Probabilistic framework to detect suitable object region for grasping

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Introduction

- How to grasp an object? Which part of the object to grasp? What do we need to take in consideration for a grasping configuration?
- We need to know some object properties and the task context to find the best option.
- The choice of an object graspable part is influenced by the shape. Assumptions on objects for everyday tasks: usually the objects are **designed to facilitate the grasping**, i.e. the **object handle**.
- Assuming a new or unknown object with a similar graspable part of a known object can be grasped in the same manner:

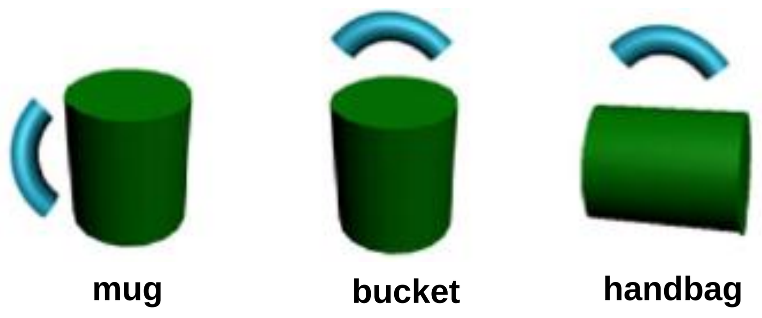
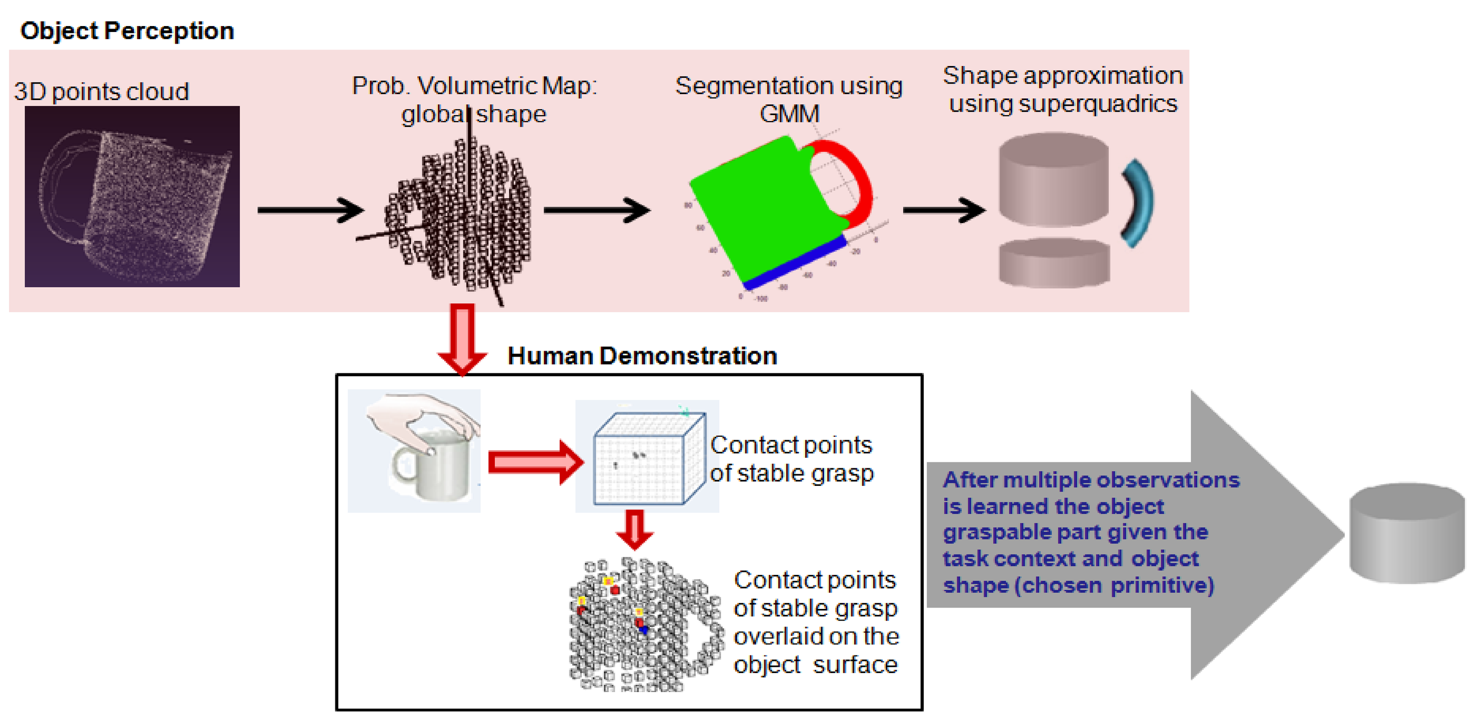


