Unknown object grasping: Techniques and benchmarks for challenging robotic platforms

G. Vezzani, C. Fantacci, F. Bottarel, U. Pattacini, V. Tikhanoff,
L. Natale

The work presented in this talk has been entirely carried out at the **Istituto Italiano di Tecnologia**

About me

- Robotics
- Manipulation
- Reinforcement Learning

Now | Robotics Research Engineer at DeepMind

2015 -2019 | Phd Student and PostDoc at IIT, iCub Facility

2018 | Visiting Scholar at UC Berkeley (BAIR)

About me

- Robotics
- Manipulation
- Reinforcement Learning

Now | Robotics Research Engineer at DeepMind

2015 -2019 | Phd Student and PostDoc at IIT, iCub Facility

2018 | Visiting Scholar at UC Berkeley (BAIR)

iit iCub

BAIR
BERKELEY ARTIFICIAL INTELLIGENCE RESEARCH

Grasping of unknown objects on challenging robotic platforms

- Grasping is challenging
- Grasping of unknown objects is even more challenging
- Grasping of unknown objects on “limited” robotic platforms is really really hard!

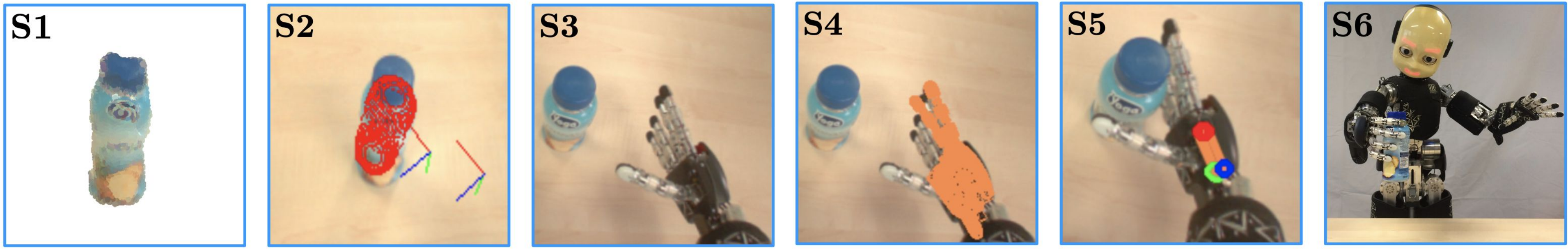
We need:

- **Algorithms** to deal with these challenges
- A fair way to **benchmark** algorithms tested on hardware with different features and limitations

[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

Grasping with kinematic errors[1]

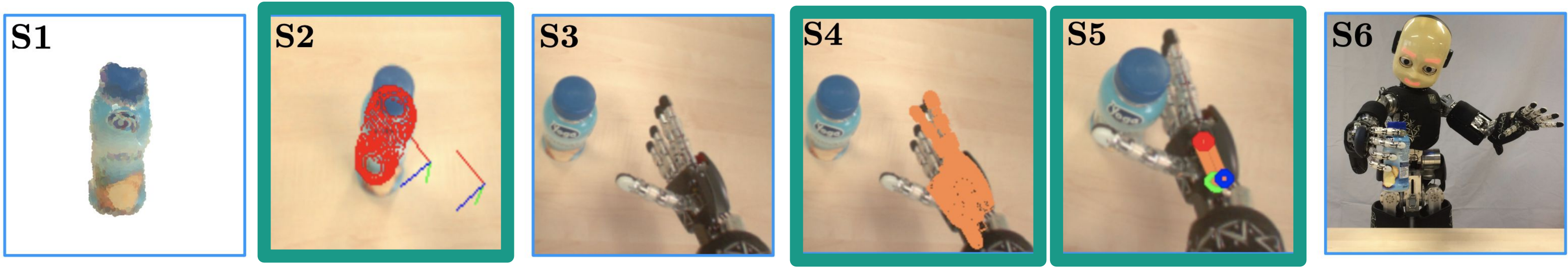
1. Object segmentation and point cloud extract
2. Object modeling and grasping pose computation
3. Open loop object approaching
4. End-effector pose estimation
5. Visual servoing towards the grasping pose
6. Grasp and lift the object



[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

Grasping with kinematic errors[1]

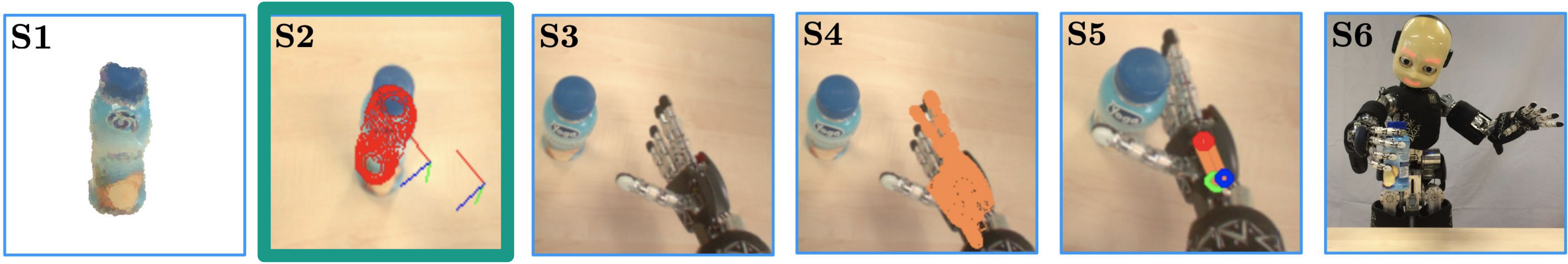
1. Object segmentation and point cloud extract
2. Object modeling and grasping pose computation
3. Open loop object approaching
4. End-effector pose estimation
5. Visual servoing towards the grasping pose
6. Grasp and lift the object



