Continuous Correlated Beta Processes for 3D Grasp Planning Under Uncertainty
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I. Introduction

Robots in warehousing and small- to medium-scale manufacturing must be able to efficiently handle to new products and parts. For example, a robot processing orders in a distribution warehouse must be able to quickly adapt to new consumer products to place them in shipping containers. Analytic methods for grasp planning requires precise knowledge of contact locations and surface normals, but a robot in the field may not measure these quantities exactly due to sensor imprecision and missing data resulting from occlusions or highly reflective surfaces. This motivates a fast and adaptive approach to grasp planning that is robust to uncertainty about the state of the robot and environment.

[TODO: I THINK THE PARTS ABOUT FORCE CLOSURE SHOULD BE GREATLY COMPRESSED HERE] Force closure, the ability to resist external forces and torques in arbitrary directions [**?**], is a commonly-used binary metric of grasp quality. Past work has measured the probability of force closure given uncertainty in robot state [9], [31], object pose [11], [39], [66], and object shape [9], [31], [37], [47]. Computing the probability of force closure requires integrating over the uncertain quantities, which many works have computed using computationally expensive Monte-Carlo integration over sampled perturbations [11], [31], [38], [39], [66] parallelized in the cloud [38] or using iterative pruning of grasps with low quality [37], [**?**].

Recently, Laskey et al. [41] showed that it was possible to jointly compute the integral and identify the best grasp using Multi-Armed Bandit (MAB) algorithms such as Thompson Sampling, leading to $5-10\times$ speedups over previous work on a set of parallel-jaw grasps on 2D objects. However, the MAB algorithms still needed roughly 5,000 samples to identify the best grasp from a pool of 1,000 candidates for each object, which could be time-consuming for 3D objects. Also, the number of samples is prohibitively high to use the algorithms based on physical success from robot trials instead of in simulation. One possible reason for the magnitude of samples is that this work treated each grasp and object independently, when in reality grasps and objects with similar features, such as those illustrated inFig. **??**, should convey information about the probability of success of one another.

[TODO: NEED TO GET CORRECT TERMINOLOGY. TECHNICALLY NOT CONTEXTUAL OR COMBINATORIAL. ASK KEVIN.] Correlated Multi-Armed Bandits (CMABs) are an extension of standard MABs in which options have correlated rewards. On each observation, standard MAB algorithms update only the predictive model for the option chosen, while CMAB algorithms typically update a global predictive model of the reward for each option. This can lead to faster convergence if the algorithm has some knowledge of the correlation structure between options. []. A primary challenge is thus estimating a model of the global correlation structure of the arms, which may require a large amount of data.

In this work, we leverage CMABs to accelerate identification of robust grasps using a correlation structure learned from large amounts of data. We model the probability of force closure for grasps on 3D shapes as a Correlated Continuous Beta Processes (CCBPs) [], a model of 0-1 correlated options with computationally inexpensive posterior updates compared to alternative models such as Gaussian Processes []. Each option corresponds to a single grasp center and axis. Evaluating an option corresponds to sampling from Gaussian uncertainty in object pose, gripper pose, and contact friction, and measuring force closure for the grasp on the sampled state. We learn the correlation structure between grasps [TODO: WRITE UP]

Our primary contribution is [TODO: WRITE UP]. Our experiments show that [TODO: WRITE UP].

II. Related Work

Many works on grasp planning focus on finding grasps by maximizing a grasp quality metric, such as the ability to resist external perturbations to the object in wrench space [19], [51]. These metrics have been used to synthesize grasps for known objects using sampling-based optimization in software tools such as GraspIt! [51] or OpenGRASP [45]. However, analytic grasp quality metrics have been criticized for relying on perfect knowledge of object shape, pose, material properties, and locations of contact [10], [17], [66], [67] and for not taking into account the dynamics of the the grasp [2], [55]. Recent work has also suggested that grasp closure metrics may fail to accurately predict of grasp success on a physical robot [1], [66]. This has motivated work on transferring known grasps from a database to new objects, evaluating robust versions of analytic quality metrics with respect to uncertainty in the state of the robot and environment, and work on data-driven grasp synthesis.

