utilized to determine the subsequent manipulation to make the fabric as smooth as possible. Recently, Reinforcement learning combines hard-coded heuristics [10] or expert demonstrations [11] to fold fabric. Wu *et al.* [12] introduce self-supervised learning into fabric unfolding to replace the role of expert demonstrations or heuristics. However, the fabric unfolding method based on the quasi-static manipulation may require numerous iterations and interactions before achieving a relatively smooth fabric. This method's effectiveness can be hampered by the limited reach of a robotic arm and a single gripper's operational constraints, rendering the task impractical, particularly for intricate fabrics like T-shirts. Compared with quasi-static manipulation, dynamic manipulation establishes the momentum relationship of the object through the high-speed movement of the robotic arms. Then it operates the fabric to reach the target configuration [13]. Ha *et al.* [6] propose a system based on self-supervised learning that dramatically increases the effectiveness of fabric unfolding by using high-speed fling action to smooth wrinkled fabric. Dynamic flings alone, however, cannot fully unfold complicated textiles, such as long-sleeved T-shirts.

**Fabric folding** initially relies on heuristic algorithms that impose strict predefined constraints on the fabric's initial configuration [3], [7], [14]. Contemporary approaches to

fabric manipulation involve training goal-conditioned policies using reinforcement learning [15], [16], [17], [18], self-supervised learning [5], [19], [20], and imitation learning [10] in either simulated [21], [22], [23] or real robotic arms [5]. However, the strategy of employing simulation data for training essentially cannot achieve the desired effect of the simulation environment due to the sim2real gap on the robotic manipulator [15]. Moreover, a gap remains in the ability to generalize the approach to various types of fabrics [23]. To generalize fabric folding across different types of fabrics, Canberk *et al.* [24] proposed an approach that combines the detection of fabric keypoints with a heuristic for the folding process. In this work, our method also utilizes keypoint detection, which not only helps to deal with the case where the sleeves of long-sleeved T-shirts are inside the clothes but also assures that our method can be adapted to different clothing categories.

## III. METHOD

FabricFolding is a novel approach for folding fabric, which involves breaking down the process into two distinct steps. Firstly, a multi-primitive policy unfolding algorithm is applied to ensure that the fabric is unfolded and smoothed out as much as possible. Subsequently, an adaptive folding manipulation technique is employed, which leverages keypoint detection to facilitate the folding of various types of fabric. FabricFolding can achieve effective and efficient fabric folding by utilizing this two-step approach and the pipeline of the system is shown in Fig. 2.

### A. Multi-primitive Policy Fabric Unfolding

While dynamic actions can efficiently unfold fabrics but cannot entirely unfold complex garments like long-sleeved T-shirt, quasi-static actions are preferable for delicately handling fabrics but are inefficient. We propose combining both quasi-static and dynamic motion to ensure efficient unfurling of a random fabric configuration as much as possible.

FabricFolding utilizes the RGBD image output from the top RealSense 435i camera to calculate the current fabric coverage. When the coverage is below a certain threshold ( $S_1$ ), the robotic arms employ dynamic fling action to unfold the fabric efficiently. As the coverage increases and exceeds  $S_1$ , the system mainly uses quasi-static actions such as pick & place and pick & drag to operate the fabric. Finally, when the coverage is above ( $S_2$ ), the robotic arms rely solely on quasi-static actions to fine-tune the fabric. For long-sleeved T-shirt with most sleeves covered or shrunk inside the cloth, the robotic arms execute pick & drag action to increase the fabric coverage. Moreover, the pick & place action is also a quasi-static manipulation used to sufficiently smooth the fabric. The action policy selection is shown below:

$$A(x) = \begin{cases} \text{fling} & , x \leq S_1 \\ (S_2 - x) \text{ fling} + [1 - (S_2 - x)] \text{ quasi\_static} & , S_1 < x \leq S_2 \\ \text{quasi\_static} & , x > S_2 \end{cases}$$

where  $A$  represents the selected action,  $x$  represents the coverage, quasi\_static includes two actions of pick & place and pick & drag.

