Object grasping and arrangements extracted from virtual reality for a household robot

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Abstract

There are two currents in the organization of conceptual knowledge area according to Handjaras et al. [3]. This two currents agree in that the organization of knowledge is based on semantic categories, even though in different levels. By following this idea, I make use of the KnowRob framework introduced by Tenorth and Beetz [8], which includes a knowledge base of semantically annotated concepts and reasoning methods to perform inference about. In this work, humans performing a table setting for breakfast in virtual reality (VR) were recorded following the method presented by Haidu and Beetz [2]. Then, grasping and arrangement order is extracted in order to understand relations between actions and objects.

The data includes six manipulated objects, bowl, cereal, glass, juice, milk and spoon inside a kitchen scenario. Some of this objects hold already a semantic relation to each other, e.g. the bowl and glass are containers, the juice and milk are drinks. Which can make us believe that they would be grasped together. However, they also hold another semantic relations regarding to their function, which are more related to actions. One interesting example is the relation between a bowl and cereal, which were grasped and arranged first together more times. In this case a concept usability arises as, in a breakfast scenario, the bowl normally would contain the cereal. Similarly, the second pair juice and glass were grasped together in most of the cases, adding sense to this concept. However, the glass can be also paired with the milk, for the same reason.

Some examples of human data used in robots can be found in the literature related to learning from human demonstrations (LfD) or imitation learning. However, the focus of this type of learning is directly from a human demonstrator [1]. As in this work the main focus is reasoning about tasks, imitation is not explored further.

There are some works in the object tabletop arrangement area. For example, the system presented by Krontiris and Bekris [5], rearrange objects in a grid from random positions. In the other hand, the work presented by Srivastava et al. [7], solves grasping in a obstructed scenario and then rearrange one object per time. In this work, objects are grasped from a different location, the kitchen counter, and then put down on an almost uncluttered dining table, two objects per round, usually one per hand.

Similar to this work, Jiang et al. [4] present object arrangement with semantic relations between objects and human poses. Here, we take into account semantic relations between objects and actions instead.

This kind of information is useful when a robotic platform makes a decision about object manipulation ordering [6], e.g. take the bowl and cereal as pairs, one in each hand. It also gives an intuition on which object to arrange first, e.g. the cereal, glass, and milk go behind. For this reason we use human demonstrations for improving the decision process of a robotic platform.

Acknowledgements

This work is partially funded by Deutsche Forschungsgemeinschaft (DFG) through the Collaborative Research Center 1320, *EASE*.

Lisset Salinas Pinacho acknowledge support from the German Academic Exchange Service (DAAD) PhD scholarship.

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