

VisuoSpatial Foresight for Multi-Step, Multi-Task Fabric Manipulation

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Abstract—Robotic fabric manipulation has applications in home robotics, textiles, senior care and surgery. Existing fabric manipulation techniques, however, are designed for specific tasks, making it difficult to generalize across different but related tasks. We extend the Visual Foresight framework to learn fabric dynamics that can be efficiently reused to accomplish different fabric manipulation tasks with a single goal-conditioned policy. We introduce VisuoSpatial Foresight (VSF), which builds on prior work by learning visual dynamics on domain randomized RGB images and depth maps simultaneously and completely in simulation. We experimentally evaluate VSF on multi-step fabric smoothing and folding tasks against 5 baseline methods in simulation and on the da Vinci Research Kit (dVRK) surgical robot without any demonstrations at train or test time. Furthermore, we find that leveraging depth significantly improves performance. RGBD data yields an 80% improvement in fabric folding success rate over pure RGB data. Code, data, videos, and supplementary material are available at <https://sites.google.com/view/fabric-vs/>.

I. INTRODUCTION

Advances in robotic manipulation of deformable objects has lagged behind work on rigid objects due to the far more complex dynamics and configuration space. Fabric manipulation in particular has applications ranging from senior care [18], sewing [47], ironing [30], bed-making [50] and laundry folding [35, 29, 66, 51] to manufacturing upholstery [59] and handling surgical gauze [55]. However, prior work in fabric manipulation has generally focused on designing policies that are only applicable to a *specific* task via manual design [35, 29, 66, 51] or policy learning [49, 65].

The difficulty in developing accurate analytical models of highly deformable objects such as fabric motivates using data-driven strategies to estimate models, which can then be used for general purpose planning. While there has been prior work in system identification for robotic manipulation [28, 20, 5, 43, 8, 9], many of these techniques rely on reliable state estimation from observations, which is especially challenging for deformable objects. One popular alternative is visual foresight [15, 17], which uses a large dataset of self-supervised interaction data in the environment to learn a visual dynamics model directly from raw image observations and has shown the ability to generalize to a wide variety of environmental conditions [12]. This model can then be used for planning to perform different tasks at test time. The technique has been successfully applied to learning the dynamics of complex

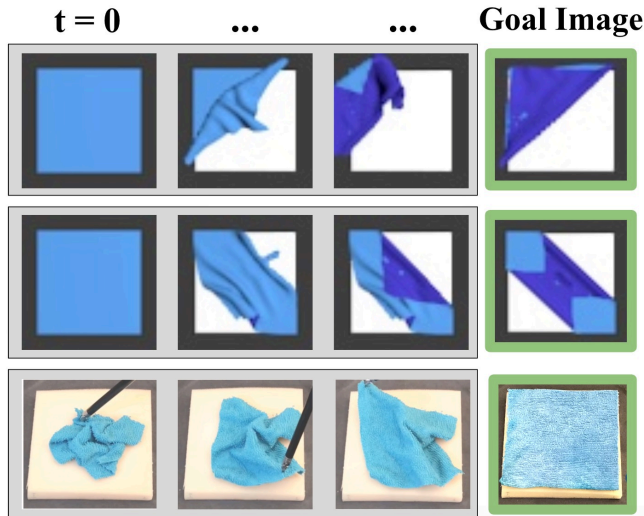


Fig. 1: Using VSF on domain randomized RGBD data, we learn a goal-conditioned fabric manipulation policy in simulation without any task demonstrations. We evaluate the same policy on several goal images in simulation (top two rows) and on the physical da Vinci surgical robot (bottom row). The rows display the RGB portions of subsampled frames from episodes for folding, double folding, and smoothing, respectively, toward the goal images in the right column.

tasks, such as pushing and basic fabric folding [15, 17]. However, two limitations of prior work in visual foresight are: 1) the data requirement for learning accurate visual dynamics models is often very high, requiring several days of continuous data collection on real robots [12, 15], and 2) while prior work reports experiments on basic fabric manipulation tasks [15], these are relatively short-horizon tasks with a wide range of valid goal images.

In this work, we present a system (Figure 1) that takes steps towards addressing these challenges by integrating RGB and depth sensing to learn visual-spatial (visuospatial) dynamics models in simulation using only random interaction data for training and domain randomization techniques for sim-to-real transfer. This paper introduces: 1) “VisuoSpatial Foresight” on domain randomized, simulated RGB and depth data to facilitate rapid data collection and transfer to physical systems, 2) simulated experiments demonstrating how the learned dynamics can be used to define a goal-conditioned fabric manipulation policy which can perform a variety of multi-step fabric smoothing and folding tasks, and 3) results suggesting that the learned policy transfers to a real physical system with promising smoothing and folding results. In

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physical smoothing experiments, the learned policy is able to outperform an imitation learning baseline by 2% despite using no task demonstrations.

II. RELATED WORK

Manipulating fabric is a long-standing challenge in robotics. Fabric smoothing in particular has received attention since it helps standardize the configuration of the fabric for subsequent tasks such as folding [6, 46]. A popular approach in prior work is to first hang fabric in the air and allow gravity to “vertically smooth” it [40, 27, 26, 14]. Maitin-Shepard et al. [32], use this approach to achieve a 100% success rate in single-towel folding. In contrast, the approach we present is targeted towards larger fabrics like blankets [50] and for single-armed robots which may have a limited range of motion, making such “vertical smoothing” infeasible. Similar work on fabric smoothing and folding, such as by Balaguer and Carpin [2] and Jia et al. [22, 23] assume the robot is initialized with the fabric already grasped, while we initialize the robot’s end-effector away from the fabric. Willimon et al. [64] and Sun et al. [53, 54] address a similar problem setting as we do, but with initial fabric configurations much closer to fully smoothed than those we consider.