Fig.1. El-Koury S. and Sahbani A. ***A new strategy combining empirical and analytical approaches for grasping unknown 3D objects***. Robotics and Autonomous Systems, 2010

Objectives

- Encompass in a framework the object perception and human demonstrations of stable grasps to learn object regions for grasping



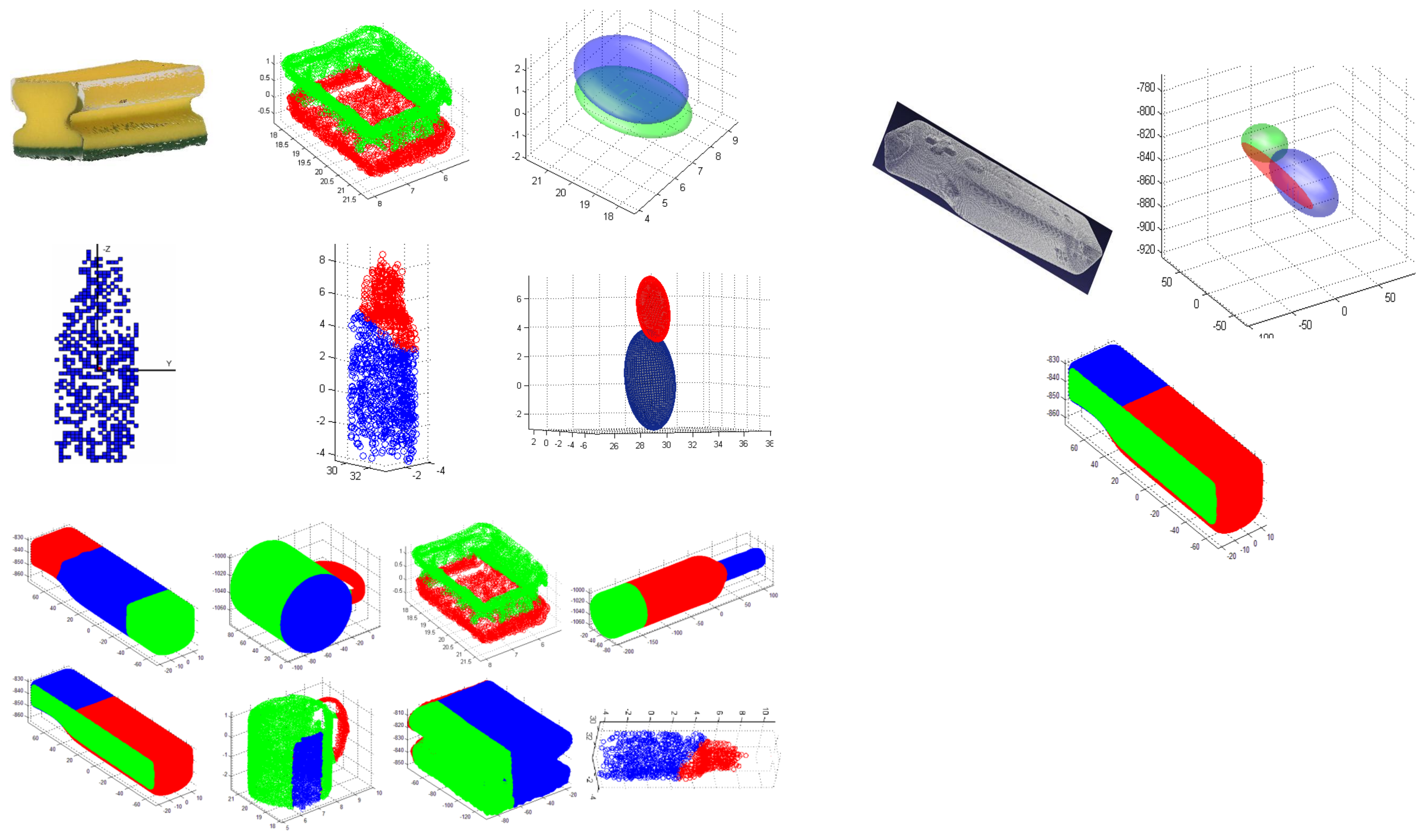
Phase I: Object Perception

- Probabilistic Representation of object shape using volumetric map based on occupancy grid;
- Acquiring the point cloud of the object by in-hand exploration or other modality, e.g.: vision, 3D scanner, etc.