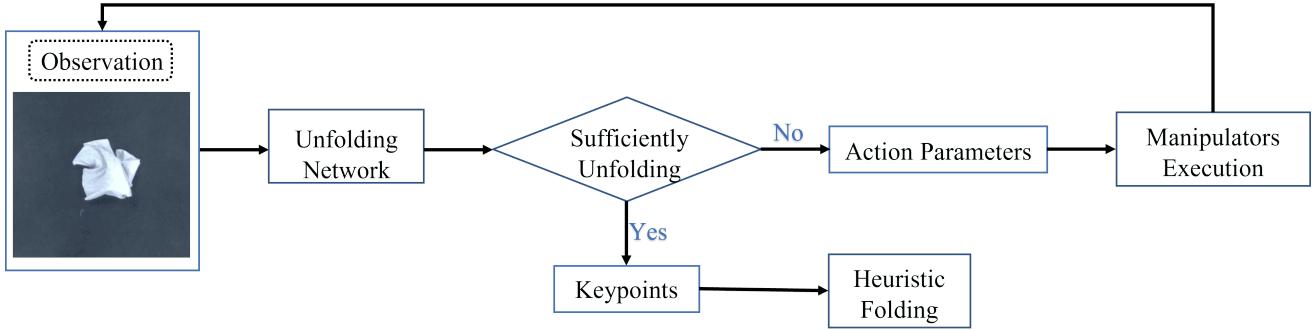


Fig. 2. **FabricFolding pipeline:** The RGB image and depth image obtained from the overhead camera serve as inputs to the unfolding network, which generates a set of keypoints and action parameters. If the fabric is sufficiently unfolded, the system will proceed to fold the fabric using heuristics based on the keypoints. Otherwise, the dual-arm system will execute relevant primitive actions to unfold the fabric.

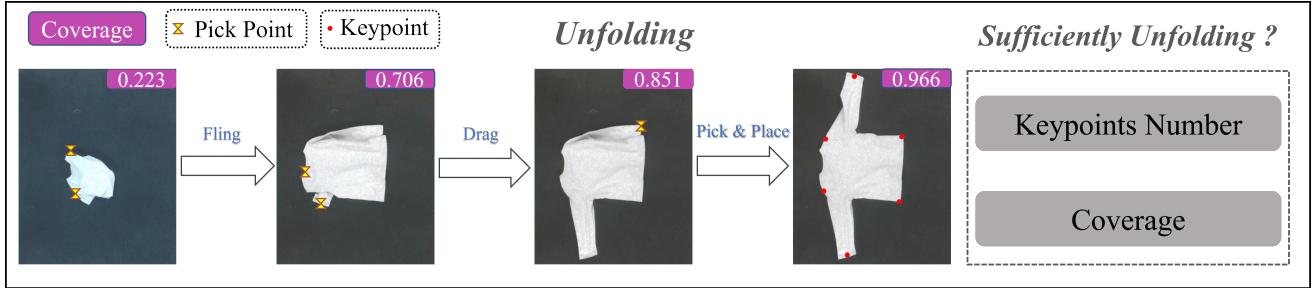


Fig. 3. **Fabric unfolding:** The system adopts a dynamic fling action to unfold the fabric when it is in a low-coverage stacking configuration. However, when the fabric coverage exceeds  $S_1$ , quasi-static actions such as pick & place and pick & drag are mainly used to fine adjustments. If the coverage of the fabric is greater than  $S_2$  and the number of detected keypoints meets the requirements, the fabric is considered to be fully unfolded.

To determine whether the fabric is ready for the downstream folding task, we have two indicators: the current coverage of the fabric and the number of detected keypoints. The fabric is considered smooth enough when the current coverage exceeds threshold  $S_2$  and the number of detected keypoints meets the requirements. Fig. 3 illustrates the fabric unfolding pipeline with a multi-primitive policy. In our experiments,  $S_1 = 0.65$  and  $S_2 = 0.8$  perform best.