[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

Grasping with kinematic errors[1]

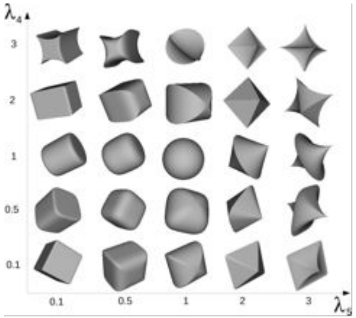
1. Object segmentation and point cloud extract
2. Object modeling and grasping pose computation
3. Open loop object approaching
4. End-effector pose estimation
5. Visual servoing towards the grasping pose
6. Grasp and lift the object



[2] G. Vezzani , U. Pattacini , and L. Natale, “A grasping approach based on superquadric models”, ICRA 2016.

Superquadric modeling and grasping[2]

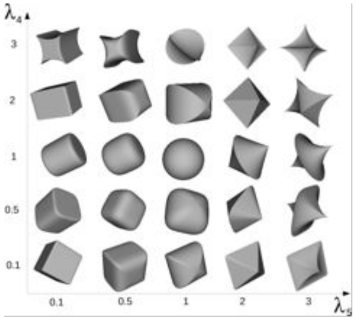
$$F(x,y,z,\boldsymbol{\lambda}) = \left(\left(\frac{x}{\lambda_1}\right)^{\frac{2}{\lambda_5}} + \left(\frac{y}{\lambda_2}\right)^{\frac{2}{\lambda_5}} \right)^{\frac{\lambda_5}{\lambda_4}} + \left(\frac{z}{\lambda_3}\right)^{\frac{2}{\lambda_4}}$$

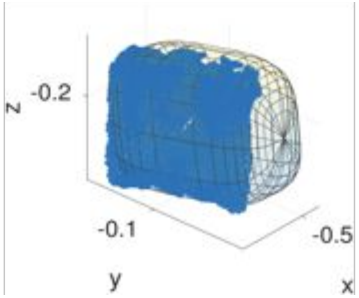


[2] G. Vezzani , U. Pattacini , and L. Natale, “A grasping approach based on superquadric models”, ICRA 2016.

Superquadric modeling and grasping[2]

$$F(x,y,z,\boldsymbol{\lambda}) = \left(\left(\frac{x}{\lambda_1}\right)^{\frac{2}{\lambda_5}} + \left(\frac{y}{\lambda_2}\right)^{\frac{2}{\lambda_5}} \right)^{\frac{\lambda_5}{\lambda_4}} + \left(\frac{z}{\lambda_3}\right)^{\frac{2}{\lambda_4}} \quad \min_{\boldsymbol{\lambda}} \sum_{i=1}^{N} \left(\sqrt{\lambda_1 \lambda_2 \lambda_3} \left(F(\boldsymbol{s}_i, \boldsymbol{\lambda}) - 1 \right) \right)^2$$

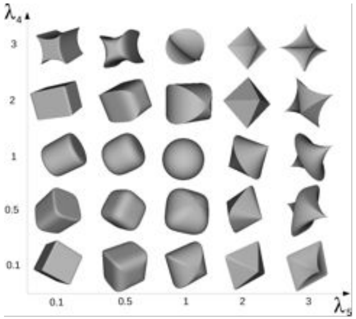


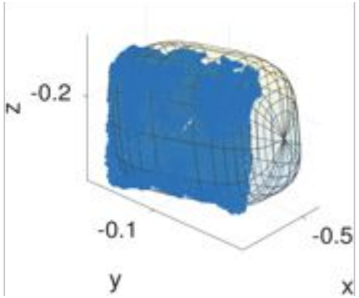


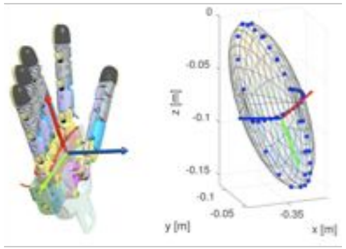
[2] G. Vezzani , U. Pattacini , and L. Natale, “A grasping approach based on superquadric models”, ICRA 2016.

Superquadric modeling and grasping[2]

$$F(x,y,z,\boldsymbol{\lambda}) = \left(\left(\frac{x}{\lambda_1}\right)^{\frac{2}{\lambda_5}} + \left(\frac{y}{\lambda_2}\right)^{\frac{2}{\lambda_5}}\right)^{\frac{\lambda_5}{\lambda_4}} + \left(\frac{z}{\lambda_3}\right)^{\frac{2}{\lambda_4}} \quad \min_{\boldsymbol{\lambda}} \sum_{i=1}^{N} \left(\sqrt{\lambda_1\lambda_2\lambda_3}\,\left(F(\boldsymbol{s}_i,\boldsymbol{\lambda})-1\right)\right)^2$$







[2] G. Vezzani , U. Pattacini , and L. Natale, “A grasping approach based on superquadric models”, ICRA 2016.