Many works have approached grasp synthesis for unknown or familiar objects by transferring grasps from a benchmark set of exemplar objects in a large database. Li and Pollard [46] generated grasps by matching object shapes to human hand postured in a database. Goldfelder et al. [25] developed the Columbia grasp database, a database of 1,814 distinct models and over 200,000 form closure grasps generated using the Eigengrasp planner in GraspIt! [13]. The authors later used synthetic partial depth maps of objects in the database to match robot sensor data to precomputed grasps, using the Iterated Closest Point (ICP) algorithm to align the coordinate frames of the depth maps [26], [24]. Several works have also transferred grasps from objects of the same category by warping contacts betwen corresponding points on a shape surface and locally replanning using local rigid alignment and contact interpolation [29], [62] or by interpolating a shape and grasp over a Grasp Moduli Space [54], [53]. Detry et al. [15] create a low-dimensional representation of object parts and cluster object parts that are grasped similarly to form a shape library of prototypical grasp parts, and show that this representation can be transferred to real sensor data [14].

Work on evaluating grasp quality metrics under uncertainty, such as the probability of force closure, has considered uncertainty in the state of a robotic gripper [23], [63] and uncertainty in contact locations with an object [67]. Recent work has also studied the effects of uncertainty in object pose and gripper positioning [9], [31]. Brook, Ciocarlie, and Hsiao [9], [31] studied a Bayesian framework to evaluate the probability of grasp success given uncertainty in object identity, gripper positioning, and pose by simulating grasps on deterministic mesh and point cloud models. Weisz et al. [66] and Kim et al. [39] independently found that grasps ranked by probability of force closure subject to perturbations of object pose in simulation were empirically more successful on a physical robot than grasps planned using deterministic wrench space metrics. Many works have also studied grasping under object shape uncertainty resulting from imprecision of object segmentations in images [11], part tolerancing in manufacturing [37], [38], or missing and noisy data from depth sensors such as the Kinect modeled with Gaussian process implicit surfaces [47], [41]. Many have also studied caging gripper configurations [59], which are a waypoint to form closure grasps for two fingers [64], [60] and may be robust to perturbations in object pose and shape [18], [65].

Another approach for synthesizing grasps on objects is to sample grasps and rank them according to metrics derived from human labels or physical execution [4]. Saxena et al. [34], [61] used a logistic regression classified to predict grasp afordances in images from human annotated training data. Several other works have examined predicting grasp points using depth edges [56], combinations of 2D and 3D edges [43], and global shape descriptors [3]. Lenz et al [44] used deep learning to detect grasp bounding boxes in color and depth images, which was later extended to real time by Redmon and Angelova [58]. Many works have also considered predicting grasp success from 3D point clouds. Herzog et al. [27], [28] extract "heightmaps" of local object curvature from human demonstrated grasps, construct a library of heightmap templates, and match new sensor data to templates to select grasps similar to the demonstrations. Kappler et al. [36] trained a deep neural network to predict human labelled grasps for a Barett hand on a database of synthetic pointclouds of objects. Recently, several other works have proposed to form a huge database of grasps on synthetic objects from simulation outcomes [50] or physical execution [**?**]. In comparison, our work studies the convergence rate for adaptively acquiring samples for evaluating and ranking grasps by their likelihood of success through the use of data-driven grasp correlations based on local and global features of an object surface.

Many works have also considered using data-driven approaches for actively selecting grasps. Several works have studied active search for successful grasps by minimzing uncertainty about the state of the envirnoment [32], [35], [20], but without use of an explicit grasp quality metric to guide the search. Kehoe et al. [37] proposed iterative pruning, an algorithm for evaluating the probability of force closure for a set of candidate grasps while discrading grasps known to have poor quality. Tellex et al. [] proposed an initiative to adaptively collect a dataset of grasps and point clouds for one million objects using MAB and reinforcemen learning. Detry et al. [16] estimated a full continuous density function over grasp poses using kernel density estimation and adaptively acquired samples by pruning unsuccessful grasps. Recently, Laskey et al. [41] showed that Multi-Armed Bandit algorithms can be used to accelerate the identification of grasps with high probability of force closure under uncertainty in shape, pose, and friction in 2D over candidate sets of 1,000 grasps on 88 objects. MAB algorithms select the next grasp to sample by trading off gaining information about grasps with few samples and exploiting the success of grasps known to work well. In robotics, MAB algorithms have also been for speeding up probabilistic roadmap motion planning by adaptively sampling waypoints [33], searching for the best state machine for a particular task [49], solving mixed observable POMDPs [42], and multi-agent navigation [21].