1) *Primitive Policy:* To efficiently manipulate the fabric into a desired configuration, we utilize a combination of quasi-static and dynamic primitives that are capable of delicate handling and efficient unfolding, respectively. All action primitives are shown in Fig. 4, and the following are several primitive actions that we have defined:

- **Pick & Place:** The pick & place action is a quasi-static primitive. With a given pick pose and place pose, a single robotic arm grasps the fabric at the pick point, lifts it, moves it over the place point, and releases it. This primitive policy effectively handles situations where the hem or sleeves of the cloth are stacked on top of each other.
- **Drag:** It is a quasi-static primitive policy. Two pick poses are given, and the two robotic arms grasp the two pick points of the fabric, respectively. Then, one robotic arm remains stationary (close to the center of the fabric mask), while the other robotic arm drags the fabric away from the center point of the fabric mask for a certain distance. This primitive policy is effective in dragging

out most of the sleeves that are shrunk inside the long-sleeved T-shirt and dealing with situations where most of the long sleeves are covered by the clothes.

- **Fling:** This is a dynamic primitive policy designed for fabric manipulation. Given two pick poses. After the robotic arms grasp the two pick points of the fabric, the fabric is lifted to a certain height and stretched, while the camera in front of the robotic arms is used to estimate whether the fabric has been fully stretched. Then the two robotic arms simultaneously fling the fabric forward for a certain distance, then retreat for a certain distance while gradually reducing the height, and then release the fabric. This policy efficiently spreads the fabric and increases coverage, but it may not be effective in dealing with smaller wrinkles in the cloth.
- **Fold:** Both robotic arms execute the pick & place primitive action simultaneously. The two pick poses and their corresponding place poses are obtained through keypoint detection of the fabric.

2) *Grasping Policy:* To enhance the effectiveness of fabric unfolding and ensure that the fabric becomes smoother, we have made enhancements to the grasping framework of DextAIRity [25]. These improvements include modifying the grasping action parameters and incorporating an action primitive selection module. These modifications allow for more accurate and efficient predictions of the pick poses required for subsequent primitive actions.

- **Grasping Action Parameterization:** DextAIRity [25]

