Grasp Moduli Spaces, Gaussian Processes, and Multimodal Sensor Data

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Motivation

Humans can transfer grasps between similar objects such as various types of hammers, cups, or bottles. In robotics, on the other hand, a common approach to grasp synthesis has been to solve the grasping problem for each object instance by completely reinitializing the developed algorithms at hand. We are interested in developing a representation of the space of object shapes and grasps – a *Grasp Moduli Space* [2, 3] – where both objects and grasps can continuously be deformed in order to reason about, generalize and transfer grasps.

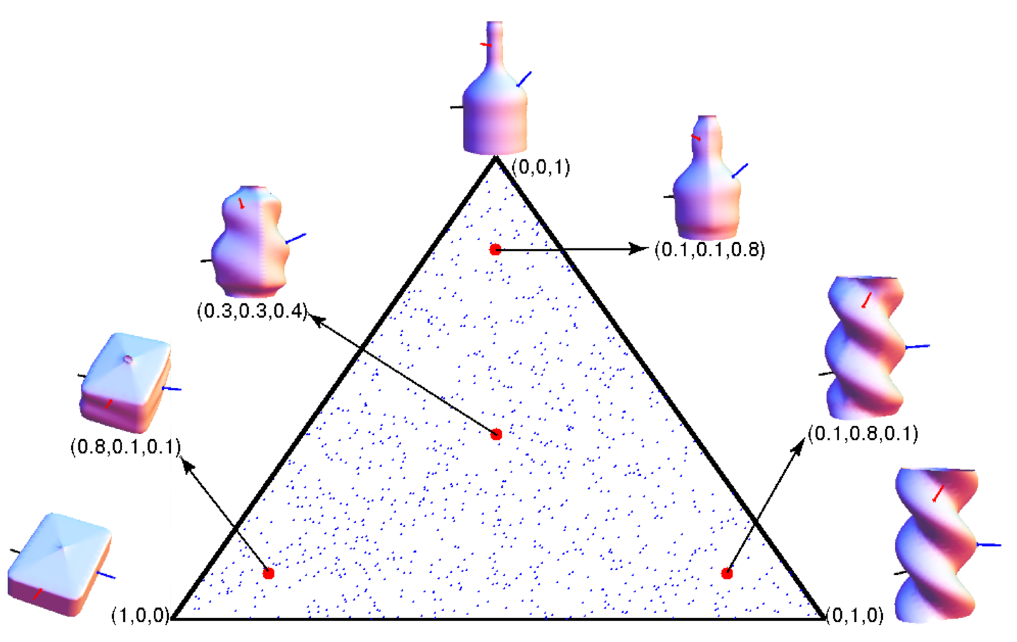
Grasp Moduli Spaces

A point-contact Grasp Moduli Space $\mathcal{G}$ consists of grasps g with m contact points c_i, normals n_i and an object center of mass z, where each $g = (c_1, \ldots, c_m, n_1, \ldots, n_m, z) \in \mathbb{R}^{3m} \times (\mathbb{S}^2)^m \times \mathbb{R}^3$ is constrained by a surface S_h in a continuously parametrized family $\{S_h : h \in \mathcal{M}\}$ of surfaces and where $\mathcal{G}$ is designed with the following goals:

- $\mathcal{G}$ captures a large family of surfaces.
- In $\mathcal{G}$, grasps and shapes can *jointly* be deformed and optimized, *e.g.* with respect to the L^1 grasp quality measure of [4].
- We can define probability distributions over grasps and shapes in $\mathcal{G}$ to reason about grasp configurations probabilistically.
- We can endow $\mathcal{G}$ with a metric to study deformations in grasps and shapes.

Shape space representations

Two classes of shape representations are **parametric surfaces** and **implicit surfaces**. In [2], we considered the shape space $\mathcal{M}^{cyl}$ of smooth parametric surfaces with cylindrical coordinates $S_{f,a,b} = \{(f(u,\theta)\cos\theta, f(u,\theta)\sin\theta, (1-u)a + ub) : u \in [0,1], \theta \in \mathbb{S}^1\}$, $f : [0,1] \times \mathbb{S}^1 \to \mathbb{R}_{>0}$, $a < b$ and defined a resulting Grasp Moduli Space $\mathcal{G}^{cyl}(m)$.



