Solving Perception Uncertainty Problems in Robotics

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Overview

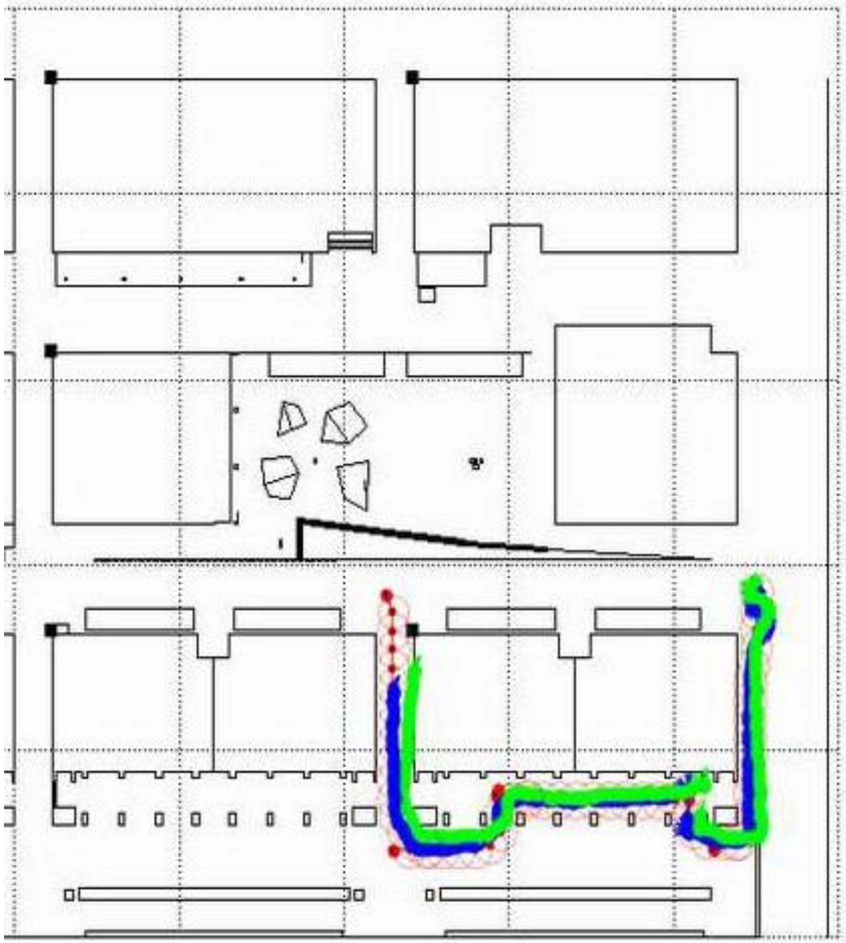
- Problem statement
- Solving perception uncertainty using probabilistic models:
  - Robot localization and navigation
  - Grasping deformable objects
  - Taken care of plants
  - Assembly with aerial robotics
- Solving perception uncertainty using probabilistic and un/supervised learning models in the loop:
  - Online Human-Assisted Learning using Random Ferns
  - Human Motion Prediction to Accompany People

Problem Statement

- **Robot environment** are inherently unpredictable. The uncertainty is particularly high for robot operating in the proximity of people
- **Sensors** are limited in what they can perceive and they are subject to noise.
- **Robot actuation** involves actuators (motors,…) and motion elements (wheels, legs, …) which produces sometimes unpredictable movements (for example due to dead reckoning)
- **Robot tasks** with people are inherently unpredictable, due to the aforementioned issues and the people task behavior

Some Robotic Challenges

Robot localization and navigation (FP6 URUS project)



The perception uncertainty is due to **sensors** and **data association**

Some Robotic Challenges

Manipulation and grasping of objects (FP7 GARNICS and IntellAct projects)

Taken care of plants

(FP7 GARNICS project)

Manipulating deformable objects

(FP7 IntellAct project)

The perception uncertainty is due to **sensor information** and **robot manipulation**

Some Robotic Challenges

Aerial assembly by robots (FP7 ARCAS project)

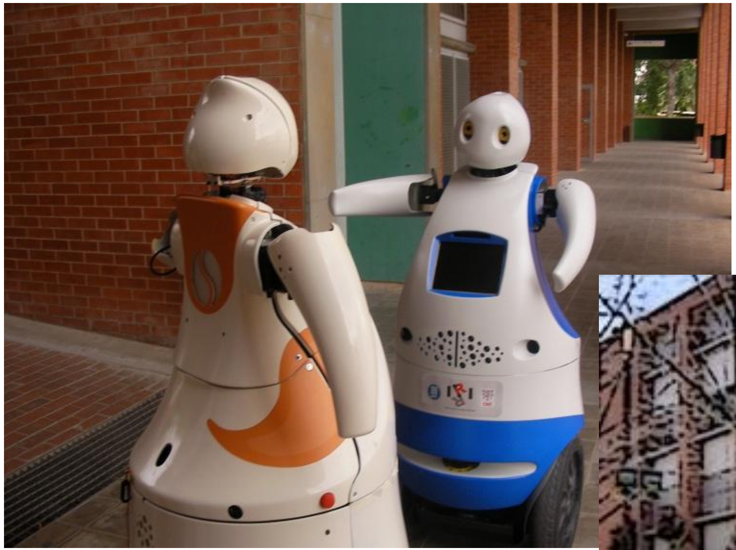
Assembly structures

Transporting structures

The perception uncertainty is due to **sensor, robot actuation and robot task**

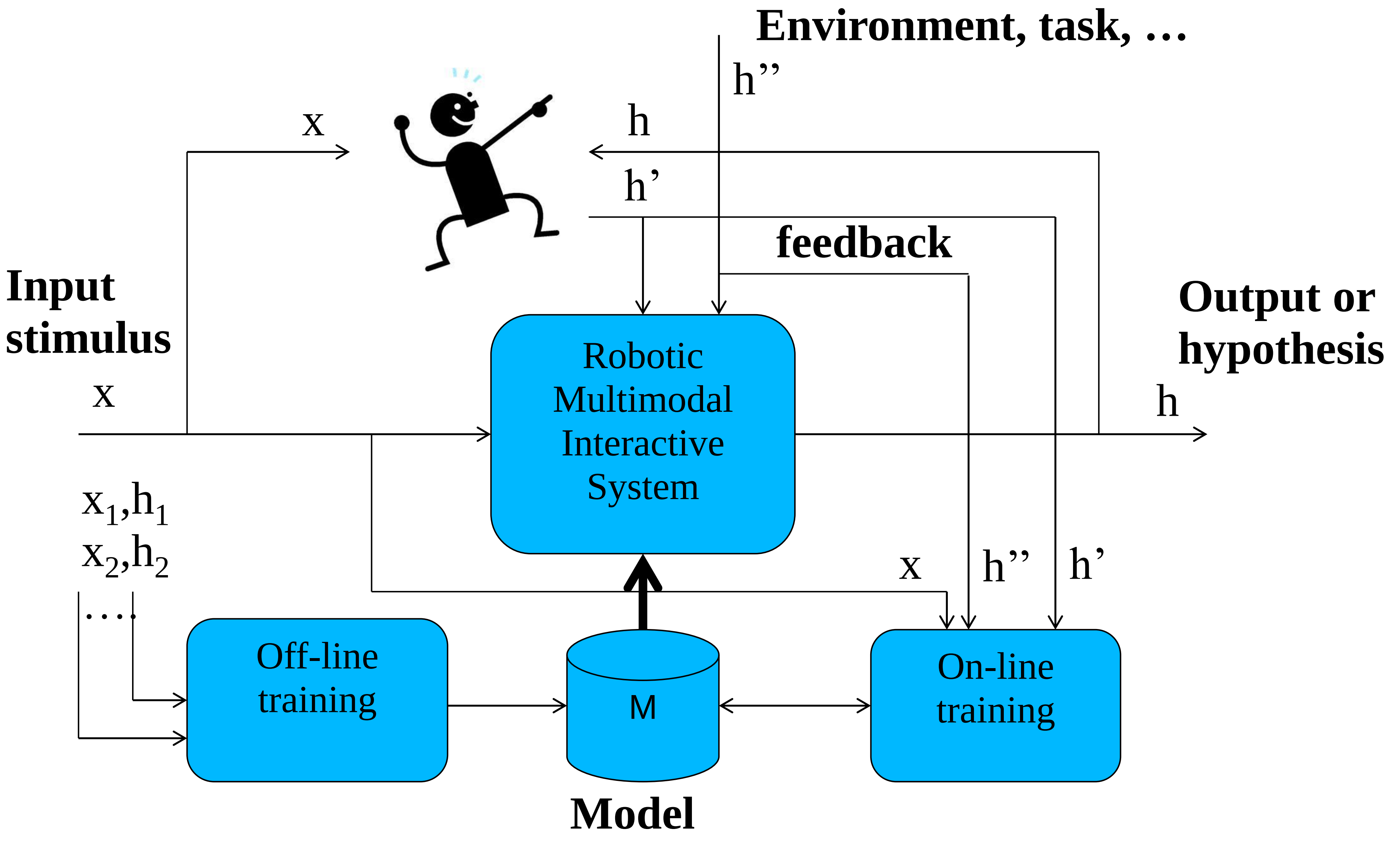
Some Robotic Challenges

Human Robot Interaction (FP6 URUS and RobTaskCOOP projects)



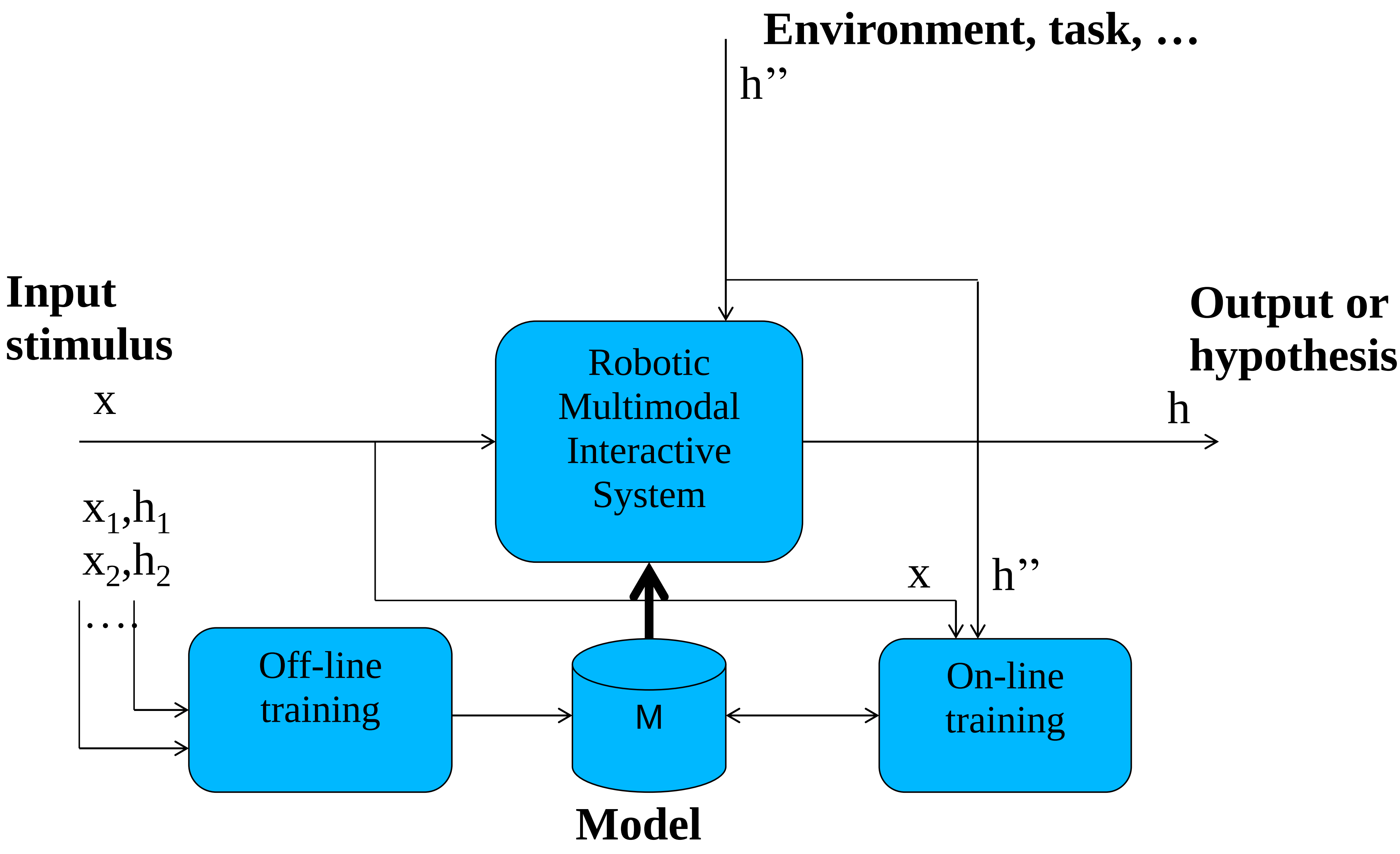
The uncertainty is due to **sensor, robot actuation, person behavior**

General Multimodal Scheme



Solving Perception Uncertainty using Probabilistic Models

General Multimodal Scheme

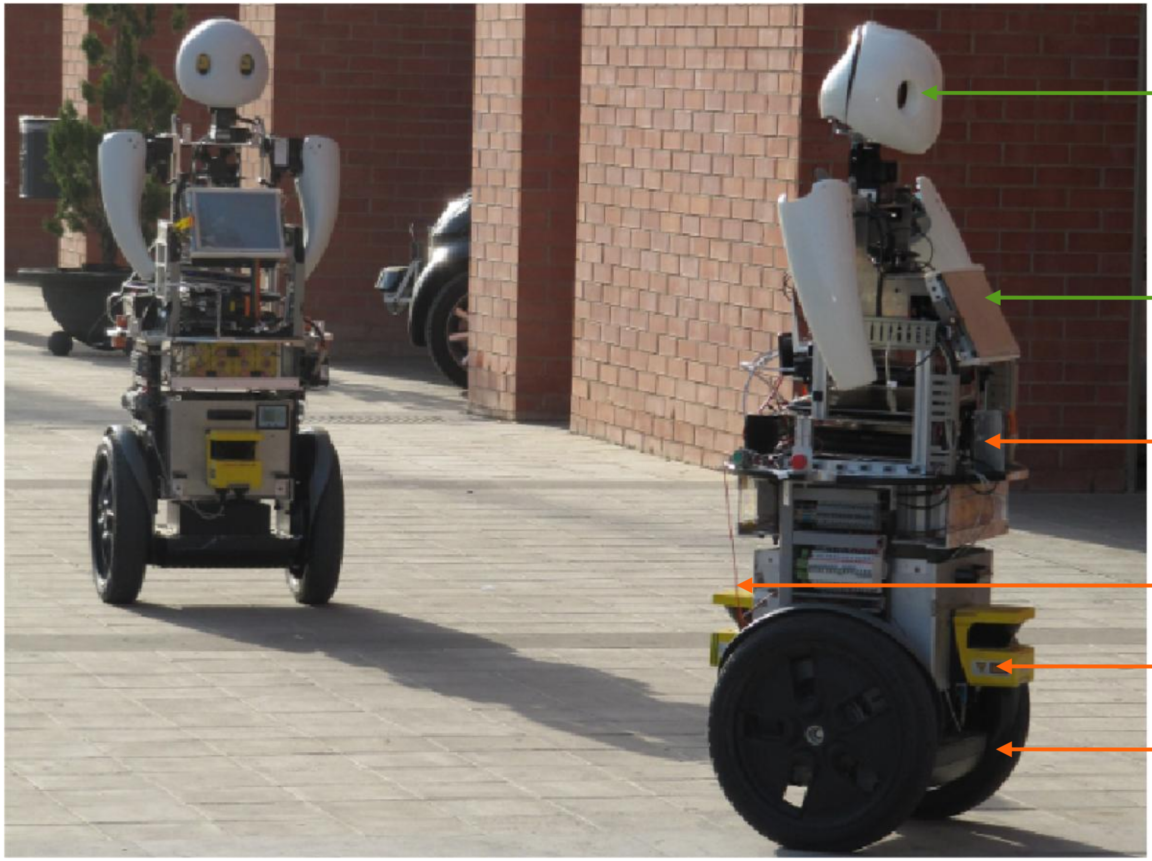


Solving Perception Uncertainty in Robot Localization and Navigation

Tibi and Dabo

Tibi & Dabo Robots

HRI sensors
Navigation Sensors



Bumblebee Stereo Camera

Touch Screen

Front Vertical Hokuyo Laser Scanner

Back Horizontal Leuze Laser Scanner

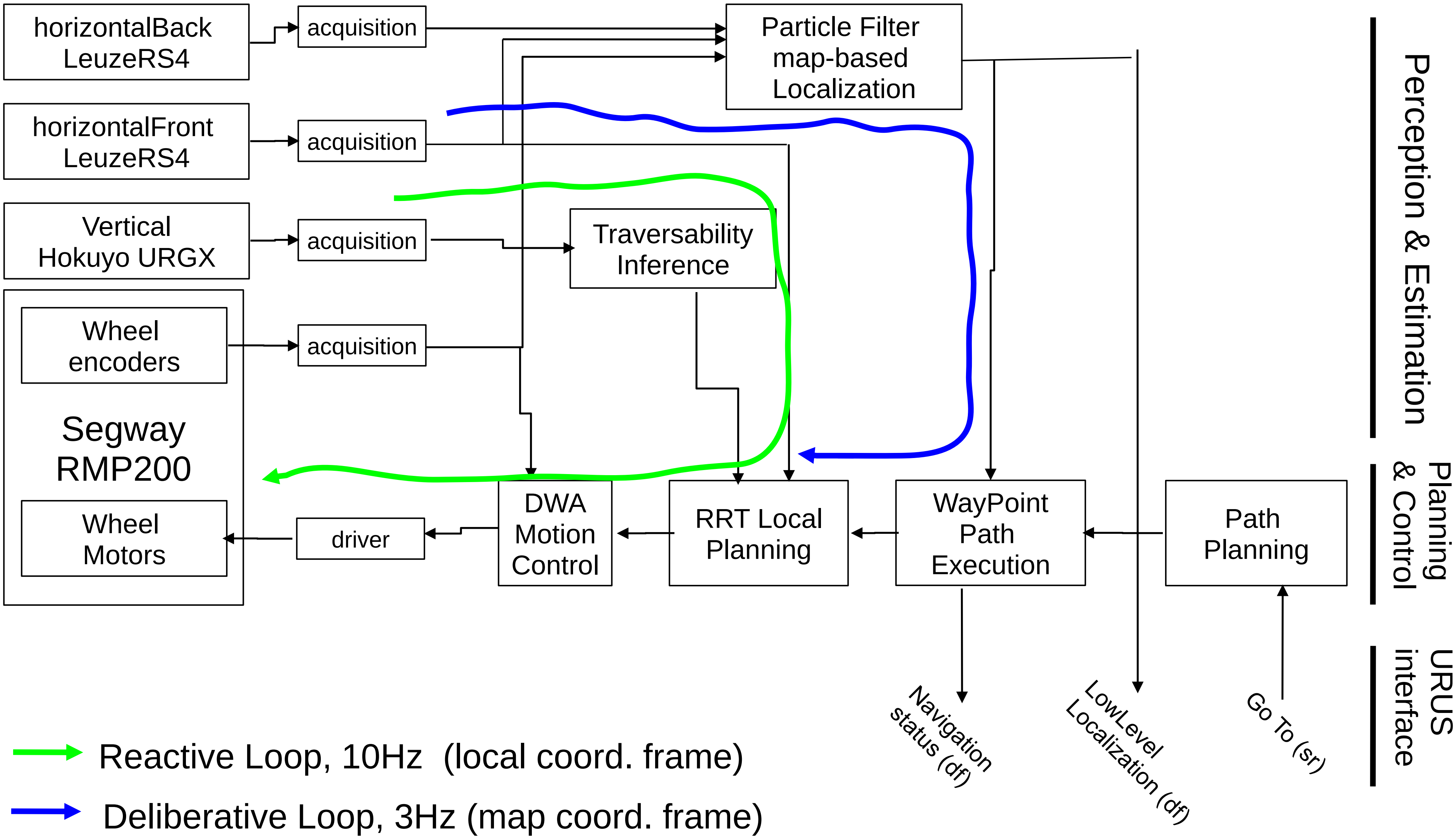
Front Horizontal Leuze Laser Scanner

Wheel encoders (2D odometry)

