Autobots VIP Spring 2023
VisMan Progress Presentation 1

Anthony Miyaguchi
acmiyaguchi@gatech.edu

2023-03-14

Outline

- Manipulators in the Lab
  - Handy and Mary
  - Theory of operation
  - ROS nodes via Docker Compose
- Reproducing GKNet Benchmarks
  - Overview of grasp detection
  - Benchmark results
  - Ideas for further exploration
- Future Work
  - Simulating pick and place with Gazebo and GKNet
  - TSRB Gazebo world

Manipulators in the Lab

Overview

- Handy and Mary
- Theory of operation
- ROS nodes via Docker Compose

Manipulators in the Lab: Handy

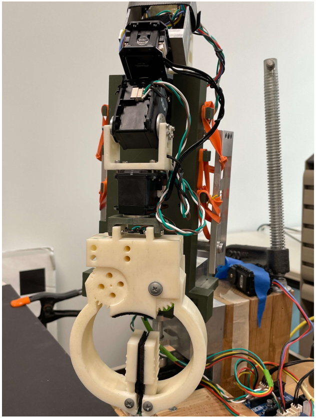


Figure 1: Handy manipulator

- Video of Handy in action

Manipulators in the Lab: Mary

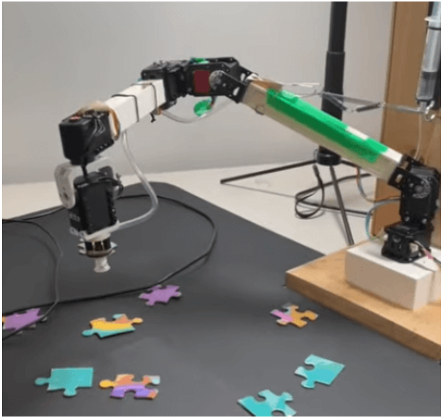


Figure 2: Mary manipulator

- Video of Mary in action

Manipulators in the Lab: Theory of Operation

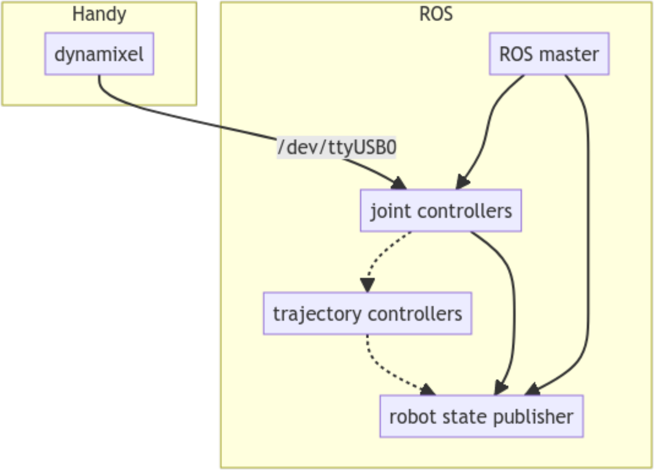


Figure 3: Handy ROS Nodes

Reproducing GKNet Benchmarks

Overview

- Overview of grasp detection
- Datasets: Cornell and abridged Jacquard
- Docker builds with GPU support
- Benchmark results
- Ideas for further exploration