One shortcoming of the MAB model used by Laskey et al. is that it did not take into account correlations between grasps [41]. In reality, grasp correlations may occur from grasps with similar configurations [13], [16], objects with similar global structure [54], or on point cloud surfaces with similar local geometry [7], [27], [40], [61]. Correlated Multi-Armed Bandit (CMAB) models, sometimes also referred to as Bayesian Optimization models [8], have been used to trading off infromation gathering and exploitation in applicatoins such as ad-serving [12] and envrionmental monitoring in robotics [30], [48]. Perhaps the most common model of correlations in a CMAB is a linear model [12], however this depends on the selection of features are linearly related to a success criteria. Another common model of correlations is a Gaussian Process (GP) [57], which can model nonlinear relationships between options and rewards. Kroemer et al. [40] developed a reinforcement learning approach to grasp selection based on seeding hypothesse via imitation learning and Gaussian process upper-confidence bounds to predict grasp successeses and determine the next grasp to select. Boularias et al. [5] used a Gaussian process Bayesian Optimization model for selecting grasps on cluttered piles of rocks. However, GP models are expensive to update with new observations ($O(n^2)$ where n is the number of observations so far) [57], which limited the scale of experiments in both simulation and the physical world that the authors could perform. To make the model more tractable, Boularias et al. later extended their work to use an heuristic upper confidence bound-based reinforcement learning [6]. Recently, Goetschalckx et al. [22] developed the Continuous Correlated Beta Process (CCBP), a nonlinear model of 0-1 reward probabilities. CCBPs are inexpensive to update compared to GPs, requiring $O(n)$ time in the worst case and a much smaller factor when efficient nearest neighbor queries can be performed [22]. Montesano and Lopes [52] used CCBPs (although the authors did not refer to them as CCBPs) to actively acquire grasp executions, measuring correlations from the responses to a bank of 151 image filters. In this work we also utilize CCBPs to model correaltions between grasps, and study their performance on grasping simulations over thousands of objects.

III. Definitions and Problem Statement

[TODO: FILL IN MORE DETAILS. THIS IS A STRIPPED DOWN VERSION TO GET IDEAS DOWN ON THE PAGE] Let $\mathbf{g} = [\mathbf{x}, \mathbf{w}]^T$ be a parallel-jaw grasp parameterized by its center in 3D space $\mathbf{x} \in \mathbb{R}^3$ and approach direction $\mathbf{v} \in \mathcal{S}^2$. Let $\mathcal{G} = \{[\mathbf{x}, \mathbf{w}]^T \big| \mathbf{x} \in \mathbb{R}^3, \}$ denote the space of all grasps.

We will assume a known object shape ν, and known uncertainty in object pose, gripper pose, and friction coefficient resulting from sensing uncertainties and missing data following the model of Laskey et al. [41]. Let ξ be uncertainty in object pose distributed as a Gaussian with mean $\mu_\xi \in \mathfrak{se}(3)$ and covariance Σ_ξ. Let ρ be uncertainty in gripper pose distributed as a Gaussian with mean $\mu_\rho \in \mathcal{G}$ and covariance Σ_ρ. Let ζ denote uncertainty in friction coefficient distributed as a Gaussian with mean $\mu_\zeta \in \mathbb{R}$ and covariance Σ_ζ. Given object shape and samples of object pose, and gripper pose, we let $\mathbf{c}_i(\mathbf{g}, \theta, \xi, \rho) \in \mathbb{R}^3$ for $i \in 1, 2$ denote the 3D location of contact between the i-th gripper jaw and surface. Furthermore, let $\mathbf{n}_i(\mathbf{c}_i, \nu) \in \mathcal{S}^2$ denote the surface normal at this contact. A graphical model describing the relationship between these quantities is given in Fig. **??**.

We measure grasp quality by the probability of force closure subject to these uncertain quantities. Let $F \in \{0, 1\}$ denote the occurence of force closure, or the ability to resist wrenches in arbitrary directions [19]. Then the probability of force closure for a grasp $\mathbf{g}$ is

$$P_F(\mathbf{g}) = \mathbb{P}\left(F = 1 \mid \mathbf{g}, \xi, \rho, \zeta\right).$$

We are interested in finding the candidate grasp that maximizes the probability of force closure $P_F(g)$ [39], [41], [47], [66] subject to these sources of uncertainty over a budgeted maximum number of samples T. To perform this as q uickly as possible we formulate this as a maximization over the sum of the true P_F for the grasps sampled at iteration t, where $I(i)$ denotes the grasp selected at time t

$$\max_{g_{I(1)}, \ldots, g_{I(T)} \in \mathcal{G}} \sum_{t=1}^{T} P_F(g_{I(t)}) \tag{III.1}$$