D. R. Faria, R. Martins, J. Lobo, J. Dias - Probabilistic Representation of 3D Object Shape by In-Hand Exploration - in Proceedings of The 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS'10, pp. 1560-1565 - Taipei, Taiwan - October 2010

Object Segmentation using Gaussian Mixture Models

- Segmentation of object parts (Clustering) byGMM to find the suitable clusters given the points cloud:
  - To find the GMM: Expectation-Maximization Algorithm
  - K_{max} (maximum number of clustering) is informed, in this work K_{max} = 3.



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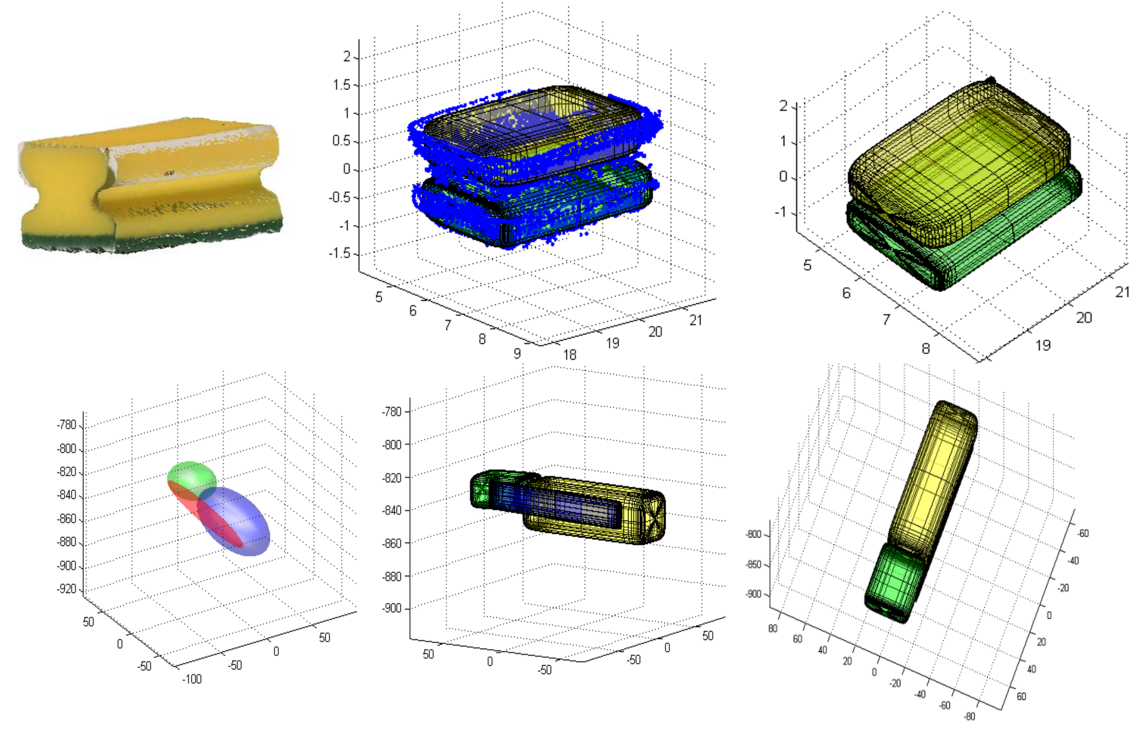
Approximating the object shape using superquadrics