There has been recent interest in learning sequential fabric manipulation policies with fabric simulators. For example, Seita et al. [49] and Wu et al. [65] learn fabric smoothing in simulation, the former using DAgger [44] and the latter using model-free reinforcement learning (MFRL). Similarly, Matas et al. [34] and Jangir et al. [21] learn policies for folding fabrics using MFRL augmented with task-specific demonstrations. All of these works obtain large training datasets from fabric simulators; examples of simulators with support for fabric include ARCSim [38], MuJoCo [58], Py-Bullet [11], and Blender [10]. While these algorithms achieve impressive results, they are designed or trained for specific fabric manipulation tasks (such as folding or smoothing), and do not reuse learned structure to generalize to a wide range of tasks. This motivates learning fabric dynamics to enable more general purpose fabric manipulation strategies.

Model-predictive control (MPC) is a popular approach for leveraging learned dynamics for robotics control that has shown success in learning robust closed-loop policies even with substantial dynamical uncertainty [56, 3, 16, 52]. However, many of these prior works require knowledge or estimation of underlying system state, which can often be infeasible or inaccurate. Finn and Levine [17] and Ebert et al. [15] introduce *visual foresight*, and demonstrate that MPC can be used to plan over learned video prediction models to accomplish a variety of robotic tasks, including deformable object manipulation such as folding pants. However, the trajectories shown in Ebert et al. [15] are limited to a single pick and pull, while we focus on longer horizon sequential tasks that are enabled by a pick-and-pull action space rather than direct end effector control. Furthermore, the cloth manipulation tasks reported have a wide range of valid goal configurations, such as covering a utensil with a towel or moving a pant leg

upwards. In contrast, we focus on achieving precise goal configurations via multi-step interaction with the fabric. Prior work on visual foresight [17, 15, 12] also generally collects data for training visual dynamics models in the real world, which is impractical and unsafe for robots such as the da Vinci surgical robot due to the sheer volume of data required for the technique (on the order of 100,000 to 1 million actions, often requiring several days of physical interaction data [12]). One recent exception is the work of Nair et al. [37] which trains visual dynamics models in simulation for Tetris block matching. Finally, prior work in visual foresight utilizes visual dynamics model for RGB images, but we find that depth data provides valuable geometric information for cloth manipulation tasks.

III. PROBLEM STATEMENT

We consider learning goal-conditioned fabric manipulation policies that enable planning to specific fabric configurations given a goal image of the fabric in the desired configuration. We define the fabric configuration at time t as ξ_t , represented via a mass-spring system with an $N \times N$ grid of point masses subject to gravity and Hookean spring forces. Due to the difficulties of state estimation for highly deformable objects such as fabric, we consider overhead RGBD observations $\mathbf{o}_t \in \mathbb{R}^{56 \times 56 \times 4}$, which consist of three-channel RGB and single-channel depth images.

We assume tasks have a finite task horizon T and can be achieved with a sequence of actions (from a single robot arm) which involve grasping a specific point on the fabric and pulling it in a particular direction, which holds for common manipulation tasks such as folding and smoothing. We consider four dimensional actions,

$$\mathbf{a}_t = \langle x_t, y_t, \Delta x_t, \Delta y_t \rangle. \quad (1)$$

Each action \mathbf{a}_t at time t involves grasping the top layer of the fabric at coordinate (x_t, y_t) with respect to an underlying background plane, lifting, translating by $(\Delta x_t, \Delta y_t)$, and then releasing and letting the fabric settle. When appropriate, we omit the time subscript t for brevity.

The objective is to learn a goal-conditioned policy which minimizes some goal conditioned cost function $c_g(\tau)$ defined on realized interaction episodes with goal g and episode τ , where the latter in this work consists of one or more images.

IV. APPROACH

A. Goal Conditioned Fabric Manipulation

To learn goal-conditioned policies, we build on the visual foresight framework introduced by Finn and Levine [17]. Here, a video prediction model (also called a visual dynamics model) is trained, which, given a history of observed images and a sequence of proposed actions, generates a sequence of predicted images that would result from executing the proposed actions in the environment. This model is learned from random interaction data of the robot in the environment. Then, MPC is used to plan over this visual dynamics model with some cost function evaluating the discrepancy between

predicted images and a desired goal image. In this work, we: 1) learn a visual dynamics model on RGBD images instead of RGB images as in prior work, and 2) learn visual dynamics entirely in simulation. We find that these choices improve performance on complex fabric manipulation tasks and accelerate data collection while limiting wear and tear on the physical system.

To represent the dynamics of the fabric, we train a deep recurrent convolutional neural network [19] to predict a sequence of RGBD output frames conditioned on a sequence of RGBD context frames and a sequence of actions. This visuospatial dynamics model, denoted as f_θ , is trained on thousands of self-supervised simulated episodes of interaction with the fabric, where an episode consists of a contiguous trajectory of observations and actions. We use Stochastic Variational Video Prediction [1] as discussed in Section IV-D.