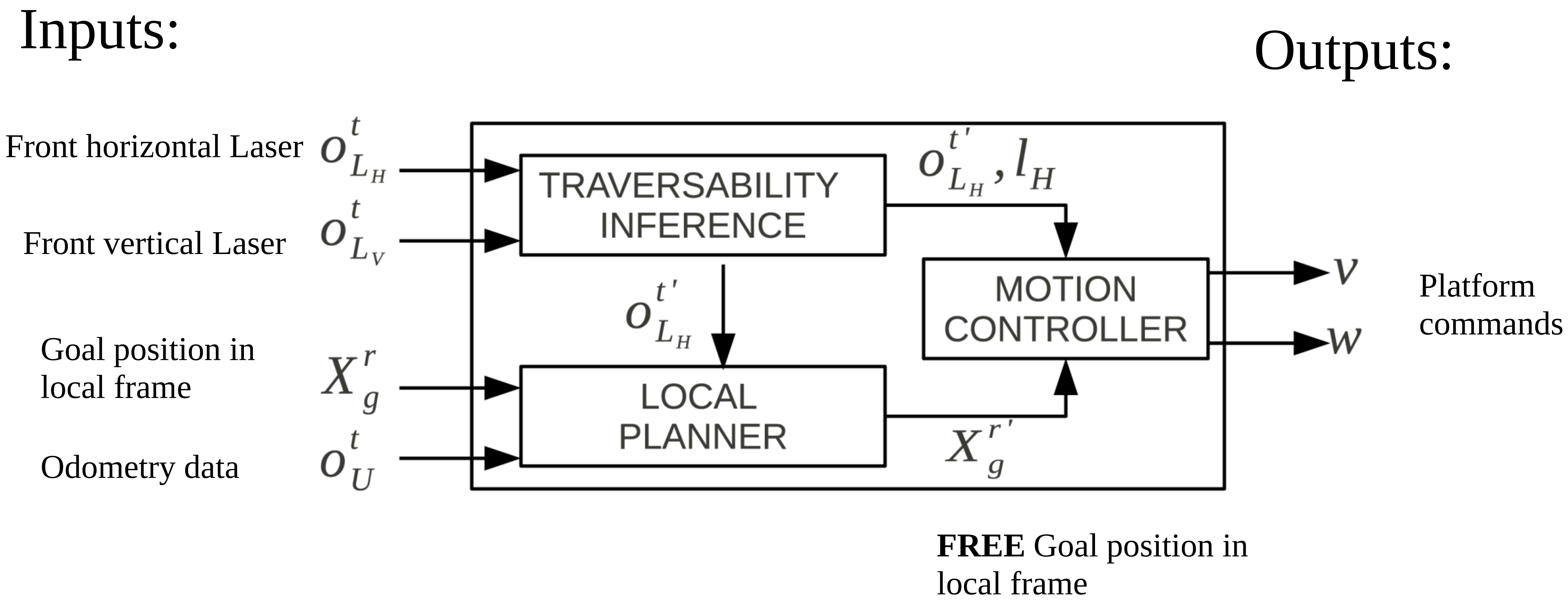
[Corominas, Mirats, Sanfeliu, 2008]

[Sanfeliu et. al., 2010] [Trulls et al., 2011]

Autonomous Navigation Framework



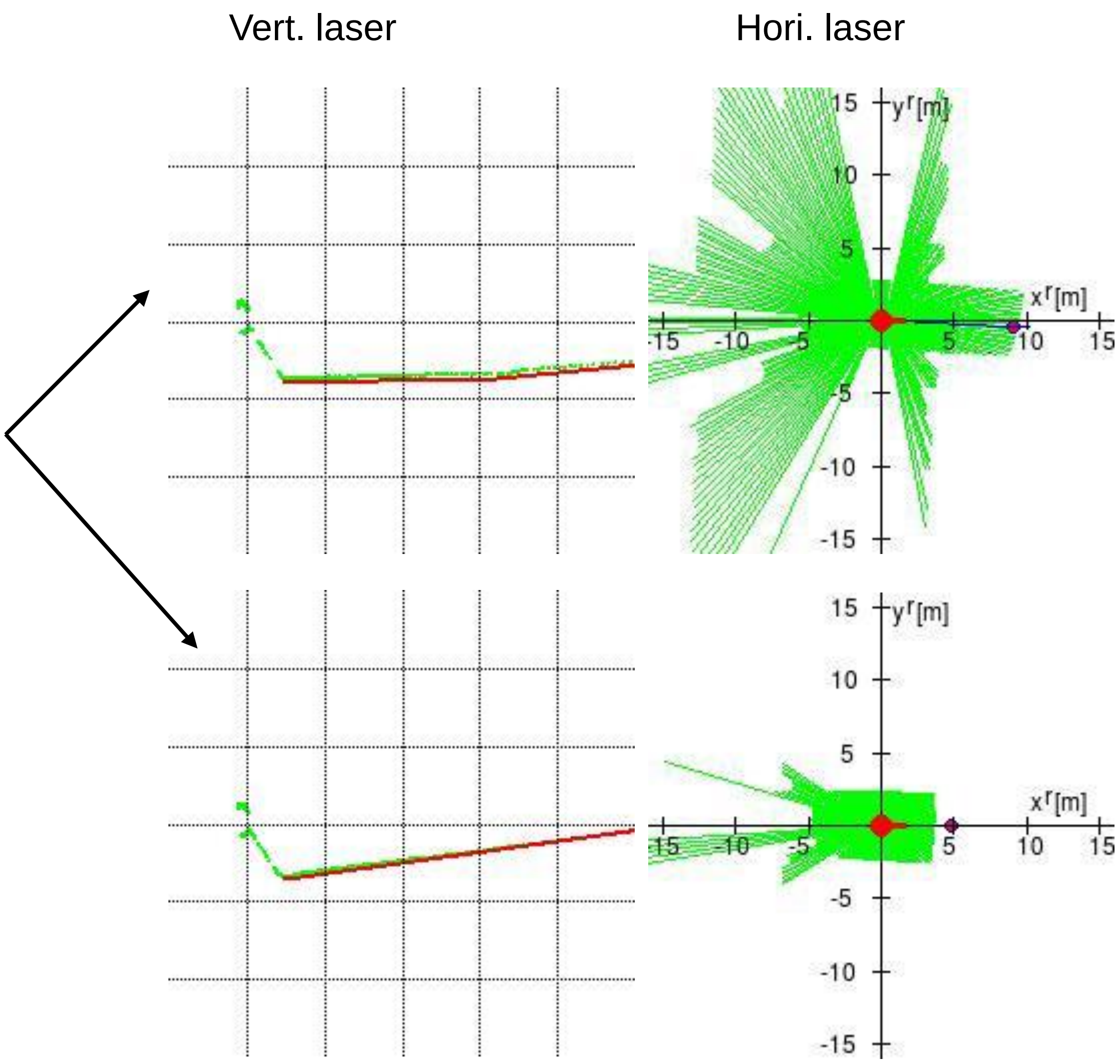
Obstacle Avoidance Diagram



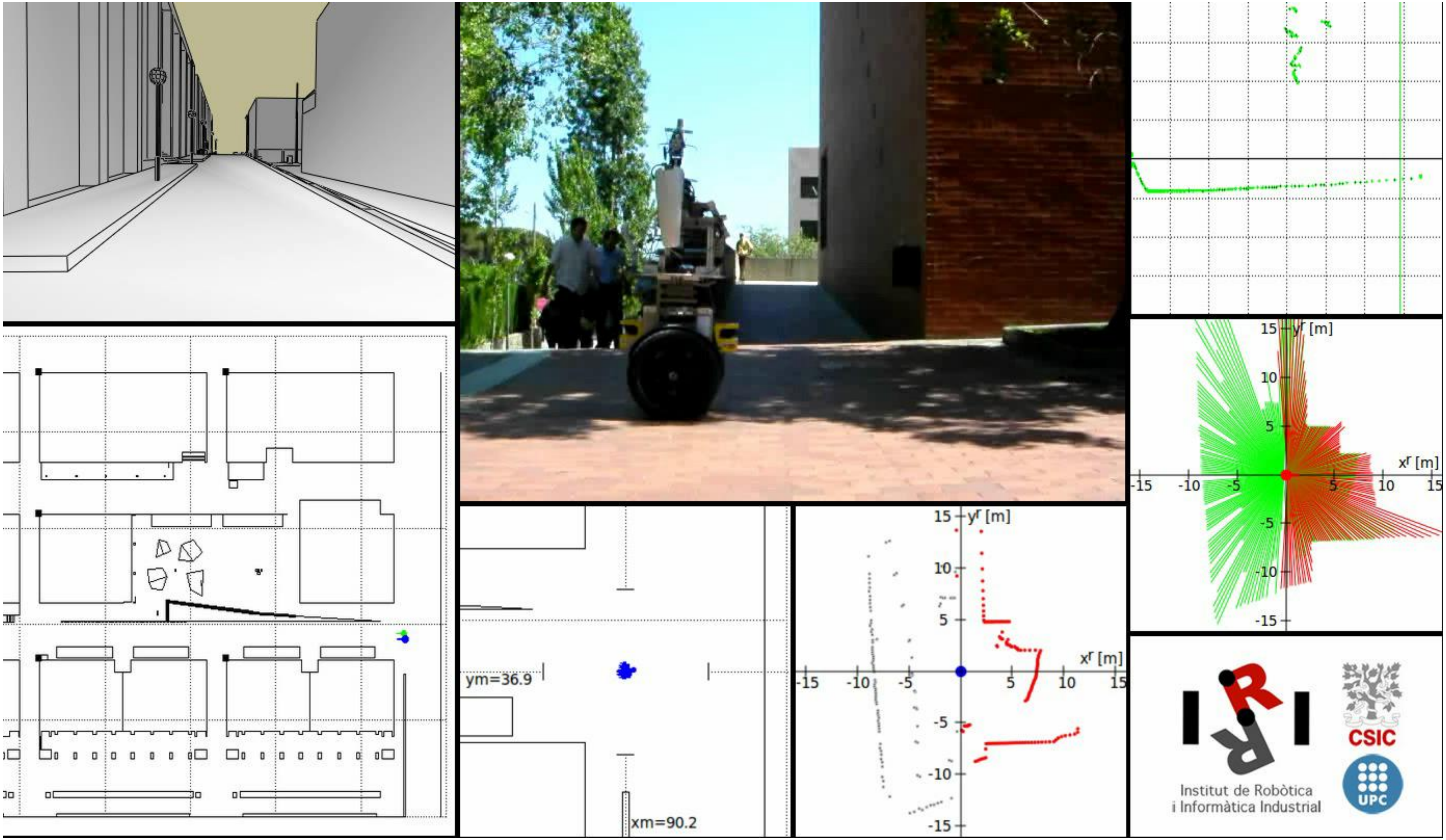
Obstacle Avoidance: Traversability Inference

- Two situations where Traversability Inference is required (ramp zones)

- Extraction of vertical regression line from vertical laser data to detect ramps



Videos



Videos_pruebas\Tibi_Navegando_BRL_2010_WMV V9_002.wmv

Solving Perception Uncertainty in Deformable Object Grasping

Objective

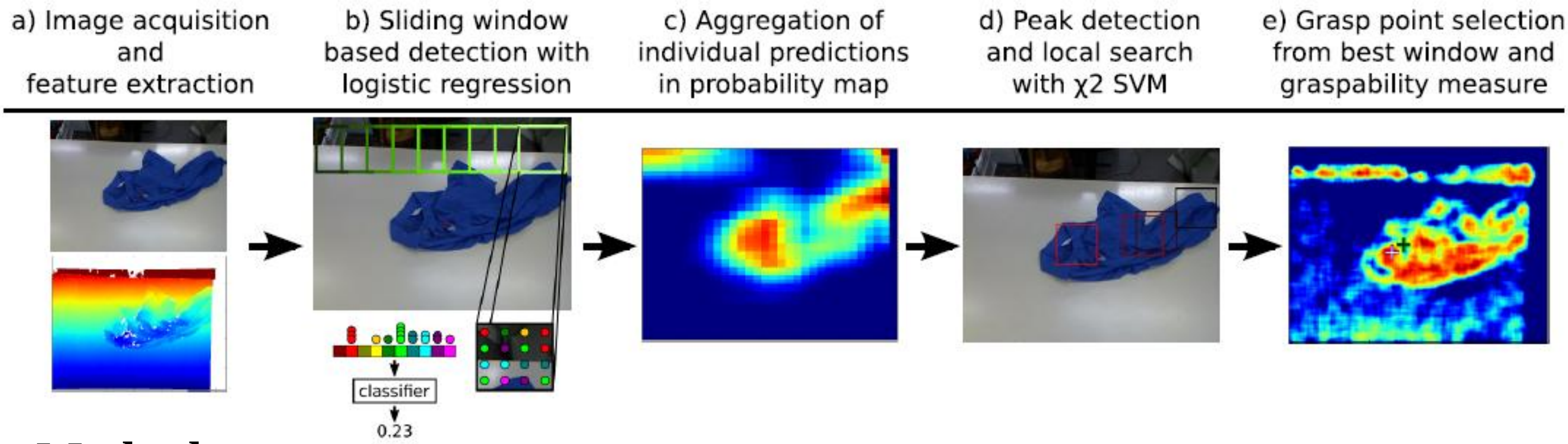
Objective

Using depth and appearance features for informed robot grasping of highly wrinkled clothes

[Ramisa, Alenya, Moreno, Torras, 2012]

[Monso, Alenya, Torras, 2012]

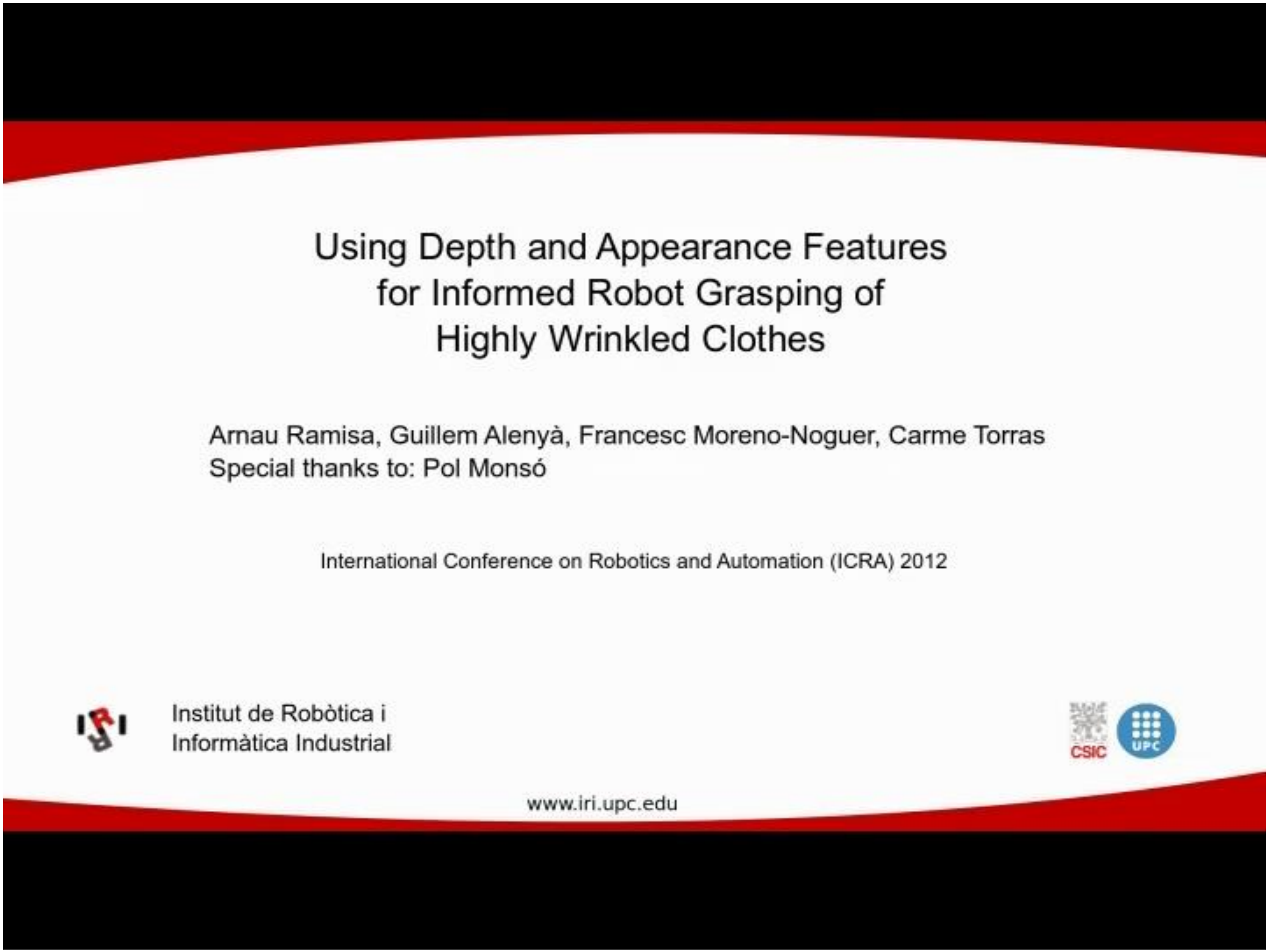
Method



Method

In order to handle the large variability a deformed cloth may have, we build a Bag of Features based detector that combines appearance and 3D geometry features. An image is scanned using a sliding window with a linear classifier, and the candidate windows are refined using a non-linear SVM and a "grasp goodness" criterion to select the best grasping point. For this work we have used polo shirt collars as test cloth part.