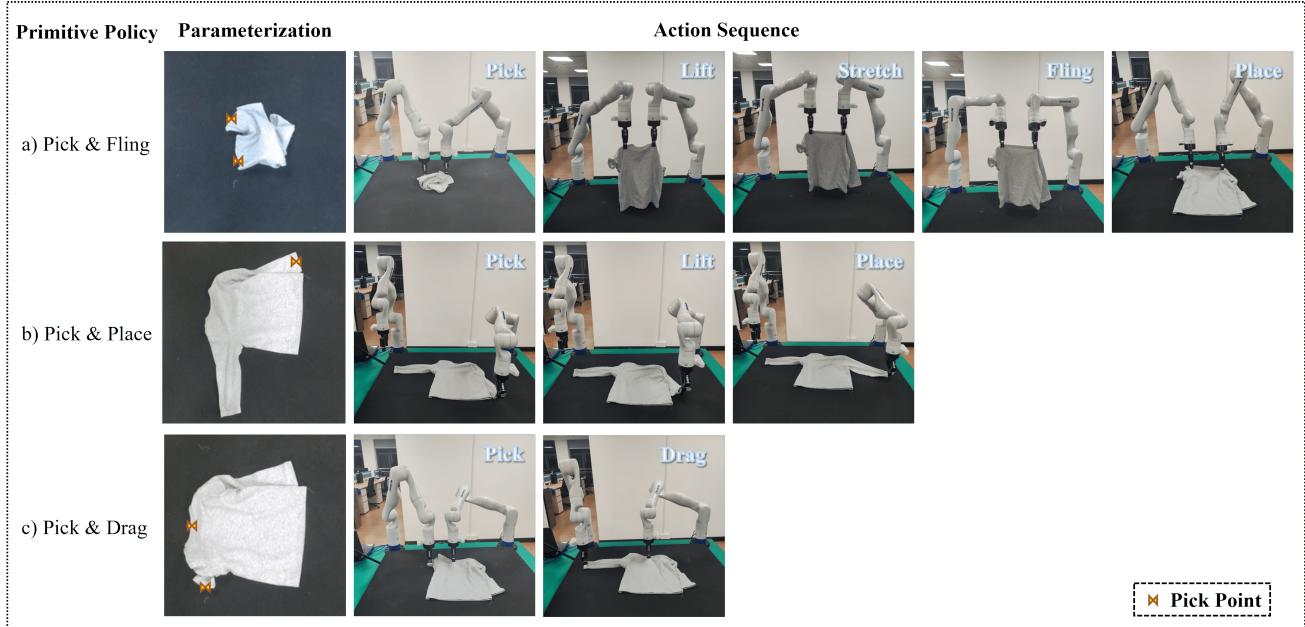


Fig. 4. **Action primitives:** Based on the input received from the overhead RGBD camera, the grasping network can predict a series of pick poses for the upcoming primitive actions.

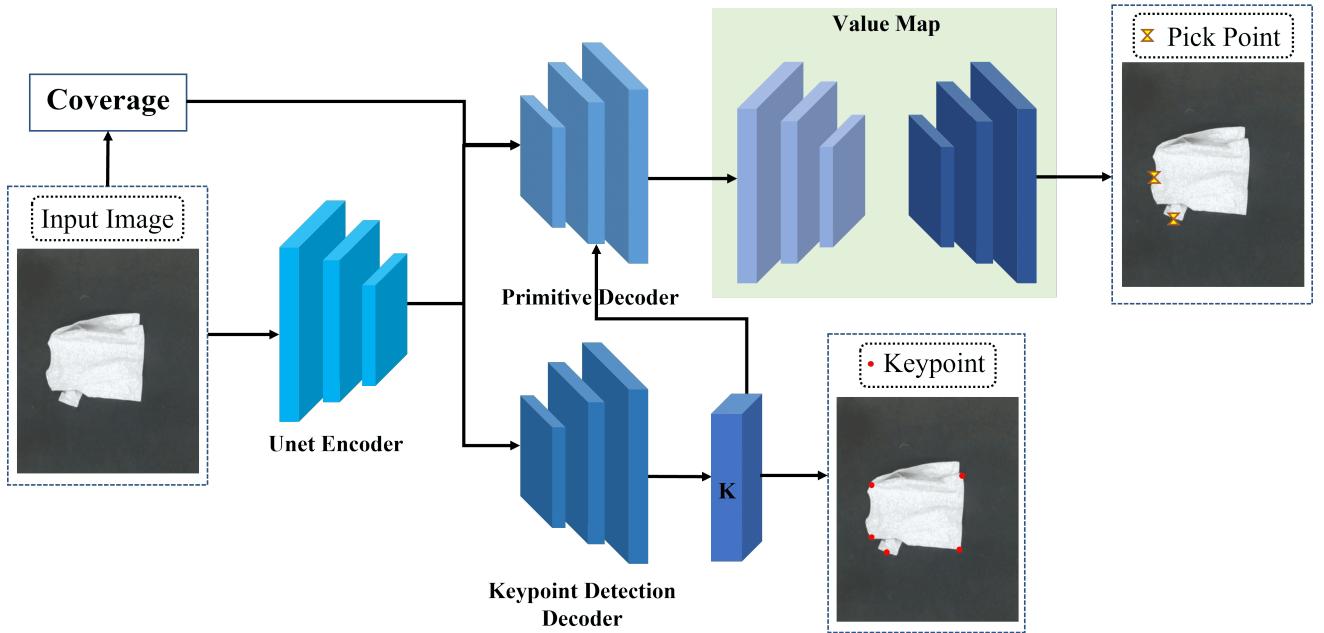


Fig. 5. **FabricFolding:** The RGB image captured by the overhead RealSense 435i camera serves as the input for our system. Our primitive decoder offers three primitive actions and based on the coverage of the fabric and the detected keypoints, either dynamic primitive or quasi-static primitive is chosen appropriately.

