Urban Robots

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de Robòtica
i Informàtica
Industrial

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http://www.iri.upc.edu

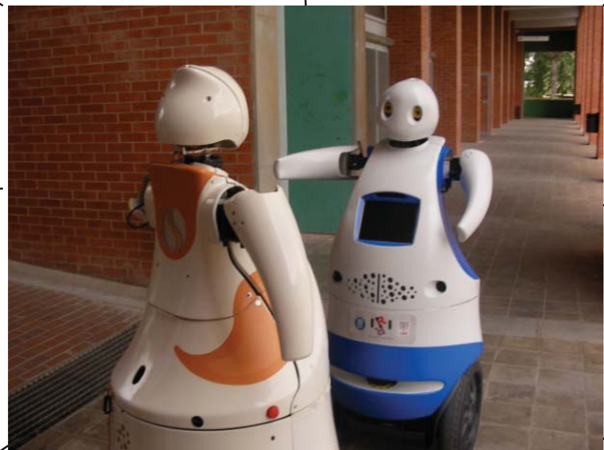
Robotic Application Services

Urban Services

Surveillance

Urban Transport

Help systems for emergency



Mobility and Help to the Citizens

Information systems for citizens

Monitoring

House assistance

UNR

UBIQUITOUS NETWORKED ROBOTS

What is an UNR (EU)

Definition:

A Network Robot System is a group of artificial autonomous systems that are mobile and that makes important use of wireless communications among them or with the environment and living systems in order to fulfill their tasks.

Elements:

Autonomous robot
Communication network
Environment sensors
People

[Sanfeliu, Hagita and Saffiotti, 2008]

UNR in EU
URUS: Robots in Urban Areas

http://www.urus.upc.edu

Cameras and ubiquitous sensors

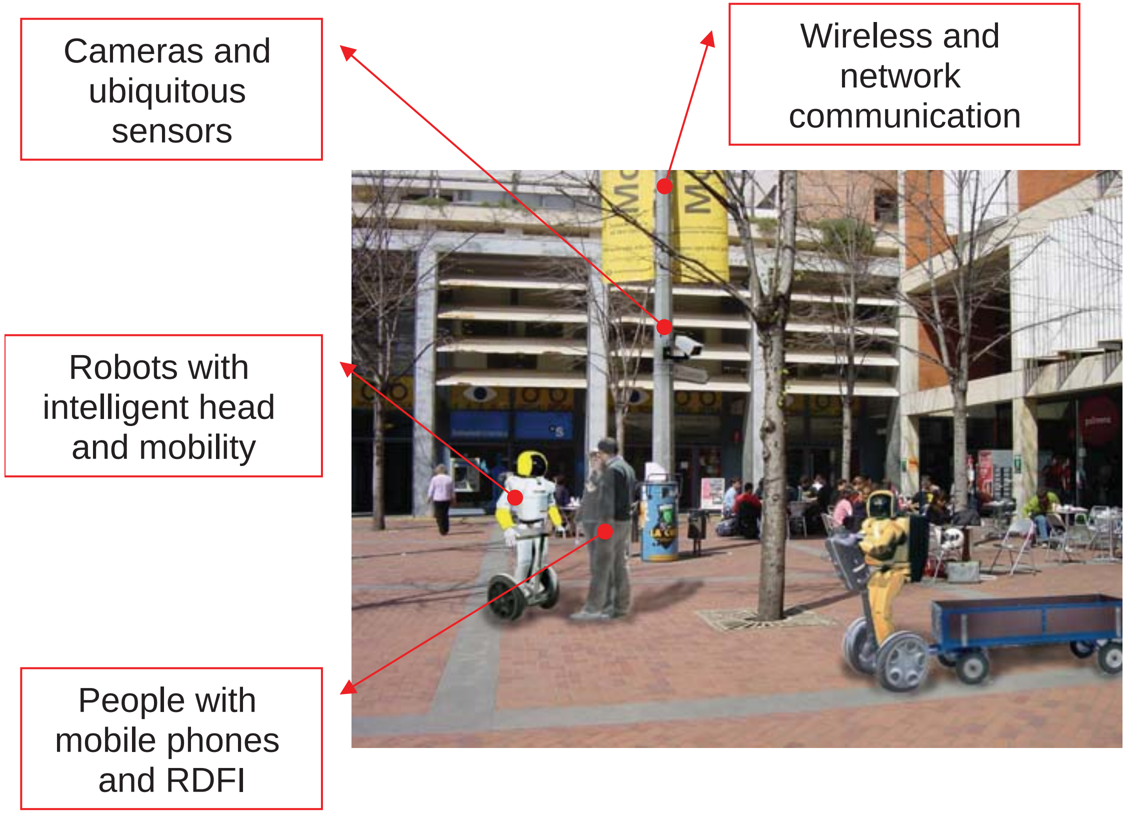
Robots with intelligent head and mobility