As the maximization over the continuous space $\mathcal{G}$ is computationally expensive, past work has solved this objective using a discrete set of K candidate grasps $\Gamma = \{\mathbf{g}_1, ..., \mathbf{g}_K\}$. In practice Γ has been set using Gaussian sampling of grasp centers and poses [41] or using heuristics such as antipodality [**?**]. [TODO: SWITCH TO TASK-BASED QUALITY METRIC (E.G. RESITING GRAVITY)? I THINK IT WOULD BE MORE COMPELLING BUT DOESN'T SEEM TO HAVE MUCH PRECEDENT]

Even with a discrete set of candidates, evaluating $P_F(\mathbf{g})$ for any grasp requires an expensive integration over possible contact locations between the grasp and surface and the surface normals at these contacts [47]. Thus, past work has evaluated the probability of force closure using Monte-Carlo integration [37], [38], [66], approximating the expression by minimzing uncertainty at the contact locations [47], and using Multi-Armed Bandit algorithms to jointly evaluate $P_F(\mathbf{g})$ using Monte-Carlo integration while allocating samples to more promising grasps. In this work, we propose to use Multi-Armed Bandits with correlations between arms to further accelerate convergence.

IV. Continuous Correlated Beta Processes

Finding an approximate solution of Equation III.1 using Multi-Armed Bandits requires a model of the reward distribution of each arm. We use Continuous Correlated Beta Processes (CCBPs) to model the probability of force closure of grasps as a Bernoulli random variable with correlations between grasps. We refer the reader to Goetschalckx et al. [] for a detaled description of CCBPs. In practice, correlations may occur between grasps that contact the shape in similar locations may have similar probabilities of force closure. Correlations may also occur between grasps on different shapes, such as grasping the handle of a mug and the handle of a teapot.

A. Beta-Bernoulli Processes

For clarity we first review Beta-Bernoulli Processes, the uncorrelated version of CCBPs. Let $\Gamma = \{g_k\}_{k=1}^K$ denote our discrete set of K candidate grasps. Let $F(\mathbf{g}_k) \in \{0, 1\}$ denote the occurence of force closure for a grasp $\mathbf{g}_k$. We model $F(\mathbf{g}_k)$ as a Bernoulli random variable with probability of success $\theta_k = P_F(\mathbf{g}_k)$. Since we do not know the value of θ_k for each grasp, we can specify a distribution of θ_k based on our prior belief about the likelihood of force closure. A common choice for a prior on the Bernoulli parameter θ_k is the Beta distribution, which is specified by shape parameters $\alpha > 0$ and $\beta > 0$:

$$\text{Beta}(\alpha, \beta) = \frac{1}{B(\alpha, \beta)} \theta_k^{\alpha-1} (1 - \theta_k)^{\beta-1}$$

This combination of indepdent Bernoulli random variables with Beta priors is known as a *Beta-Bernoulli process*.

Let our prior distribution on θ_k be a beta distribution with parameters $\alpha_{k,0}$, $\beta_{k,0}$. Then after observing force closure for t samples $F_1(g_k), ..., F_t(g_k)$ from our uncertainty model, our posterior distribution on the Bernoulli success probability θ_k is obtained using Bayes rule. This yields [41]

$$p\left(\theta_k | F_1(g_k), ..., F_t(g_k)\right) = \text{Beta}\left(\alpha_{k,t}, \beta_{k,t}\right)$$

$$\alpha_{k,t} = \alpha_{k,0} + \sum_{i=1}^{t} F_i(g_k)$$

$$\beta_{k,t} = \beta_{k,0} + \sum_{i=1}^{t} (1 - F_i(g_k))$$

Therefore the belief distribution on the probability of force closure θ_k can be updated by incrementing the value of α and β for each force closure observed. The expected value of θ_k after the observations is

$$\begin{aligned}\mathbb{E}\left[\theta_k | F_1(g_k), ..., F_t(g_k)\right] &= \frac{\alpha_{k,t}}{\alpha_{k,t} + \beta_{k,t}} \\ &= \frac{\#\text{Successes} + \alpha_{k,0}}{\#\text{Trials} + \alpha_{k,0} + \beta_{k,0}}.\end{aligned}$$

B. Continuous Correlated Beta Processes

Continuous Correlated Beta Processes(CCBPs) were independently developed by Goetschalckx et al. [22] and Montesano and Lopes [52] to model correlations between the Bernoulli random variables in a Beta-Bernoulli process, which may lead to faster convergence in Multi-Armed Bandit problems [12]. Such correlations may exist when the Bernoulli random variables depend on common latent factors. For example, two probability of force closure variables θ_k may be correlated when two grasps have similar poses or when the surface geometry near the points at which they contact an object are similar.