Superquadric modeling and grasping[2]

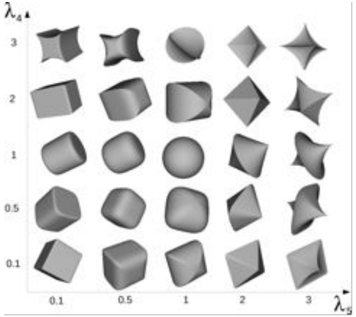
$$F(x,y,z,\boldsymbol{\lambda}) = \left(\left(\frac{x}{\lambda_1}\right)^{\frac{2}{\lambda_5}} + \left(\frac{y}{\lambda_2}\right)^{\frac{2}{\lambda_5}}\right)^{\frac{\lambda_5}{\lambda_4}} + \left(\frac{z}{\lambda_3}\right)^{\frac{2}{\lambda_4}}$$

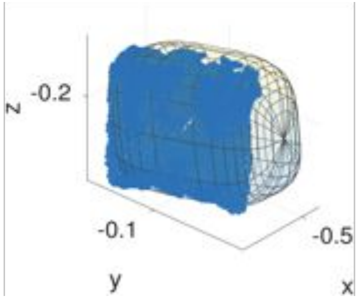
$$\min_{\boldsymbol{\lambda}} \sum_{i=1}^{N} \left(\sqrt{\lambda_1\lambda_2\lambda_3}\,(F(\boldsymbol{s}_i,\boldsymbol{\lambda})-1)\right)^2$$

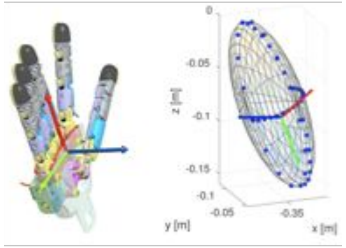
$$\min_{\boldsymbol{x}} \sum_{i=1}^{L} \left(\sqrt{\lambda_1\lambda_2\lambda_3}\,(F(\boldsymbol{p}_i^{\boldsymbol{x}},\boldsymbol{\lambda})-1)\right)^2,$$

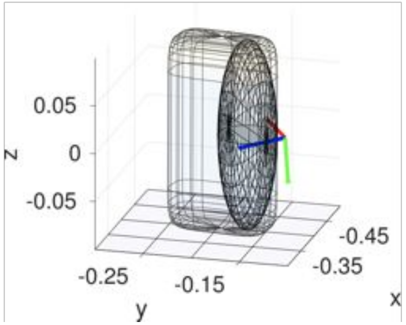
subject to:

$$h(\boldsymbol{a}, f(\boldsymbol{p}_1^{\boldsymbol{x}},\dots,\boldsymbol{p}_L^{\boldsymbol{x}}))>0.$$



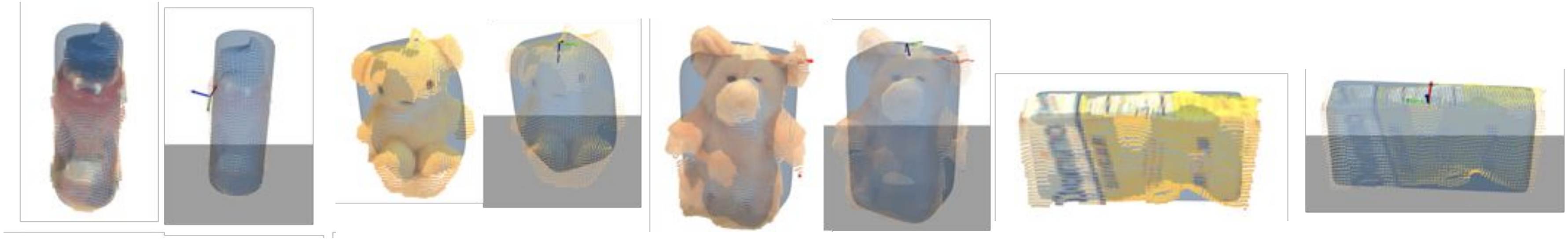






[2] G. Vezzani , U. Pattacini , and L. Natale, “A grasping approach based on superquadric models”, ICRA 2016.