People with mobile phones and RDFI

Wireless and network communication

Robots for transportation of people and goods

Sharing Information for Guiding People



The UNR elements, networked cameras, communications and the embedded sensors of the robots are used for guiding people in the urban sites.

The information is **shared** by the robots and people through the UNR elements in order to accomplish the guiding task.

- Robots know the **localization** and **motion** of the people trough the network cameras an own sensors.

- Robots have to **predict** people movements to **anticipate** them and have to plan their re-grouping.

- Robots **explain** the itinerary and dialogue with people.

-People can **visualize** by themselves or trough the networked cameras the itinerary.

Transporting People in an Urban Site

RobotsTibi and Dabo

Autonomous vehicle

The UNR elements, networked cameras, communications and the embedded sensors of the robots are used for transporting people.

The information is **shared** by the robots and people through the UNR elements in order to accomplish the transportation task.

- Robots know the **localization** and **motion** of the people trough the network cameras an own sensors.

- A person **communicate** with robots to ask to be transported and they **share** the **plan** information

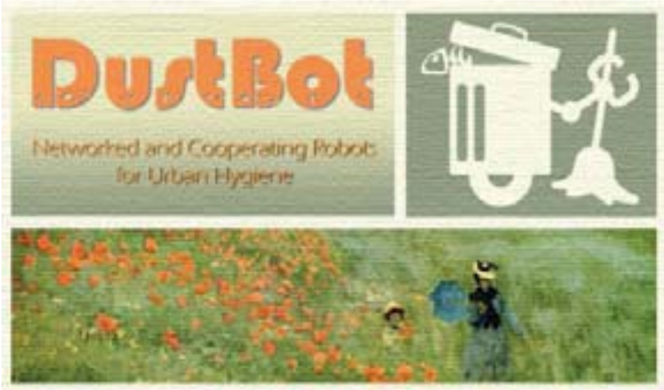
- Robots **synchronize** themselves to transport the person..

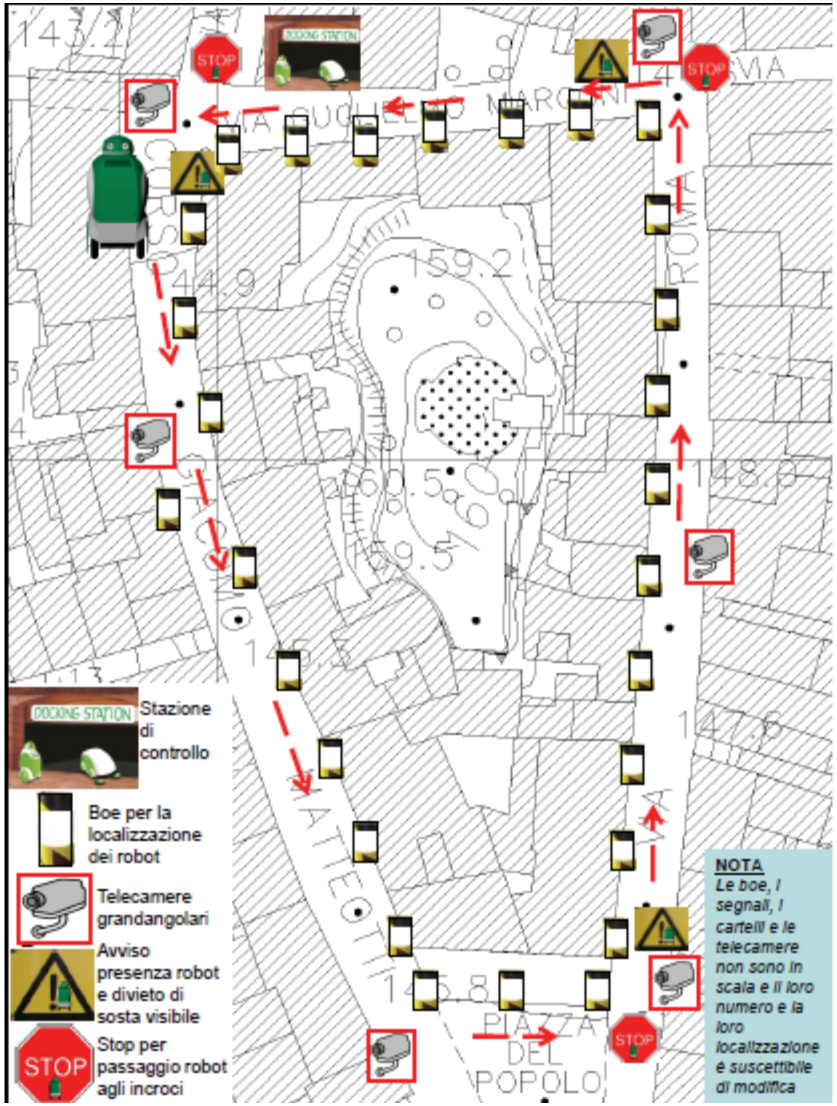
- Robots do the motions in the urban site to transport the person.