Video



Using Depth and Appearance Features
for Informed Robot Grasping of
Highly Wrinkled Clothes
Arnau Ramisa, Guillem Alenyà, Francesc Moreno-Noguer, Carme Torras
Special thanks to: Pol Monsó
International Conference on Robotics and Automation (ICRA) 2012
Institut de Robòtica i
Informàtica Industrial
CSIC
UPC
www.iri.upc.edu

Solving Perception Uncertainty in Taken Care of Plants

Objective

Objective

Using ToF and color cameras to segment plant images into their composite surface patches by combining hierarchical color segmentation with quadratic surface fitting using ToF depth data.

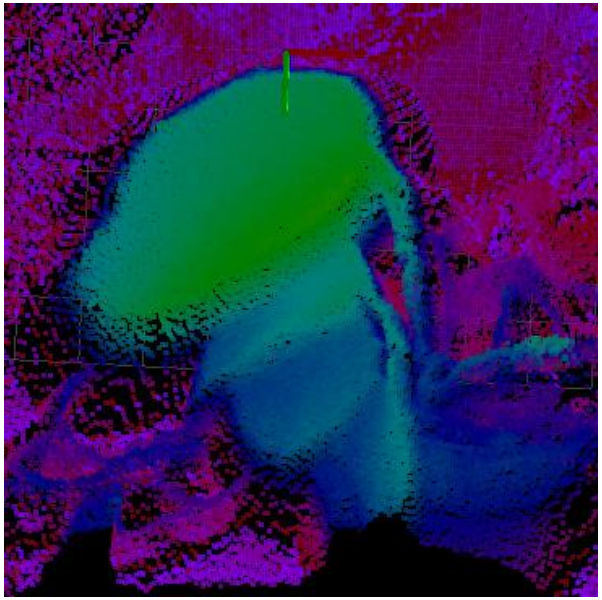
[Alenya, Dellen, Foix, Torras, 2012]
[Alenya, Dellen, Torras, 2011]

European project GARNICS

(Gardening with a Cognitive System)

WARN Robot with a ToF camera

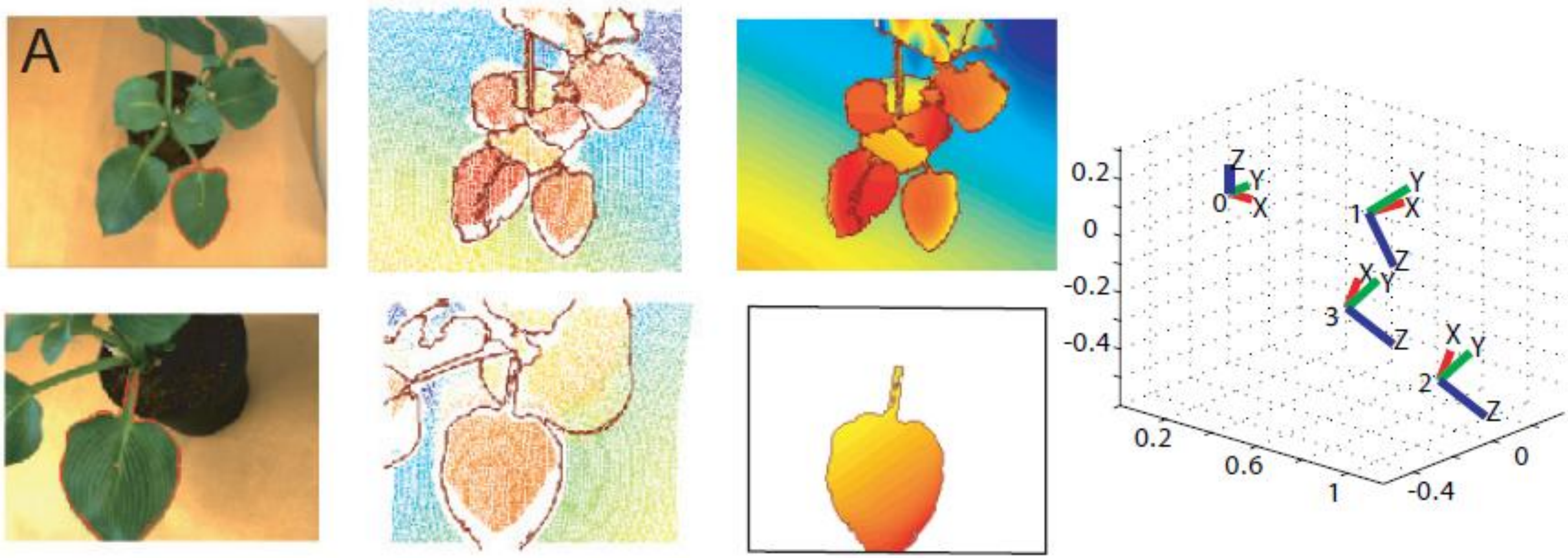
Color image



Point cloud

The process consists of three stages.

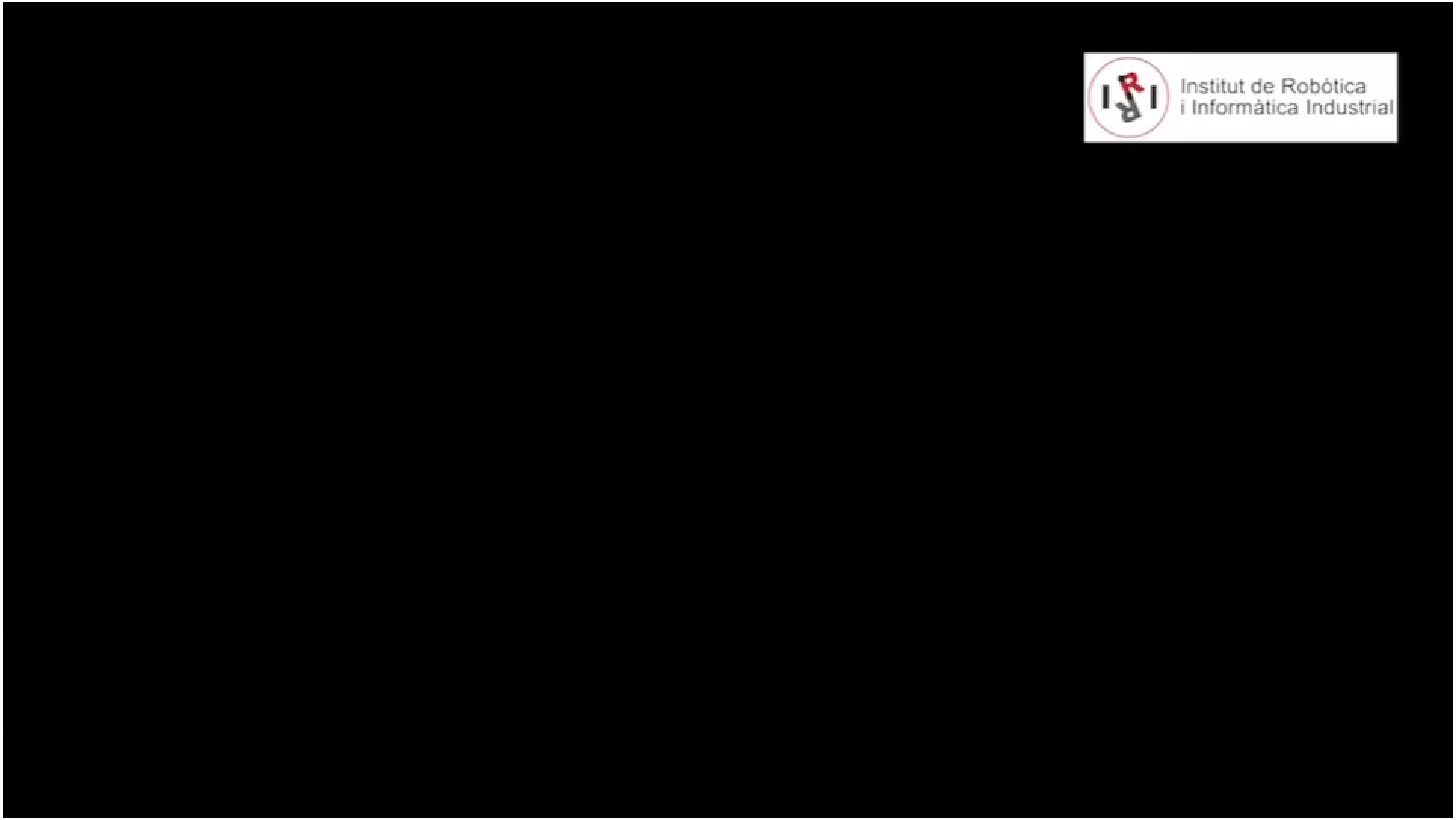
- First, color and depth images are acquired and combined to obtain a colored point cloud.
- Second, the different leaves are segmented from the point cloud, and a plane or a quadratic surface is fitted to each of them. The surface model provides the position and orientation of each leaf. This first segmentation may contain some errors, e.g., several superimposed leaves may fall in the same region, and regions including few points may lead to a relatively large fitting error.
- Third, using the position and orientation of the best leaf candidate, the robot moves the camera system closer to it to obtain a more detailed view, which is used to obtain a better model and eventually separate different leaves.



Experimental results for different views of plants. **A** Color image first view (upper left panel). Sparse depth with segment boundaries (middle upper panel). Fitted depth (right upper panel). Color image close view (lower left panel). Sparse depth with segment boundaries of close view (middle lower panel). Fitted depth of selected segment (right lower panel). The selected segment is marked in red in the color images. A schematic showing the robot base position (0), the initial camera position (1), the leaf position (2) and the computed target position of the camera to capture the second viewpoint (3) are shown in the left panel. Distances are given in meters.

Video

Video



Solving Perception Uncertainty in Aerial Robot Applications

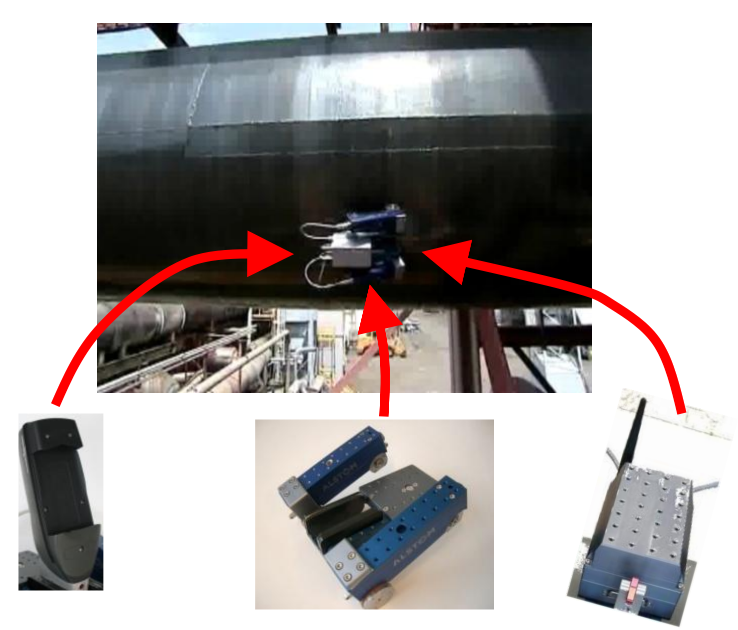
Aerial Robotics Cooperative Assembly System (ARCAS)

ARCAS Objectives:

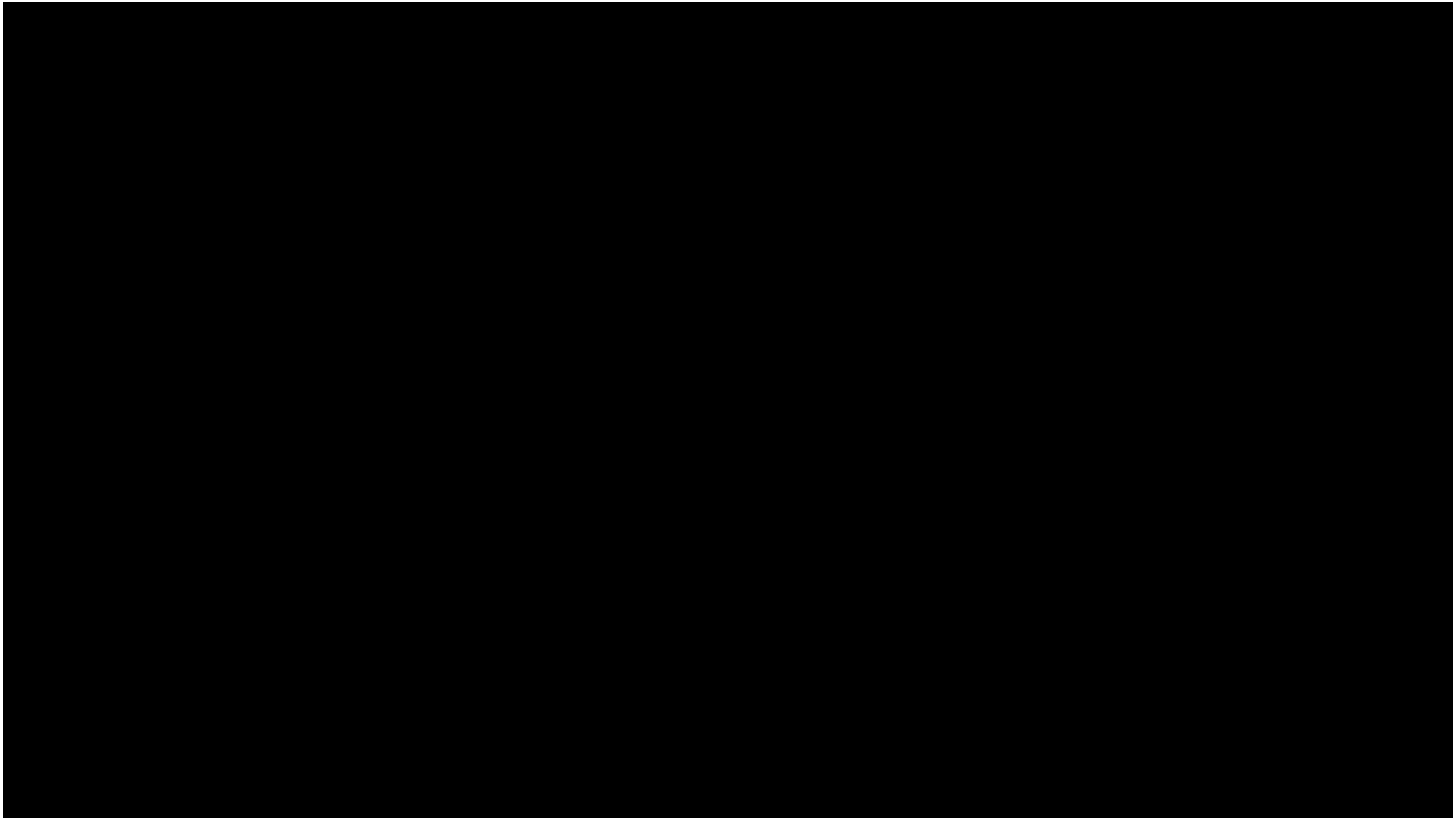
Development and experimental validation of the **first cooperative free-flying robot system** for assembly and structure construction

Application Scenarios

Flying + Manipulation + Perception + Multi-robot Cooperation



Video



3D Object Tracking

- The 3D object tracking component involves the identification and tracking of objects using on-board cameras in aerial robots.
  - ***FeatureDetection:*** This component localizes and identifies relevant features in the input image for object detection and tracking.
  - ***3DPoseEstimation-Tracking:*** Using the information concerning to image features, provided by the FeatureDetection component, this component estimates the pose of assembly objects and tracks their image features during the assembly task and transportation.
  - ***3DVisualServo:*** This component is used to perform visual servoing in flying robots using the estimated object pose and the tracked features given by the 3DPoseEstimation-Tracking component.

Factors that Provoke Uncertainties

- ***Environment conditions:***
  - Wind
  - Lighting changes (due to clouds, the hour of the day, etc.)
  - Shadows (cast shadows, etc.)

