Grasp Transfer for Deformable Objects by Functional Map Correspondence

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***Abstract*— Handling object deformations for robotic grasping is still a major problem to solve. In this paper, we propose an efficient learning-free solution for adapting grasp hypothesis to deformed versions of an object. To this end, we investigate the applicability of functional map (FM) correspondence, where the shape matching problem is treated as searching for correspondences between geometric functions in a reduced basis. For a user selected region of an object, we apply the local contact moment (LoCoMo) grasp planner to generate grasp candidates. Next, these candidates are transferred to an instance of the object that has suffered an arbitrary level of deformation. Finally, the best feasible grasp, is executed on the object while respecting the original finger configuration as much as possible. Experimental validation in simulation shows the efficiency in our approach.**

I. Introduction

Reliable robotic grasping of non-rigid deformable objects is a challenging research problem. The grasp planning literature predominantly focuses on searching for stable grasps over the surfaces of rigid objects [1]–[4]. On the other hand, not many works focus on grasping articulated or deformable objects [5]. In this work, we present a method for transferring grasps between objects that have suffered deformation.

The problem of adapting a grasp between two objects, can be formulated as transferring information between similar surface regions. One approach to solve this problem is to exploit similarities between familiar objects of the same category [6]–[12]. Authors in [10], [11] have proposed a method to transfer grasps between same category objects by rigid alignment of similar shapes, contact wrapping, and local re-planning. Similarly, [12] solved this problem by means of bijective contact mapping and grasp re-planning. In this case, rigid alignment was found by sampling the surface of two objects and minimising the deviation between points. A non-rigid registration method based on Coherent Point Drift (CPD) is used in [6] to transfer manipulation skills between objects. In [9], the authors have used CPD to transfer and refine grasps between the same class of objects. A learning method using CPD to account for shape deviations when transferring manipulation skills between objects is proposed in [7], [8]. We note that, variations of CPD are the main choice for non-rigid shape matching in previous works. Although an efficient choice, CPD requires a good initial pose to work well and is prone to get stuck in local minima; thus, leading to subpar results in the presence of larger deformations.

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Fig. 1. Deformable object grasping by the proposed grasp transfer method. (left) Source and target meshes, and their functional maps. (middle) Transferred possible grasp configurations. (right) Executed best grasp.

We believe that functional map (FM) correspondence, which was first formulated in [13], can be an efficient alternative to CPD for handling object deformations. In [13], the authors propose that the non-rigid shape matching problem can be treated as searching for correspondences between geometric functions in a reduced basis. This choice to treat point correspondences between objects as functions leads to simpler convex least-square optimisation problems and provide greater flexibility to incorporate linear constraints to the problem. Particularly, FM has been shown to perform well in challenging settings with large deformation [14].

Our main contribution in this work is to exploit the FM framework to propose a robust learning-free solution to the problem of transferring grasps between objects that have suffered non-rigid deformations. Our solution leverages user input and grasps generated by our Local Contact Moments (LoCoMo) based grasp planner [1] to create a ranked list of grasps focused on a region of interest of an object. We then propose a FM-based method to map these grasps to an instance of the object that has suffered arbitrary level of deformation (see Fig. 1). Finally, we transform and adapt the grasps to the deformed object and execute the best (kinematically feasible) grasp. We validate our method by performing a number of experiments, using a simulated 7-axis robot fitted with a 2-finger gripper, on different objects with multiple deformations. For more details, we refer the reader to [15].

II. Grasp Transfer Through Functional Maps

The pipeline of our method is shown in Fig. 2. It consists of three main steps: grasp model generation, shape correspondence, and grasp transfer and evaluation.

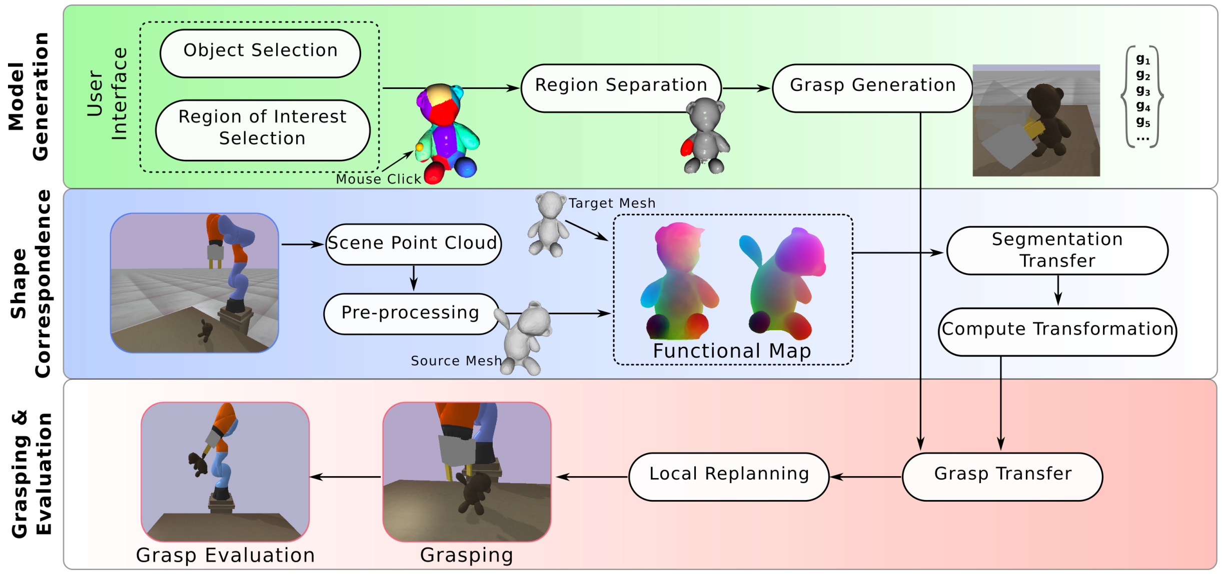

Fig. 2. Proposed pipeline of our methodology to transfer non-rigid grasps using functional maps. It consists of three steps: grasp model generation (top – green); finding shape correspondences (middle – blue); and, grasp transfer (last – red).