A CCBP is a Beta-Bernoulli process with an additional parameter $k(\mathbf{g}_i, \mathbf{g}_j) : \mathcal{G} \times \mathcal{G} \to [0, 1]$, called the kernel, that measures similarity between two grasps. The kernel approaches 1 as the arguments become increasingly similar and approaches 0 as the arguments become dissimilar. One common choice of kernel is the squared exponential kernel

$$k(\mathbf{g}_i, \mathbf{g}_j) = \exp\left(-d(\mathbf{g}_i, \mathbf{g}_j)^2\right)$$

where $d(\cdot) : \mathcal{G} \times \mathcal{G} \to \mathbb{R}_+$ is a distance metric between grasps. A common choice of distance metric is

$$d(\mathbf{g}_i, \mathbf{g}_j) = \left(\varphi(\mathbf{g}_i) - \varphi(\mathbf{g}_j)\right)^T C^{-1} \left(\varphi(\mathbf{g}_i) - \varphi(\mathbf{g}_j)\right)$$

where $\varphi(\cdot) : \mathcal{G} \to \mathbb{R}^m$ is an m-dimensional feature representation of grasps and $C \in \mathbb{R}^{m \times m}$ is the *kernel bandwidth*. The bandwidth C scales dimensions of the feature space to mark some dimensions as being more or less relevant for measuring similarity between grasps.

Given a kernel, on each observation we update the belief of each grasp proportional to how similar it is to the observed grasp as measured by the kernel. Let $F_1(\mathbf{g}_{I(1)}), ..., F_t(\mathbf{g}_{I(t)})$ be t observations of force closure from samples of our uncertainty models for grasps $g_{I(1)}, ..., g_{I(t)}$, where $I(j)$ is the index of the grasp sampled at time j. Then the CCBP posterior update for θ_k is []:

$$p\left(\theta_k | F_1(g_{I(1)}), ..., F_t(g_{I(t)})\right) = \text{Beta}\left(\alpha_{k,t}, \beta_{k,t}\right)$$

$$\alpha_{k,t} = \alpha_{k,0} + \sum_{j=1}^{t} k(g_k, g_{I(j)}) F_i(g_{I(j)})$$

$$\beta_{k,t} = \beta_{k,0} + \sum_{=1}^{t} k(g_k, g_{I(j)})(1 - F_i(g_{I(j)}))$$

Intuitively, this allows observations of a grasp to constitute ”effective” observations of other grasps.

References

[1] R. Balasubramanian, L. Xu, P. D. Brook, J. R. Smith, and Y. Matsuoka, “Physical human interactive guidance: Identifying grasping principles from human-planned grasps,” *Robotics, IEEE Transactions on*, vol. 28, no. 4, pp. 899–910, 2012.

[2] A. Bicchi and V. Kumar, “Robotic grasping and contact: A review,” in *ICRA*. Citeseer, 2000, pp. 348–353.

[3] J. Bohg and D. Kragic, “Learning grasping points with shape context,” *Robotics and Autonomous Systems*, vol. 58, no. 4, pp. 362–377, 2010.

[4] J. Bohg, A. Morales, T. Asfour, and D. Kragic, “Data-driven grasp synthesisa survey,” *Robotics, IEEE Transactions on*, vol. 30, no. 2, pp. 289–309, 2014.

[5] A. Boularias, J. A. Bagnell, and A. Stentz, “Efficient optimization for autonomous robotic manipulation of natural objects,” 2014.

[6] ——, “Learning to manipulate unknown objects in clutter by reinforcement,” in *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.

[7] A. Boularias, O. Kroemer, and J. Peters, “Learning robot grasping from 3-d images with markov random fields,” in *Intelligent Robots and Systems (IROS), 2011 IEEE/RSJ International Conference on*. IEEE, 2011, pp. 1548–1553.