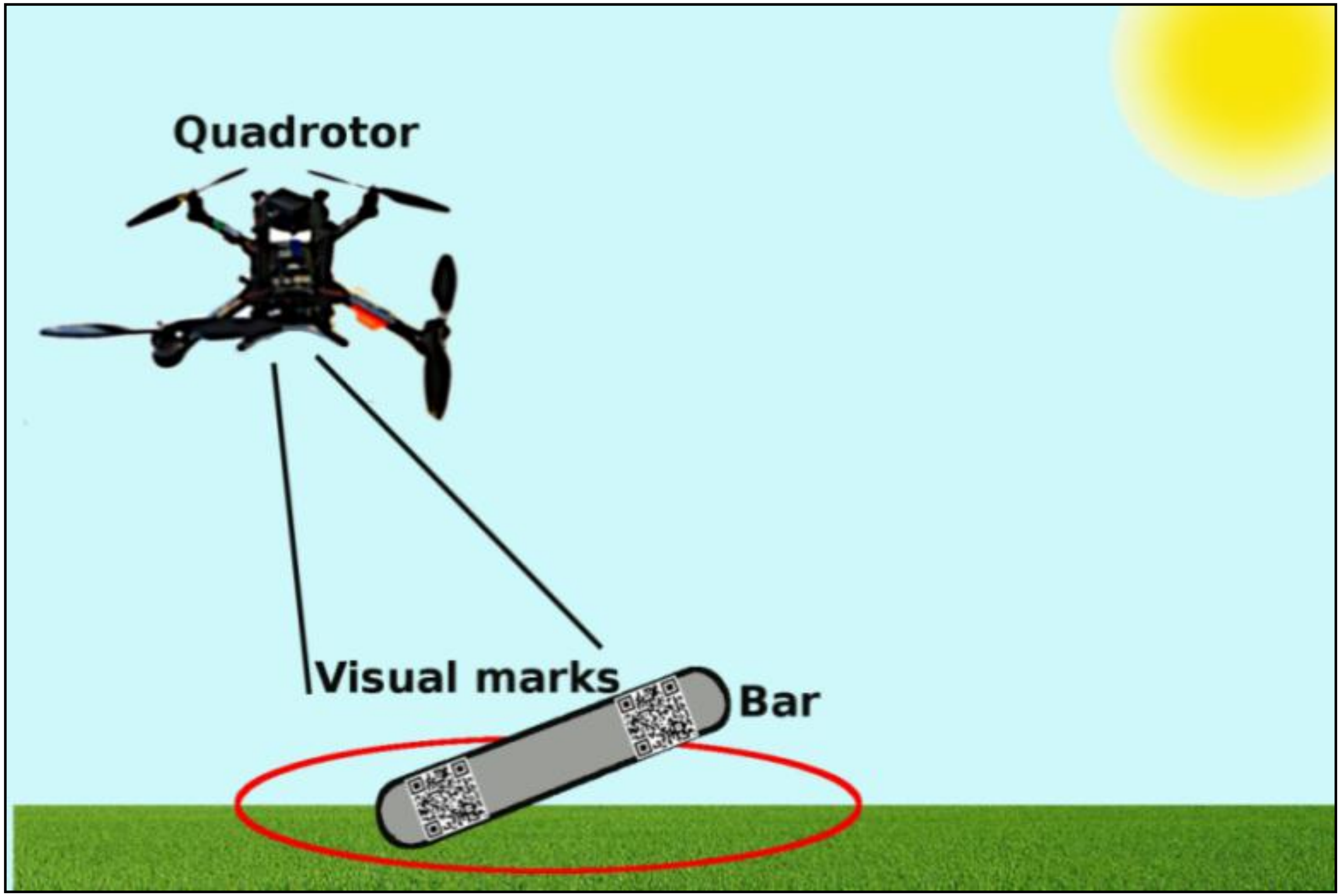
- ***Object/scene appearance:***
  - 3D rotations and translations
  - Scale variations
  - Perspective projections
  - Cluttered background
  - Surface reflections and color variations

- ***Aerial robot platform:***
  - Camera pose
  - Camera lens
  - Vibrations
  - Real time processing
  - Cooperative delay of the information

- ***Task:***
  - Partial occlusions
  - Relative pose between components to be assembly

Bar Detection During Assembly Operations

Onboard Camera



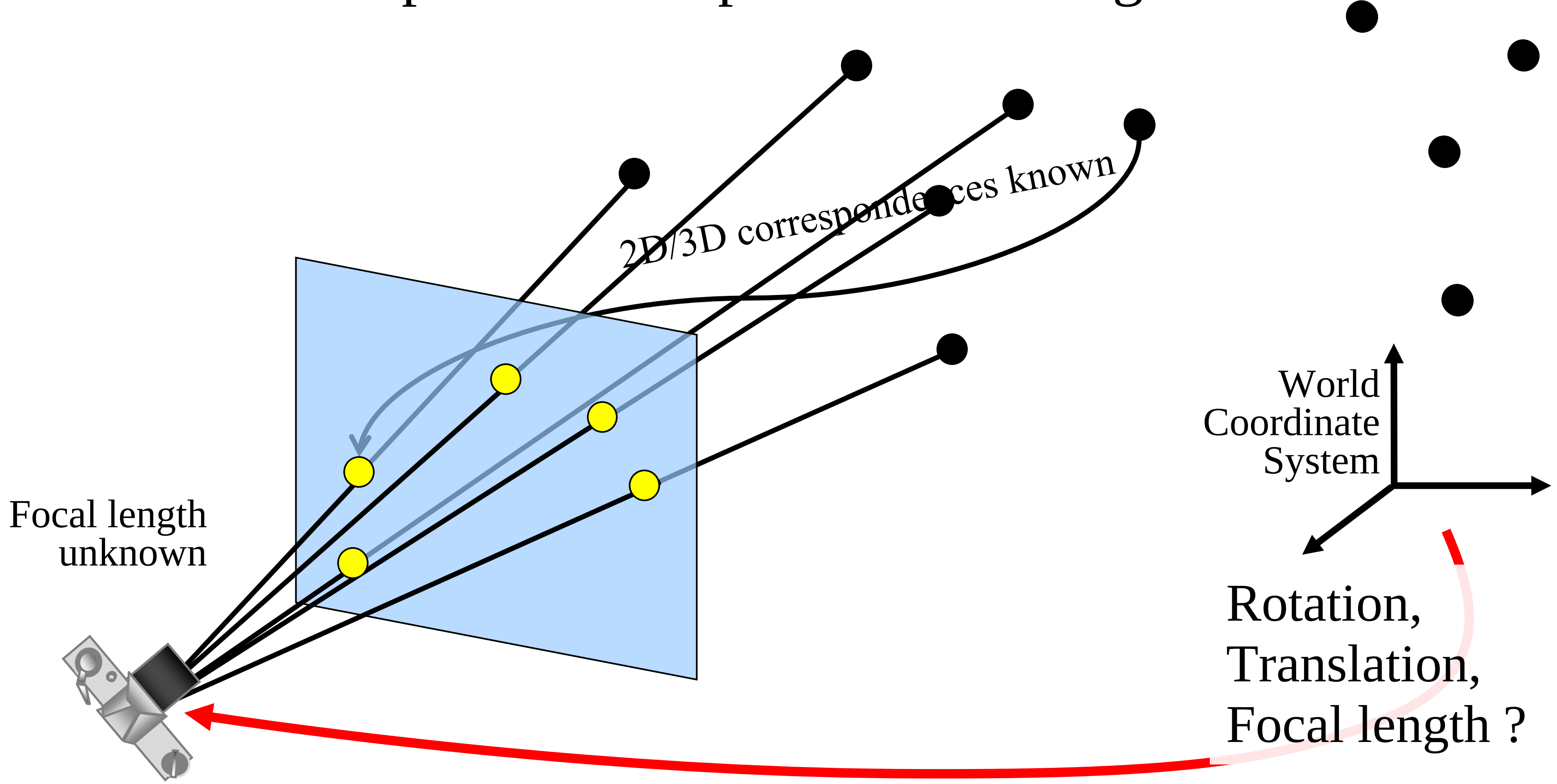
Visual marks: Outdoor challenges

Vibrations, noise outdoor and cluttered background

Video: Visual Marks in Indoor

The (uncalibrated) PnP Problem

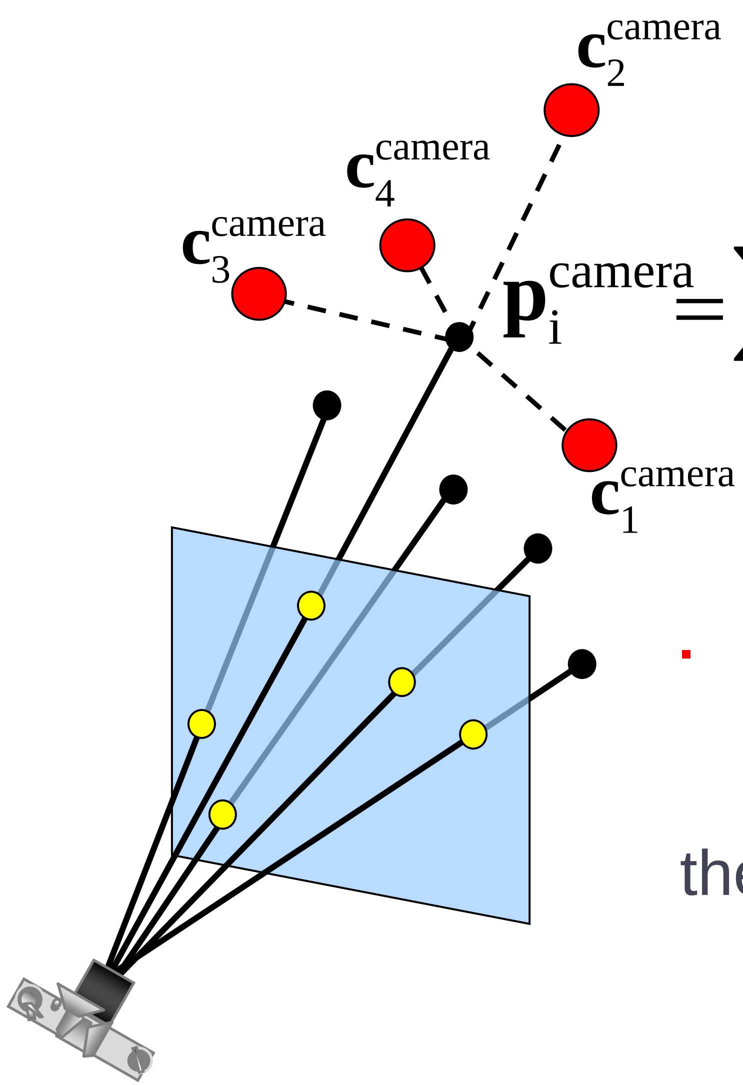
- **Given:** 2D/3D correspondences
- **We want:** Compute camera pose + focal length



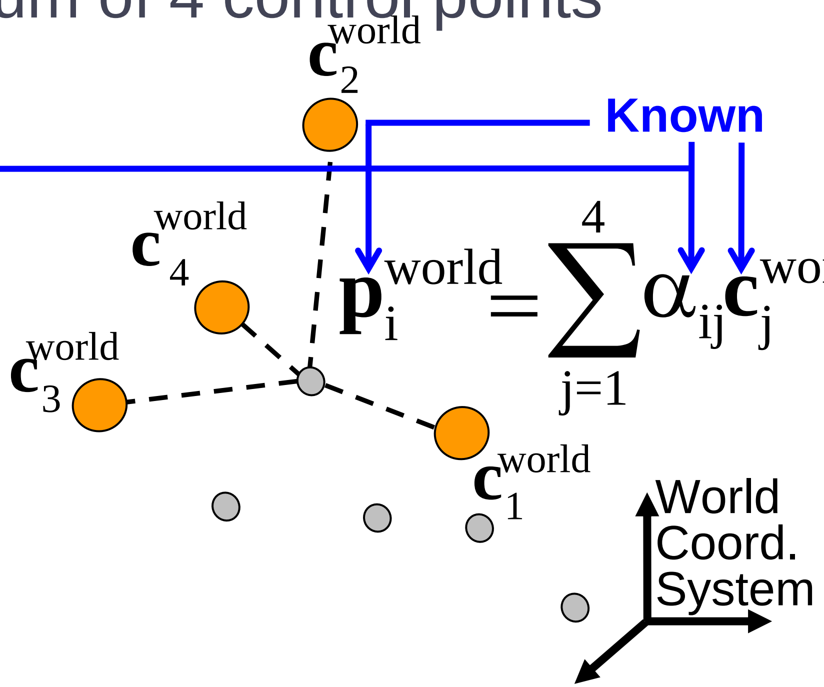
[Peñate, Andrade, Moreno, 2013]

Introducing Control Points

- 3D points expressed as a weighted sum of 4 control points



$$\mathbf{p}_i^{camera} = \sum_{j=1}^{4} \alpha_{ij} \mathbf{c}_j^{camera}$$



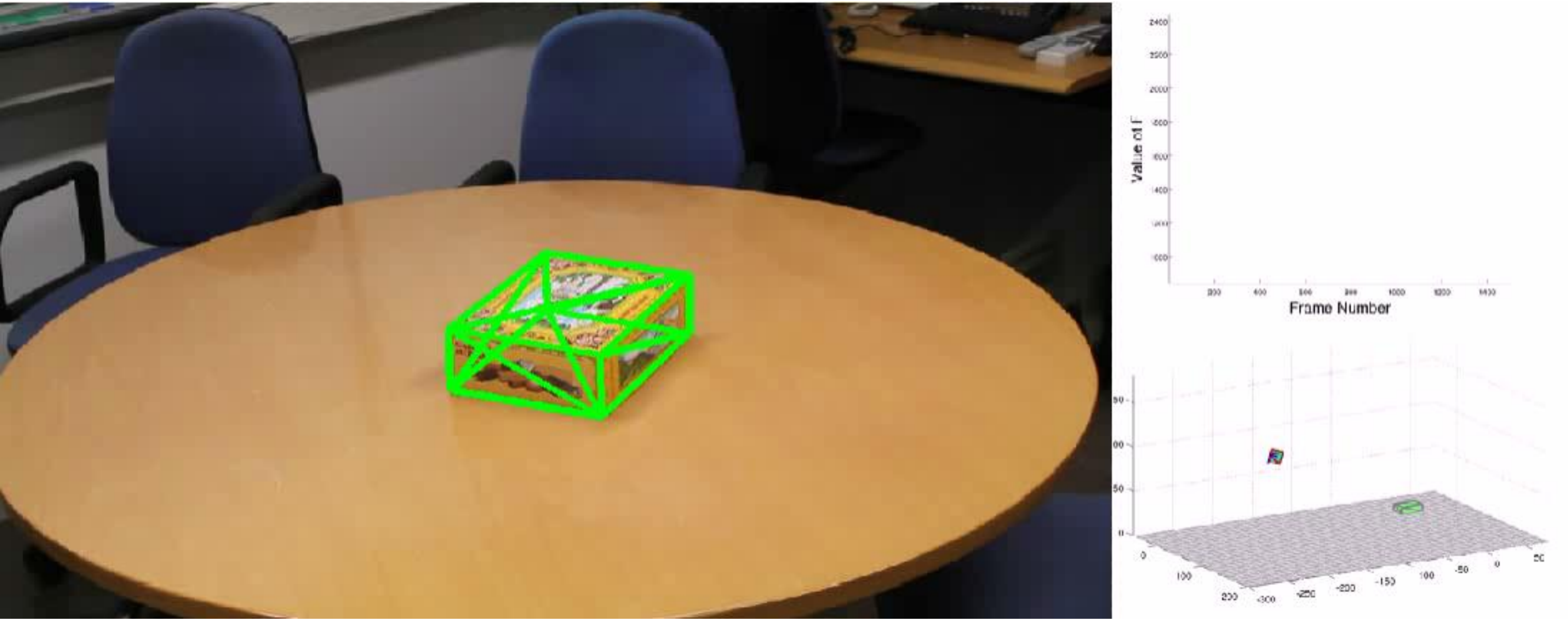
$$\mathbf{p}_i^{world} = \sum_{j=1}^{4} \alpha_{ij} \mathbf{c}_j^{world}$$

- Unknowns: $\mathbf{x} = [x_1^c, y_1^c, z_1^c/f, \ldots, x_4^c, y_4^c, z_4^c/f]^\top$