Reproducing GKNet Benchmarks: Grasp Detection

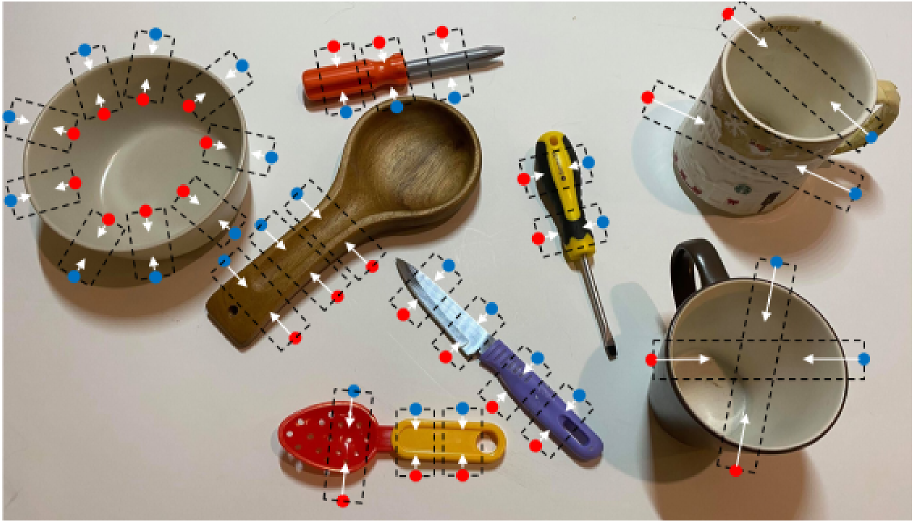


Figure 4: GKNet demonstration

Reproducing GKNet Benchmarks: Grasp Detection (cont.)

Grasp detection is the task of detecting graspable objects in an image and predicting the grasp pose of the object.

Xu, Ruinian, Fu-Jen Chu, and Patricio A. Vela. “Abridged Jacquard Dataset for GKNet: Grasp Keypoint Network for Grasp Candidates Detection.” (2021).

Reproducing GKNet Benchmarks: Datasets

```
datasets
|-- Cornell
|   `-- rgd_5_5_5_corner_p_full
|       `-- data
|           |-- Annotations
|           |-- ImageSets
|           `-- Images
`-- Jacquard
    `-- coco
        `-- 512_cnt_angle
            |-- test
            `-- train
```

Reproducing GKNet Benchmarks: Cornell Dataset

pcd0100r_rgd_preprocessed_1

pcd0100r_rgd_preprocessed_2

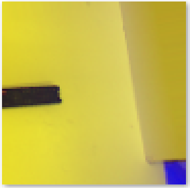
pcd0100r_rgd_preprocessed_3

pcd0100r_rgd_preprocessed_4

pcd0100r_rgd_preprocessed_10

pcd0100r_rgd_preprocessed_11

pcd0100r_rgd_preprocessed_12



pcd0100r_rgd_preprocessed_13

Figure 5: Images for `pcd0100r_rgd_preprocessed_1`

Reproducing GKNet Benchmarks: Cornell Dataset (cont.)

Annotation for `pcd0100r_rgd_preprocessed_1`

```
2 177.842467 110.189953 217.684406 128.688189 -1.193646
2 161.668984 111.392738 199.603883 137.878183 -1.250606
2 150.723138 118.692707 187.143203 137.258827 -1.232340
2 131.461796 126.084075 175.492871 140.997830 -1.164588
```

Reproducing GKNet Benchmarks: Jacquard Dataset

Figure 6: Example image from the Jacquard dataset

Reproducing GKNet Benchmarks: Jacquard Dataset (cont.)