[8] E. Brochu, V. M. Cora, and N. De Freitas, “A tutorial on bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning,” *arXiv preprint arXiv:1012.2599*, 2010.

[9] P. Brook, M. Ciocarlie, and K. Hsiao, “Collaborative grasp planning with multiple object representations,” in *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*. IEEE, 2011, pp. 2851–2858.

[10] J.-S. Cheong, H. Kruger, and A. F. van der Stappen, “Output-sensitive computation of force-closure grasps of a semi-algebraic object,” vol. 8, no. 3, pp. 495–505, 2011.

[11] V. N. Christopoulos and P. Schrater, “Handling shape and contact location uncertainty in grasping two-dimensional planar objects,” in *Intelligent Robots and Systems, 2007. IROS 2007. IEEE/RSJ International Conference on*. IEEE, 2007, pp. 1557–1563.

[12] W. Chu, L. Li, L. Reyzin, and R. E. Schapire, “Contextual bandits with linear payoff functions,” in *International Conference on Artificial Intelligence and Statistics*, 2011, pp. 208–214.

[13] M. T. Ciocarlie and P. K. Allen, “Hand posture subspaces for dexterous robotic grasping,” *Int. J. Robotics Research (IJRR)*, vol. 28, no. 7, pp. 851–867, 2009.

[14] R. Detry, C. H. Ek, M. Madry, and D. Kragic, “Learning a dictionary of prototypical grasp-predicting parts from grasping experience,” in *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. IEEE, 2013, pp. 601–608.

[15] R. Detry, C. H. Ek, M. Madry, J. Piater, and D. Kragic, “Generalizing grasps across partly similar objects,” in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012, pp. 3791–3797.

[16] R. Detry, D. Kraft, O. Kroemer, L. Bodenhagen, J. Peters, N. Krüger, and J. Piater, “Learning grasp affordance densities,” *Paladyn, Journal of Behavioral Robotics*, vol. 2, no. 1, pp. 1–17, 2011.

[17] R. Diankov, “Automated construction of robotic manipulation programs,” Ph.D. dissertation, Citeseer, 2010.

[18] R. Diankov, S. S. Srinivasa, D. Ferguson, and J. Kuffner, "Manipulation planning with caging grasps," in *Humanoid Robots, 2008. Humanoids 2008. 8th IEEE-RAS International Conference on*. IEEE, 2008, pp. 285–292.

[19] C. Ferrari and J. Canny, "Planning optimal grasps," in *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*, 1992, pp. 2290–2295.

[20] D. Fischinger, A. Weiss, and M. Vincze, "Learning grasps with topographic features," *Int. J. Robotics Research (IJRR)*, p. 0278364915577105, 2015.

[21] J. E. Godoy, I. Karamouzas, S. J. Guy, and M. Gini, "Adaptive learning for multi-agent navigation," in *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2015, pp. 1577–1585.

[22] R. Goetschalckx, P. Poupart, and J. Hoey, "Continuous correlated beta processes," in *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, vol. 22, no. 1. Citeseer, 2011, p. 1269.

[23] K. Y. Goldberg and M. T. Mason, "Bayesian grasping," in *Robotics and Automation, 1990. Proceedings., 1990 IEEE International Conference on*. IEEE, 1990, pp. 1264–1269.

[24] C. Goldfeder and P. K. Allen, "Data-driven grasping," *Autonomous Robots*, vol. 31, no. 1, pp. 1–20, 2011.

[25] C. Goldfeder, M. Ciocarlie, H. Dang, and P. K. Allen, "The columbia grasp database," in *Robotics and Automation, 2009. ICRA'09. IEEE International Conference on*. IEEE, 2009, pp. 1710–1716.

[26] C. Goldfeder, M. Ciocarlie, J. Peretzman, H. Dang, and P. K. Allen, "Data-driven grasping with partial sensor data," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*. IEEE, 2009, pp. 1278–1283.

[27] A. Herzog, P. Pastor, M. Kalakrishnan, L. Righetti, T. Asfour, and S. Schaal, "Template-based learning of grasp selection," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012, pp. 2379–2384.

[28] A. Herzog, P. Pastor, M. Kalakrishnan, L. Righetti, J. Bohg, T. Asfour, and S. Schaal, "Learning of grasp selection based on shape-templates," *Autonomous Robots*, vol. 36, no. 1-2, pp. 51–65, 2014.