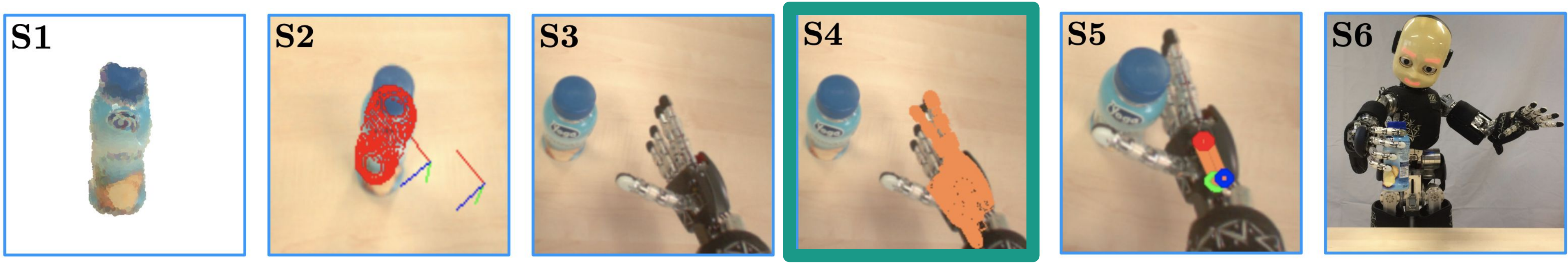
Superquadric modeling and grasping[2]



[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

Grasping with kinematic errors[1]

1. Object segmentation and point cloud extract
2. Object modeling and grasping pose computation
3. Open loop object approaching
4. End-effector pose estimation
5. Visual servoing towards the grasping pose
6. Grasp and lift the object



[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

End-effector pose estimation[1]

Due to the robot **imprecise kinematics**, we **estimate 6D pose** of robot end-effector **using cameras**

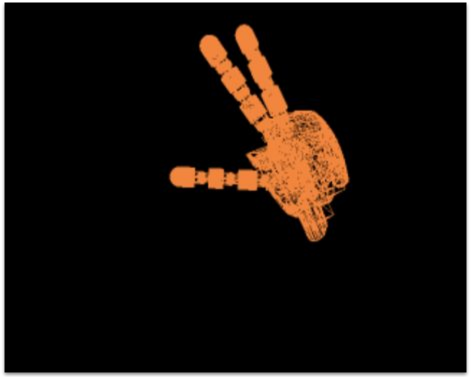
Technique

Recursive Bayesian Estimation and in particular **Particle Filter**

[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

End-effector pose estimation[1]

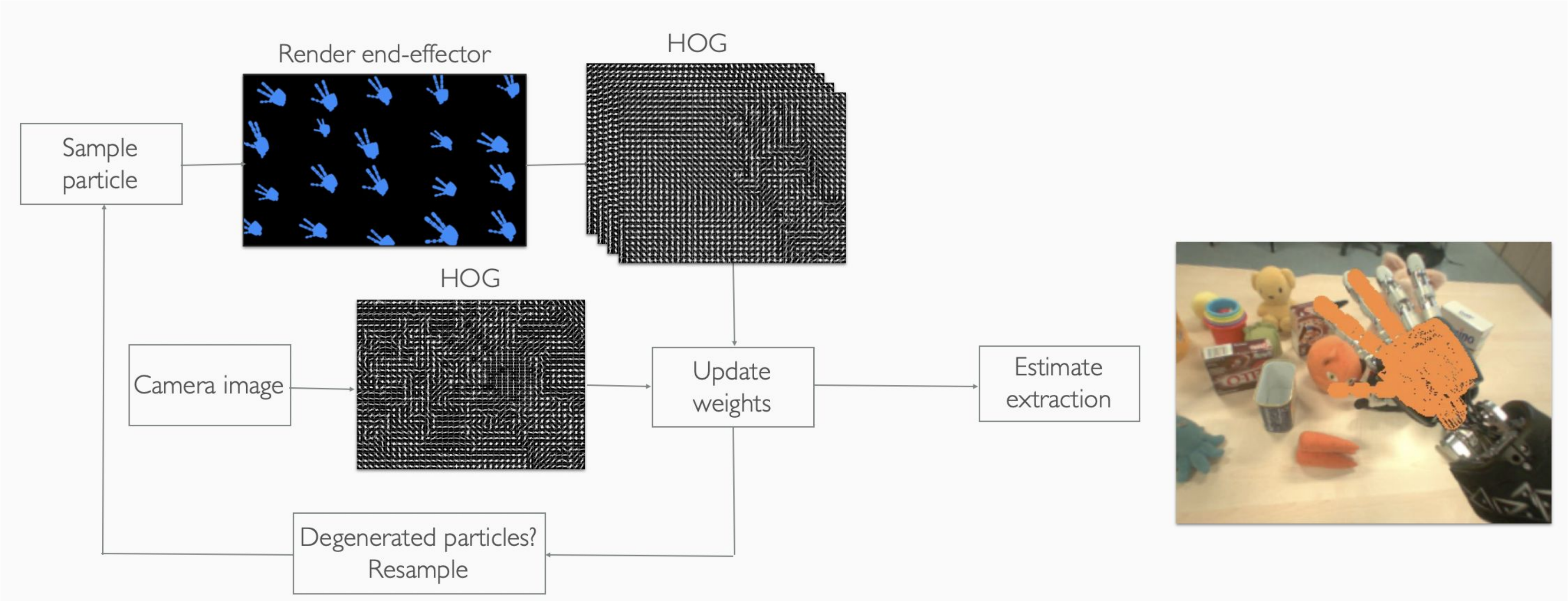
For each particle, **render an end-effector image** as it would appear from the robot view



Use this state representation to directly estimate the 6D pose using **2D image descriptors**