For planning, we utilize a goal-conditioned planning cost function $c_g(\hat{\mathbf{o}}_{t+1:t+H})$ with goal g , which in the proposed work is a target image $\mathbf{o}^{(g)}$. The cost is evaluated over the H -length sequence of predicted images $\hat{\mathbf{o}}_{t+1:t+H}$ sampled from f_θ conditioned on the current observation \mathbf{o}_t and some proposed action sequence $\hat{\mathbf{a}}_{t:t+H-1}$. While there are a variety of cost functions that can be used for visual foresight [15], we utilize the Euclidean pixel distance between the final predicted RGBD image at timestep t and the goal image $\mathbf{o}^{(g)}$ across all 4 channels as this works well in practice for the tasks we consider. Precisely, we define the planning cost as follows:

$$c_g(\hat{\mathbf{o}}_{t+1:t+i^*}) = \|\mathbf{o}^{(g)} - \hat{\mathbf{o}}_{t+i^*}\|_2 \quad (2)$$

where

$$i^* = \min\{H, T - t\} \quad (3)$$

As in prior work [17, 15, 12], we utilize the cross entropy method [45] to plan action sequences to minimize $c_g(\hat{\mathbf{o}}_{t+1:t+H})$ over a receding H -step horizon at each time t . See Figure 2 for intuition on the VSF planning phase.

B. Fabric Simulator

The fabric and robot simulator we use is built on top of the open-source code from Seita et al. [49]. We briefly review the most relevant aspects of the simulator, with emphasis on the changes from the original.

1) *Simulator Design*: VisuoSpatial Foresight requires a large amount of training data to predict full-resolution RGBD images. Since getting real data is cumbersome and imprecise, we use a fabric simulator to generate data quickly and efficiently. We use the fabric simulator from Seita et al. [49], which was shown to be sufficiently accurate for learning reasonable fabric smoothing policies with imitation learning.

The fabric is represented as a mass-spring system with a 25×25 grid of point masses [42] with springs connecting it to its neighbors. Verlet integration [62] is used to update point mass positions using finite difference approximations and self-collision is implemented by adding a repulsive force between points that are too close [4]. Damping is also applied to simulate friction. See Section II and Appendix A for further

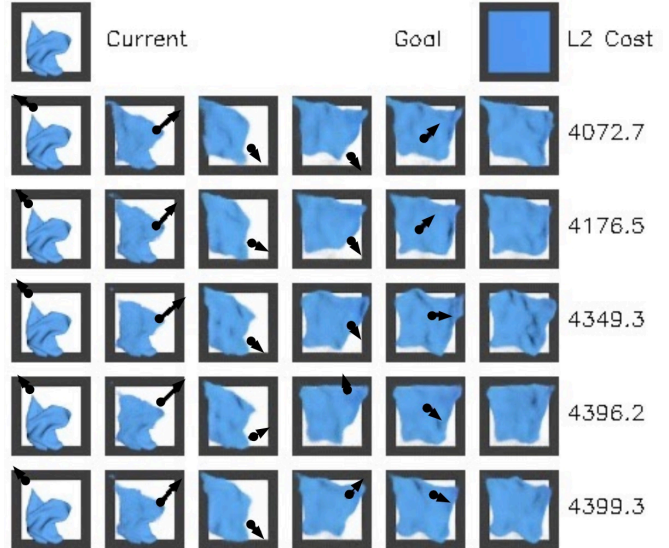


Fig. 2: Real plans generated by the system at test time for the smoothing task. We generate action sequences with the Cross Entropy Method (CEM) to approximately minimize the cost function, which evaluates L2 distance between the final image in the predicted trajectory and a provided goal image. Here we show the five CEM trajectories with the lowest cost, where the image sequences in each row are outputs of the video prediction model and the black arrows are the pick-and-pull actions projected onto the images.

detail on alternate fabric simulators and the simulation used in this work. (The appendix is available on the project website <https://sites.google.com/view/fabric-vsff/>).

2) *Manipulation Details*: Similar to [49], actions are represented as four-dimensional vectors as described in Section III with pick point $(x, y) \in [-1, 1]^2$ and pull vector $(\Delta x, \Delta y) \in [-0.4, 0.4]^2$. We use the open-source software Blender to render (top-down) image observations \mathbf{o}_t of the fabric. We make several changes for the observations relative to [49]. First, we use four-channel images: three for RGB, and one for depth. Second, we reduce the size of observations to 56×56 from 100×100 , to make it more computationally tractable to train visual dynamics models. Finally, to enable transfer of policies trained in simulation to the real-world, we adjust the domain randomization [57] techniques so that color, brightness, and positional hyperparameters are fixed *per episode* to ensure that the video prediction model learns to only focus on predicting changes in the fabric configuration, rather than changes due to domain randomization. See Appendix C for more details on the domain randomization parameters.

C. Data Generation

We collect 7,115 episodes of length 15 each for a total of 106,725 $(\mathbf{o}_t, \mathbf{a}_t, \mathbf{o}_{t+1})$ transitions for training the visuospatial dynamics model. The episode starting states are sampled from three tiers of difficulty with equal probability. These tiers are the same as those in [49], and largely based on *coverage*, or the amount that a fabric covers its underlying plane:

- **Tier 1 (Easy): High Coverage.** $78.3 \pm 6.9\%$ initial coverage, all corners visible. Generated by two short

random actions.

- **Tier 2 (Medium): Medium Coverage.** $57.6 \pm 6.1\%$ initial coverage, one corner occluded. Generated by a vertical drop followed by two actions to hide a corner.
- **Tier 3 (Hard): Low Coverage.** $41.1 \pm 3.4\%$ initial coverage, 1-2 corners occluded. Generated by executing one action very high in the air and dropping.

All data was generated using the following policy: execute a randomly sampled action, but resample if the grasp point (x, y) is not within the bounding box of the 2D projection of the fabric, and take the additive inverse of Δx and/or Δy if $(x + \Delta x, y + \Delta y)$ is out of bounds (off the plane by more than 20% of its width, causing episode termination).