- Each cluster (object part) is fitted to a Superquadric model by computing:

$$f(x,y,z) = \left(\left(\frac{x}{a_1}\right)^{\frac{2}{\epsilon_2}} + \left(\frac{y}{a_2}\right)^{\frac{2}{\epsilon_2}} \right)^{\frac{\epsilon_2}{\epsilon_1}} + \left(\frac{z}{a_3}\right)^{\frac{2}{\epsilon_1}}$$

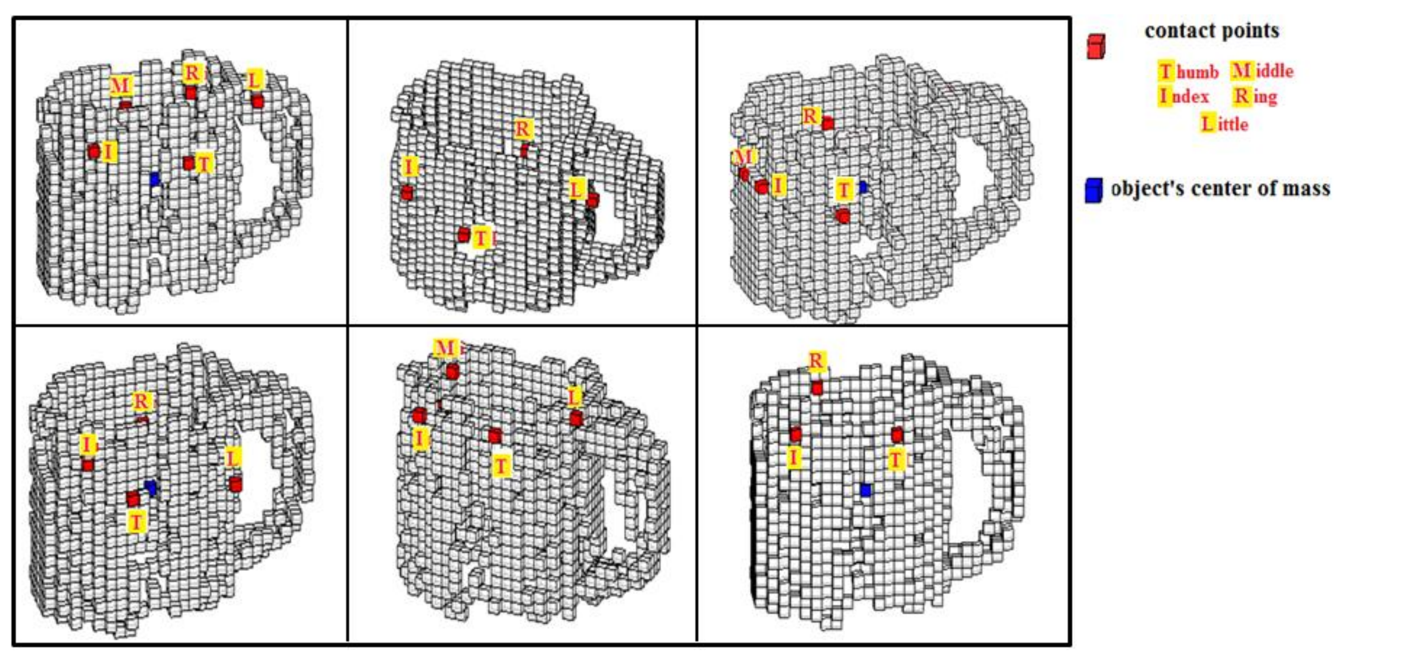
f(x,y,z) = function representing a 3D point of a object part that are being fitted to a **SQ**