[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

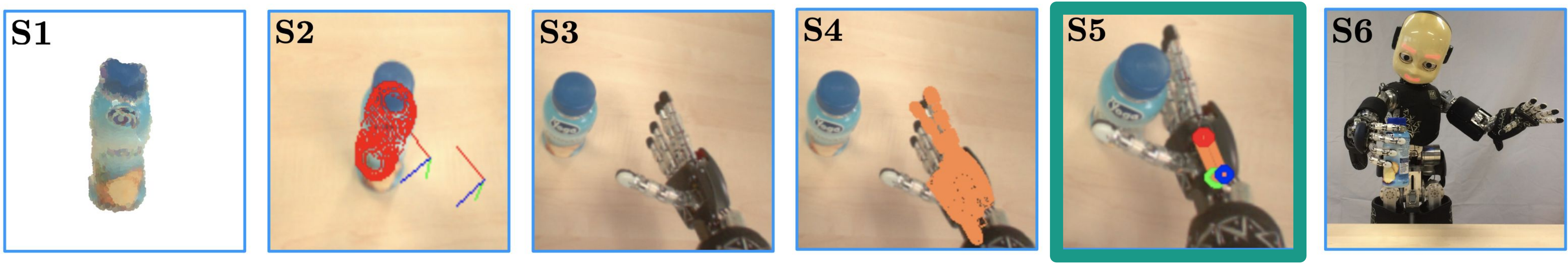
End-effector pose estimation[1]



[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, "Markerless visual servoing on unknown objects for humanoid robot platforms", ICRA 2018.

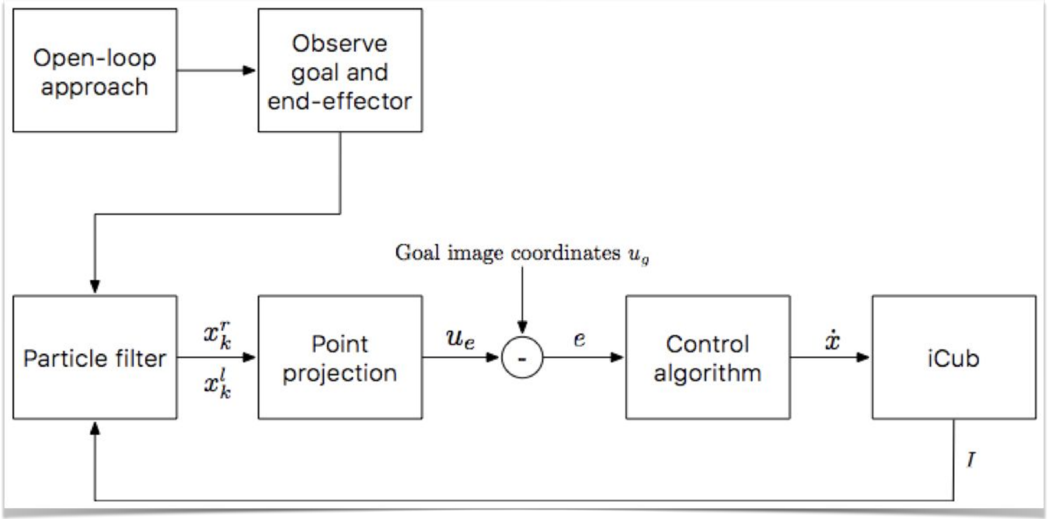
Grasping with kinematic errors[1]

1. Object segmentation and point cloud extract
2. Object modeling and grasping pose computation
3. Open loop object approaching
4. End-effector pose estimation
5. Visual servoing towards the grasping pose
6. Grasp and lift the object



[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

Image-based visual servoing[1]



Two image-based visual servoing problems:

1. Solves for the translation motion assuming the rotation completed.
2. Computes the rotation motion under the assumption of achieved translation

The need for a benchmarking protocol

- Several complex grasping pipeline
- Different robotic platforms
- Different features and limitations

How to compare fairly different algorithms tested on different robots?

[3] F. Bottarel*, G. Vezzani*, U. Pattacini, and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

The need for a benchmarking protocol

- Several complex grasping pipeline
- Different robotic platforms
- Different features and limitations

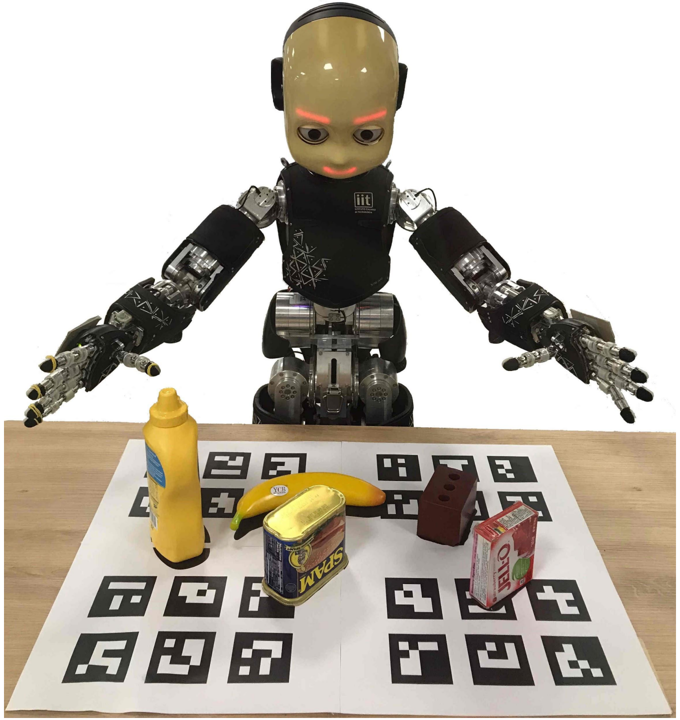
How to compare fairly different algorithms tested on different robots?