D. VisuoSpatial Dynamics Model

Due to the inherent stochasticity in fabric dynamics, we use Stochastic Variational Video Prediction (SV2P) from Babaeizadeh et al. [11], a state-of-the-art method for action-conditioned video prediction. Here, the video prediction model f_θ is designed as a latent variable model, enabling the resulting posterior distribution to capture different modes in the distribution of predicted frames. Precisely, [11] trains a generative model which predicts a sequence of n output frames conditioned on a context vector of m frames and a sequence of actions starting from the most recent context frame. Since the stochasticity in video prediction is often a consequence of latent events not directly observable in the context frames as noted in [11], predictions are conditioned on a vector of latent variables $z_{t+m:t+m+n-1}$, each sampled from a fixed prior distribution $p(z)$. See Babaeizadeh et al. [11] for more details on the model architecture and training procedure. For this work, we utilize the SV2P implementation provided in [60]. This gives rise to the following generative model.

$$p_\theta(\hat{\mathbf{o}}_{t+m:t+m+n-1} | \hat{\mathbf{a}}_{t+m-1:t+m+n-2}, \mathbf{o}_{t:t+m-1}) = p(z_{t+m}) \prod_{t'=t+m}^{t+m+n-1} p_\theta(\hat{\mathbf{o}}_{t'} | \hat{\mathbf{o}}_{t':t'-1}, z_{t'}, \hat{\mathbf{a}}_{t'-1}). \quad (4)$$

Here $\mathbf{o}_{t:t+m-1}$ are image observations from time t to $t+m-1$, $\hat{\mathbf{a}}_{t+m-1:t+m+n-2}$ is a candidate action sequence at timestep $t+m-1$, and $\hat{\mathbf{o}}_{t+m:t+m+n-1}$ is the sequence of predicted images. Since the generative model is trained in a recurrent fashion, it can be used to sample an H -length sequence of predicted images $\hat{\mathbf{o}}_{t+m:t+m+H-1}$ for any $m > 0, H > 0$ conditioned on a current sequence of image observations $\mathbf{o}_{t:t+m-1}$ and an $H-1$ length sequence of proposed actions taken from \mathbf{o}_{t+m-1} , given by $\hat{\mathbf{a}}_{t+m-1:t+m+H-2}$.

During training, we set the number of context frames $m = 3$ and number of output frames $n = 7$ (the SV2P model learns to predict 7 frames of an episode from the preceding 3 frames). We train on domain-randomized RGBD data, where we randomize fabric color (in a range centered around blue), shading of the plane, image brightness, and camera pose. At test time, we utilize only one context frame $m = 1$ and a planning horizon of $n = 5$ output frames. This yields the model $p_\theta(\hat{\mathbf{o}}_{t+1:t+5} | \hat{\mathbf{a}}_{t:t+4}, \mathbf{o}_t)$.

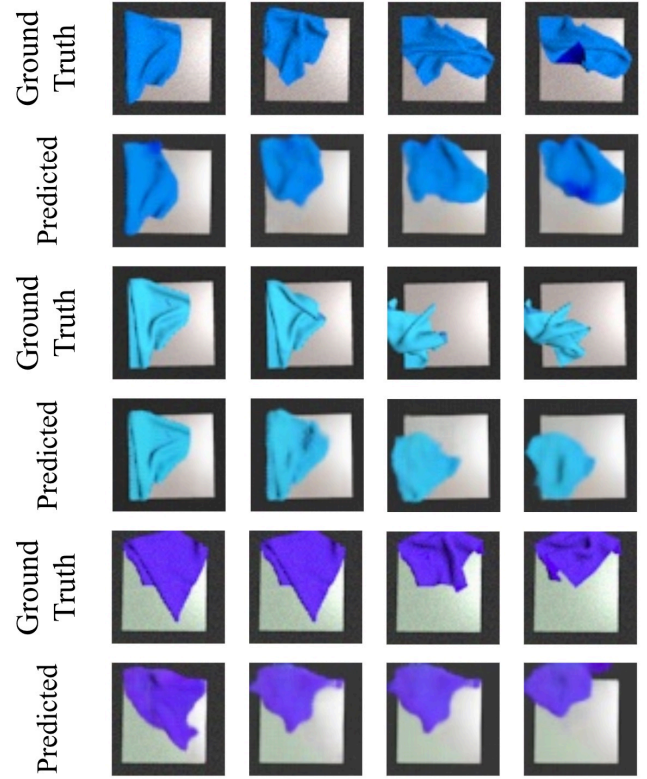


Fig. 3: Three pairs of a sequence of four simulated image observations in ground truth compared against a sequence of the corresponding predictions from the visuospatial dynamics model. Here we show the RGB portion of the observations. Each episode is a test example and has randomized camera angle, fabric color, brightness, and shading. Prediction quality varies and generally gets blurrier across time, but is sufficient for planning.

E. VisuoSpatial Foresight

To plan over the learned visuospatial dynamics model, we leverage the Cross-Entropy Method (CEM) [45] as in [15]. CEM repeatedly samples a population of action sequences from a multivariate Gaussian distribution, uses the learned dynamics model to predict output frames for each action sequence, identifies a set of “elite” sequences with the lowest cost according to the cost function in Section IV-A, and refits the Gaussian distribution to these elite sequences. We run 10 iterations of CEM with a population size of 2000 action sequences, 400 elites per iteration, and a planning horizon of 5. See Appendix B-C for additional hyperparameters. Finally, to mitigate compounding model error we leverage Model-Predictive Control (MPC), which replans at each step and executes only the first action in the lowest cost action sequence found by CEM.

V. SIMULATED EXPERIMENTS

A. VisuoSpatial Dynamics Prediction Quality

One advantage of VSF, and visual foresight more generally, is that we can inspect the model to see if its predictions are accurate, which provides some interpretability. Figure 3 shows three examples of predicted image sequences within

episodes compared to ground truth images from the actual episodes. All episodes are from test time rollouts of a random policy, meaning that the ground truth images did not appear in the training data for the visuospatial dynamics model (see Sections IV-C and IV-D).