  Camera coord. of the 4 control points and the focal length

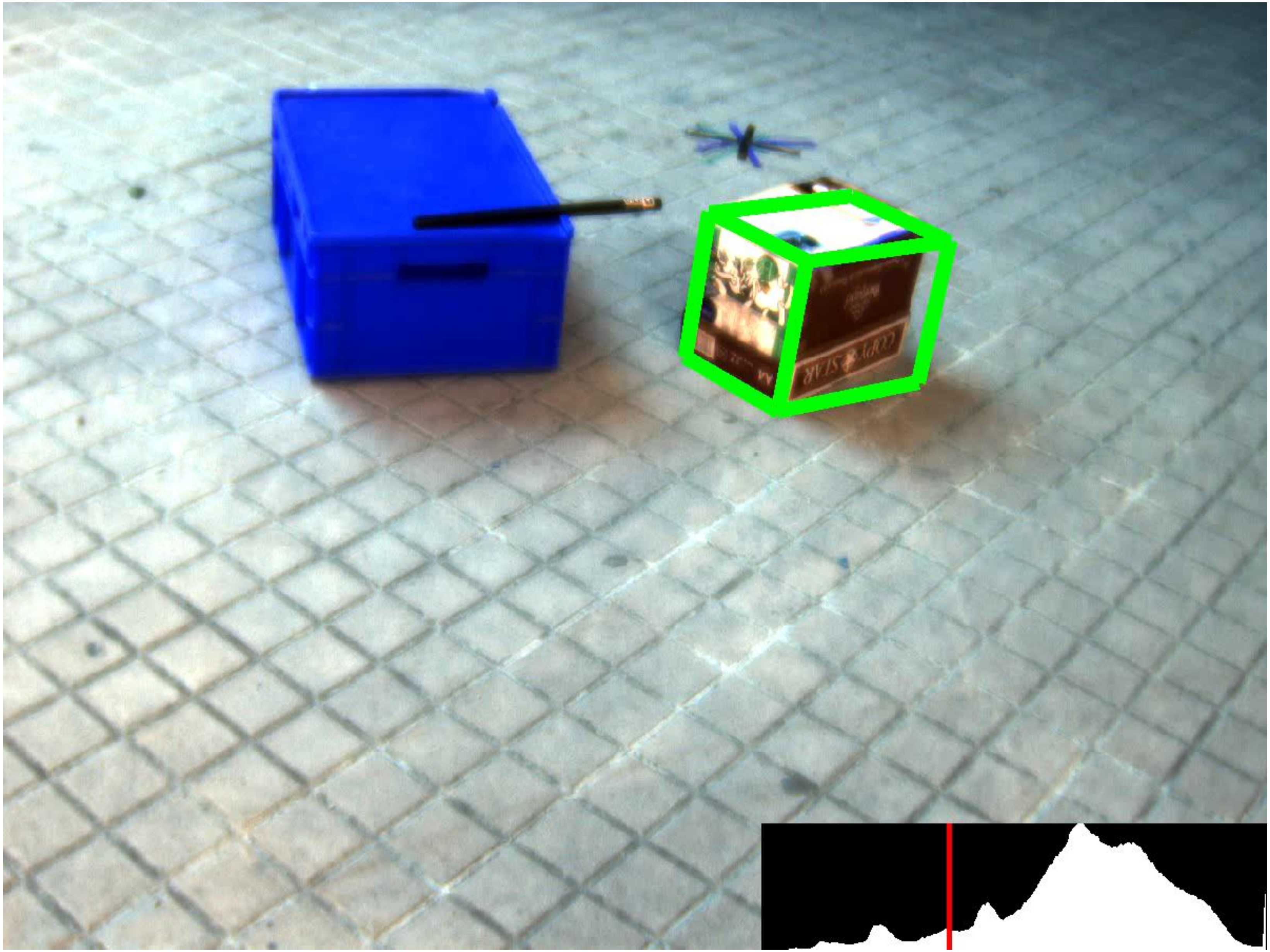
Number of unknowns = 12

3D Pose Estimation: the UPnP



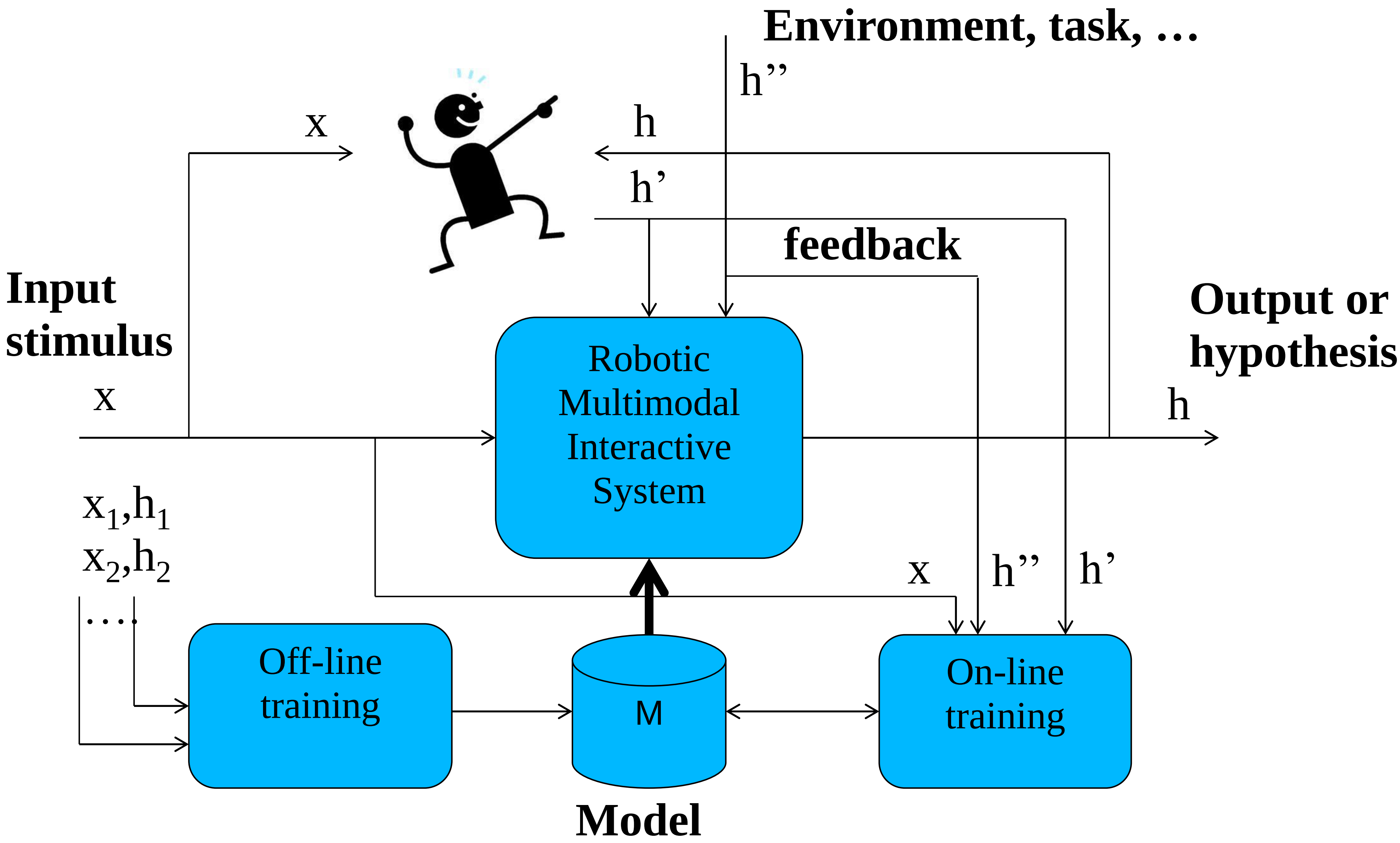
Independent detection in every frame.

3D Pose Estimation: the UPnP



Solving Perception Uncertainty using Probabilistic Models and un/supervised learning models in the loop

General Multimodal Scheme



Solving Perception Uncertainty in Online Human-Assisted Learning using Random Ferns

Motivation

Robot TIBI learns and improves its visual perception capabilities by means of interactions with humans

Robot TIBI

Robot TIBI

[Villamizar, Moreno, Andrade, Sanfeliu, 2010]
[Villamizar, Andrade, Sanfeliu, Moreno, 2012]
[Villamizar, Garrell, Sanfeliu, Moreno, 2012]

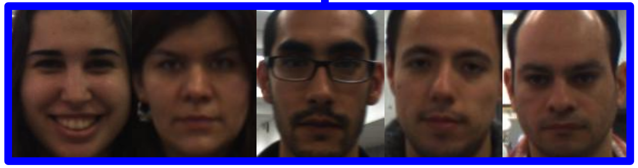
Objective

Robot TIBI learns to recognize faces and objects using human assistance

Objective

Robot TIBI learns to recognize faces and objects using human assistance

Face Recognition



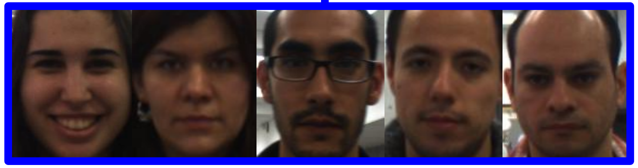
Faces

Objective

Robot TIBI learns to recognize faces and objects using human assistance

Face Recognition

Object Recognition



Faces

3D Objects

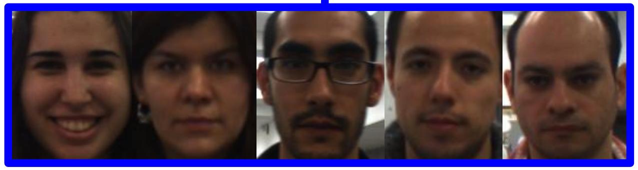
Objective

Robot TIBI learns to recognize faces and objects using human assistance

The interaction takes a couple of minutes (~ 5 min.)

Face Recognition

Object Recognition



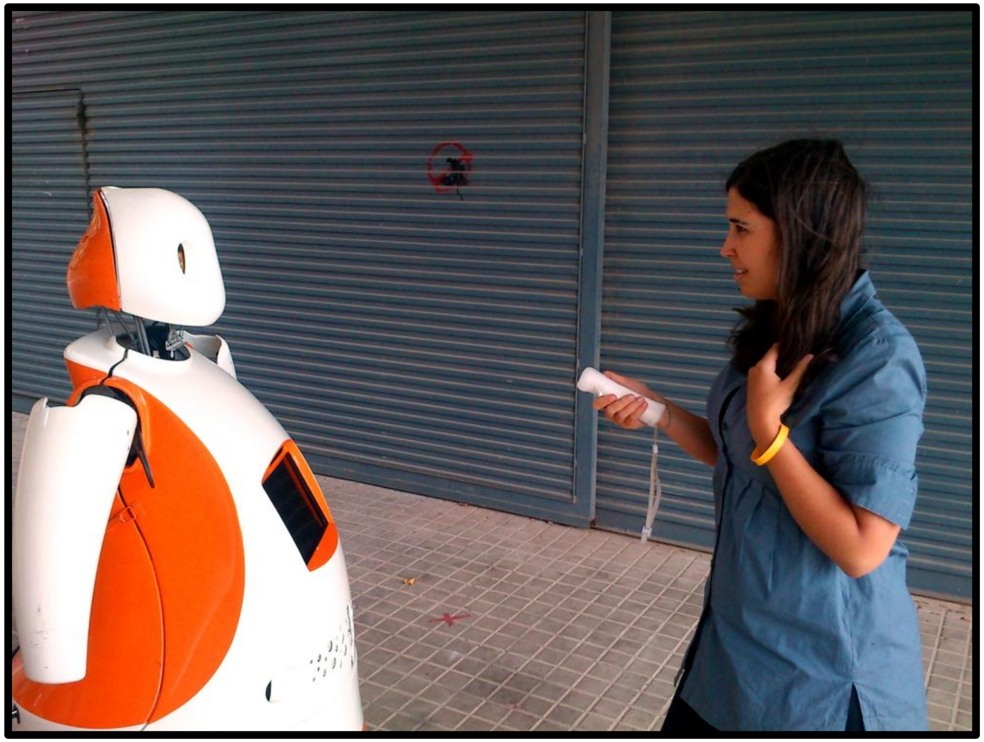
Faces

3D Objects

Approach

Online Human-Assisted Learning

Human-Robot Interaction



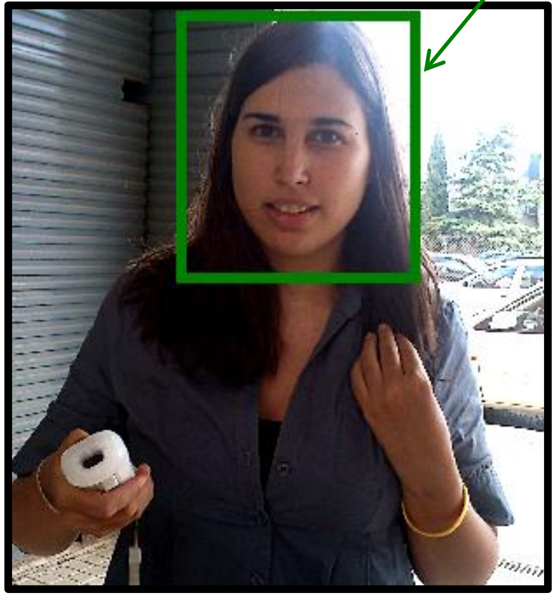
Approach

Online Human-Assisted Learning

Human-Robot Interaction

Robot Camera

hypothesis



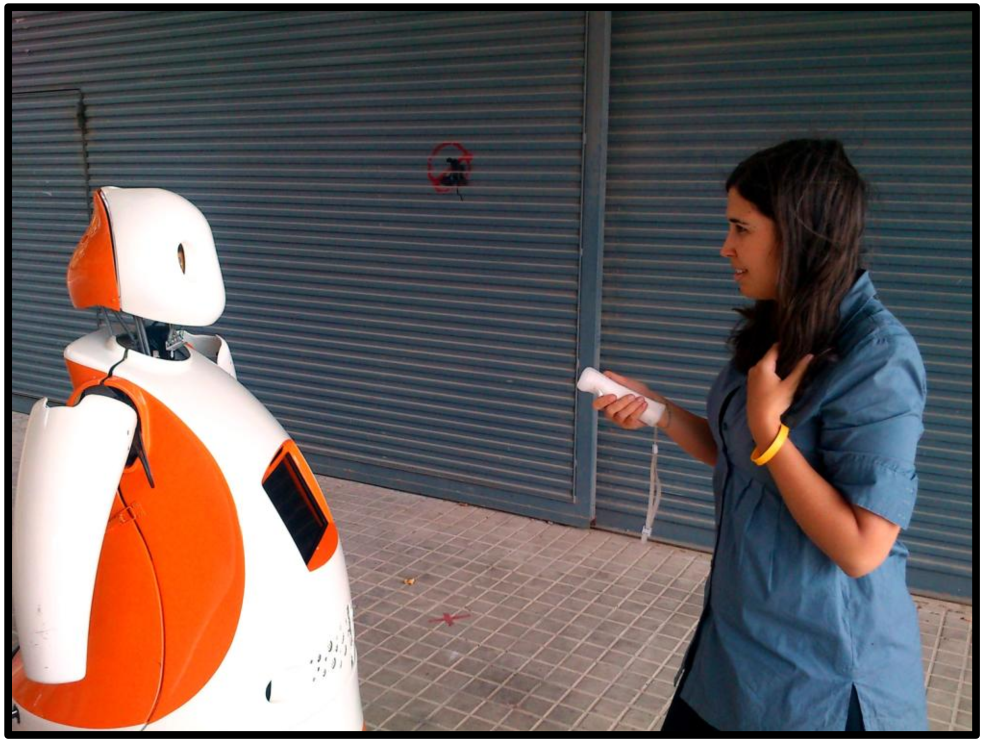
Recognition Results

Online Learning: ***The visual system is updated continuously using its own detection hypotheses***