Grasp/shape space induced by 3 surfaces from [2].

$$\mathcal{G}^{cyl}(m) = \mathcal{M}^{cyl} \times [0,1]^m \times (\mathbb{S}^1)^m$$

References

[1] M. Björkman, Y. Bekiroglu, V. Högman, and D. Kragic *Enhancing visual perception of shape through tactile glances* In IEEE/RSJ IROS 2013

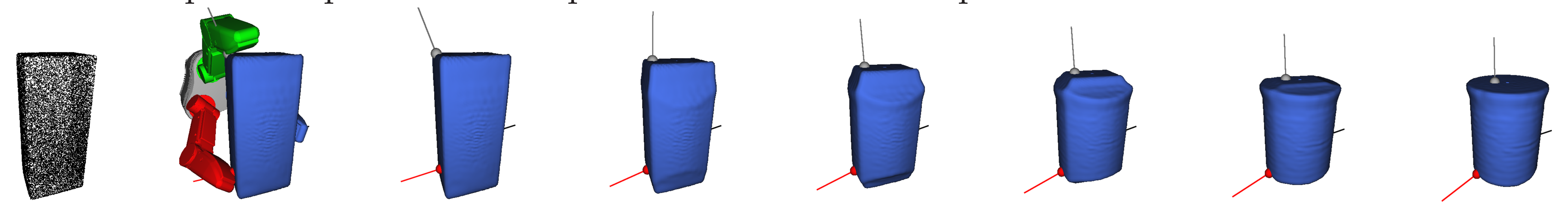
[2] F. T. Pokorny, K. Hang, and D. Kragic *Grasp moduli spaces* In Robotics: Science and Systems, Berlin, 2013

[3] F. T. Pokorny, Y. Bekiroglu, and D. Kragic *Grasp Moduli Spaces and Spherical Harmonics* In IEEE ICRA 2014

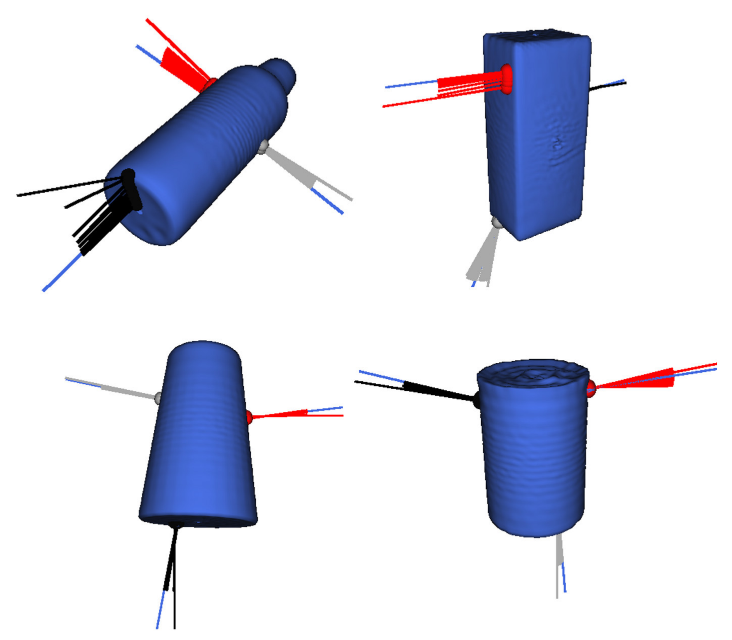
[4] C. Ferrari and J. Canny Planning optimal grasps In IEEE ICRA 1992

Parametric Surfaces and Grasp Moduli Spaces

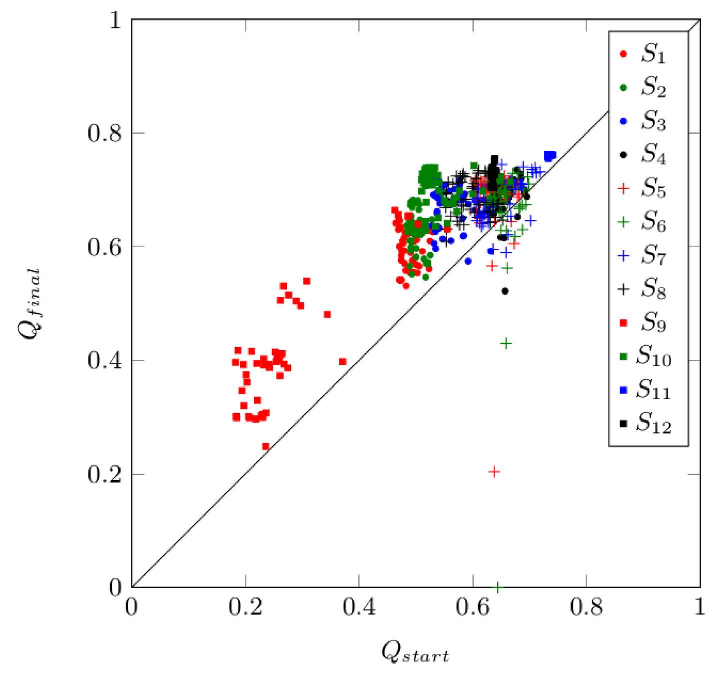
In [3], we performed least-squares regression using a spherical harmonics based expansion of smooth surfaces S from point-cloud data. In our experiments, this resulted in a Grasp Moduli Space isomorphic to $\mathcal{G}^{rad} = \mathbb{R}^{2601} \times (\mathbb{S}^2)^m$, where $x \in \mathbb{R}^{2601}$ determines a smooth parametric surface and each $(\theta, \varphi) \in \mathbb{S}^2$ determines a contact point on such a surface. This approach is applicable for surfaces that are homeomorphic to spheres and for point-clouds for which spherical coordinates can be determined.