made some adjustments to Flingbot’s [6] action parameterization, extending the two grasping positions L and R to the edge of the fabric mask, thereby reducing the likelihood of the gripper grasping multiple layers of fabric. Based on the action parameterization form of DextAIRity ( $C$ ,  $\theta$ ,  $\omega$ ), we have made some minor adjustments, and our action parameters are shown in following equation.

$$P_{epo} = [(x_l, y_l, \phi_l), (x_r, y_r, \phi_r)]$$

Where  $(x, y)$  represents the pixel coordinates of the grasping point and  $\phi$  represents the gripping angle of the gripper in the y-axis. Moreover, we design a constraint where the pick point L ( $x_l, y_l$ ) is always on the left of the center point of L and R. This ensures that the two robotic arms can work simultaneously without any collisions or interference.

- **Unfolding Network:** We design an Unet encoder [26] to extract information from the input image after rotation and scale transformations. After decoding with the primitive decoder, a set of action parameterizations  $P_{epo}$  is obtained using the action value map module with the maximum value as the grasping parameters. To improve the efficiency of fabric unfolding, an appropriate action is selected by feeding the current fabric coverage and detected keypoints as auxiliary inputs to the primitive decoder. The spatial action map [6], [27] is used to better obtain the equivariance between the grasping action and the physical transformation of the fabric. The network structure is shown in Fig. 5.

3) *Training Setting*: Before training the grasping network, the keypoint detection network is trained first through supervised learning. The grasping network is trained using self-supervised learning during the training episode, where the coverage and detected keypoints serve as the supervision signals.

### B. Heuristic Fabric Folding

1) *Dataset for Keypoint Detection*: Due to the sim2real gap, the keypoint detection performance of the fabric is not optimal when using the fabric keypoint dataset generated in the simulation, which includes various configurations of fabric. For example, certain configurations of fabric cannot detect all the expected keypoints. Additionally, there is no existing public dataset that is suitable for keypoint detection in fabric folding tasks. In order to address this issue, we created a fabric keypoint dataset consisting of 1809 images that include four types of long-sleeved T-shirts and ten types of towels. Among them, all fabrics are configured to have a coverage rate of more than 65%. For each fabric configuration, the long-sleeved T-shirt is rotated 360° for sampling, with each rotation being 10°; while the towel is rotated 180°, with each rotation being 18°.

For towels, we define four keypoints, starting with the upper left corner of the image as corner1, and continuing in clockwise order as corner2, corner3, and corner4. Long-sleeved T-shirts have five key points, includ-

ing right\_shoulder, left\_shoulder, right\_sleeve, right\_waist, left\_waist, and left\_sleeve, which is marked according to the outward direction of the vertical image. An example of the fabric keypoint dataset can be seen in Fig. 7.

2) *Keypoint Detection Network*: The keypoint detection network we designed uses Unet [26] as the backbone. We divide the data into training and validation sets in an 8:2 ratio. After training for 4 hours on an NVIDIA RTX3080Ti, the average pixel error of the detected keypoints on a 640x480 validation set image can be guaranteed to be within 3 pixels.

3) *Heuristic Folding*: Taking inspiration from the Cloth Funnels [24] heuristic folding method, as depicted in Fig. 6, we use a similar approach for folding a long-sleeved T-shirt. Initially, we utilize the pick & place action primitive to fold the two sleeves of the garment onto the main part of the garment. Following this, we pick the keypoints of the shoulders and place them at the keypoints of the waist.

## IV. EVALUATION

### A. Metrics

We evaluate FabricFolding on both the fabric unfolding and fabric folding tasks. Performance in the fabric unfolding task is evaluated based on the coverage achieved at the end of each episode. Furthermore, we evaluate the algorithm’s success rate for the folding task, as well as its generalization ability to handle unseen fabrics on real robotic arms. To reduce experimental randomness, each experiment is repeated 25 times, and the weighted average of all results is calculated. If the folding result is deemed a failure by the majority of the 5 judges or if the folding cannot be completed after 20 action sequences, the experiment is considered a failure.