[29] U. Hillenbrand, M. Roa, *et al.*, "Transferring functional grasps through contact warping and local replanning," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*. IEEE, 2012, pp. 2963–2970.

[30] G. Hitz, A. Gotovos, F. Pomerleau, M.-E. Garneau, C. Pradalier, A. Krause, and R. Y. Siegwart, "Fully autonomous focused exploration for robotic environmental monitoring," in *Robotics and Automation (ICRA), 2014 IEEE International Conference on*. IEEE, 2014, pp. 2658–2664.

[31] K. Hsiao, M. Ciocarlie, and P. Brook, "Bayesian grasp planning," in *ICRA 2011 Workshop on Mobile Manipulation: Integrating Perception and Manipulation*, 2011.

[32] K. Hsiao, L. P. Kaelbling, and T. Lozano-Perez, "Grasping pomdps," in *Robotics and Automation, 2007 IEEE International Conference on*. IEEE, 2007, pp. 4685–4692.

[33] D. Hsu, G. Sánchez-Ante, and Z. Sun, "Hybrid prm sampling with a cost-sensitive adaptive strategy," in *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*. IEEE, 2005, pp. 3874–3880.

[34] Y. Jiang, S. Moseson, and A. Saxena, "Efficient grasping from rgbd images: Learning using a new rectangle representation," in *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. IEEE, 2011, pp. 3304–3311.

[35] G. Kahn, P. Sujan, S. Patil, S. Bopardikar, J. Ryde, K. Goldberg, and P. Abbeel, "Active exploration using trajectory optimization for robotic grasping in the presence of occlusions."

[36] D. Kappler, J. Bohg, and S. Schaal, "Leveraging big data for grasp planning," in *Robotics and Automation (ICRA), 2015 IEEE International Conference on*. IEEE, 2015, pp. 4304–4311.

[37] B. Kehoe, D. Berenson, and K. Goldberg, "Estimating part tolerance bounds based on adaptive cloud-based grasp planning with slip," in *Proc. IEEE Conf. on Automation Science and Engineering (CASE)*. IEEE, 2012, pp. 1106–1113.

[38] ——, "Toward cloud-based grasping with uncertainty in shape: Estimating lower bounds on achieving force closure with zero-slip push grasps," in *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*. IEEE, 2012, pp. 576–583.

[39] J. Kim, K. Iwamoto, J. J. Kuffner, Y. Ota, and N. S. Pollard, "Physically-based grasp quality evaluation under uncertainty," in *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*. IEEE, 2012, pp. 3258–3263.

[40] O. Kroemer, R. Detry, J. Piater, and J. Peters, "Combining active learning and reactive control for robot grasping," *Robotics and Autonomous Systems*, vol. 58, no. 9, pp. 1105–1116, 2010.

[41] M. Laskey, J. Mahler, Z. McCarthy, F. Pokorny, S. Patil, J. van den Berg, D. Kragic, P. Abbeel, and K. Goldberg, "Multi-arm bandit models for 2d sample based grasp planning with uncertainty." in *Proc. IEEE Conf. on Automation Science and Engineering (CASE)*. IEEE, 2015.

[42] M. Lauri and R. Ritala, "Optimal sensing via multi-armed bandit relaxations in mixed observability domains," in *Robotics and Automation, 2015. ICRA 2015. Proceedings of the 2005 IEEE International Conference on*. IEEE, 2015.

[43] Q. V. Le, D. Kamm, A. F. Kara, and A. Y. Ng, "Learning to grasp objects with multiple contact points," in *Robotics and Automation (ICRA), 2010 IEEE International Conference on*. IEEE, 2010, pp. 5062–5069.

[44] I. Lenz, H. Lee, and A. Saxena, "Deep learning for detecting robotic grasps," *The International Journal of Robotics Research*, vol. 34, no. 4-5, pp. 705–724, 2015.

[45] B. León, S. Ulbrich, R. Diankov, G. Puche, M. Przybylski, A. Morales, T. Asfour, S. Moisio, J. Bohg, J. Kuffner, *et al.*, "Opengrasp: a toolkit for robot grasping simulation," in *Simulation, Modeling, and Programming for Autonomous Robots*. Springer, 2010, pp. 109–120.

[46] Y. Li and N. S. Pollard, "A shape matching algorithm for synthesizing humanlike enveloping grasps," in *Humanoid Robots, 2005 5th IEEE-RAS International Conference on*. IEEE, 2005, pp. 442–449.