The predictions are reasonably robust to domain randomization, as the model is able to produce fabrics of roughly the appropriate color, and can appropriately align the angle of the light gray background plane. For a more quantitative measure of prediction quality, we calculate the average Structural SIMilarity (SSIM) index [63] over corresponding image pairs in 200 predicted sequences against 200 ground truth sequences to be 0.701. A higher SSIM $\in [-1,1]$ corresponds to higher image similarity.

B. Fabric Smoothing Simulations

We first evaluate VSF on the smoothing task: maximizing fabric coverage, defined as the percentage of an underlying plane covered by the fabric. The plane is the same area as the fully smoothed fabric. We evaluate smoothing on three tiers of difficulty as reviewed in Section IV-C. Each episode lasts up to $T = 15$ time steps. Following [49], episodes can terminate earlier if a threshold of 92% coverage is triggered, or if any fabric point falls sufficiently outside of the fabric plane.

To see how the general VisuoSpatial Foresight policy performs against existing smoothing techniques, for each difficulty tier, we execute 200 episodes of VisuoSpatial Foresight (trained on random, domain-randomized RGBD data) with L2 cost and 200 episodes of each baseline policy in simulation. The L2 cost is taken with respect to a smooth goal image (see Figure 4). Note that VSF does *not* explicitly optimize for coverage, and only optimizes the cost function from Equation 2, which measures L2 pixel distance to a target image. We compare with the following 5 baselines:

- a) *Random*: Random pick point and pull direction.
- b) *Highest*: Using ground truth state information, pick the point mass with the maximum z -coordinate and set pull direction to point to where the point mass would be if the fabric were perfectly smooth. This is straightforward to implement with depth sensing and was shown to work reasonably well for smoothing in [50].
- c) *Wrinkle*: As in Sun et al. [54], find the largest wrinkle and then pull perpendicular to it at the edge of the fabric to smooth it out. We use the ground truth state information in the implementation of this algorithm (as done in [49]) rather than image observations.
- d) *Imitation Learning (IL)*: As in Seita et al. [49], train an imitation learning agent using DAGger [44] with a simulated “corner-pulling” demonstrator that picks and pulls at the fabric corner furthest from its target. DAGger can be considered as an oracle with “privileged” information as in Chen et al. [7] because during training, it queries a demonstrator which uses ground truth state information. For fair comparison, we run DAGger so that it consumes roughly the same number of data points (we used 110,000) as VisuoSpatial Foresight during training, and we give the policy access to four-channel RGBD

Table I: Simulated smoothing experimental results for the six policies in Section V-B. We report final coverage and number of actions per episode, averaged over 200 simulated episodes per tier. VisuoSpatial Foresight (VSF) performs well even for difficult starting states. It attains similar final coverage as the Imitation Learning (IL) agent from [49] and outperforms the other baselines. The VSF and IL agents were trained on equal amounts of domain-randomized RGBD data, but the IL agent has a demonstrator for every training state, whereas VSF is trained with data collected from a random policy.

Tier	Method	Coverage	Actions
1	Random	25.0 \pm 14.6	2.4 \pm 2.2
1	Highest	66.2 \pm 25.1	8.2 \pm 3.2
1	Wrinkle	91.3 \pm 7.1	5.4 \pm 3.7
1	DDPG and Demos	87.1 \pm 10.7	8.7 \pm 6.1
1	Imitation Learning	94.3 \pm 2.3	3.3 \pm 3.1
1	VisuoSpatial Foresight	92.5 \pm 2.5	8.3 \pm 4.7
2	Random	22.3 \pm 12.7	3.0 \pm 2.5
2	Highest	57.3 \pm 13.0	10.0 \pm 0.3
2	Wrinkle	87.0 \pm 10.8	7.6 \pm 2.8
2	DDPG and Demos	82.0 \pm 14.7	9.5 \pm 5.8
2	Imitation Learning	92.8 \pm 7.0	5.7 \pm 4.0
2	VisuoSpatial Foresight	90.3 \pm 3.8	12.1 \pm 3.4
3	Random	20.6 \pm 12.3	3.8 \pm 2.8
3	Highest	36.3 \pm 16.3	7.9 \pm 3.2
3	Wrinkle	73.6 \pm 19.0	8.9 \pm 2.0
3	DDPG and Demos	67.9 \pm 15.6	12.9 \pm 3.9
3	Imitation Learning	88.6 \pm 11.5	10.1 \pm 3.9
3	VisuoSpatial Foresight	89.3 \pm 5.9	13.1 \pm 2.9

images. We emphasize that this is a distinct dataset from the one used for VSF, which uses no demonstrations.

e) *Model-Free RL*: We run DDPG [31] and extend it to use demonstrations and a pre-training phase as suggested in Vecerik et al. [61]. We also use the Q-filter from Nair et al. [36]. We train with a similar number of data points as in IL and VSF for a reasonable comparison. We design a reward function for the smoothing task that, at each time step, provides reward equal to the change in coverage between two consecutive states. Inspired by OpenAI et al. [39], we provide a +5 bonus for triggering a coverage success, and -5 penalty for pulling the fabric out of bounds.

Further details about the implementation and training of IL, DDPG, and VSF are in Appendix B.