Approach

Online Human-Assisted Learning

Human-Robot Interaction



Difficult Cases

***<u>Human-Assisted Learning:</u>* The visual system requires the human intervetion**

Approach

Online Human-Assisted Learning

Human-Robot Interaction

Difficult Cases

Camera

Touch Screen

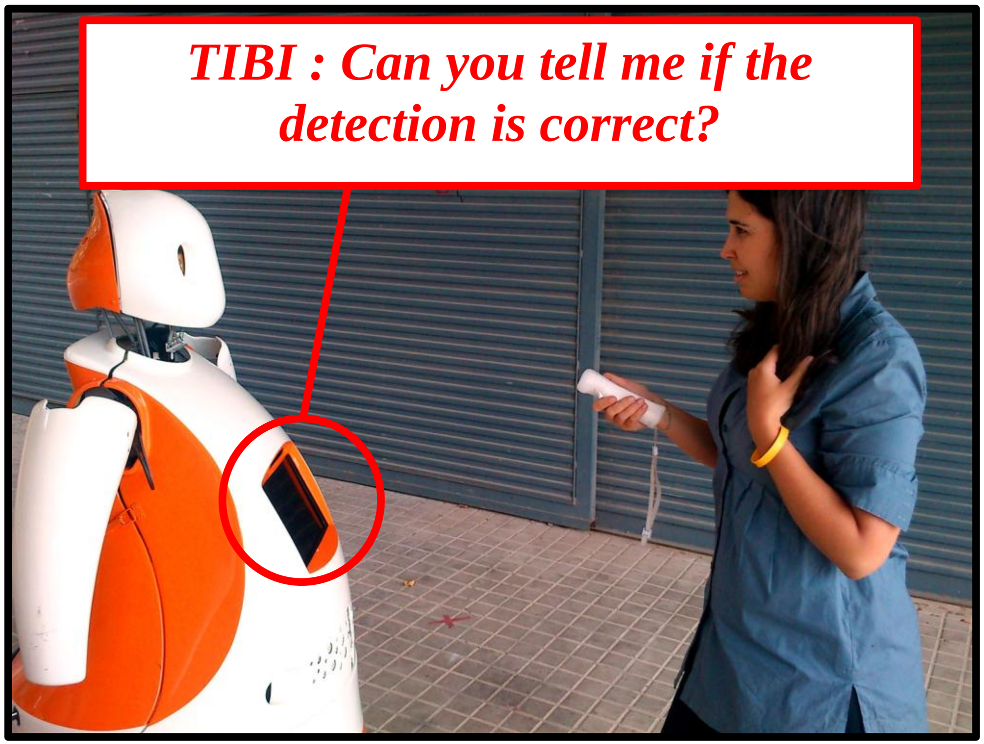
wii mote

Keyboard

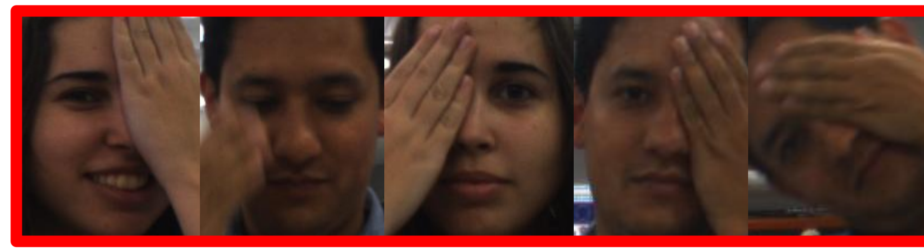
Approach

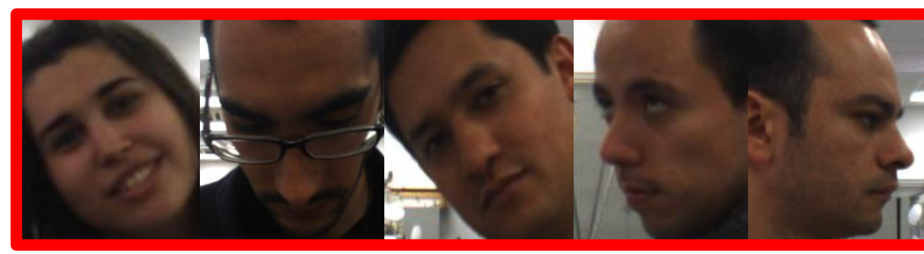
Online <u>Human-Assisted Learning</u>

Human-Robot Interaction



Difficult Cases





Camera

Touch Screen

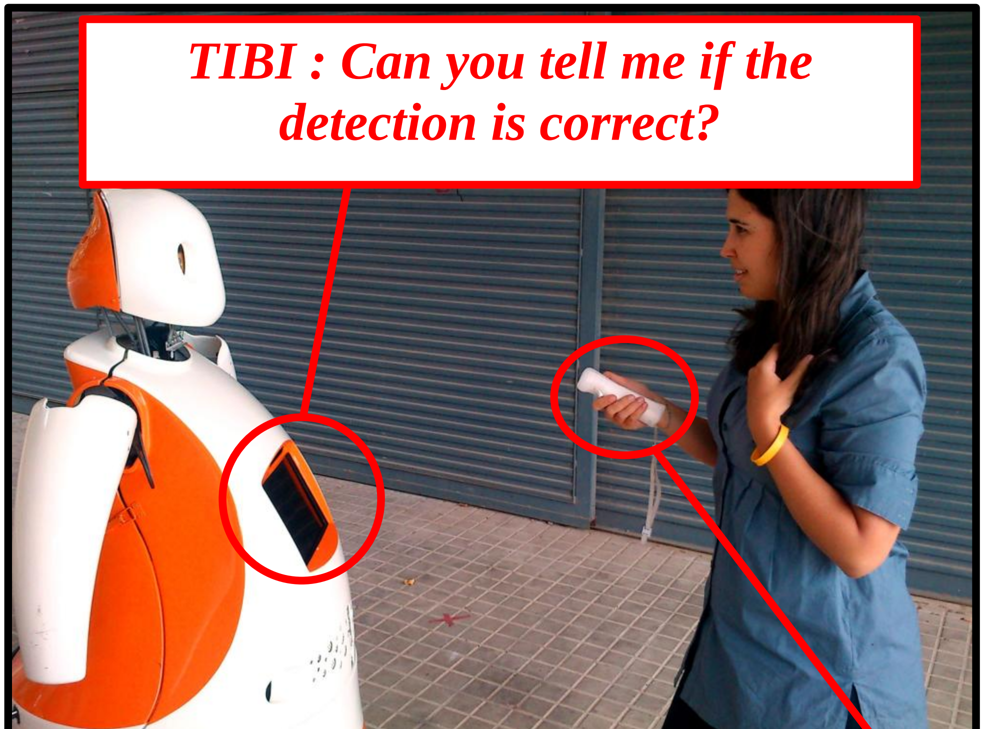
wii mote

Keyboard

Approach

Online Human-Assisted Learning

Human-Robot Interaction



Difficult Cases

Camera

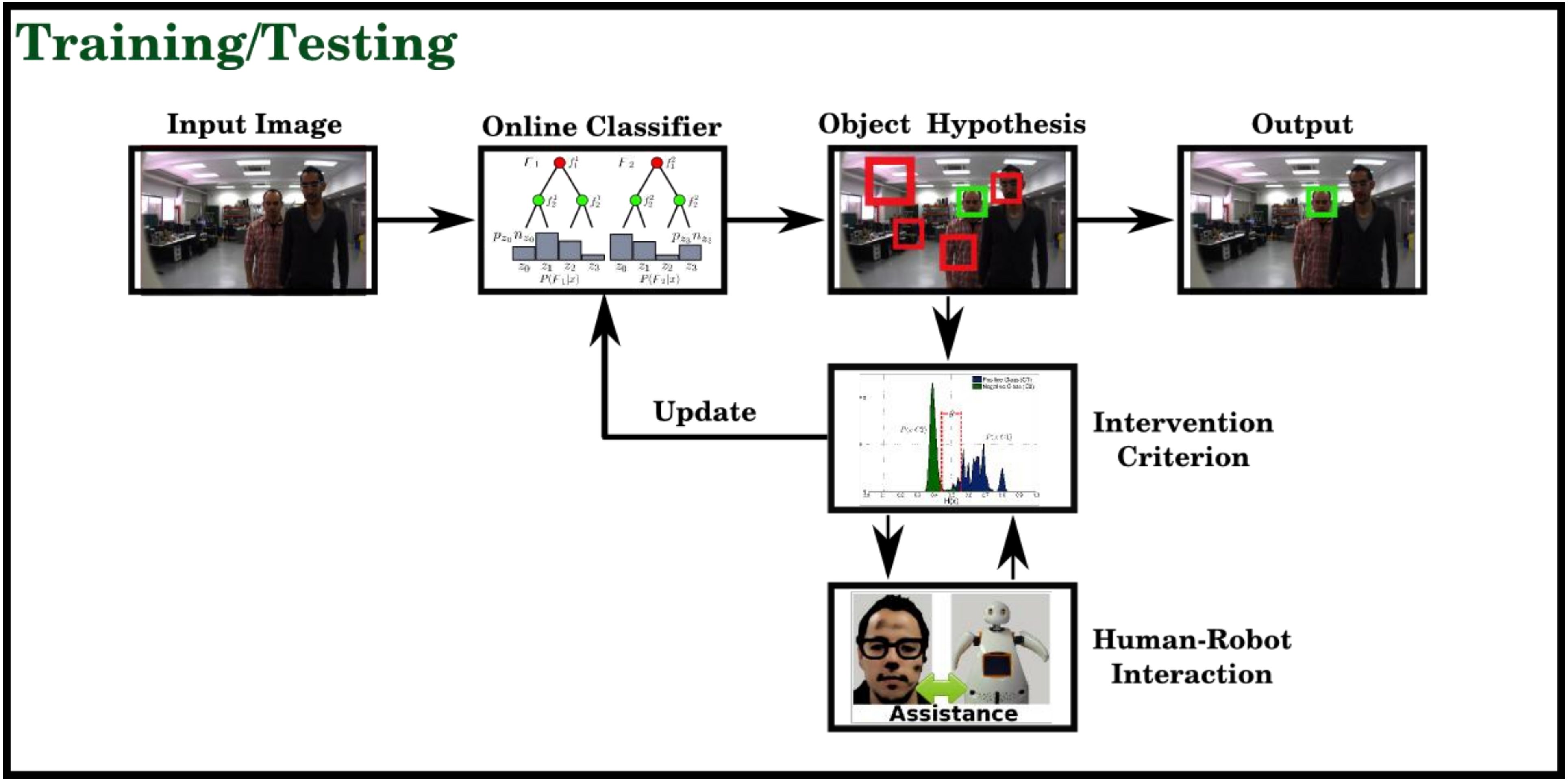
Touch Screen

wii mote

Keyboard

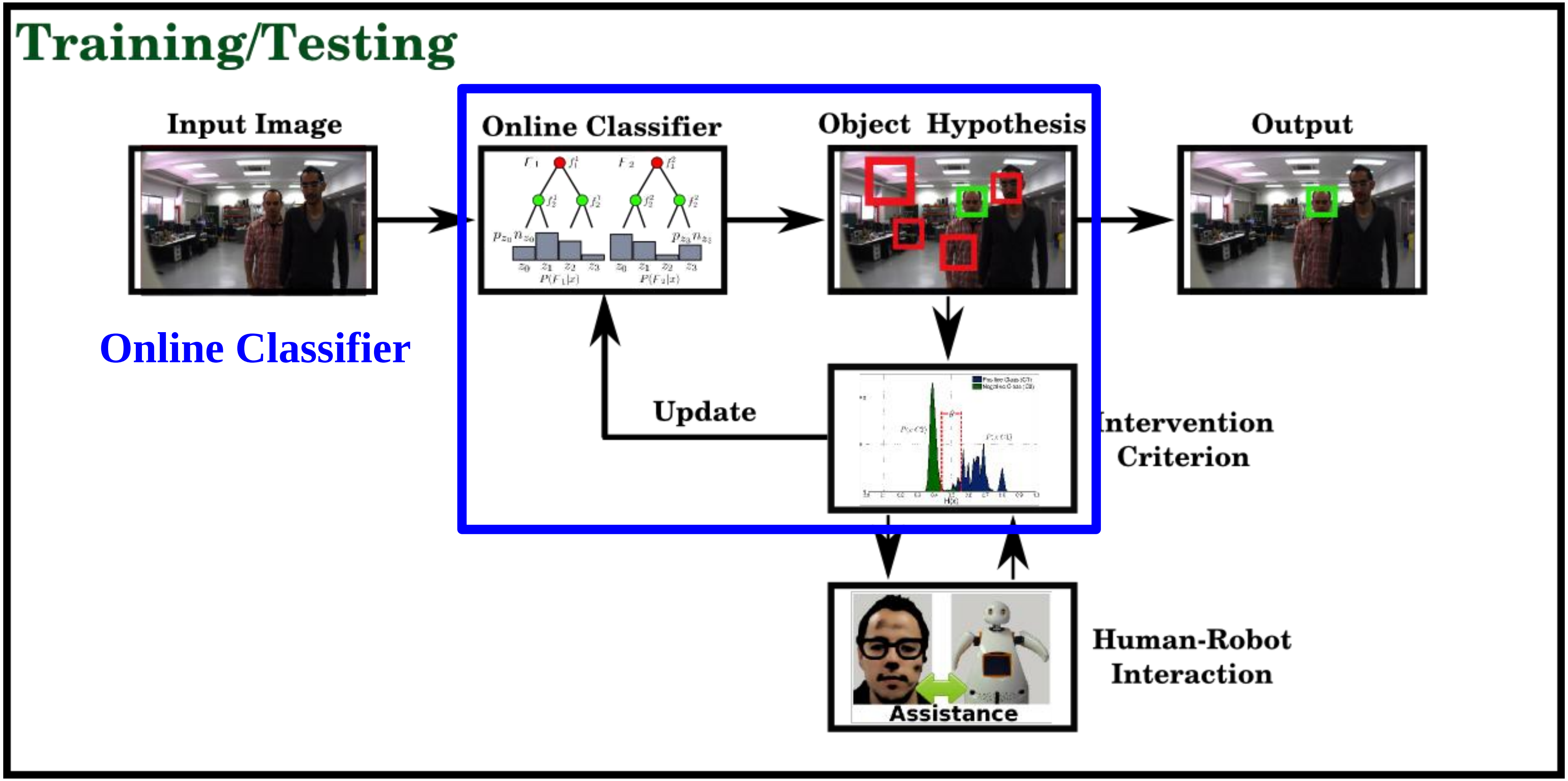
Approach

Online Human-Assisted Learning using Random Ferns



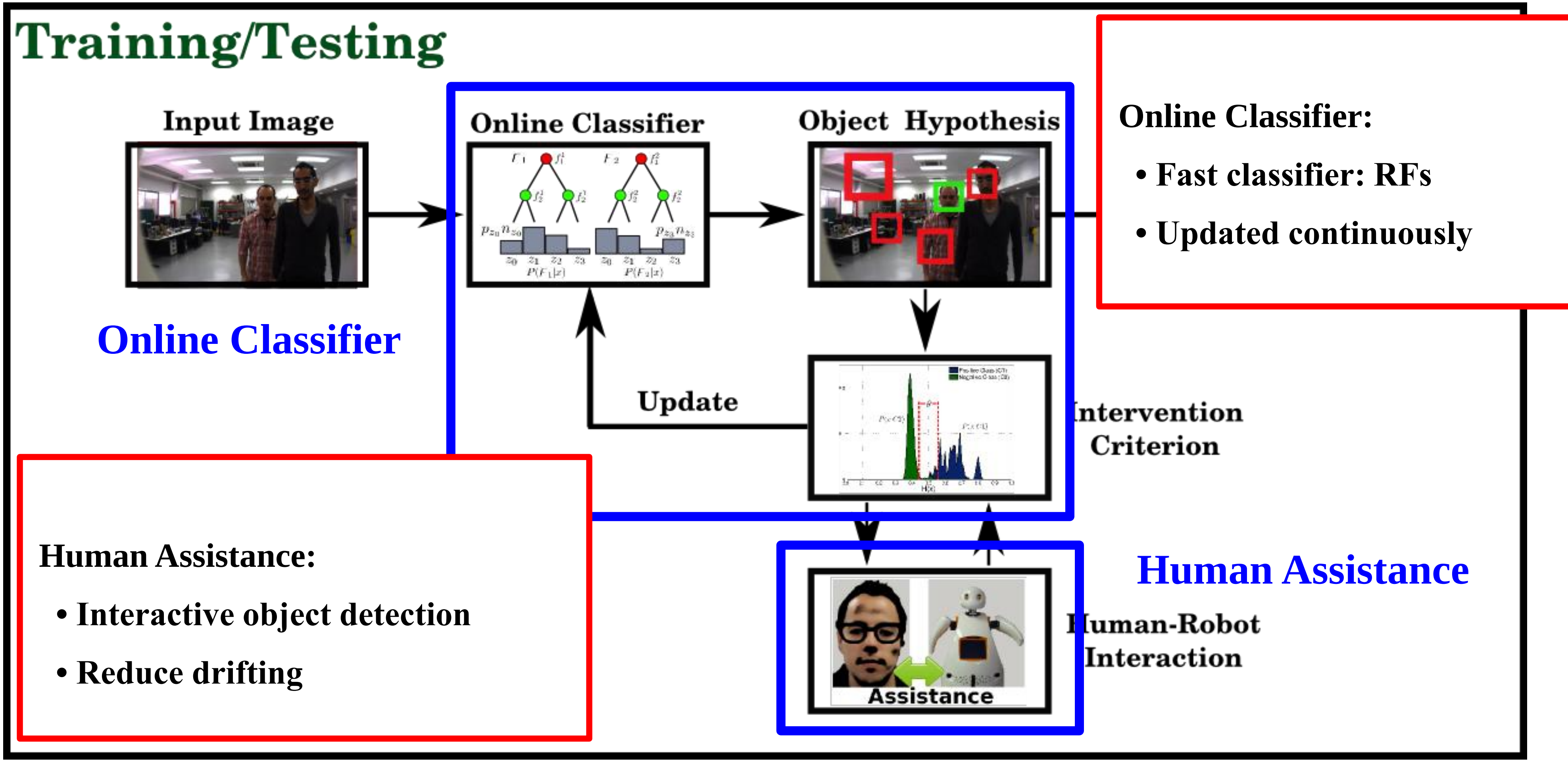
Approach

Online Human-Assisted Learning using Random Ferns



Approach

Online Human-Assisted Learning using Random Ferns

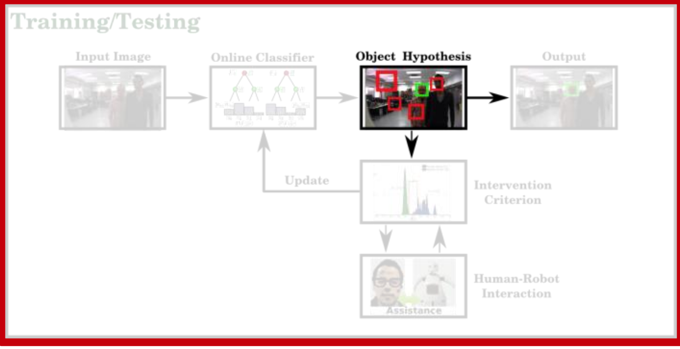


Online Classifier:

- Fast classifier: RFs
- Updated continuously

Human Assistance:

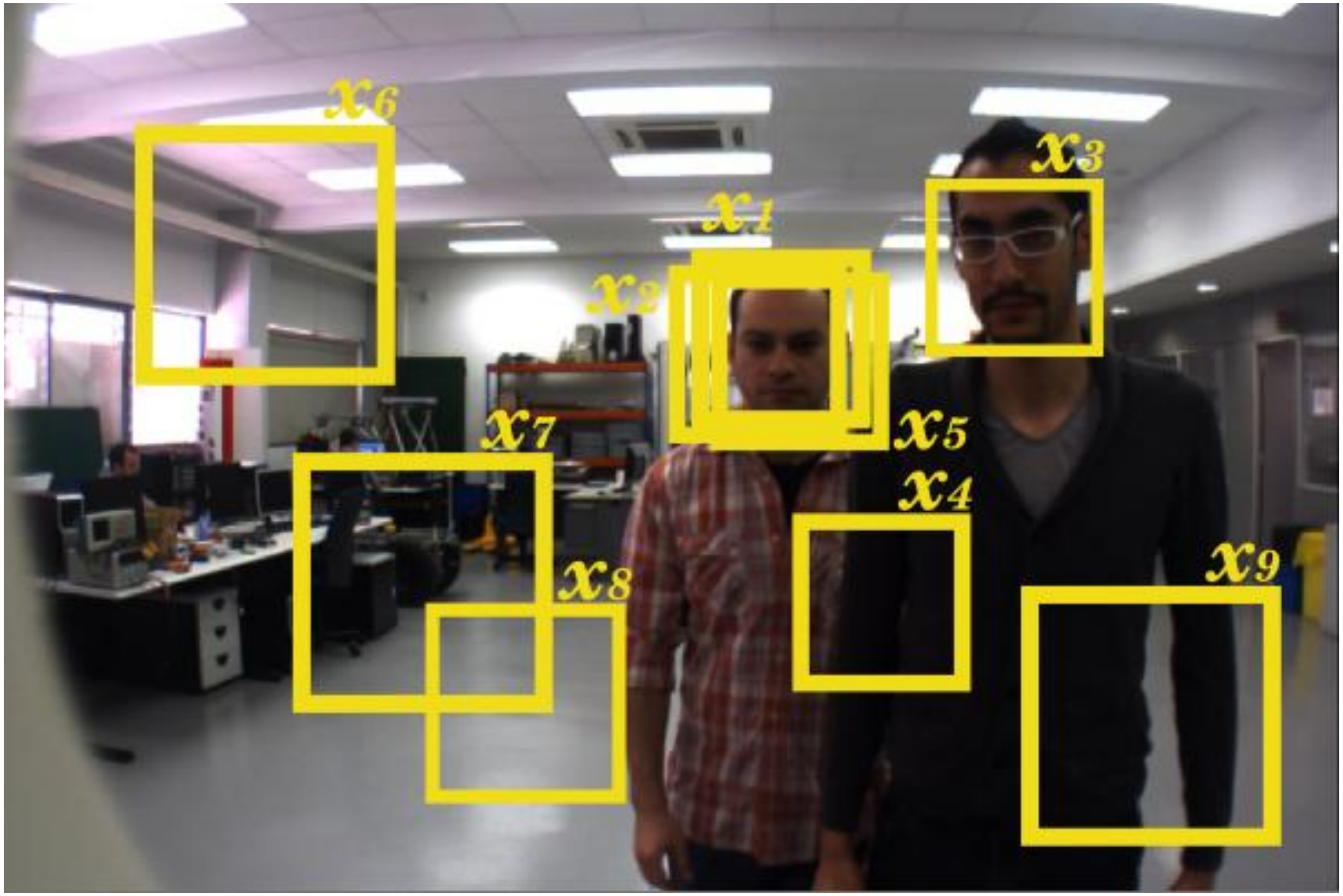
- Interactive object detection
- Reduce drifting