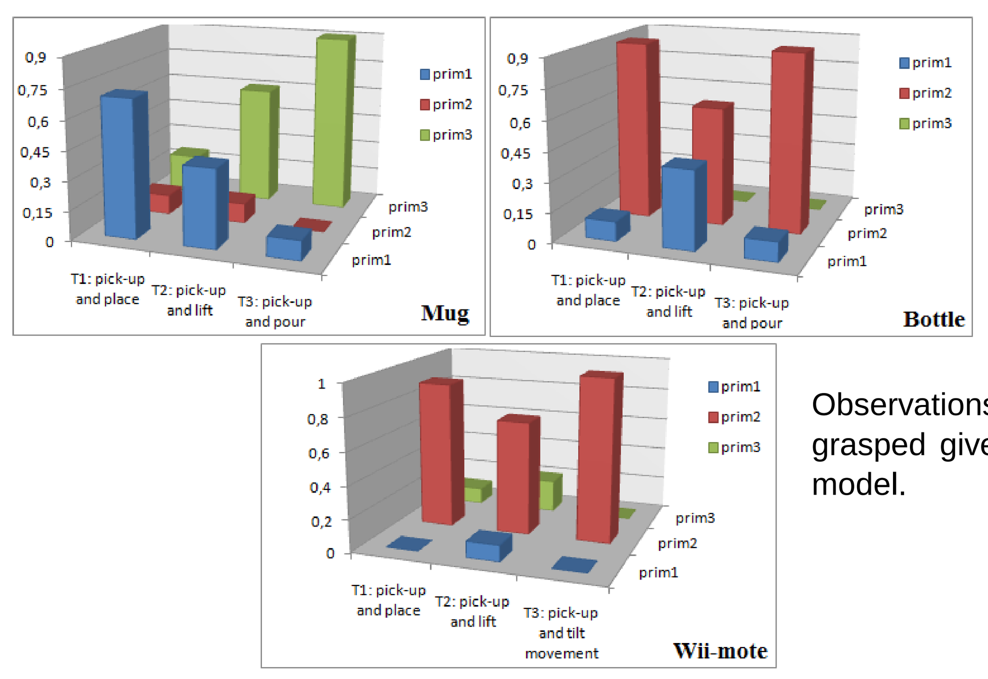
a = parameters to define the shape size in the *x*, *y* and *z* axies.

e = parameter to chose the shape

Phase II: Learning object graspable parts form human demonstrations

- Observing how the humans grasp an object we keep the contact points on the object surface and identify the part of the object where the object was grabbed.
- The contact points are acquired using the position sensors (electromagnetic tracker device) on each fingertip. As long as these points are in the same frame of reference of the object map, it is possible to overlay these points on the object surface.
- Building histograms of the human demonstration keeping information of grasp type, object part that was chosen for grasping, we can learn and estimate the part of the object to grasp given a task context and the object shape.



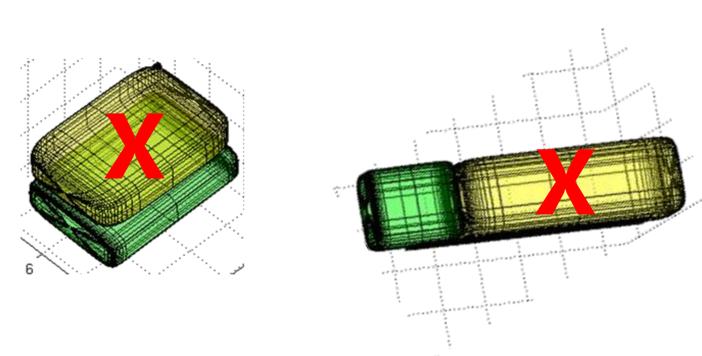


Observations of which part of the object was grasped given a task context and na object model.

Detecting suitable region of the object for grasping

- After observe the humans demonstrations, we could learn given a object model and a task context which is the best object region for grasping.
- Using a Bayesian Classification

$$P(C = prim_i | \mathcal{T}) = \frac{P(\mathcal{T} | C = prim_i) P(C = prim_i)}{\sum_j P(\mathcal{T} | C = prim_j) P(C = prim_j)}$$



Where the posterior information $P(C = prim_i | \mathcal{T} C)$ is computed for each primitive *C* of the object in a specific task *T* ; the likelihood $P(\mathcal{T} C | C = prim_i)$ is the learned probability for each primitive of the object given a task context.

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