During the model generation step we present the user with an interface where a source object can be selected as well as the grasp region for the object. We apply a segmentation technique on the object and select a grasping region, in which we use the LoCoMo grasp planner [1] to generate a ranked list of grasps. The second step is shape correspondence, which starts with the robot observing a new scene with a deformed version of the source object (referred as target object). The robot captures the point cloud of the scene and generates a mesh of the target object. We then find the relation between source and target object shapes. The FM framework helps us in accomplishing this shape correspondence and we transfer the segmented region to our target mesh. Finally, we compute the grasp transformation, transfer and adjust the grasp to the target so that it is both stable and feasible. We evaluate the grasp stability as in [16]

As mentioned, our approach exploits FM to compute the correspondences between features of two shapes and then use this mapping to transfer the grasp configuration. We denote a shape by the Riemannian manifold embedded in $\mathbb{R}^3$. Let $\mathcal{X}, \mathcal{Y}$ be respectively the source and target shapes, with $n_{\mathcal{X}}$ and $n_{\mathcal{Y}}$ vertices stored in triangular meshes. $T_p : \mathcal{Y} \rightarrow \mathcal{X}$ represents the point-wise correspondence map. This problem, given that $n_{\mathcal{X}} = n_{\mathcal{Y}}$, can also be formulated as finding the permutation matrix $\mathbf{\Pi}$ of size $n_{\mathcal{Y}} \times n_{\mathcal{X}}$ in which all lines will sum up to 1. Although intuitive, inferring $\mathbf{\Pi}$ directly can be a complex problem which lacks flexibility and is badly-suited for more general rigid deformations. FM is an alternative technique that has been widely adopted for solving this over the last few years.

The underlying idea behind FM is that it is often easier to optimise between real-valued functions rather than points in a shape. Indeed, finding matches in 3D space can lead to complex non-convex optimisation problems, whereas FM offers an elegant formalism that allows for a compact matrix representation in a low rank basis. Furthermore, this method allows for the easy incorporation of linear constrains to regularise the map, which yields simple convex least squares optimisation problems that are much more tractable [13]. For a more detailed understanding, we refer the reader to [17].

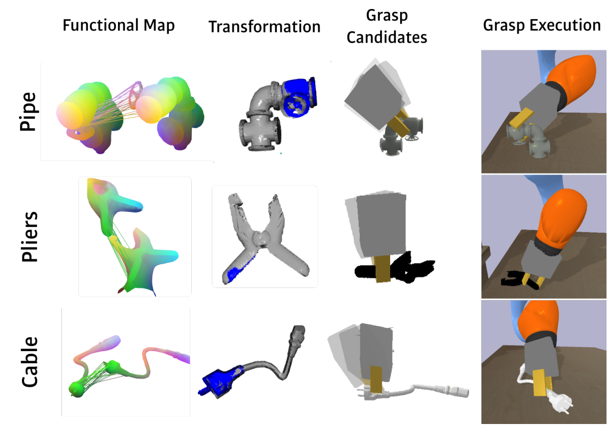

Fig. 3. Illustration of grasp transfer with our proposed method.

III. Results

In order to evaluate our pipeline, we have performed experiments in simulation using the open-source PyBullet python module [18]. Our robotic setup consists of a 7-axes robot arm fitted with a parallel jaw gripper with a camera attached to the end-effector. To run the experiments, we have prepare a data set with four different objects: teddy bear, cable, pliers, and pipe. Each in five different configuration[1]. We note that to run our pipeline we generated meshes from visual data obtained in simulation.

For each object, one of the five meshes is selected as the model mesh and the remaining four are used with robot experiments. The model mesh is segmented using k-means clustering and is presented to the user on a initial screen.

[1] Available at https://gitlab.com/cristianafar/deformable-object-dataset

For experiments, we have used $N_C = 7$ clusters for each object. The user then selects a region of interest (one of the clusters). Then a set of grasps that fall into the selected region is generated by our LoCoMo grasp planner and stored. After transferring, grasps are executed and grasping results are reported following the evaluation protocol presented in [16]. That is, the object is lifted and shaking and rotation tests are performed to verify grasp stability.

In Fig. 3 we show some of the results for the pipe, cable and pliers objects. The first column shows the shape matching results, in which similar colours represent similar regions. The transformation column shows the selected region of the source object (in blue) being transformed to the target shape in gray. Then, we show the generated grasp candidates and finally the executed grasp.

Additionally, to compare our method's performance, we have conducted baseline experiments by replacing the FM module in our pipeline to both CPD [19] and ICP [19]. CPD is implemented using PyPCD library and the ICP using Open3D Python library.

Our results have shown that our method can effectively grasp objects with a high level of deformation. Out of all object configurations, the proposed FM-based pipeline showed $\mathbf{93.75}\%$ success rate for accuracy tests, as well as an overall success rate of $\mathbf{100}\%$ in lifting objects and $\mathbf{81.25}\%$ of success after rotation and shaking tests are performed. For this set of experiments CPD had a performance of 56% in grasping the correct region, 68.75% in lifting and 43.74% after shaking and rotation tests, whereas ICP grasped the correct region in 31.24% attempts and had 31.25% success after lifting and 12.5% after the tests.

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