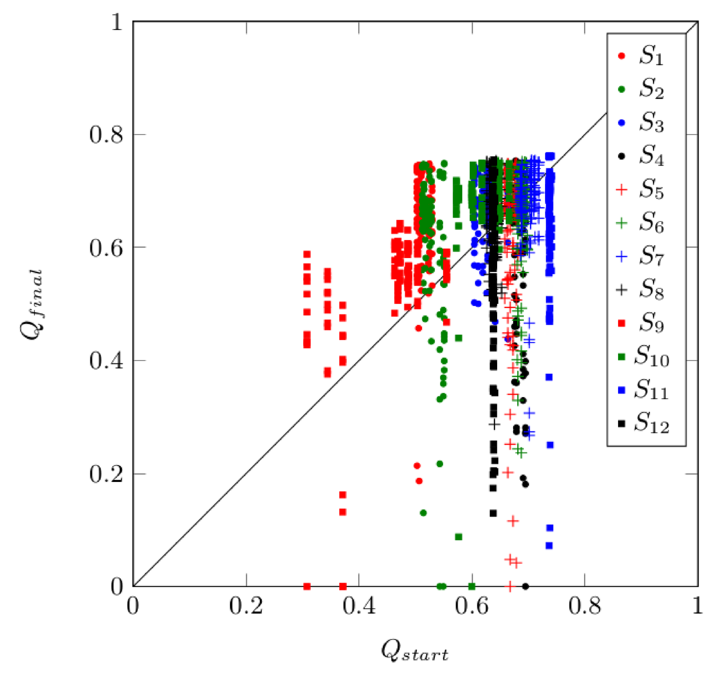
Example grasp transfer via a joint object/grasp deformation and optimization in $\mathcal{G}^{rad}$.



Grasp optimization in $\mathcal{G}^{rad}$ with fixed shape coordinate [3].



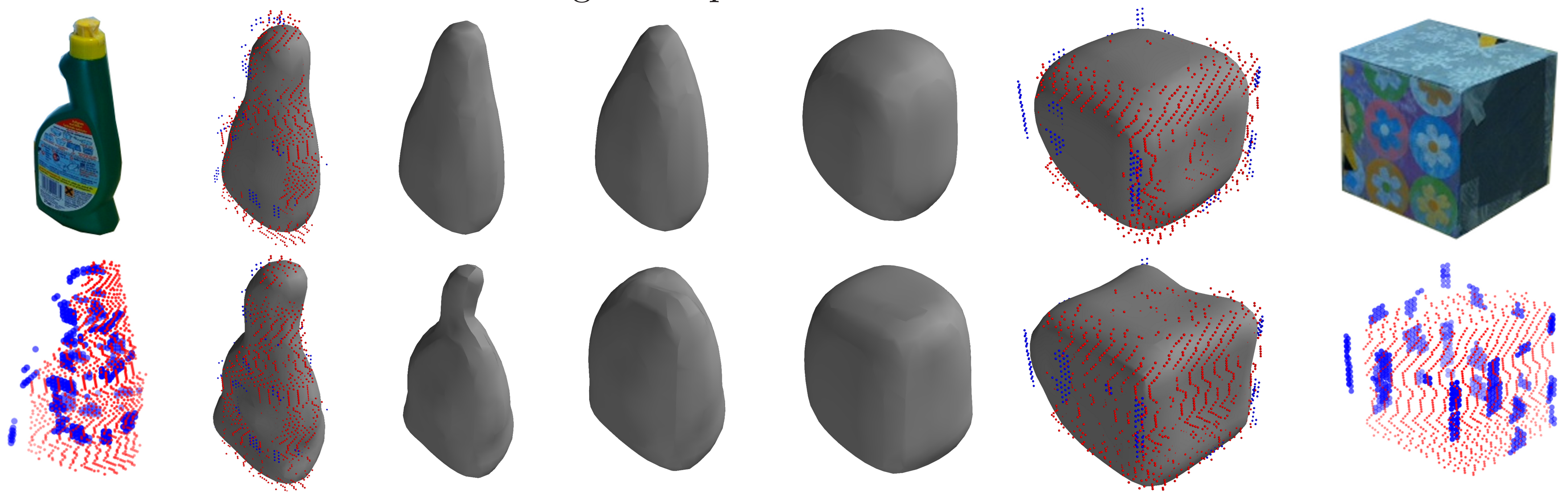
Initial vs. final grasp quality with grasp optimization in $\mathcal{G}^{rad}$ on fixed surfaces [3].