GRASPA 1.0: GRASPA is a Robot Arm graSping Performance benchmArk[3]

https://github.com/robotology/GRASPA-benchmark

GRASPA 1.0

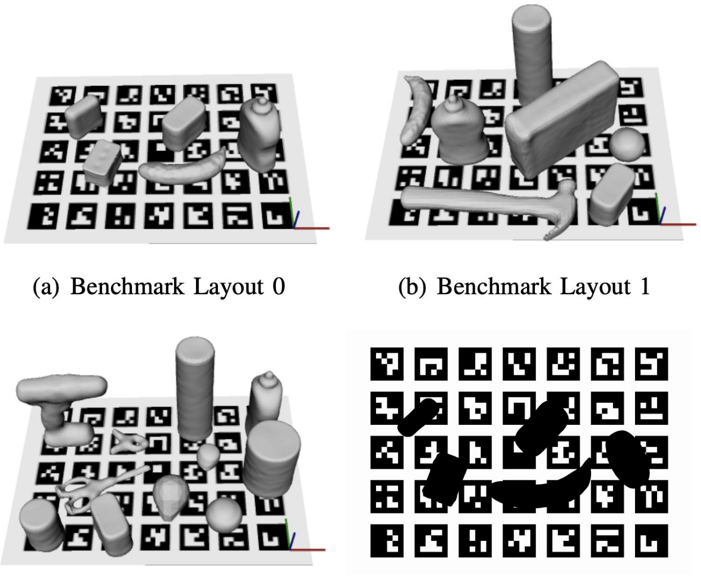
- **Printable layouts** of grasping scenarios (with YCB objects)
- A protocol to assess robot **reachability** and the **calibration of the vision system**
- **Grasp quality** metric to evaluate candidate grasping poses
- A score to assess **grasp stability**
- **Isolation or in clutter**
- A **composite score** to quantify the **overall performance**



https://github.com/robotology/GRASPA-benchmark

GRASPA 1.0

- **Printable layouts** of grasping scenarios (with YCB objects)
- A protocol to assess robot **reachability** and the **calibration of the vision system**
- **Grasp quality** metric to evaluate candidate grasping poses
- A score to assess **grasp stability**
- **Isolation or in clutter**
- A **composite score** to quantify the **overall performance**

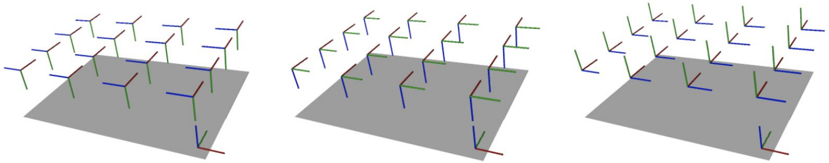


(a) Benchmark Layout 0 (b) Benchmark Layout 1

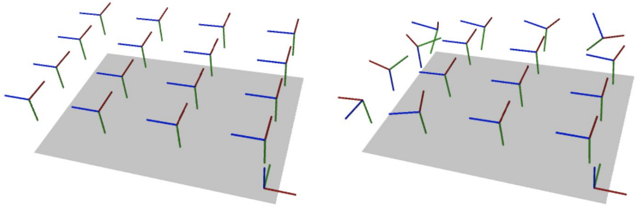
(c) Benchmark Layout 2 (d) Printable Layout 0 https://github.com/robotology/GRASPA-benchmark

GRASPA 1.0

- **Printable layouts** of grasping scenarios (with YCB objects)
- A protocol to assess robot **reachability** and the **calibration of the vision system**
- **Grasp quality** metric to evaluate candidate grasping poses
- A score to assess **grasp stability**
- **Isolation or in clutter**
- A **composite score** to quantify the **overall performance**



(a) Set no. 0 (b) Set no. 1 (c) Set no. 2

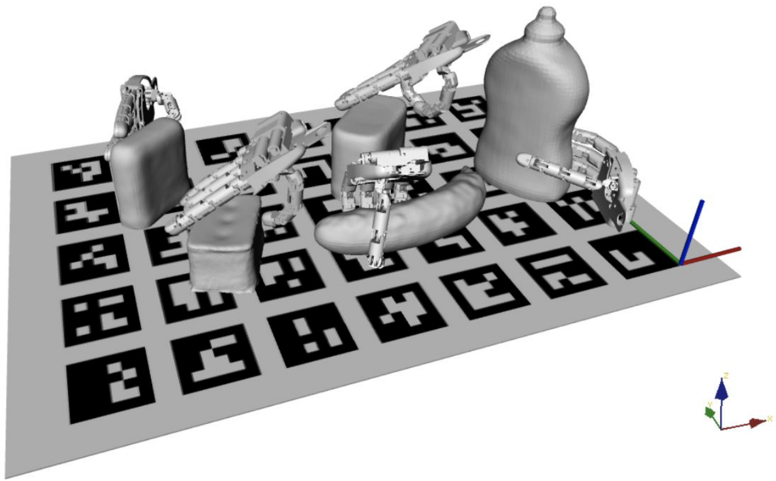


(a) Desired poses (set no. 1) (b) Reached poses (set no. 1)