Tibi and Dabo Guiding People

Autonomous robot guiding and accompany people at UPC

UNR in EU
DustBot: Urban Hygiene





Networked Robots Proposed by Japan

Ubiquitous Network

Network Robots

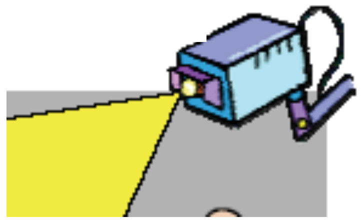
"Visible" type

Apri-alpha

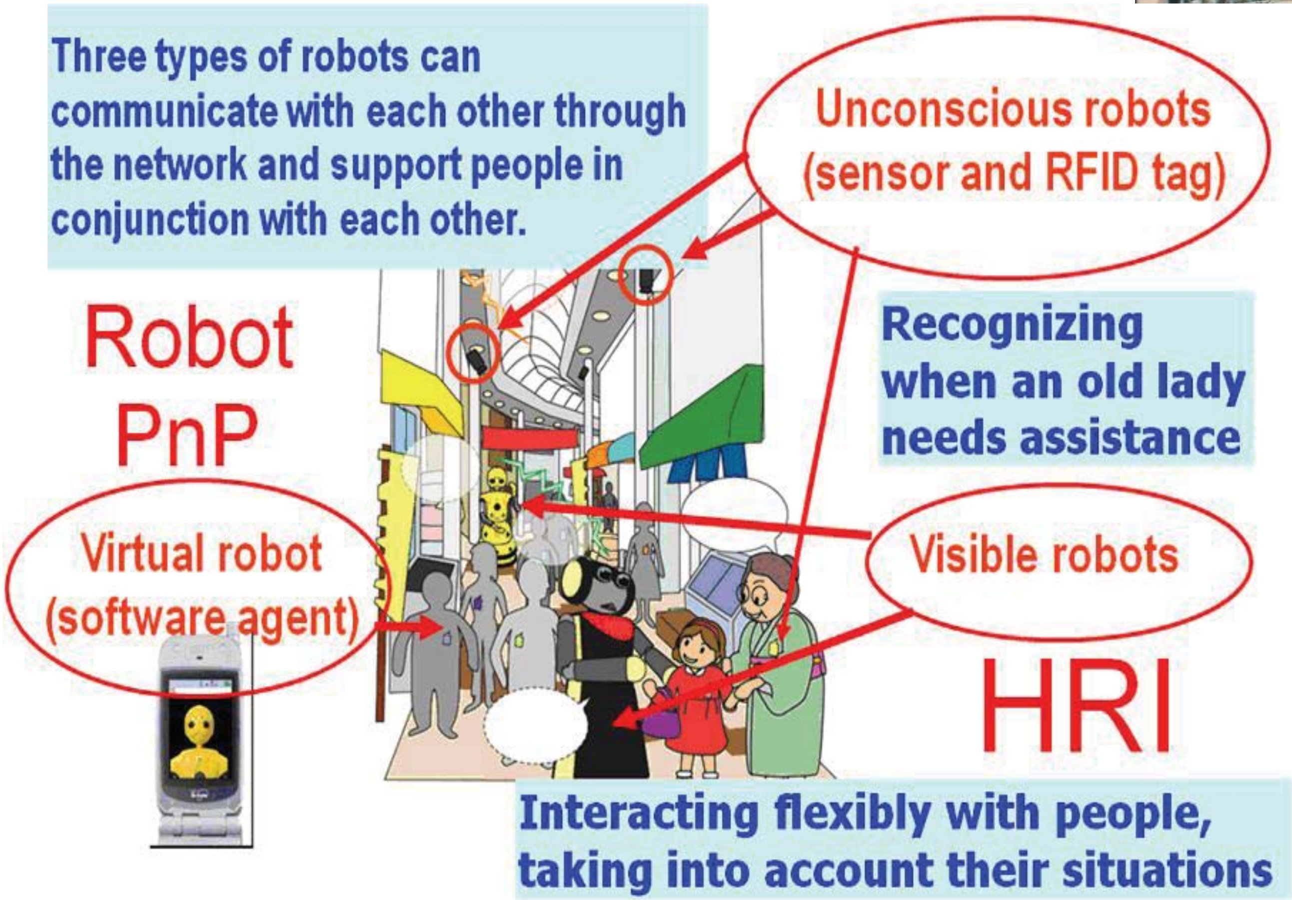
Robovie

"Virtual" type

"Unconscious" type



The NRS Project in Japan



The NRS Project in Japan
Some Results

Sequence of videos showing mobile robots helping people to find specific shops in a market mall

The NRS Project in Japan
Some Results

Semi autonomous robot helping a person to buy and bring supermarket goods

Semi autonomous Geminoid talking with a person

TASKS THAT CAN BE DONE BY URBAN ROBOT SERVICES

Urban Tasks

- **Cleaning the streets and garbage collector**: This is a task that the robots can do more efficiently and at lower cost.
- **Transportation of people:** This is the Taxi task in urban areas. The transportation can be individual or collective.
- **Transportation of goods.** This is an essential part in commercial life and a main need for shopkeepers and markets. In the superblock there will be two phases for merchandise distribution.
- **Transportation of other materials**. Robots can have a role also in the transportation of different materials or elements that could be eventually needed in the repairing of services or ground pavement, working as a complement to specialized personnel.
- **Monitoring and Maintenance service.** As a variation of the later point, robots could be an ideal tool to check continuously pipes, and communications and electricity cables located in the underground and more specifically in services galleries.

Urban Tasks

- **Social assistance:** To help people trough tele-operation.
- **Emergency calls**. A number of emergency situations can develop in a given area: an accidental flooding due to a broken pipe, a gas leaking which involves the risk of explosion, a fire. Robots can be prepared to face this kind of situations with specific protocols.
- **Security**. Robots equipped with cameras can contribute to public space surveillance. Connected with the police station it would be possible to accelerate security forces response to any situation. This is related to emergency calls but is independent in the sense that involves crime.
- **Helping the disabled and people with mobility handicaps to overcome limitations**. The right to move through the streets extends to everybody. The contemporary city must take into account all of its citizens and help them to overcome physical limitations.
- **Others …**

SOME RESEARCH WORK IN URBAN ROBOTICS AT IRI (CSIC-UPC)