Initial vs. final grasp quality with grasp optimization and transfer in $\mathcal{G}^{rad}$ [3].

Implicit Surfaces and Grasp Moduli Spaces

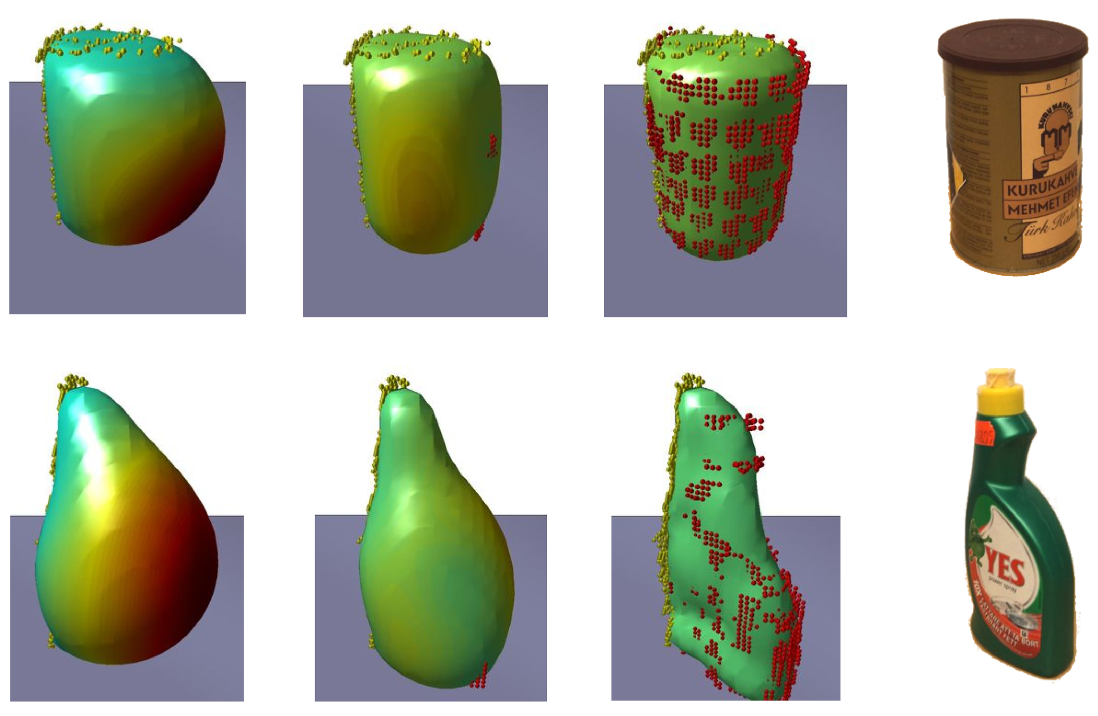
In our current work, we start with haptic and visual (kinect) data and represent a surface as $S_f = f^{-1}(0)$ for a function $f : \mathbb{R}^3 \to \mathbb{R}$ which we determine via Gaussian Process Regression. The figures in the 2^{nd} and 6^{th} column below show such reconstructions for two kernel choices: the Matérn kernel $k_{\nu=\frac{3}{2}}(x_i, x_j) = (1 + \frac{\sqrt{3}r}{l})\exp(-\frac{\sqrt{3}r}{l})$ (first row) and the thin-plate kernel $k(x_i, x_j) = 2|r|^3 - 3Rr^2 + R^3$ (second row) where $r = |x_i - x_j|$. Here, shapes are now continuously parametrized by GP means and each grasp contact point c_i on S_f has to satisfy $f(c_i) = 0$. Surface normals can then be calculated using this equation.



Shape approximations from haptic (blue) and single-view kinect (red) data and shape deformations using a convex combination of the corresponding GP means.

Using the GP's Variance

By iteratively touching points with maximal uncertainty under the GP regression model, we showed in [1] how a reconstruction from single view kinect data can be improved using a haptic exploration with a Schunk Dexterous Hand.



Evolution of implicit shape approximation as more tactile data becomes available and where the objects are positioned to show the back-side not visible from a single-view kinect capture (from [1]).

Open Challenges

Many interesting open problems exist in developing a full grasp/shape representation based on our approach:

- Which optimization methods are most effective in optimizing a grasp's quality, and more generally a grasp's *task specific utility*, in a general Grasp Moduli Space where shapes are parametrized using Gaussian Processes?
- How can the GP's variance information be incorporated in a deformation-based grasp synthesis framework?
- How can grasp configurations best be modeled probabilistically in conjunction with the GP's shape estimate?
- How can prototypical grasp/shape configurations in $\mathcal{G}$ be determined automatically?