https://github.com/robotology/GRASPA-benchmark

GRASPA 1.0

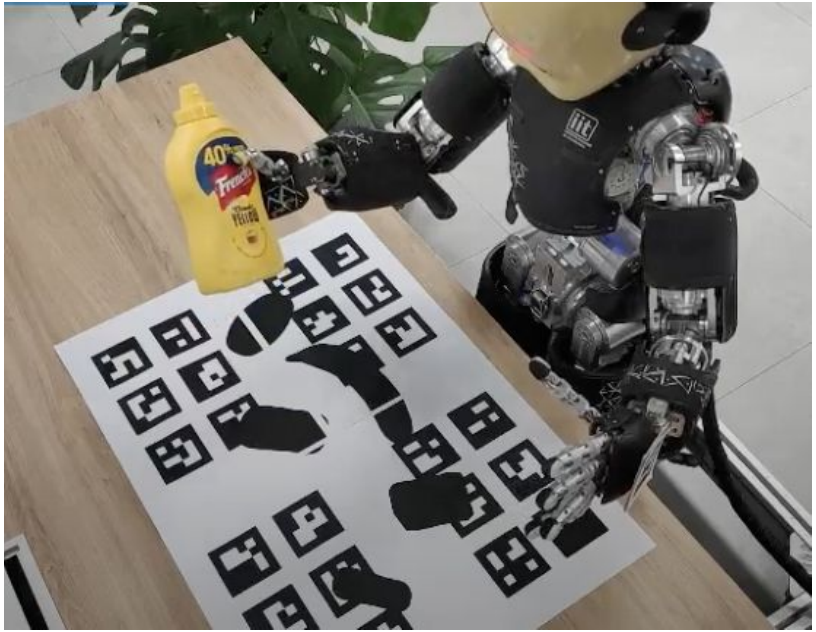
- **Printable layouts** of grasping scenarios (with YCB objects)
- A protocol to assess robot **reachability** and the **calibration of the vision system**
- **Grasp quality** metric to evaluate candidate grasping poses
- A score to assess **grasp stability**
- **Isolation or in clutter**
- A **composite score** to quantify the **overall performance**



https://github.com/robotology/GRASPA-benchmark

GRASPA 1.0

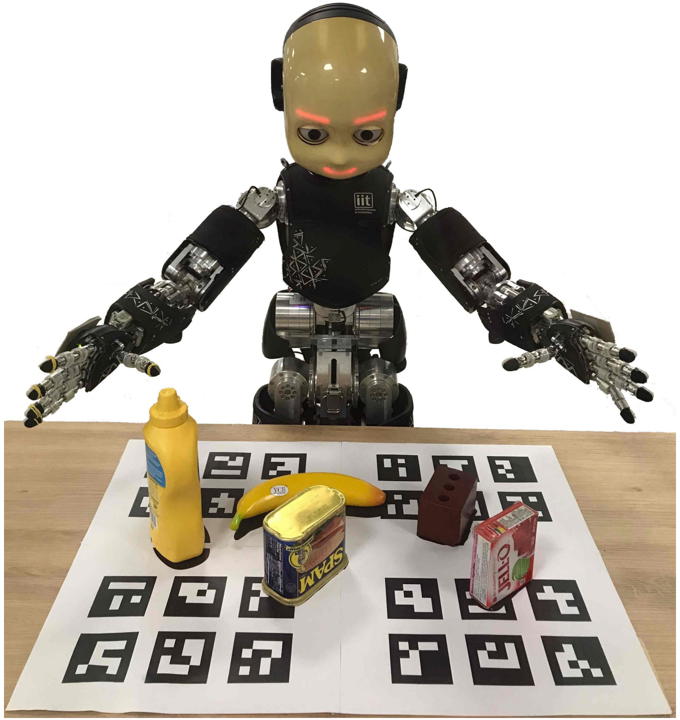
- **Printable layouts** of grasping scenarios (with YCB objects)
- A protocol to assess robot **reachability** and the **calibration of the vision system**
- **Grasp quality** metric to evaluate candidate grasping poses
- A score to assess **grasp stability**
- **Isolation or in clutter**
- A **composite score** to quantify the **overall performance**