Research Work at IRI in Urban Robotics

Mobile Robotics

- Building maps
- Robot navigation

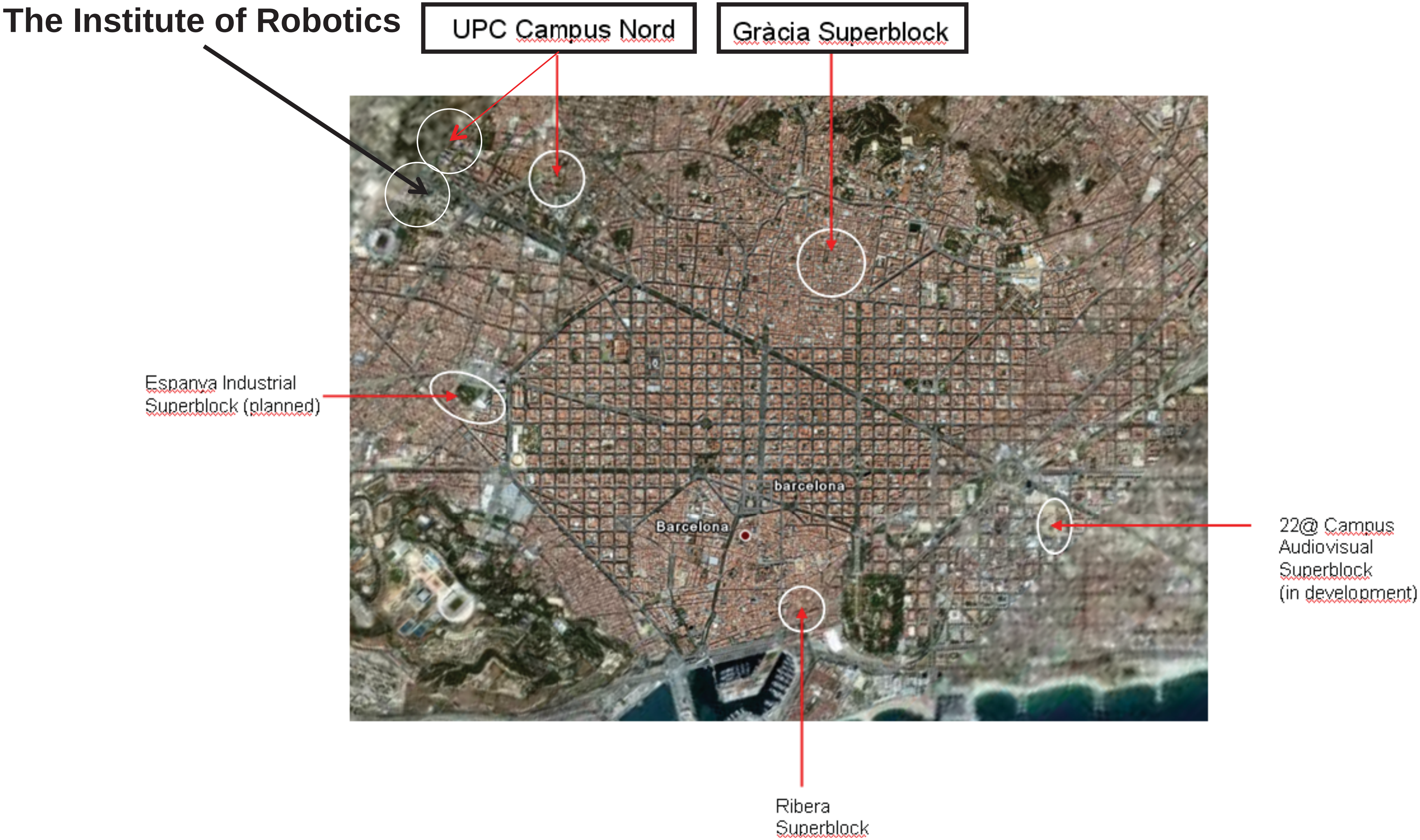
Mobile Robotics dealing with people

- Robot navigation being aware of people
- Guiding/accompany people
- Looking for a person
- Learning faces and objects
- Human-Robot task collaboration

