# Grasp Densities for Grasp Refinement in Industrial Bin Picking

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# Motivation

Figure: SCAPE bin picker.

- Automatic picking of randomly distributed objects from bins: 'Holy Grail' in the world of robot automation
- Distinctive feature of bin-picking scenario: grasp errors are allowed
  - Conveyor belt with queue
- Idea: Utilization of huge amount of grasp data generated in industrial bin-picking for grasp learning
- Basic technique: Novel concept of **grasp densities** (Detry et al. (2010))
- Our hypotheses: *analysis of relative success of different grasp poses can improve performance of bin picking robot*

# Pose Space and Representation

- Pose: Elements of the six dimensional space of the special Euclidean group $SE(3) = \mathbb{R}^3 \times SO(3)$
  - Position $\boldsymbol{p} \in \mathbb{R}^3$
  - Orientation $R \in SO(3)$
- Object relative gripper pose
- Distribution of grasp densities in pose space represented nonparametrically by particles
  - Calculation of each particle via Kernel density estimation $\boldsymbol{K}_{\mu,\sigma}(x) = \mathbf{N}_{\mu_t,\sigma_t}(\lambda)\boldsymbol{\Theta}_{\mu_r,\sigma_r}(\theta)$
  - Position part: trivariate Normal distribution $\mathbf{N}_{\mu_t,\sigma_t}(\lambda)$
  - Orientation part: $\boldsymbol{\Theta}_{\mu_r,\sigma_r}(\theta)$ : (two antipodal) von Mises Fisher distributions

# Calculation of of grasp densities

- Calculation of **grasp densities** $p_{X|O=s}(x)$ follows Detry et al. (2011)

$$p_{X|O=o}(x) = \frac{p_{O|X=x}(o)p_X(x)}{p_O(o)}$$

with pose $X$ and output $O$ (either success $O = s$ or failure $O = f$)

1. Generation of samples from $p_{O,X}(o, x)$ by selecting grasp $x_i$ and observing outcome $o_i$
2. Keeping only successful samples generates set $T$ of samples from distribution $p_{O,X}(s, x)$: i.e. $T = \{x_i : (s_i, x_i) \in S\}$
3. Continous grasp density representation through kernel density estimation i.e. elements of $T$

# Calculation of of grasp densities

$$p_{X|O=o}(x) = \frac{p_{O|X=x}(o)p_X(x)}{p_O(o)}$$

- Outcome: our continuous representation $d(x)$ of grasp densities is distributed proportional to $p_{X|O=s}(x)$

$$d(x) = \sum_{i=1}^{n} w_i \mathbf{K}_{\widehat{x}_i,\sigma}(x) \propto p_{X|O=s}(x)$$

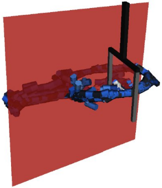
  - Prior $p_O(o)$ is constant/independent of $x$
- Problem: Determining prior $p_X(x)$
  - Importance sampling to consider non-uniform sampling
  - Samples are weighted by importance weight $w_i$

# Application of grasp densities

- Usage of grasp densities $p_{X|O=s}(x)$ for different types of analysis (unrestricted/restricted pose space or only downward grasp etc)
- Degree of opaqueness of greenly colored area codes likelihood values

(a) Averaged over **z** and orientations

(b) Averaged over **z**, downward grasp



(a) Best grasp within region of reach

(b) Constrained grasp density (green) and optimal grasp position (red)

Figure: Detry et al. (2011).

# Grasp densities

- Different visualization of grasp densities for $T$-shaped object from simulation (intensity of red codes likelihood values)

Figure: Left: grasp density. Right: failure-conditional density

# Success probabilities

Additional approach

- Going beyond grasp densities: calculating the success probability for given pose, i.e. $p_{0|X=x}(s)$
- In general two ways
  1. Generative approach (using grasp densities)
  2. Discriminative approach
- Generative model
  - Produces distribution that allows sampling of $p_X(x)$ as marginal distribution of $p_{O,X}(o,x)$
- Discriminative model
  - Direct calculation of $p_{0|X=x}(s)$

# Generative approach to grasp success prediction

Calculation of $p_{O|X=x}(o)$

$$p_{O|X=x}(o) = \frac{p_{X|O=s}(x) p_O(o)}{p_X(x)}$$

- Calculation of $p_{O|X=x}(o)$ for $o = s, f$ based on KDE on respective set of sample $\{x_i, s_i\}$ or $\{x_i, f_i\}$
  - Sum rule gives $p_X(x) = p_{X|O=s}(x) p_O(s) + p_{X|O=f}(x) p(f)$
- Other values also calculated from sample
  - $p_0(o)$ is calculated from the relative frequency of success and failures

# Discriminant methods

- Discriminant methods
  - Learning $p_{O|x=x}(s)$ directly (e.g. kernel logistic regression, Gaussian process classification)
- Simple supervised learning
  - Based on labeled data (pose $x_i$ and output $o_i$) each sample $i$
  - Coding output value for success $(+1)$ and $(-1)$ for failure
    - Output from learning machine: probability for success/failure $p_{O|X=x}(s)/p_{O|X=x}(f)$ for certain pose $x$
- Remark
  - Noisy data, i.e. noise in input variable $X$ and output variable $O$
  - Unbalanced data (numbers of failures/successes)
- Discriminative methods under consideration
  - Support vector machines
    - Probabilistic output based on Platt (1999)
  - Gaussian process classification
  - Kernel logistic regression

# Grasp densities and probabilities for suction gripper

- Example from empirical data/industrial application
- Only certain grasp were performed (restriction by external partner) with suction gripper

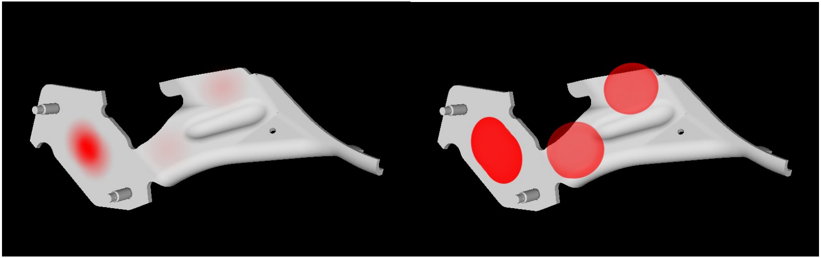


Figure: Analysis of grasp density left and probability right (dark red: high propability).

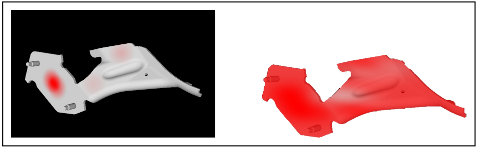
# Grasp probabilities from discriminative model for for suction gripper

- Ramifications the same, but discriminative model
- Success probabilities are given for the surface plane (coded by intensity in red)
- Problem of extrapolation for non-tested regions: need for wider exploration of the whole object (e.g. by simulation)

Figure: Left: Output from support vector machine. Right: Output from Gaussian process classification

# Summary

- Starting point: improvement of bin picking by empirical analysis of grasping trials
- Several alternatives based on different theoretical underpinnings available



- Current research/suggestions:
  - Extending analysis by simulation
    - Allows easier sampling of pose space (or subspace of it)
  - Use results from different sources (real robot/simulation) for mutual improvements
  - Use different methods (generative/discriminative) in combination

# References

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