Table I indicates that VSF significantly outperforms the analytic and model-free reinforcement learning baselines. It has similar performance to the IL agent, a “smoothing specialist” that rivals the performance of the corner pulling demonstrator used in training (see Appendix B). See Figure 4 for an example Tier 3 VSF episode. Furthermore, we find coverage values to be statistically significant compared to all baselines other than IL and not much impacted by the presence of domain randomization. Results from the Mann-Whitney U test [33] and a domain randomization ablation study are reported in Appendix C. VSF, however, requires more actions than DAGger, especially on Tier 1, with 8.3 actions per episode compared to 3.3 per episode. We hypothesize that this leads to VSF being more conservative and reliable, which is supported by VSF having lower variance in performance on Tier 2 and Tier 3 settings (Table I).

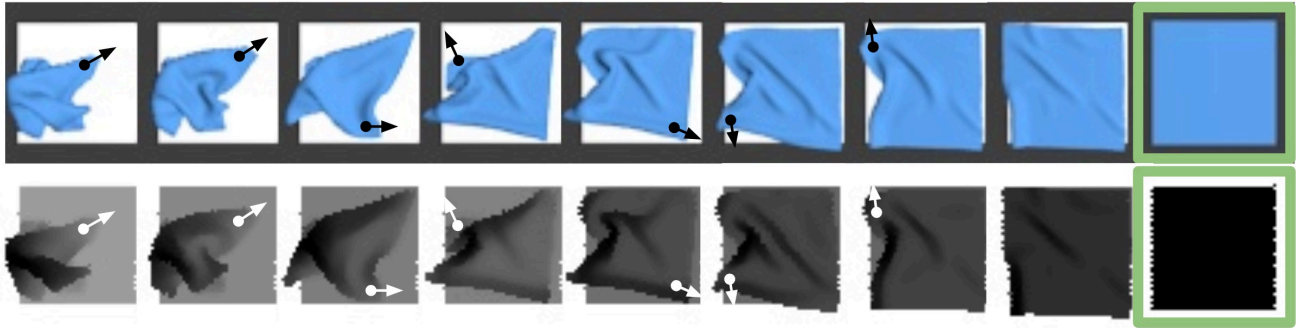


Fig. 4: A simulated episode executed by the VisuoSpatial Foresight policy on a Tier 3 starting state, given a smooth goal image (shown in the far right). The first row shows RGB images and the second shows the corresponding depth maps. In this example, the policy is able to successfully cross the coverage threshold of 92% after executing 7 actions. Actions are visualized with the overlaid arrows.

Table II: Single folding results in simulation. VisuoSpatial Foresight is run with the goal image in Figure 5 for 20 episodes when L2 is taken on the depth, RGB, and RGBD channels. The results suggest that adding depth allows us to significantly outperform RGB-only Visual Foresight on this task.

Cost Function	Successes	Failures	% Success
L2 Depth	0	20	0%
L2 RGB	10	10	50%
L2 RGBD	18	2	90%

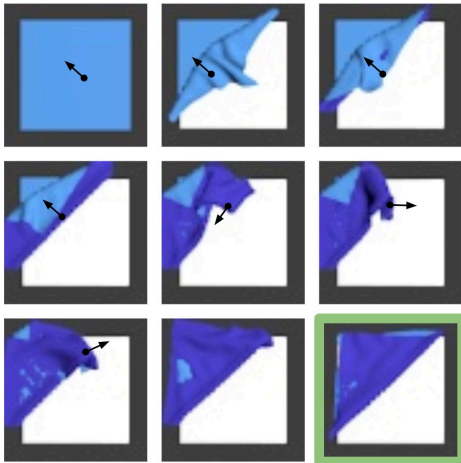


Fig. 5: Simulated RGB observations of a successful folding episode. The RGB portion of the goal image is displayed in the bottom right corner. The rest is an 8-step episode (left-to-right, top-to-bottom) from smooth to approximately folded. There are several areas of the fabric simulator which have overlapping layers due to the difficulty of accurately modeling fabric-fabric collisions in simulation, which explain the light blue patches in the figure.

C. Fabric Folding Simulations

Here we demonstrate that VSF is not only able to smooth fabric, but also directly generalizes to folding tasks. We use the same video prediction model, trained only with random interaction data, and keep planning parameters the same besides the initial CEM variance (see Appendix B-C). We change the goal image to the triangular, folded shape shown in Figure 5 and change the initial state to a smooth state (which can be interpreted as the result of a smoothing policy from Section V-B). The two sides of the fabric are shaded

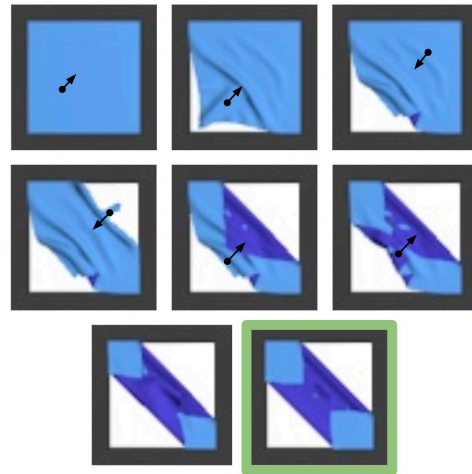


Fig. 6: An example of a successful double folding episode. The RGB portion of the goal image is displayed in the bottom row. The rest is an 7-step trajectory (left-to-right, top-to-bottom) from smooth to approximately matching the goal image. The two folds are stacked in the correct order.

differently, with the darker shade on the bottom layer. Due to the action space bounds (Section IV-B2), getting to this goal state directly is not possible in under three actions and requires a precise sequence of pick and pull actions.

We visually inspect the final states in each episode, and classify them as successes or failures. For RGBD images, this decision boundary empirically corresponds to an L2 threshold of roughly 2500; see Figure 5 for a typical success case. In Table II we compare performance of L2 cost taken over RGB, depth, and RGBD channels. RGBD significantly outperforms the other modes, which correspond to Visual Foresight and “Spatial Foresight” respectively, suggesting the usefulness of augmenting Visual Foresight with depth maps. For a more complete analysis of the impact of input modality, we also provide a histogram of coverage values obtained on the simulated *smoothing* task for RGB, D, and RGBD in Figure 7. Here RGBD also performs the best but only slightly outperforms RGB, which is perhaps unsurprising due to the relatively low depth variation in the smoothing task.

