MMGSD: Multi-Modal Gaussian Shape Descriptors for Correspondence Matching in 1D and 2D Deformable Objects

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Abstract—We explore learning pixelwise correspondences between images of deformable objects in different configurations. Traditional correspondence matching approaches such as SIFT, SURF, and ORB can fail to provide sufficient contextual information for fine-grained manipulation. We propose Multi-Modal Gaussian Shape Descriptor (MMGSD), a new visual representation of deformable objects which extends ideas from dense object descriptors to predict all symmetric correspondences between different object configurations. MMGSD is learned in a self-supervised manner from synthetic data and produces correspondence heatmaps with measurable uncertainty. In simulation, experiments suggest that MMGSD can achieve an RMSE of 32.4 and 31.3 for square cloth and braided synthetic nylon rope respectively. The results demonstrate an average of 47.7% improvement over a provided baseline based on contrastive learning, symmetric pixel-wise contrastive loss (SPCL), as opposed to MMGSD which enforces distributional continuity.

I. INTRODUCTION

Robotic manipulation of deformable objects is a growing area of research that has exposed many limitations in perception systems [1][5][6][9][11][15][16][18][20]. Acquiring useful visual state representations of deformable objects for manipulation is a central focus in prior work [8][13][10][17][19][21]. Inferring such representations is challenging due to the infinite dimensional state space, tendency to self-occlude, and often textureless and symmetric nature of deformable objects. One successful prior approach is learning pixelwise correspondences between images of deformable objects in different configurations as in Florence [3], Florence et al. [4], Ganapathi et al. [5], Javdani et al. [7], Schulman et al. [14], Sundaresan et al. [16], and Tang et al. [17]. However, these methods can fail to address uncertainty and symmetries, which can cause issues for downstream planning and control. Consider a robotic agent attempting to identify a corner of a towel to fold it according to a video demonstration. The agent could leverage the fabric’s inherent symmetry to manipulate the corner of the towel for which its uncertainty in its location is the lowest, since all four corners are viable options. To enable such behaviors, we extend the correspondence learning algorithms from [4][5][16] to (1) provide measures of uncertainty in predicted correspondences by formulating a distribution matching objective for correspondence learning inspired by [3] and (2) explicitly predicting symmetric correspondences. Experiments suggest that the learned correspondences for both 1D and 2D deformable objects are more stable and continuous than those used in prior work and are less prone to symmetrical ambiguities and provide uncertainty estimates.

II. PROBLEM STATEMENT

Given two images, Ia and Ib, of a deformable object in two different configurations respectively, and a source pixel location (ua, va) (such that the pixel is Ia[ua, va]), find its n(ua, va) pixel correspondences ((ub, vb))n(ua,va)=1 in Ib. There may be multiple possible matches due to symmetry, such as when matching a corner of a square cloth in Ia to all four corners of the cloth in Ib. We assume access to a dataset of pairs of images of deformable objects, for which n(ua, va) is known, and a collection of correspondences and non-correspondences between each pair. We use Blender 2.8 [2] to both generate arbitrary configurations of cloth and rope in simulation as well as to render images of these configurations for dataset curation. Blender gives us access to the underlying mesh vertices that these objects are composed of which allows us to densely sample mesh vertex locations at any point.

III. METHODS

A. Preliminaries: Pixel-wise Contrastive Loss

We first review the unimodal matching method from [4][5][12][16]. A neural network network f maps Ia to a D-dimensional descriptor volume: f : ℝW×H×3 → ℝW×H×D. During training, a pair of images and sets of both matching pixels and non-matching pixels are sampled between the image pair. The following contrastive loss minimizes descriptor distance between matching pixels and pushes descriptors for non-matching pixels apart by a fixed margin M:
We then fit an A. In contrast, the predicted 2-modal and 4-modal MMGSD heatmaps for rope and cloth, respectively, appear to be sensitive to object cross-entropy loss function with respect to a target distribution suggested in [3] to learn an estimator ˆC. Symmetric Distributional Loss (MMGSD) heatmap and take the destination pixels matches for the same source pixel ball to the end of the rope. Conditions. The authors of [16] break symmetry by adding a square fabric to be between a model trained on 3500 image pairs of cloth and rope each. While this method addresses the symmetry issue from a distributional descriptor network method that outputs the probability that \( p(u,v) = v|I_a,u_a,v_a,I_b \) that outputs the probability that \((u,v)\) in \(I_b\) matches with \((u_a,v_a)\) in \(I_a\). Specifically, we let \( \hat{p}(u_b = u, v_b = v|I_a,u_a,v_a,I_b) = \sum_{v'} \exp(f(I_b|u_a,v_a)−f(v|u_a,v'))/\|v−v'\|^2 \), where \( f \) is a neural network with trainable parameters. To fit \( \hat{p} \), we use the cross-entropy loss function with respect to a target distribution \( p \) that is an isotropic Gaussian mixture model with modes at all the ground truth pixel correspondences in \( I_b \), thus accounting for all symmetric matches. For the ground truth target distributions, \( \sigma \) is empirically fine-tuned to tradeoff spatial continuity in the learned distribution with overlap and collapse of modes. Using this distributional divergence loss function maintains spatial continuity between matches, and we find that this can be more stable than the method in Section III-B. Additionally, predicting a distribution instead allows uncertainty estimation by computing the entropy of the predicted distribution. This method is similar to [3] but uses a multi-modal target distribution due to the multiple symmetric correspondences. As illustrated in Figure 2B and Figure 1B, this method is successfully able to place its mass at the multiple possible matches in the target image. We fit an \( n(u_a,v_a) \)-modal Gaussian distribution to the predicted output distribution \( \hat{p} \) and take the \( n(u_a,v_a) \) pixel modes as the predicted symmetric correspondences.

IV. Quantitative Results

We evaluate the quality of the symmetric learned correspondences (methods III-B and III-C) using the root-mean-square error (RMSE) metric. Both the rope and cloth networks are trained on 3,500 training images each and evaluated on a held-out test set of 500 images. All training and testing is carried out with images of a synthetic square cloth and braided synthetic nylon rope. The cloth images are 485 x 485 and the rope images are 640 x 480 in aspect ratio. We compute the \( n(u_a,v_a) \) pixel mode predictions and compare them directly to the ground truth pixel locations:

\[
\frac{1}{n(u_a,v_a)} \sum_{r=1}^{n(u_a,v_a)} ||[u_b,v_b] − [u_a,v_a]|^2\]

where \([u_a,v_a]\) is the ground truth pixel correspondence in \( I_b \) for the source pixel \([u_a,v_a]\). We average over 625 source pixel locations in each of 500 test image pairs from simulation (Figure 3) using a model trained on 3500 image pairs of cloth and rope each. In Figure 3 we compare MMGSD against SPCL with the probability density function of percentage of correspondences below an L2 pixel threshold (as a percentage of the pixel dimensions of the object). We note that while MMGSD is able to predict multi-modal correspondences more effectively than SPCL, it exhibits high uncertainty and modal collapse for highly occluded regions, such as rope knots (Figure 2C), object interiors, or occluded fabric corners. This high
degree of variance in the resulting heatmaps is a consequence of MMGSD attempting to preserve spatial continuity, at the expense of concentrating probability mass in isolated symmetric regions. We illustrate this in the bottom half of Figure 3 by visualizing the source of high RMSE error on both rope and cloth. The top half of Figure 3 also reveals this second mode centered at higher RMSE error.

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