Object Categorization through Annotated Reeb Graph and Grasping by Parts

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Recently, the proliferation of cheap and effective sensor devices for 3D perception, like depth cameras and 3D laser systems, has promoted the development of accurate and detailed object detection. The perception, representation and classification of objects is not only relevant for navigation tasks and semantic description of unstructured environments, but also has great importance for robot manipulation and grasping. Grasping action is better guided by object affordances that can be extracted from the object parts like protruding segments. Some categories of human artifacts often exhibit specific parts made for grasping, like the handles in hammers and mugs. Thus, the affordances of such objects could be detected through their categorization and semantic segmentation. Classification is often based on appearance features extracted from specific observed objects. On the other hand, categorization is the identification of the class an object belongs to and must depend on invariant attributes related to the shape and structure.

In this work, we extend the manipulation planning system presented in [1] for a robot arm with eye-in-hand laser scanner that is capable of performing 3D object reconstruction, segmentation, categorization and grasp planning on selected parts of the objects. The experimental setup consists of a Comau SMART SiX manipulator (6 dofs) equipped with a Schunk PG-70 gripper and a SICK LMS 400 laser range-finder mounted in eye-in-hand configuration on the manipulator wrist. The range measurements are gathered during the motion of the robotic arm and registered to achieve a complete point cloud. The system observes one or more objects lying on a dominant plane. Objects are detected by removing outliers, extracting the dominant plane and clustering the points above the plane. In particular, clustering is efficiently performed by exploiting the spatial and temporal coherence of scans to build a proximity graph.

Since polygonal mesh representation is required to plan motion and grasping, the object surface is reconstructed using power crust algorithm [2]. The obtained mesh is segmented by constructing its corresponding Reeb graph based on the integral geodesic function [3]. The Reed graph allows the identification of object parts which are candidate for being grasped. In our experiments, four categories have been considered: doll, jug, horse and table. Object class is recognized by matching the computed graph with the graph of each category. Figure 1 illustrates the processing steps for two instances of the horse class. Finally, the grasping and robot arm motion are planned and performed on the proper affordance for the object class.

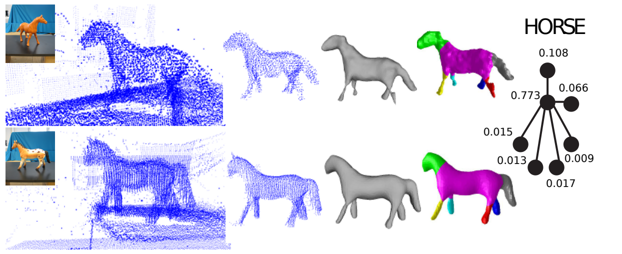

Fig. 1. From left to right the raw scan data (with a small picture of the real object), the clustered point cloud of the object, the reconstructed mesh (in gray), the colored segmented mesh and the annotated Reeb Graph for two instances of horse class (for clarity only the vertex labels are shown).

Reeb graph segmentation provides a topological decomposition of the shape of an object which is likely to identify semantic object's parts that are candidate components for being grasped. However, it could occur that two different classes have the same Reeb graph. To overcome this ambiguity we improve the categorization method proposed in [1] by using the *annotated Reeb Graph*. We propose to label each node corresponding to an object part with its normalized volume and each edge with the cosine of the angle between the principal inertial axes of the object parts connected by the edge. The prototypical Reeb graph is annotated with the average values and variance of the weigths computed on a training set. The categorization of an object is solved as a labeled graph matching problem by manipulating the weighted adjacency matrices. The permutation matrix P that maps the vertices of the graph to classify to those of each prototype graph is computed. Then, the distance between the object and a class prototype is measured by the distance between their corresponding adjacency matrices $\|A_1 - P\ A_2\ P^{-1}\|$. Thus, the proposed metric allows to discriminate between topologically similar object classes without relying on too specific geometric features.

References

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