We then attempt to reach a more complex goal image with

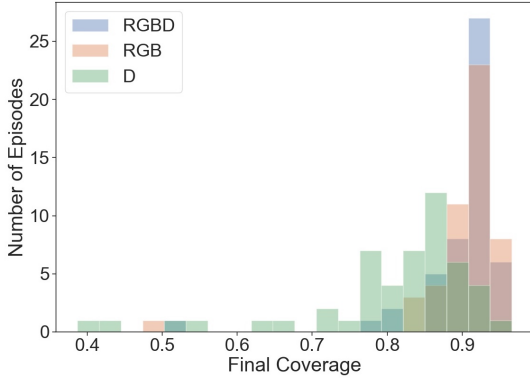


Fig. 7: Final coverage values on 50 simulated smoothing episodes from Tier 3 starting states. We fix the random seed so that each input modality (RGB, D and RGBD) begins with the same starting states.

Table III: Physical smoothing robot experiment results for Imitation Learning (IL), i.e. DAgger, and VisuoSpatial Foresight (VSF). For both methods, we choose the policy snapshot with highest performance in simulation, and each are applied on all tiers (T1, T2, T3). We show results across 10 episodes of IL per tier and 5 episodes of VSF per tier, and show average starting and final coverage, maximum coverage at any point per episode, and the number of actions. Results suggest that VSF attains final coverage comparable to or exceeding that of IL despite not being trained on demonstration data, though VSF requires more actions per episode.

Tier	(1) Start	(2) Final	(3) Max	(4) Actions
1 IL	74.2 ± 5	92.1 ± 6	92.9 ± 3	4.0 ± 3
1 VSF	78.3 ± 6	93.4 ± 2	93.4 ± 2	8.2 ± 4
2 IL	58.2 ± 3	84.2 ± 18	86.8 ± 15	9.8 ± 5
2 VSF	59.5 ± 3	87.1 ± 9	90.0 ± 5	12.8 ± 3
3 IL	43.3 ± 4	75.2 ± 18	79.1 ± 14	12.5 ± 4
3 VSF	41.4 ± 3	75.6 ± 15	76.9 ± 15	15.0 ± 0

two overlapping folds for a total of three layers at the center of the fabric, again with the same VSF policy. Here 8 out of 20 trials succeed, and 7 of the 8 successes arrange the two folds in the correct ordering. Folding two opposite corners in the right order may be difficult to do solely with RGB data, since the bottom layer of the fabric has a uniform color. The depth maps, in contrast, provide information about one fold lying on top of another. See Figure 6 for an example of a successful rollout. Failure cases are often characterized by the robot picking at a point that just misses a fabric corner, but where the visual dynamics model predicts that the resulting pull will behave as if the robot had picked at the fabric corner.

VI. PHYSICAL EXPERIMENTS

We next deploy the domain randomized policies on a physical da Vinci surgical robot [24]. We use the same experimental setup as in Seita et al. [49], including the calibration procedure to map pick points (x, y) into positions and orientations with respect to the robot’s base frame. The sequential tasks we consider are challenging due to the robot’s imprecision [48]. We use a Zivid One Plus camera mounted 0.9 meters above the workspace to capture RGBD images.

A. Experiment Protocol

We evaluate the best Imitation Learning and the best VisuoSpatial Foresight policies as measured in simulation and reported in Table I. We do not test with the model-free DDPG policy baseline, as it performed significantly worse than the other two methods. For IL, this is the final model trained with 110,000 actions based on a corner-pulling demonstrator with access to state information. This uses slightly more than the 106,725 actions used for training the VSF model. We reiterate that VSF uses a video prediction model that is trained on *entirely random data*, requiring no labeled data in contrast with IL, which uses DAgger and requires a demonstrator with “privileged” fabric state information during training. The demonstrator uses state information to determine the fabric corner furthest from its target on the underlying plane, and pulls the fabric at that fabric corner to the target.

To match the simulation setup, we limit each episode to a maximum of 15 actions. For both methods on the *smoothing* task, we perform episodes in which the fabric is initialized in highly rumpled states which mirror those from the simulated tiers. We run ten episodes per tier for IL and five episodes per tier for VSF, for 45 episodes in all. In addition, within each tier, we attempt to make starting fabric states reasonably comparable among IL and VSF episodes (e.g., see Figure 8).

B. Physical Fabric Smoothing

We present quantitative results in Table III that suggest that VSF gets final coverage results comparable to that of IL, despite not being trained on any corner-pulling demonstration data. However, it sometimes requires more actions to complete an episode and takes significantly more computation time, as the Cross Entropy Method requires thousands of forward passes through a large network while IL requires only a single pass. The actions for VSF usually have smaller deltas, which helps to take more precise actions. This is likely due in part to the initialization of the mean and variance used to fit the conditional Gaussians for CEM. Figure 13 in Appendix C-C shows histograms of the action delta magnitudes. The higher magnitude actions of the IL policy may cause it to be more susceptible to highly counter-productive actions. The fabric manipulation tasks we consider require high precision, and a small error in the pick point region coupled with a long pull may cover a corner or substantially decrease coverage.