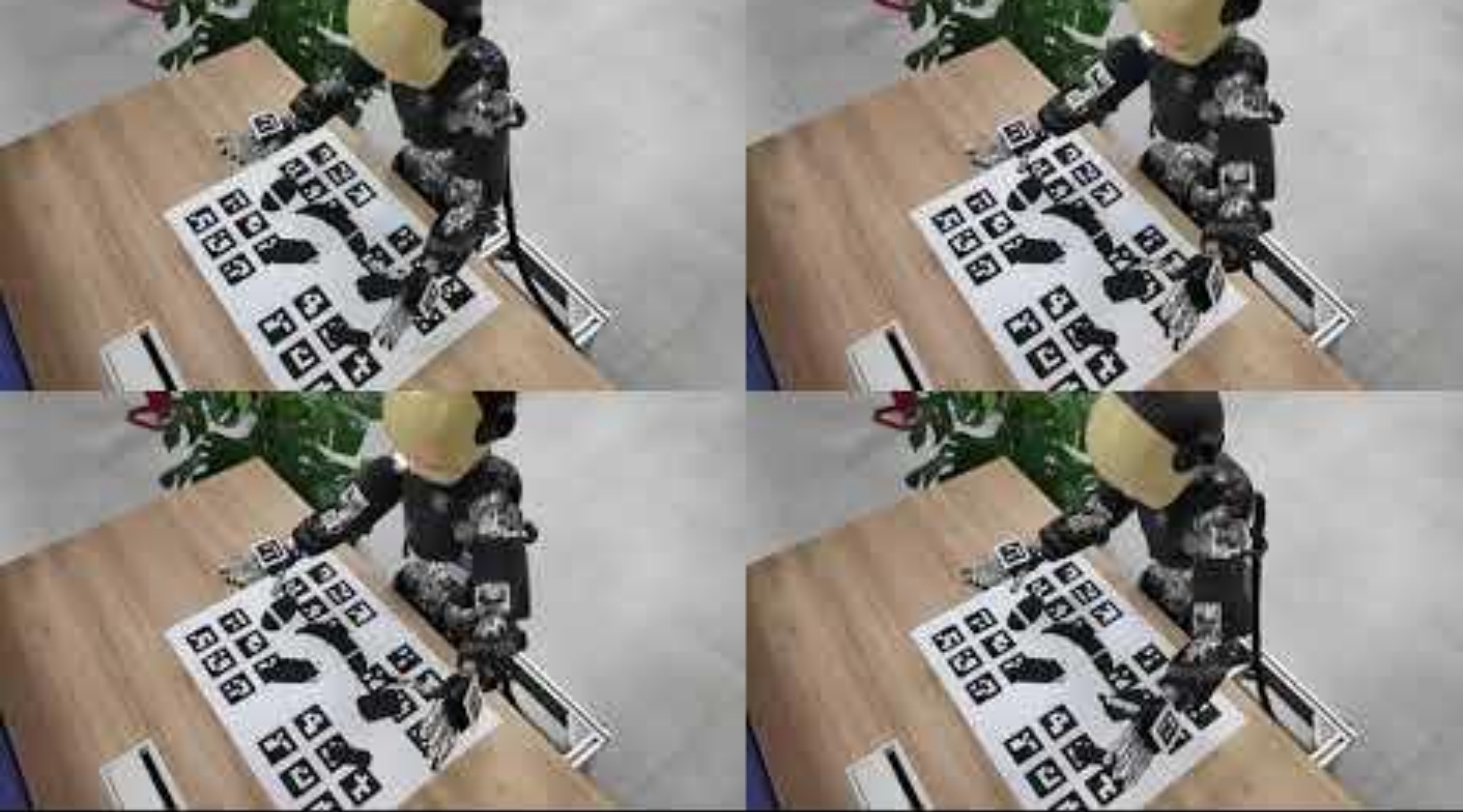


https://github.com/robotology/GRASPA-benchmark

GRASPA 1.0

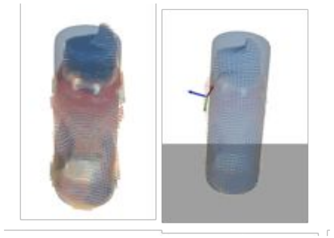
- **Printable layouts** of grasping scenarios (with YCB objects)
- A protocol to assess robot **reachability** and the **calibration of the vision system**
- **Grasp quality** metric to evaluate candidate grasping poses
- A score to assess **grasp stability**
- **Isolation or in clutter**
- A **composite score** to quantify the **overall performance**

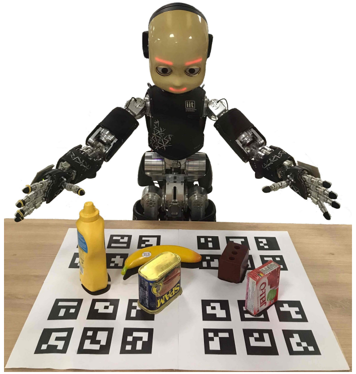




Summary

- Superquadric modeling and grasping[2]
- End-effector pose estimation[1]
- Visual servoing[1]
- GRASPA 1.0: GRASPA is a Robot Arm graSping Performance benchmArk[3]
- All the work has been carried out at the **Istituto Italiano di Tecnologia**





[1] C. Fantacci, G. Vezzani , U. Pattacini , V. Tikhanoff and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.
[2] G. Vezzani , U. Pattacini , and L. Natale, “A grasping approach based on superquadric models”, ICRA 2016.
[3] F. Bottarel*, G. Vezzani*, U. Pattacini, and L. Natale, “Markerless visual servoing on unknown objects for humanoid robot platforms”, ICRA 2018.

Thank you for your attention!
Questions :) ?

The work presented in this talk has been entirely carried out at the **Istituto Italiano di Tecnologia**