

Category-based task specific grasping

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Abstract—Interaction with an object is an important ability of the robot acting in a real environment. Grasping is a critical problem in many manipulation tasks. In many situations it is important not only to perform a stable grasp but also “useful” grasp, which means that the properties of the object and task-specific constraints should be taken into account. The concept of *object category* is useful for task-related grasping. Thus, for humans it is very natural to manipulate objects based on their properties and performing task. We propose a probabilistic approach for task-specific stable grasping of objects with shape variations inside the category. Our method can be considered belonging to the class of techniques for grasping familiar objects and more concretely to grasp synthesis by comparison where grasp hypothesis for a specific object generate by finding similar models in the database, for which good grasps are already found and stored. Our approach is close to data-driven methods during the model building stage, but it does not require a construction of the large training dataset (1 task-specific stable grasp per object is enough for the procedure). The method does not require full 3D models for new objects and partial data can be used. The approach accounts for all training objects in the category during the optimization process, which allows to better generalize for the new object and handle larger shape variations.

I. GENERAL METHOD

The main steps of our framework are shown in Fig. 1. The first step is to choose the models of some category to be a training set. The training set should express shape variability to better generalize for similar objects. After that, the task-specific grasps for each training object are generated and their relative poses with corresponding stability metrics are stored. Next step, is to collect data of a new object and perform registration. Our approach does not require a precise object model. We use partial point cloud obtained from a single RGB-D image. As a result fitting scores are obtained, which describe the similarity of the graspable object to the model objects. After preliminary calculations are done the main optimization procedure can be performed. A general model to find optimal grasp for a new object inside the category is based on finding the maximum of the grasp probability. Each grasp, in our case, is parametrized by 6DOF pose. During the optimization process task-specific grasps for all training objects, represented by density functions, are taken into account. Their importance is expressed by weights, which depend on stability metric (quality of stored model grasps) and fitting errors (how well new object fits the models in the database). We sum over all training objects and apply numerical optimization approach to find a “good” task-specific grasp for a new object in the category.

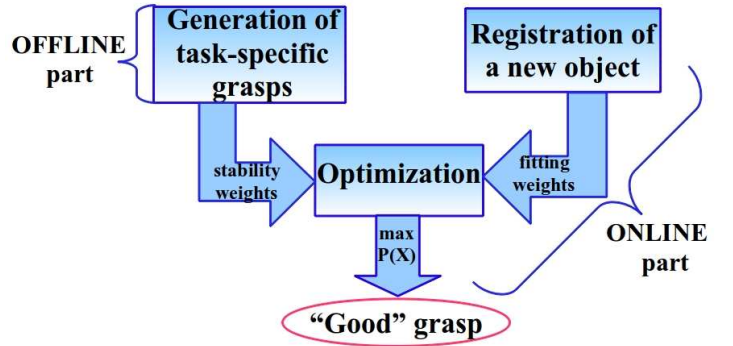


Fig. 1: General framework

II. EXPERIMENTAL RESULTS

For our experiments for training and testing we used models from Columbia Grasp Database (CGDB) [2]. We chose the objects from classes “liquid containers” and “tools”. The models grasps were generated using Barrett Hand model in GraspIt! simulator [3], in which grasp stability can be easily evaluated. For the registration part we transformed the models into point clouds. We extracted key points and calculated for them local descriptors using Point Cloud Library [1]. These results we used for initial alignment. We then applied the Iterative Closest Point algorithm to get the final transformation.