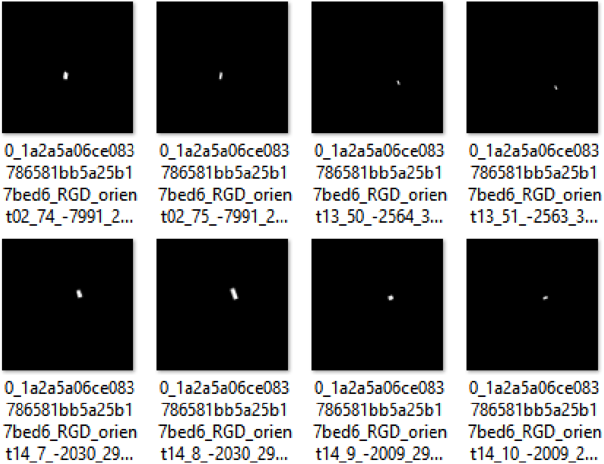


Figure 7: Example annotations from the Jacquard dataset

Reproducing GKNet Benchmarks: Docker Container

See ivalab/GraspKpNet PR #3

Changelog

- Dockerfile with Ubuntu 20.04, CUDA 11.7, and PyTorch 1.13
- Install ROS Noetic core libraries
- Fix build process of Deformable Convolutional Networks (DCNv2)
- Refactor GKNet as an importable Python package
- Add Docker Compose configuration for development and testing
- Mirror models and datasets on public Backblaze B2 bucket

Reproducing GKNet Benchmarks: Docker Container (cont.)

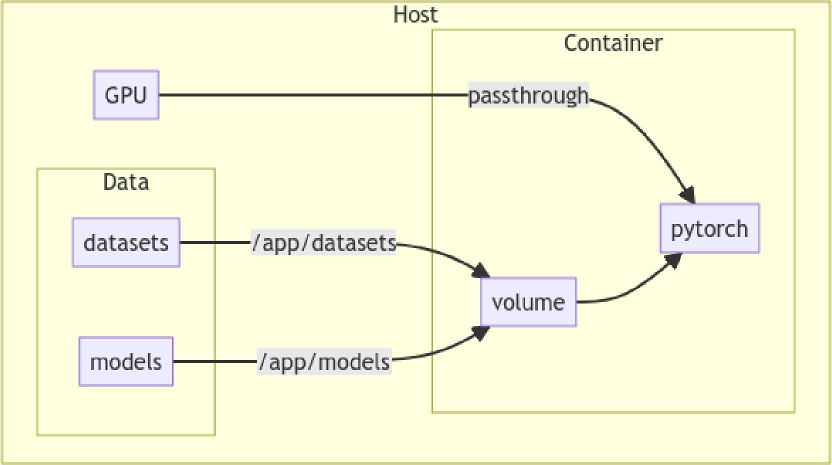


Figure 8: Docker container mounts and devices

Reproducing GKNet Benchmarks: Results

exp_id	dataset	accuracy	fps
model_alexnet_ajd	jac_coco_36	0.973701	82.4871
model_dla34_ajd	jac_coco_36	0.983857	75.2168
model_resnet18_ajd	jac_coco_36	0.979474	75.3912
model_resnet50_ajd	jac_coco_36	0.98236	76.1191
model_vgg16_ajd	jac_coco_36	0.983643	81.8511
model_alexnet_cornell	cornell	0.94663	281.826
model_dla34_cornell	cornell	0.967843	156.066
model_resnet18_cornell	cornell	0.957123	284.024
model_resnet50_cornell	cornell	0.961556	280.632
model_vgg16_cornell	cornell	0.964224	280.728

Results have similar accuracy; FPS achieved on NVIDIA 1080 Ti is higher than reported in the paper.

Reproducing GKNet Benchmarks: Further Ideas

- Pose estimation for other grasping orientations e.g. items from a shelf
- Training and evaluating GKNet on a primitive shapes dataset
  - Lin, Yunzhi, Chao Tang, Fu-Jen Chu, and Patricio A. Vela. “Using synthetic data and deep networks to recognize primitive shapes for object grasping.” In 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 10494-10501. IEEE, 2020.
- Neural Radiance Fields (NeRFs) for training augmentation or direct pose estimation
  - Dellaert, Frank, and Lin Yen-Chen. “Neural volume rendering: Nerf and beyond.” arXiv preprint arXiv:2101.05204 (2020).
  - Yen-Chen, Lin, Pete Florence, Jonathan T. Barron, Alberto Rodriguez, Phillip Isola, and Tsung-Yi Lin. “inerf: Inverting neural radiance fields for pose estimation.” In 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 1323-1330. IEEE, 2021.
  - [GitHub] awesome-NeRF/awesome-NeRF

Future Work