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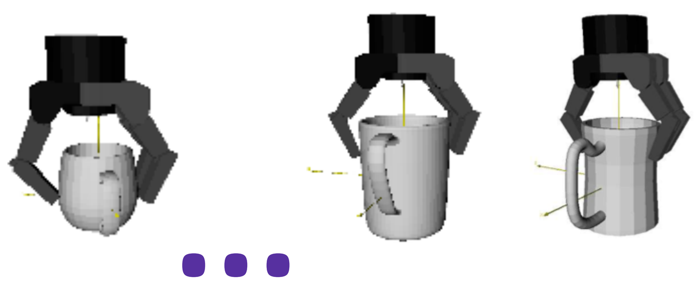
Category-based task specific grasping

OFFLINE part



Generation of task-specific grasps

Stability weights

Registration of a new object

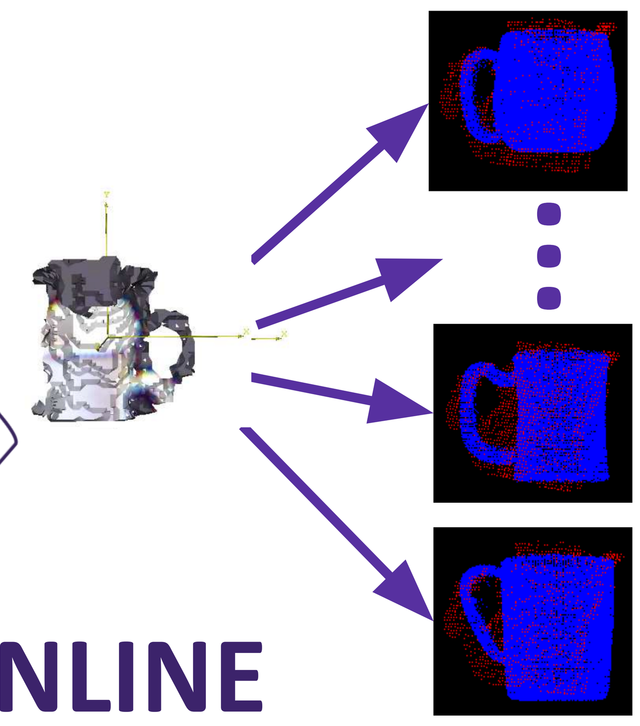
Fitting weights

Optimization

arg max P(X)

"Good" grasp

ONLINE part



1.Training stage (in GraspIt! simulator)

- Training set: objects of the same category ("mugs", "tools" from CGDB)

Columbia Grasp Database mugs models

- Generate reference grasps per each model in category using Barrett Hand model("top", "side", "handle")

Generated task-specific model grasps

- Store stability quality metric (epsilon QM)

2.Registration of a new object

- Get point cloud of a new object from a **single RGB-D image** using Kinect sensor
- Transform training models into point clouds
- Perform the registration using Point Cloud Library:
  - Extract key points and calculate local descriptors (**Fast point Feature Histograms**)
  - Apply **Iterative Closest Point** approach
- Obtain fitting scores from registration

3.Optimization

- Each task-specific grasp is parameterized by 6DOF pose (X) and represented by **weighted density function (Gaussian or Laplace distributions)**
- To find an optimal grasp we maximize the expected probability of grasp X:

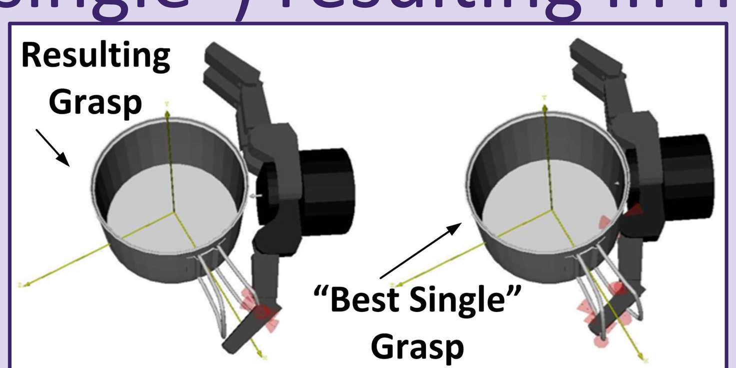
$$\arg\max_{X} P(X) = \sum_{i} P(\epsilon_i) P_i(X)$$

$P(\epsilon_i)$ - the probability of the new object to match the training object i

$P_i(X)$ - the probability of the grasp X to be stable on the training object i

4.Summary of experiments in simulation

- The method outperforms classical most similar model's grasp approach ("best single") resulting in more stable grasps



- The method can generalize for similar in shape objects from other categories