A. Experiments with mugs

In the experiments we used 7 models of “mugs” from CGDB. For each mug we generated 3 task-specific grasp configurations: from the top (“top”) and from the side opposite to the mug handle (“side”) grasps for different transportation tasks and from the side where the handle is located (“handle”) grasps for drinking or outpouring. The examples of training grasps for one of the mugs are presented in Fig. 2. To test our method we performed leave-one-out cross-validation. We compared the result with a “best single” grasp. This is a task-specific grasp configurations for the object in the training dataset which is closest to the testing object based on the fitting score values (an object with maximum fitting weight). Thus, by taking into account a similarly shaped object from the database as well as other models and corresponding stability information, we can improve indexes of stability of the grasp generated for the new object within one category. Moreover, comparing unsuccessful configurations for both approaches,

the grasp obtained from the optimization procedure was unstable, indicated by the stability metric value. However, it doesn't initially collide with an object. The handle grasp is the most difficult in the sense that even small disturbances in several directions can make grasp unstable. In that case, very high precision is needed. Therefore, for this type of grasp both methods showed the worst results. However, at resulting configurations the hand was further away from the center of object than at "best single" configurations as demonstrated in Fig. 3. Thus, smaller corrections are required for the new approach in order to avoid initial collisions.

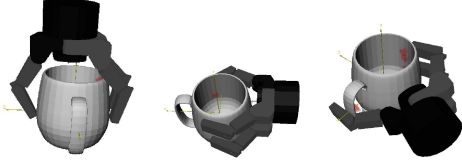
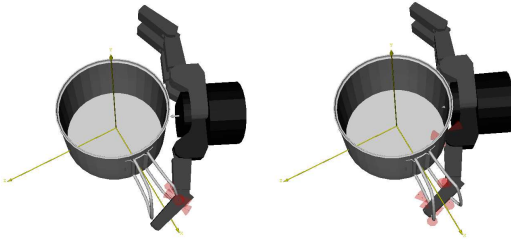


Fig. 2: Task-specific generated model grasps



(a) Resulting grasp (b) "Best single" grasp

Fig. 3: Finger colliding handle grasps from both approaches: in "best single" configuration the hand is closer to the mug.

B. Experiments with tools

These experiments allowed us to show that the proposed method can generalize for the objects of other subcategories, which share shape similarities with the class in the training set. For this we chose subclasses "hammer" and "knife" from class "tools" in CGDB. All objects have similar elongated shape and can be divided into handle and working parts. We used hammers as a training set and generated a grasp from the handle associated with a task "use" for each object. The results for 2 knives shown in Fig. 4 demonstrate the ability of the new approach to generate stable grasps for the objects from the other class. For these 2 models our method outperformed the traditional approach.

After analyzing the results for both categories we can conclude that in case of grasp failures the optimization procedure can be improved by the following generation of hand adjustments based on collected tactile feedback (experimental results showed that small perturbations in the goal hand configuration are required to make the grasp stable).

III. ON-GOING WORK

Our current goal is to validate the approach on the real platform. For this, we chose 3 mugs different in shape and collected partial point clouds for them. Additionally, we placed

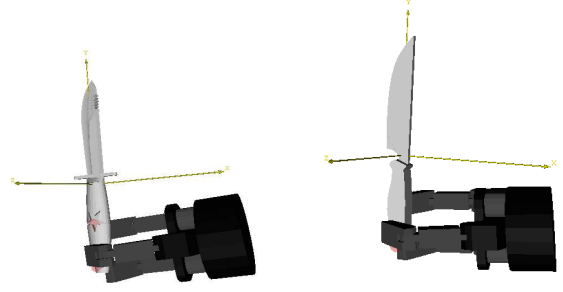


Fig. 4: Resulting grasps for knives.

mugs in the robot's environment and grabbed one snapshot from Kinect stereo camera. To visualize the results in the simulator we transformed the obtained partial point clouds into partial geometry objects by applying surface reconstruction method and imported the models into GraspIt! simulator. Test mugs are shown in Fig. 5 and reconstructed partial models are depicted in Fig. 6. As a training set we use the same 7 mugs



Fig. 5: Test objects

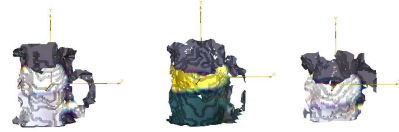


Fig. 6: Reconstructed models of test objects

from CGDB. We also test our optimization procedure using different probability density functions. We are intending to try out our method on a real robot platform consisting of KUKA LBR4+ Robotic Arm with attached 3-fingered Barrett Hand B8-282.

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