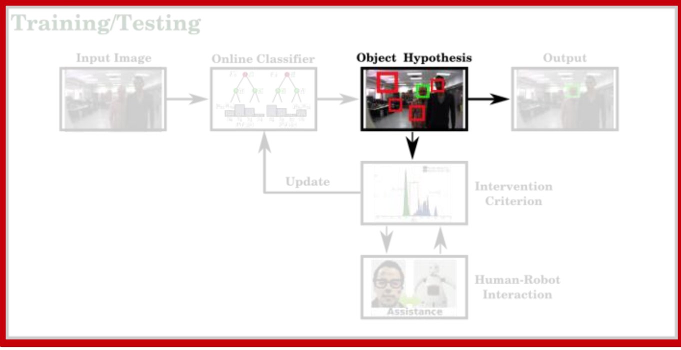


Approach

Object Hypothesis

- Object hypotheses: detections given by the classifier

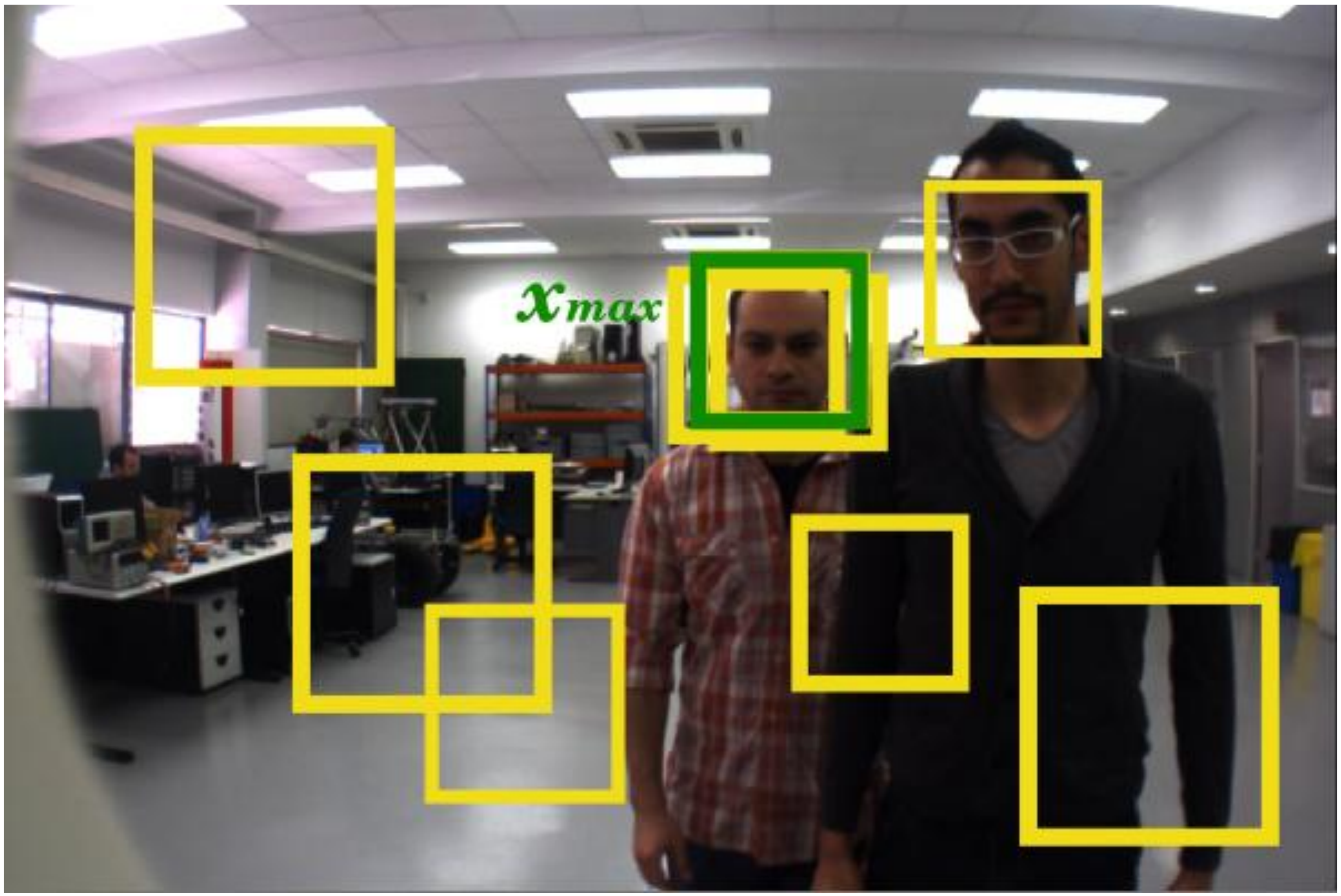


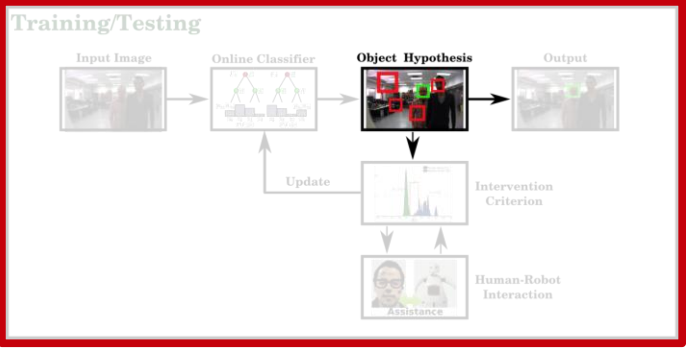


Approach

Object Hypothesis

- Object candidate: highest-confidence hypothesis (detection)