[47] J. Mahler, S. Patil, B. Kehoe, J. van den Berg, M. Ciocarlie, P. Abbeel, and K. Goldberg, "Gp-gpis-opt: Grasp planning under shape uncertainty using gaussian process implicit surfaces and sequential convex programming," 2015.

[48] R. Marchant and F. Ramos, "Bayesian optimisation for intelligent environmental monitoring," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*. IEEE, 2012, pp. 2242–2249.

[49] P. Matikainen, P. M. Furlong, R. Sukthankar, and M. Hebert, "Multi-armed recommendation bandits for selecting state machine policies for robotic systems," in *Robotics and Automation (ICRA), 2013 IEEE International Conference on*. IEEE, 2013, pp. 4545–4551.

[50] A. K. B. R. M. Michalik and B. T. R. Detry, "G3db: A database of successful and failed grasps with rgb-d images, point clouds, mesh models and gripper parameters."

[51] A. T. Miller and P. K. Allen, "Graspit! a versatile simulator for robotic grasping," *Robotics & Automation Magazine, IEEE*, vol. 11, no. 4, pp. 110–122, 2004.

[52] L. Montesano and M. Lopes, "Active learning of visual descriptors for grasping using non-parametric smoothed beta distributions," *Robotics and Autonomous Systems*, vol. 60, no. 3, pp. 452–462, 2012.

[53] F. T. Pokorny, Y. Bekiroglu, and D. Kragic, "Grasp moduli spaces and spherical harmonics," in *Robotics and Automation (ICRA), 2014 IEEE International Conference on*. IEEE, 2014, pp. 389–396.

[54] F. T. Pokorny, K. Hang, and D. Kragic, "Grasp moduli spaces." in *Robotics: Science and Systems*, 2013.

[55] D. Prattichizzo and J. C. Trinkle, "Grasping," in *Springer handbook of robotics*. Springer, 2008, pp. 671–700.

[56] D. Rao, Q. V. Le, T. Phoka, M. Quigley, A. Sudsang, and A. Y. Ng, "Grasping novel objects with depth segmentation," in *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*. IEEE, 2010, pp. 2578–2585.

[57] C. Rasmussen and C. Williams, *Gaussian processes for machine learning*. MIT Press, 2006.

[58] J. Redmon and A. Angelova, "Real-time grasp detection using convolutional neural networks," *arXiv preprint arXiv:1412.3128*, 2014.

[59] E. Rimon and A. Blake, "Caging 2d bodies by 1-parameter two-fingered gripping systems," in *Robotics and Automation, 1996. Proceedings., 1996 IEEE International Conference on*, vol. 2. IEEE, 1996, pp. 1458–1464.

[60] A. Rodriguez, M. T. Mason, and S. Ferry, "From caging to grasping," *Int. J. Robotics Research (IJRR)*, p. 0278364912442972, 2012.

[61] A. Saxena, J. Driemeyer, and A. Y. Ng, "Robotic grasping of novel objects using vision," *The International Journal of Robotics Research*, vol. 27, no. 2, pp. 157–173, 2008.

[62] T. Stouraitis, U. Hillenbrand, and M. A. Roa, "Functional power grasps transferred through warping and replanning," in *Robotics and*

Automation (ICRA), 2015 IEEE International Conference on. IEEE, 2015, pp. 4933–4940.

[63] F. Stulp, E. Theodorou, J. Buchli, and S. Schaal, "Learning to grasp under uncertainty," in *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. IEEE, 2011, pp. 5703–5708.

[64] M. Vahedi and A. F. van der Stappen, "Caging polygons with two and three fingers," *Int. J. Robotics Research (IJRR)*, vol. 27, no. 11-12, pp. 1308–1324, 2008.

[65] W. Wan, R. Fukui, M. Shimosaka, T. Sato, and Y. Kuniyoshi, "Grasping by caging: A promising tool to deal with uncertainty," in *IEEE Int. Conf. on Robotics and Automation (ICRA)*, 2012, pp. 5142–5149.

[66] J. Weisz and P. K. Allen, "Pose error robust grasping from contact wrench space metrics," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012, pp. 557–562.

[67] Y. Zheng and W.-H. Qian, "Coping with the grasping uncertainties in force-closure analysis," *Int. J. Robotics Research (IJRR)*, vol. 24, no. 4, pp. 311–327, 2005.