### B. Fabric Unfolding

To optimize the grasping network, we use  $S_1$  as a threshold to select between dynamic and quasi-static primitives. To determine the optimal value for  $S_1$ , we compare the coverage achieved after 5 primitive actions for different values of  $S_1$ . As shown in Fig. 8, the best folding efficiency is achieved when  $S_1 = 0.65$ .

Dynamic action can efficiently unfold the fabric, and quasi-static actions can make some fine adjustments to the fabric. To verify the effectiveness of our multi-primitive policy mechanism, we conduct experiments on long-sleeved T-shirts with different coverage. Table I shows that when the fabric has high initial coverage and mild self-occlusion, the quasi-static actions have better coverage compared to the dynamic action. On the other hand, when the fabric has low initial coverage and severe self-occlusion, the dynamic action effectively improves coverage. This observation is in line with the findings of Flingbot [6]. It also demonstrates that our multi-primitive policy outperforms a single primitive action in achieving higher coverage, regardless of the initial coverage of the fabric. This highlights the effectiveness of the multi-primitive policy in enhancing fabric coverage.

Table II presents the coverage attained by various algorithms on diverse real-world fabrics with initial coverage less than 30%. Unfortunately, the reproduction of SpeedFold [7]

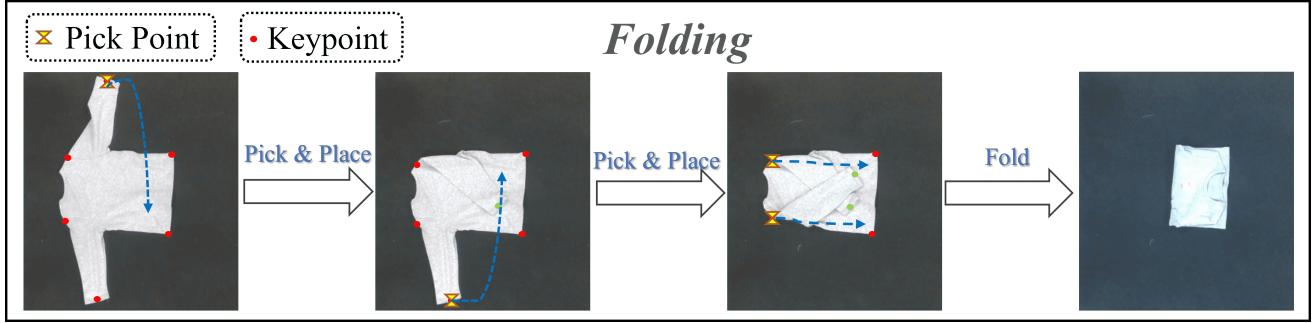


Fig. 6. **Fabric Folding:** Based on the input received from the overhead RGBD camera, the grasp network can predict a series of pick poses for the upcoming primitive actions.