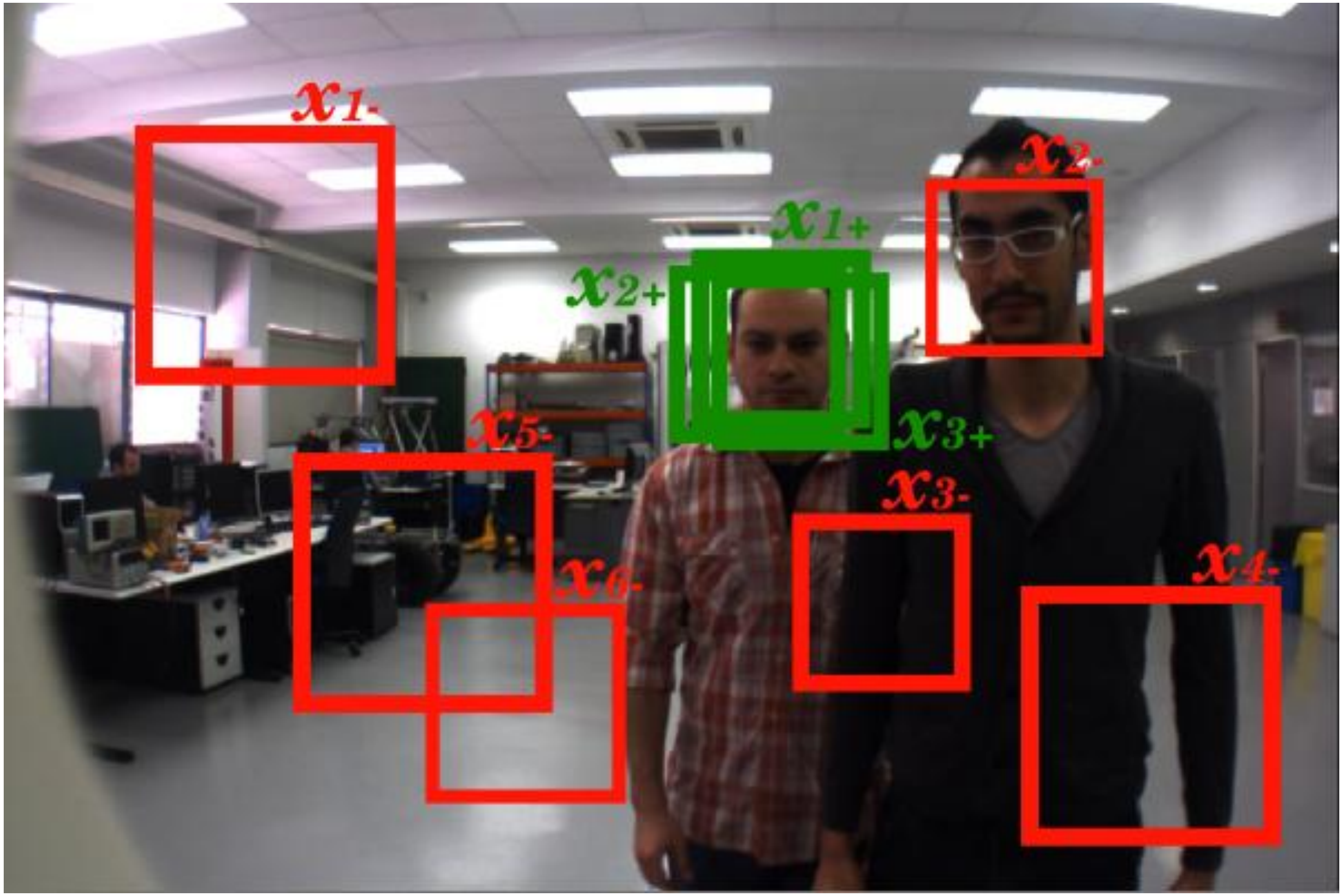




Approach

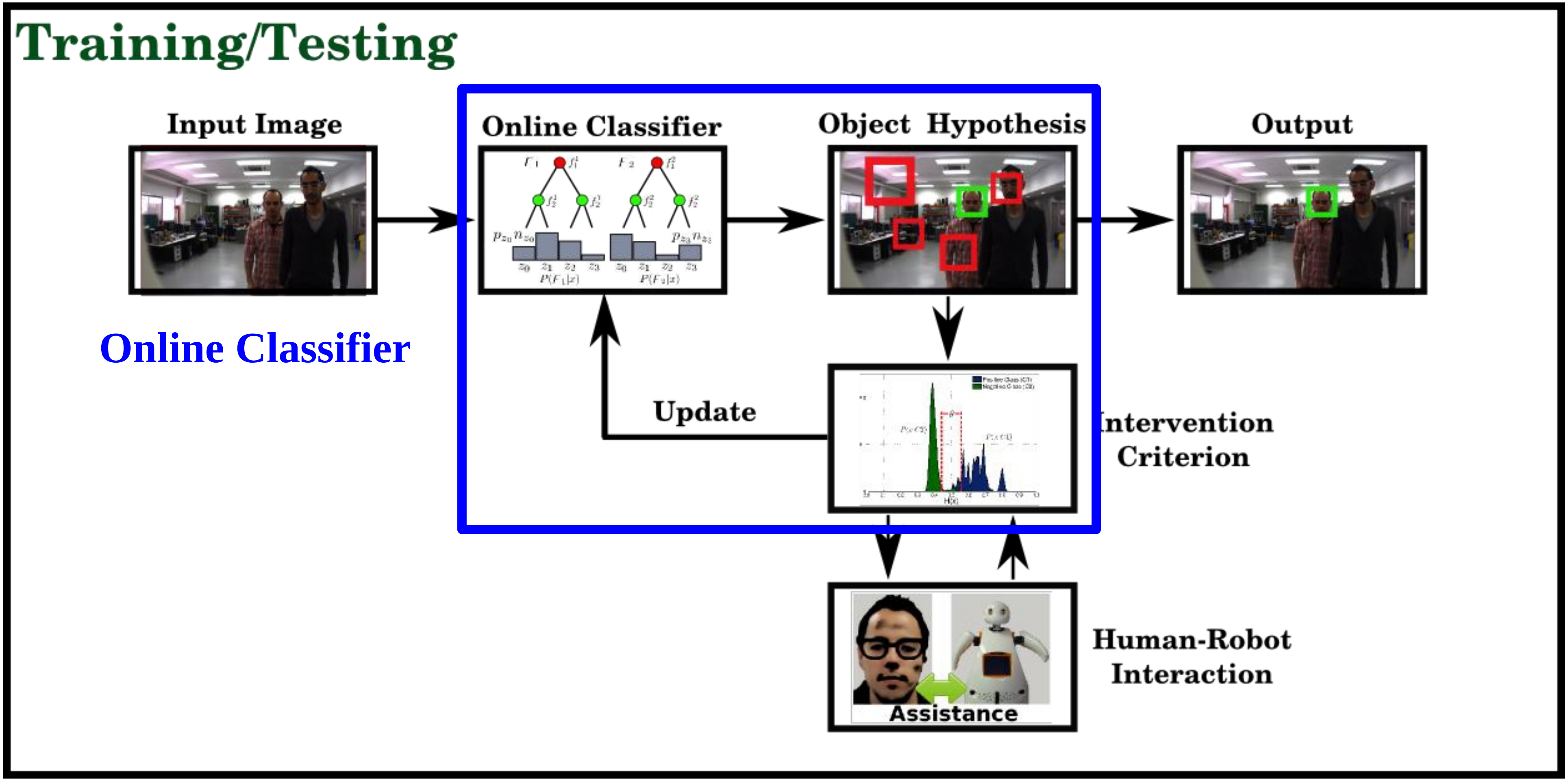
Object Hypothesis

- New samples: positive and negative samples



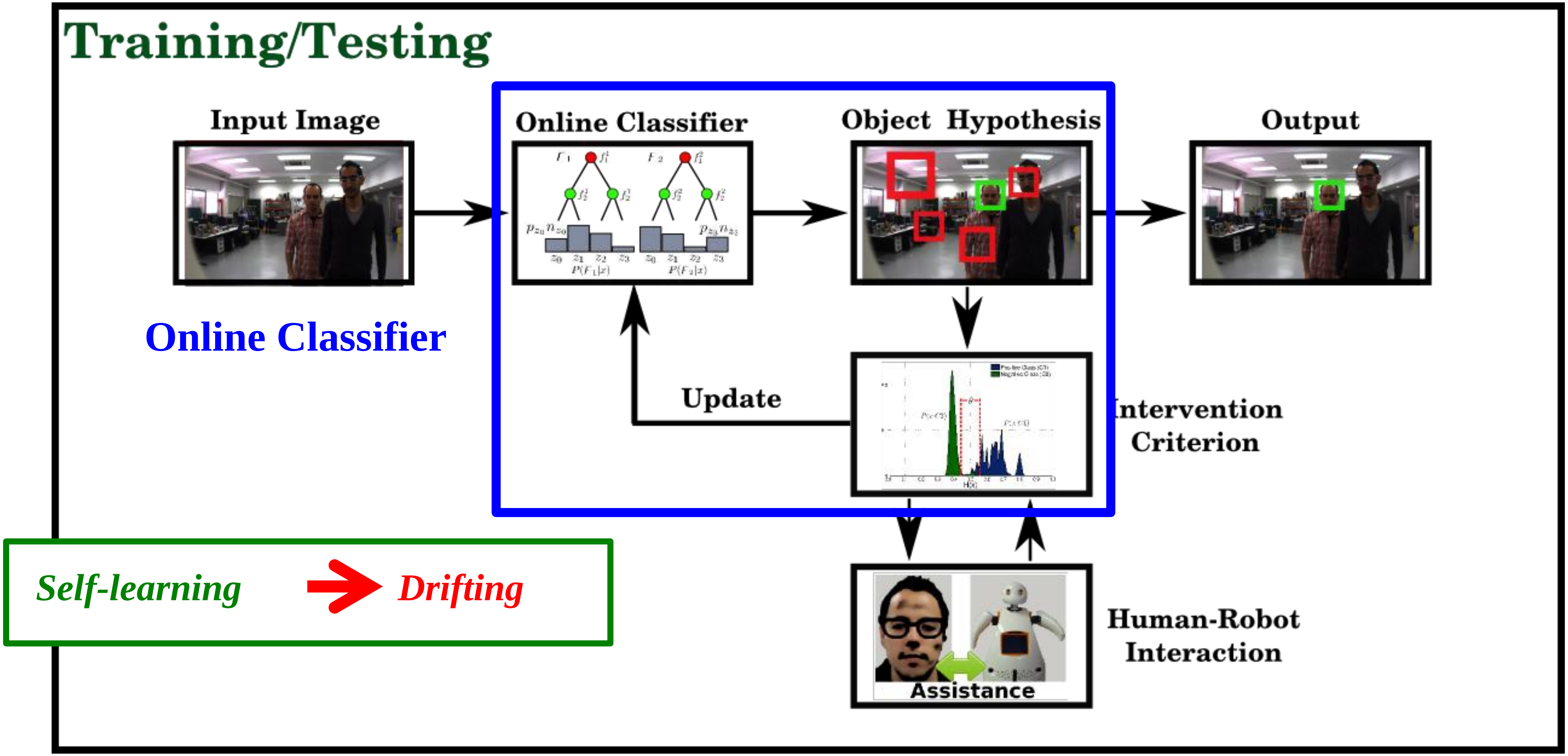
Approach

Online Human-Assisted Learning using Random Ferns



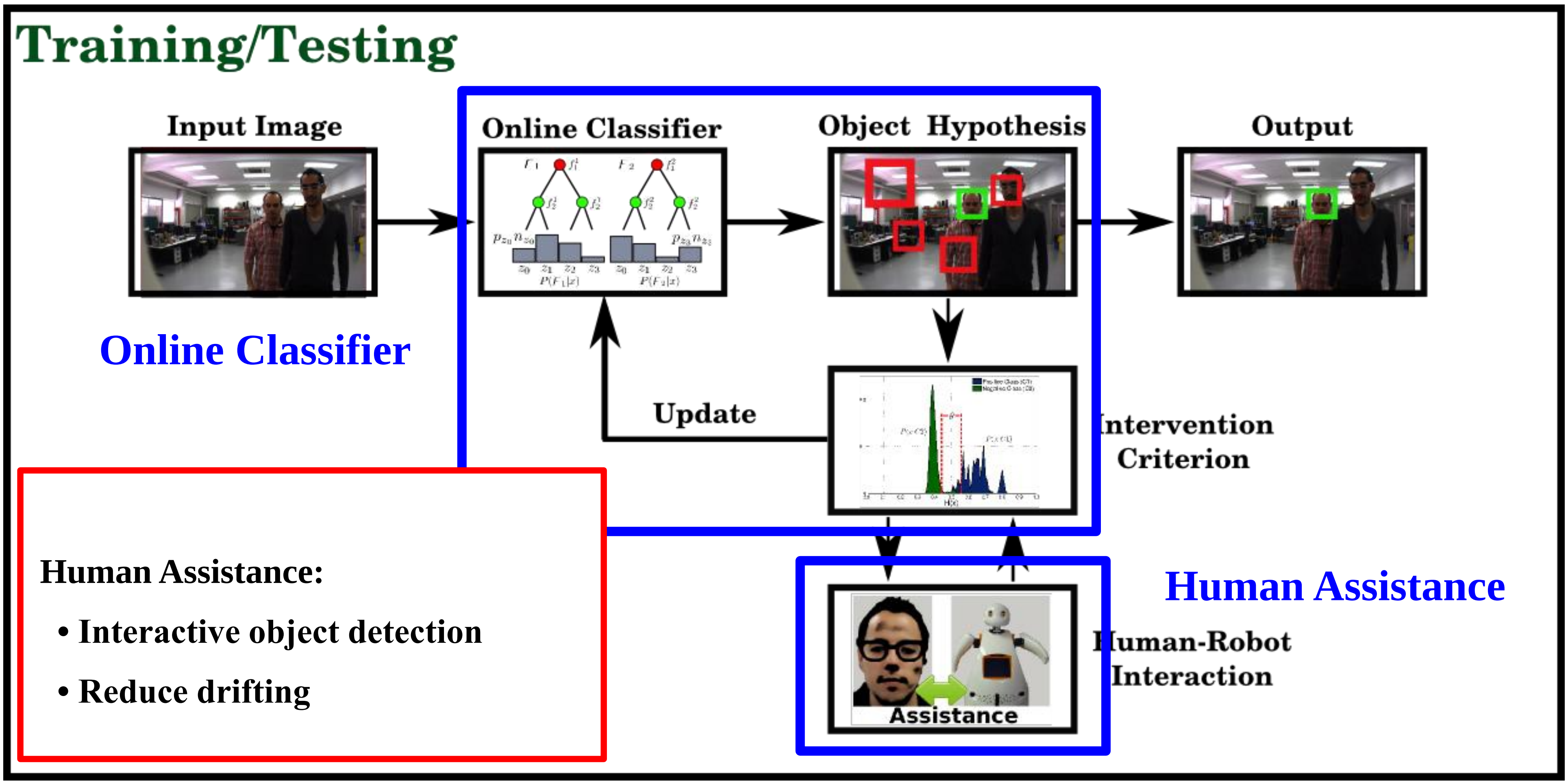
Approach

Online Human-Assisted Learning using Random Ferns



Approach

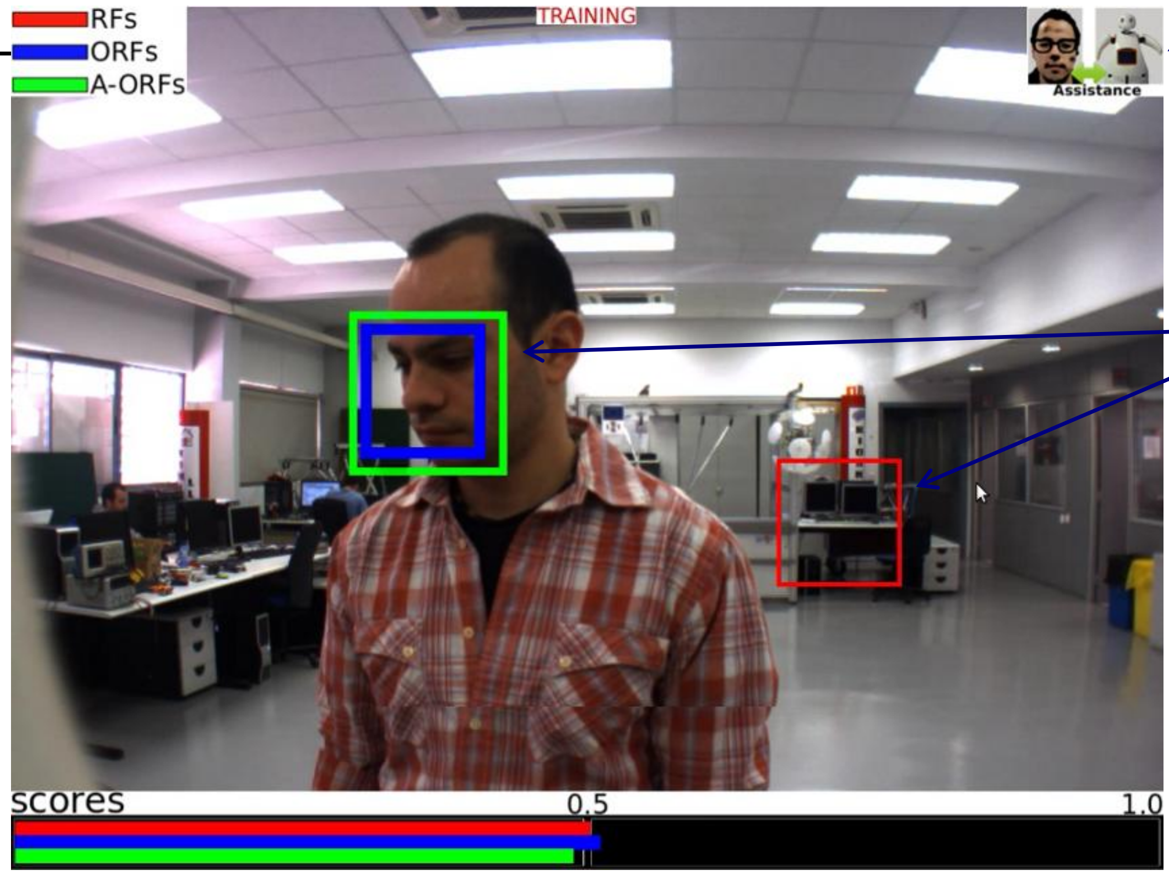
Online Human-Assisted Learning using Random Ferns



Training Step

Description

Human Assistance

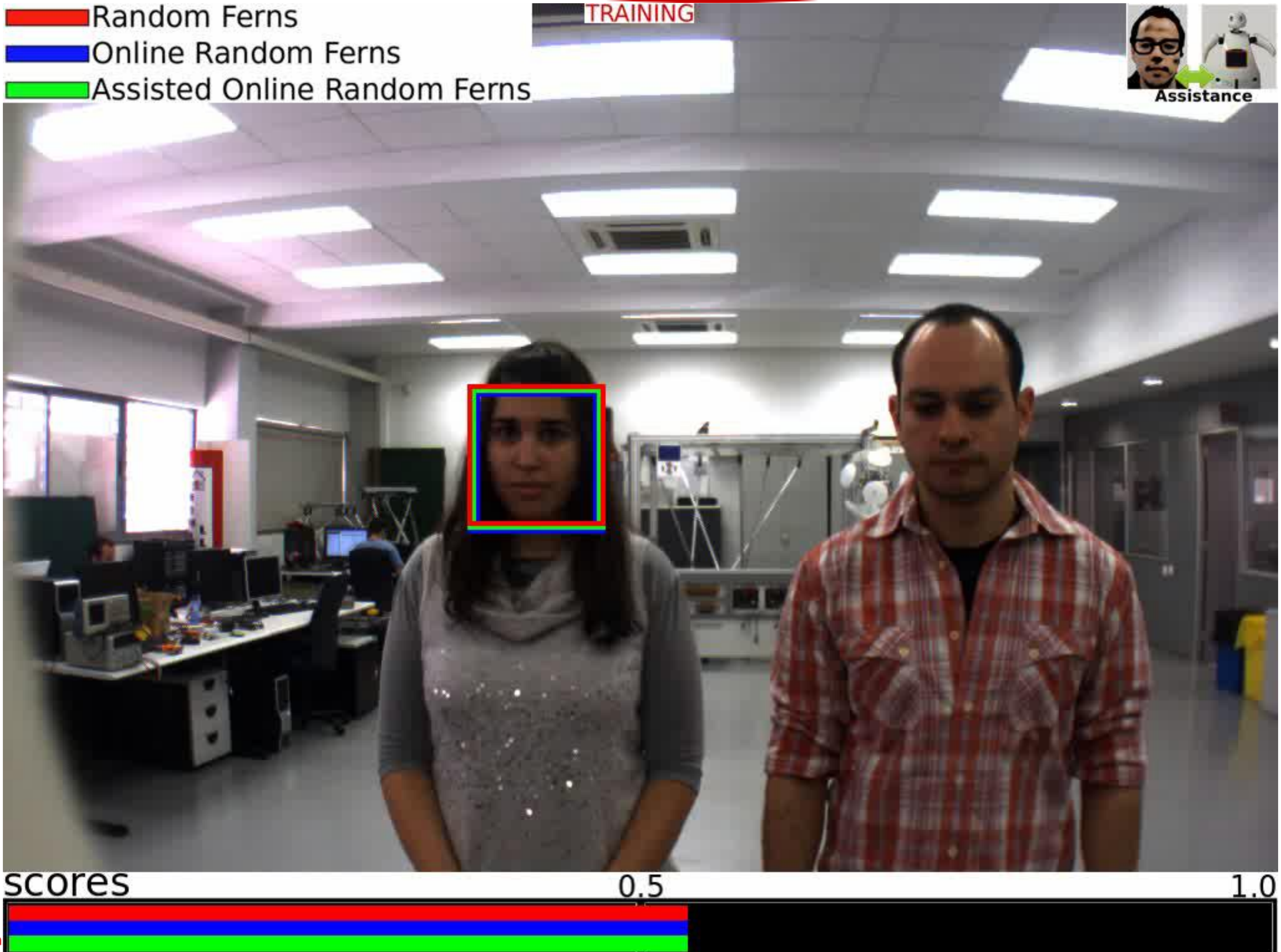


Detections

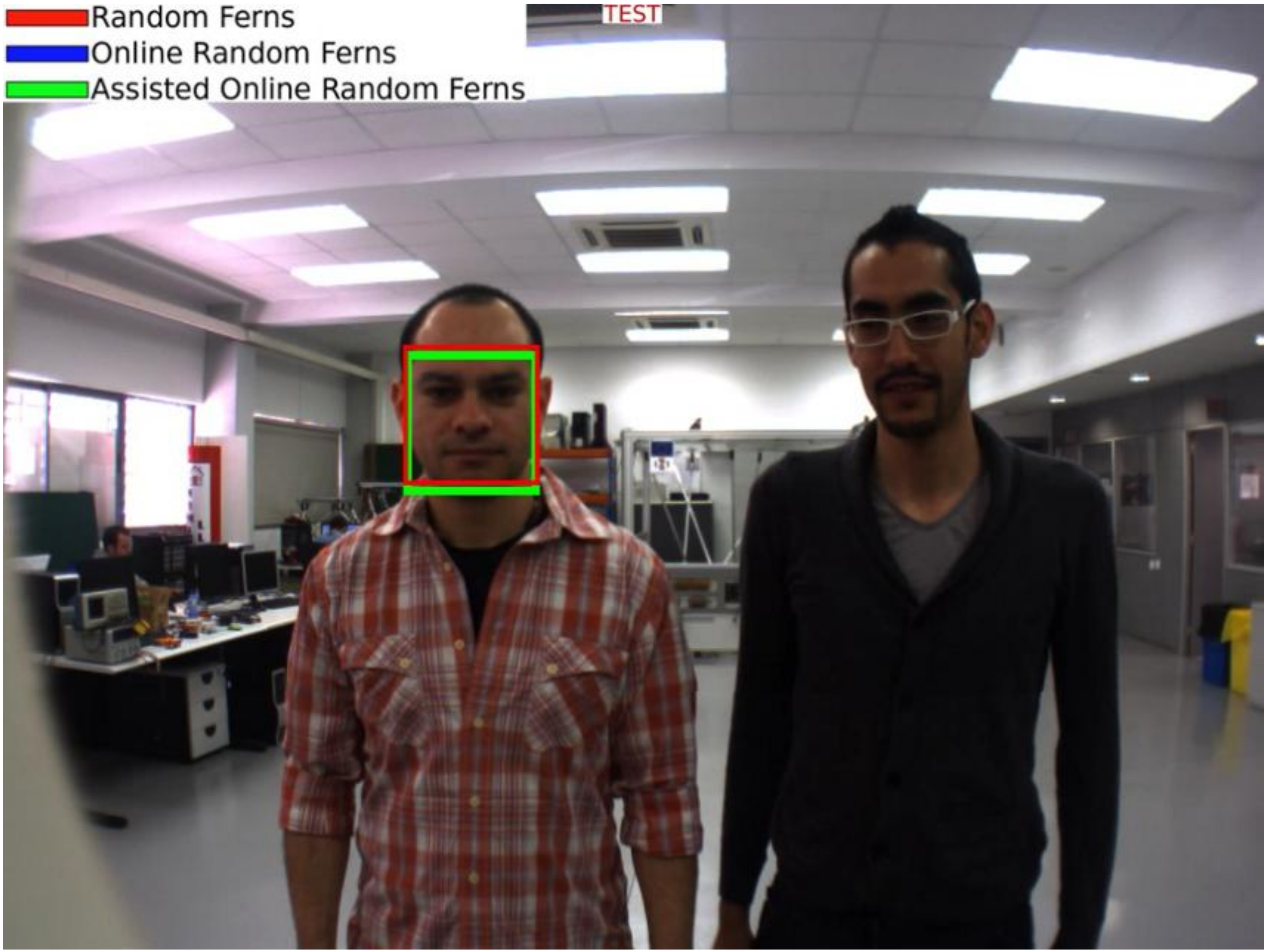
Recognition Scores

RFs: Offline Random Ferns
ORFs: Online Random Ferns
A-ORFs: Online Human-Assisted Random Ferns

Training Step



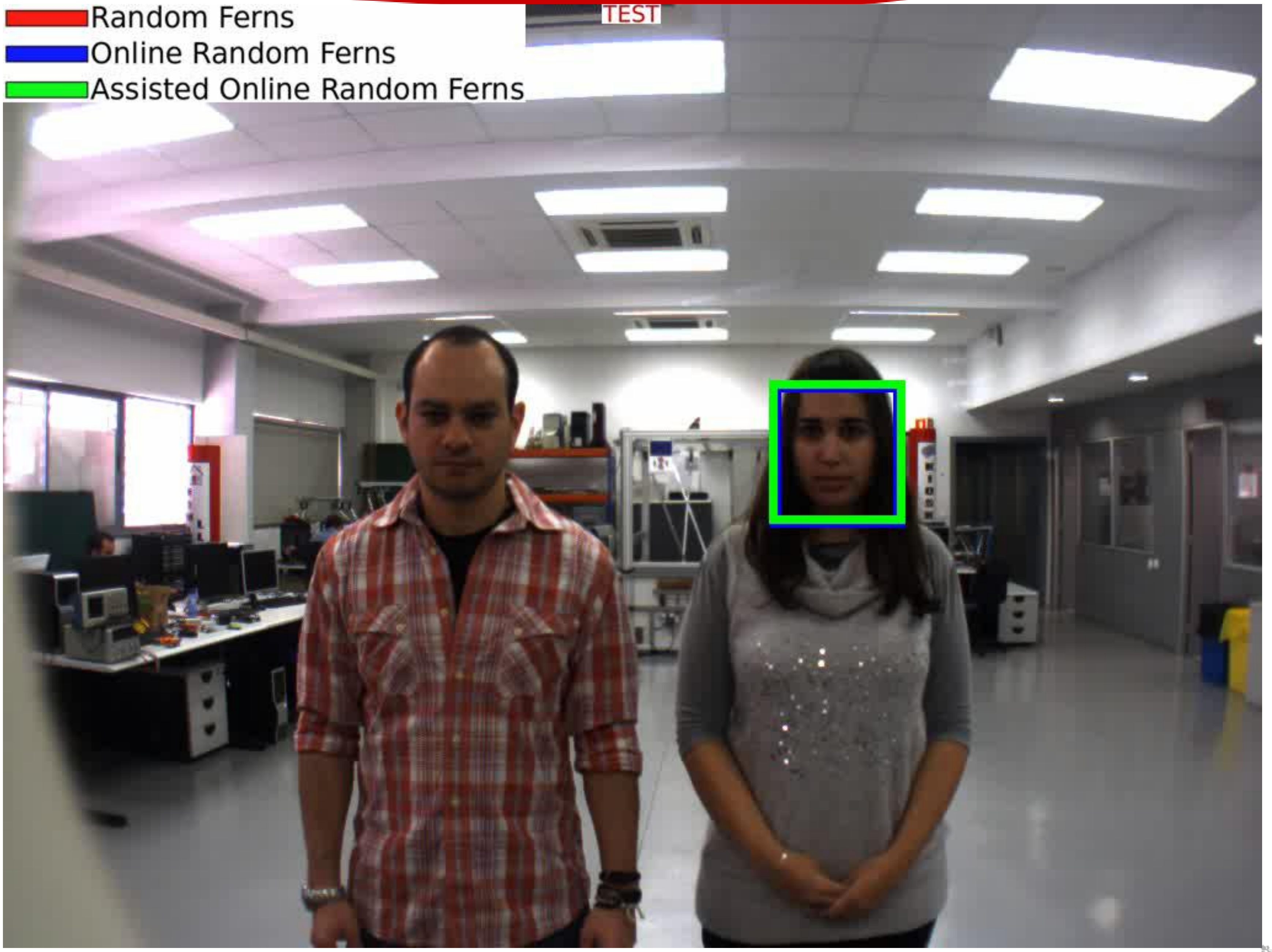
Testing Step



Testing Step

The classifiers are not updated!

Testing Step



Video: Robot Tibi Interacting with People for Face Learning

Solving Perception Uncertainty in Human Motion Prediction to Accompany People

Institut de Robòtica
i Informàtica Industrial

CSIC UPC

Robot Companion

Objective:

To accompany people in urban areas maintaining a specific distance and an angle.

Perception uncertainty problems:

- Detection of the person to be accompany
- Tracking the person
- Tracking other people and predicting their motion

[Garrell and Sanfeliu, 2012]

Robot Accompanying a Person

Real experiment

- Robot companion in a a real environment.
- Prediction used: the robot aims simultaneously to the person and its predicted destination.
- Barcelona Robot Lab (BRL) setting, using natural crossings in a large area as destinations.

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Robot Accompanying a Person in Dense Urban Area

Conclusions

- Robots must deal with uncertainty in perception and robot actuation problems in real life tasks
- There is not a unique way to solve uncertainty perception problems, but a multimodal scheme allows to solve a great diversity of problems
- Human in the loop allows to improve perception and robot behavior results

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Thank You