



#### Vision and Grasping

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# Magnox Spring Grasping

**Experiment Setup** 

#### • Sensors:

- Fixed overhead SLR
- Xtion (3D sensor) on wrist
- Gripper:
  - CloPeMa modified fingers.
  - Calibration: Full hand-eye calibration of SLR and Xtion
- Tray:
  - Standard tray and "swarf".
    Commercial springs of similar dimensions.



#### **Object Detection**

- Detection based on a state-of-the-art template matching algorithm (LINEMOD).
- Using brightness gradient image features.
- Trained on thousands of "spring" templates generated via rendering of 3D model from different viewpoints.
- Implicitly obtain also the orientation of the target.
- Orientation further refined by iterative optimization.

#### **Object Detection**

- We optimized the set of parameters (e.g. number of templates, number of features.)
- Improvement of precision from 89% to 98% percent.
- False detections may be reduced by using more templates (slower)





#### **Object Pose Estimation**

- Introduction of iterative algorithm for orientation estimation.
- Minimizing the discrepancy between rendered model and image.
- Improvement by 20% (on average 10 degrees error)



# Spring Grasping

- Grasping is robust when surrounding area is mostly clear.
- Measured grasp success rate ~85%.
- Failures due to slippage.
- Improvement: Use target singulation strategy.

## **Target Singulation**

- Use push movements to clear space around target.
- Formulate problem as a reinforcement learning.
- Clear the space with as few moves as possible.
- Training performed on a simulated environment.
- Application on the real environment.
- Exploit dual-arm capabilities





# Learning

- Environment crudely modeled in a physics simulator
- Each episode is moving the virtual gripper along chosen direction around target.
- Receive negative reward for each move.
- Use discrete state MDP
- Simple gradient feature to measure emptyness.
- Q-Learning algorithm







#### Testing

- Starts with target detection
- RL agent chooses best action based on state (gradient feature)
- Repeats target detection (target may have moved)
- Repeats until clear or max moves reached.
- Grasps spring.
- Measured error rate on 200 experiments ~1.5%
- Average: ~ 1min





#### **Future Work**

- Incorporate additional actions (pushing the object)
- Account for kinematic/environment constraints
- Use continuous state space.
- Experiment with more diverse objects/clutter.

## **Cloth Grasping**

- Adaptation of CloPeMa cloth pickup module.
- Algorithm works by 3D image analysis. Image obtain using arm mounted sensor.
- Detection of "folds" on the 3D surface.
- Grasp candidates are ranked based on several "graspability" criteria.



#### RadioRoSo adaptations

- The heap may contain other objects also.
- Challenging to recognize garments.
- Using a simple criterion: a large surface homogeneous in curvature and color/texture.
- Success rate (single trial): 93%
- Error mostly due to slippage





# Grasping of previously unseen objects

- The objects have not been seen before or are not available for training the system.
- Still grasping is possible (e.g. humans do it routinely) by means of transfer learning.
- Grasping relies on supervised training on a large dataset coupling images of objects to potential grasps.
- Using CNN for grasp stability assessment.

# Grasping of previously unseen objects

- Evaluated two state-of-the-art techniques.
- Best results obtained by method using RGB-D image features.
- Achieved a 90% detection accuracy on a small dataset.





Marcus Gualtieri, Andreas ten Pas, Kate Saenko, and Robert Platt. High precision grasp pose detection in dense clutter. In Intelligent Robots and Systems (IROS), 2016

#### Improvements

- Implemented a best next view strategy.
- Acquisition and merging of multiple point clouds from several views.
- Achieved a 6% improvement with respect to baseline.
- Approach still limited only to parallel antipodal grasps.





#### **Questions** ?