As an example, Figure 8 shows a time lapse of a subset of actions for one episode from IL and VSF. Both begin with a fabric of roughly the same shape to facilitate comparisons. On the fifth action, the IL policy has a pick point that is slightly north of the ideal spot. The pull direction to the lower right fabric plane corner is reasonable, but due to the length of the pull, combined with a slightly suboptimal pick point, the lower right fabric corner gets covered. This makes it harder for a policy trained from a corner-pulling demonstrator to get high coverage, as the fabric corner is hidden. In contrast, the VSF policy takes actions of shorter magnitudes and does not fall into this trap. The downside of VSF, however, is that it may “waste” too many actions with short magnitudes, whereas

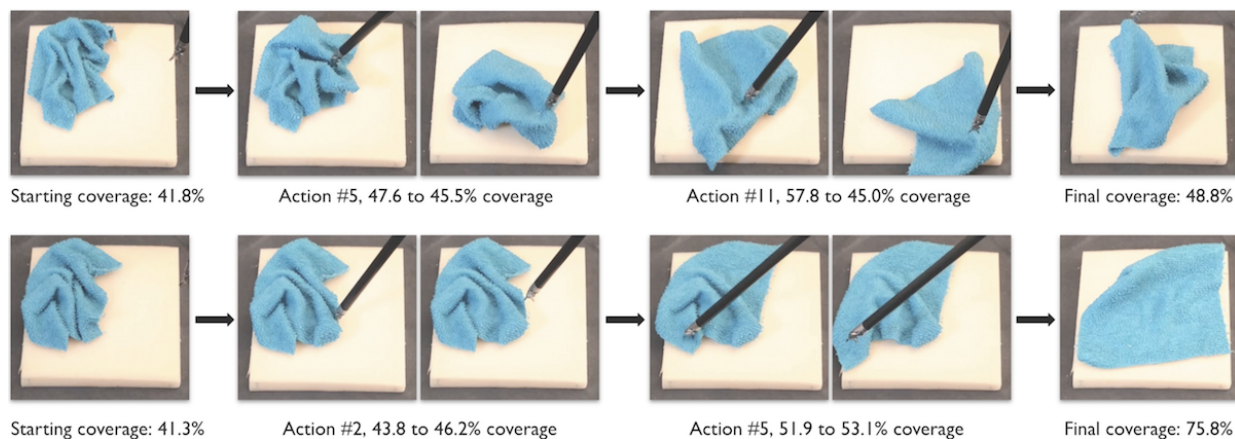


Fig. 8: A qualitative comparison of physical da Vinci episodes with an Imitation Learning policy (top row) and a VisuoSpatial Foresight policy (bottom row). The rows show screen captures taken from the third-person video view for recording episodes; these are not the input to VisuoSpatial Foresight. To facilitate comparisons among IL and VSF, we manually make the starting fabric state as similar as possible. Over the course of several actions, the IL policy sometimes takes actions that are highly counter-productive, such as the 5th and 11th actions above. Both pick points are reasonably chosen, but the large deltas cause the lower right fabric corner to get hidden. In contrast, VSF takes shorter pulls on average, with representative examples shown above for the 2nd and 5th actions. At the end, the IL policy gets just 48.8% coverage (far below its usual performance), whereas VSF gets 75.8%. For further quantitative results, see Table III

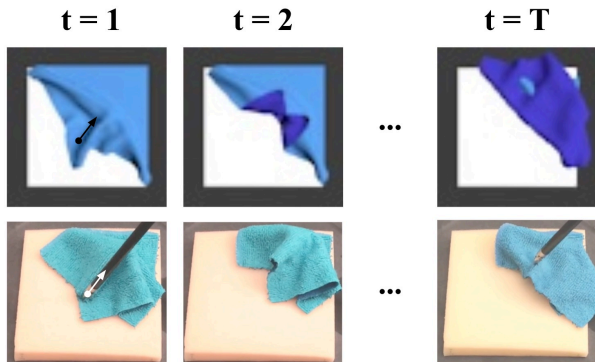


Fig. 9: Physical folding policy executed in the simulator and on the surgical robot, with actions determined from *real* image input only. Despite this, the actions are able to fold in simulation. The difference in dynamics is apparent from $t = 1$ to $t = 2$, where the simulated fabric’s bottom left corner is overturned from the action, but the corresponding corner on the real fabric is not.

IL can quickly get high coverage conditioned on accurate pick points. In future work, we will develop ways to tune VSF so that it takes longer actions as needed.

C. Physical Fabric Folding

We next evaluate the *same* VSF policy, but on a fabric *folding* task, starting from a smooth state. We conduct four goal-conditioned physical folding episodes, with one episode for each of the four possible diagonal folds. We run each episode for 15 time steps. Qualitatively, the robot tends to move the fabric in the right direction based on the target corner, but does not get the fabric in a clean two-layer fold. To evaluate the quality of the policy, we take the actions generated for a *real episode* on the physical system and run them open-loop in the fabric simulator. See Figure 9 for a comparison. Since the *same actions* are able to fold reasonably well in simulation, we conclude that the difference is due to a

dynamics mismatch between simulated and real environments, compounded with pick point inaccuracies common in cable-driven robots such as the dVRK [48]. In future work, we will improve the simulator’s physics to more closely match those of the dVRK, and we will also consider augmenting the video prediction model with a small amount of real-world data.

VII. CONCLUSION AND FUTURE WORK

We present VSF, which leverages a combination of RGB and depth information to learn goal conditioned fabric manipulation policies for a variety of long horizon tasks. We train a video prediction model on purely random interaction data with fabric in simulation, and demonstrate that planning over this model with MPC results in a policy with promising generalization across goal-directed fabric smoothing and folding tasks. We then transfer this policy to a real robot system with domain randomization. In future work, we will explore learned cost functions, test different fabric shapes, and investigate learning bilateral manipulation or human-in-the-loop policies.

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