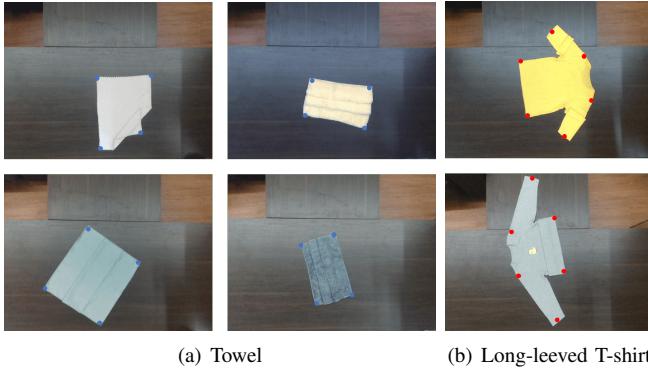


Fig. 7. Sample keypoint detection dataset for fabric folding

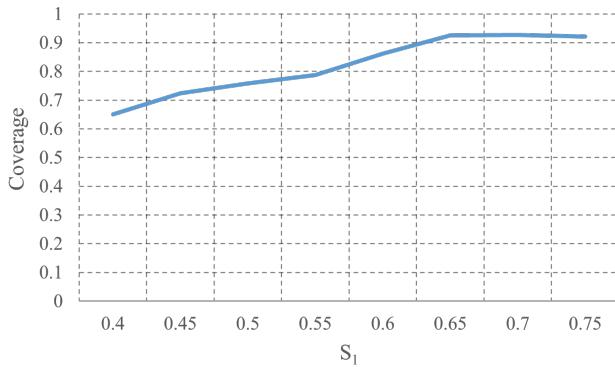


Fig. 8. The normalized coverage of a long-sleeved T-shirt (Initial coverage is 0.4) is evaluated after 5 primitive actions under various threshold parameters  $S_1$ .

is challenging despite being open-sourced, and the code for Canberk [24] is not available. Thus, the data presented in this table are the original results reported in their respective papers. To ensure a fair comparison, the fabrics tested in our algorithm are chosen to be as similar as possible to those used in the previous works. The results in Table II imply that our algorithm outperforms the other algorithms in terms of unfolded coverage on both towels and long-sleeved T-shirts.

The success rate of fabric folding is a crucial performance indicator. As shown in Table III, the complexity of the fabric has a direct effect on the success rate of folding, which

TABLE I  
VALIDITY OF PRIMITIVES: THE FABRIC IS A LONG-SLEEVED T-SHIRT.

Fabric	Primitives	Cov. $\uparrow$
Ini_cov $\geq 0.7$	Quasi-static primitive	0.872
	Pick & Place	0.876
	Pick & Drag	0.818
Ini_cov $\leq 0.3$	Dynamic primitive	P&P+P&D+Fling
	Fling	0.902
	Muti-primitive	
Ini_cov $\geq 0.7$	Quasi-static primitive	0.624
	Pick & Place	0.636
	Pick & Drag	0.742
Ini_cov $\leq 0.3$	Dynamic primitive	P&P+P&D+Fling
	Fling	0.822
	Muti-primitive	

TABLE II  
REAL-WORLD COVERAGE: \* INDICATES THE ORIGINAL DATA IN PAPER

Approach	Fabric	Cov. $\uparrow$
Flingbot [6]	Towel	0.905
	long-sleeved T-shirts	0.742
SpeedFold [7]	Towel	0.92*
	T-shirts	0.8*
Canberk [24]	long-sleeved T-shirts	\
	Towel	0.806*
Our	Towel	0.958
	long-sleeved T-shirts	0.822

decreases continuously as the fabric complexity increases. In particular, when dealing with fabrics that are not whole pieces, such as long-sleeved T-shirts with two sleeves, it is common for the fabric to self-occlude during the folding process to reduce the success rate. Among the four algorithms compared, our algorithm outperformed the others in terms of the success rate achieved in folding towels and long-sleeved T-shirts.

## V. CONCLUSIONS

In this paper, we propose FabricFolding, a system that can efficiently fold arbitrary configuration fabric without expert demonstrations, which includes a multi-primitive policy unfolding module and a keypoint detection-based heuristic folding module. Additionally, we have developed a keypoint detection dataset for fabric folding to enhance the precision of fabric keypoint detection, consisting of approximately

TABLE III

FOLDING'S SUCCESS: \* INDICATES THE ORIGINAL DATA IN PAPER

Approach	Fabric	Success ↑
Doumanoglou [3]	Towel	0.78*
	T-shirts	0.66*
SpeedFold [7]	T-shirt long-sleeved T-shirts	<b>0.93*</b> \
Canberk [24]	Towel long-sleeved T-shirts	\ 0.878*
Our	Towel long-sleeved T-shirts	<b>0.92</b> <b>0.88</b>

2,000 images. Our algorithm achieves a coverage rate of 0.822 and a folding success rate of 0.88 for long-sleeved T-shirts. During our experiments, we find that when the two pick points of fling are at diagonally opposite corners of the fabric, it can be challenging to fully unfold the fabric even after multiple interactions. In the future, we plan to investigate this issue and develop solutions to address it.

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