Aerial Robots for Emergency Situations

- Manipulation tasks with flying robots

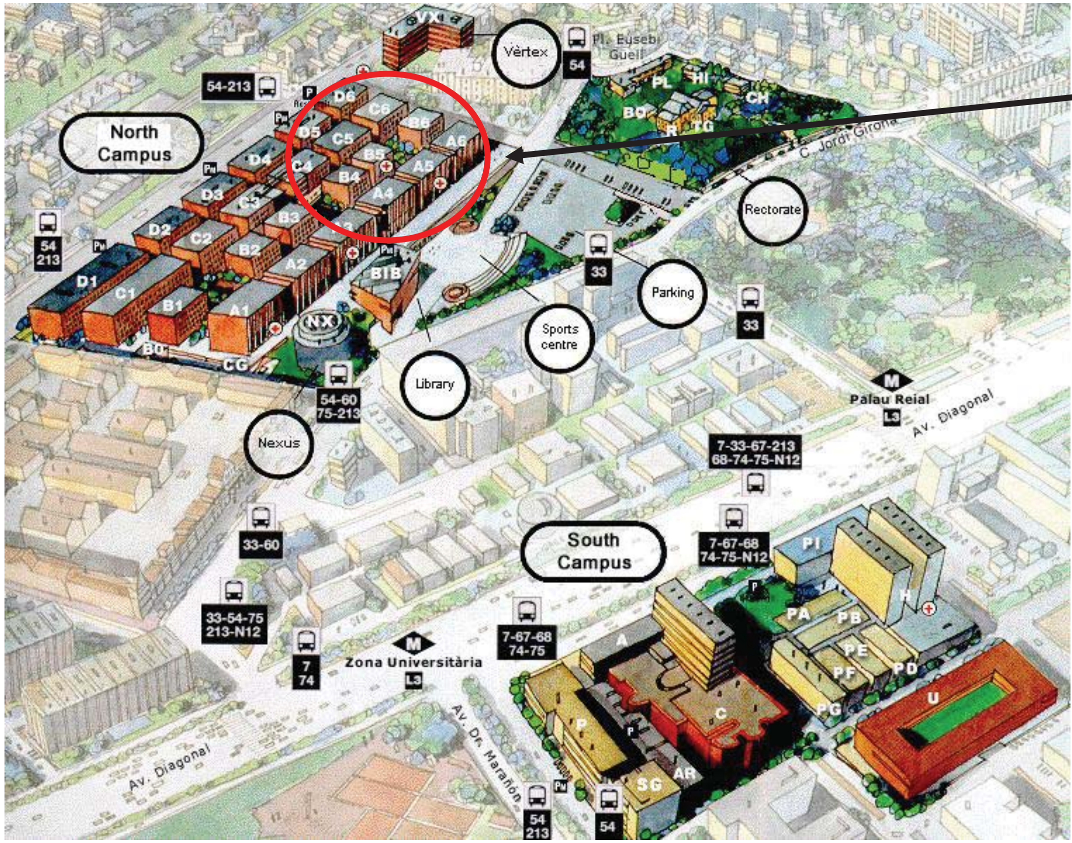
Experiment Locations in BCN

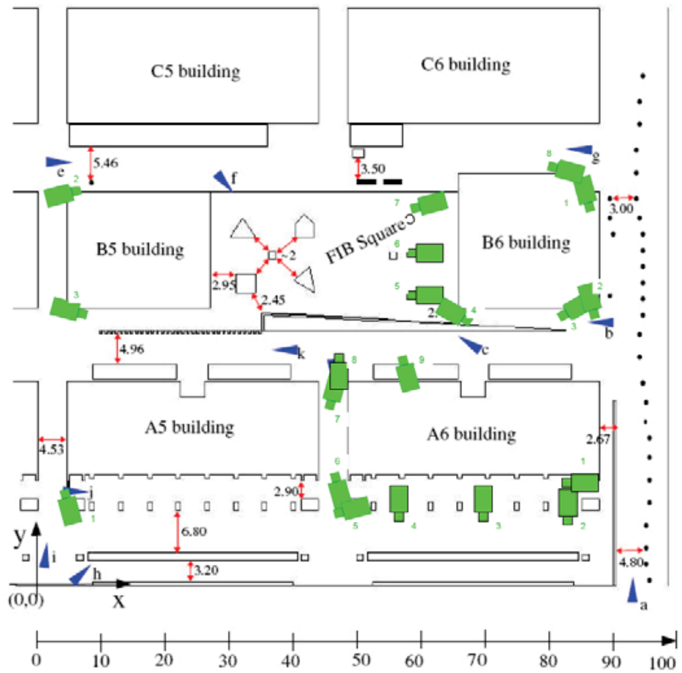


Experiment Location
BRL UPC

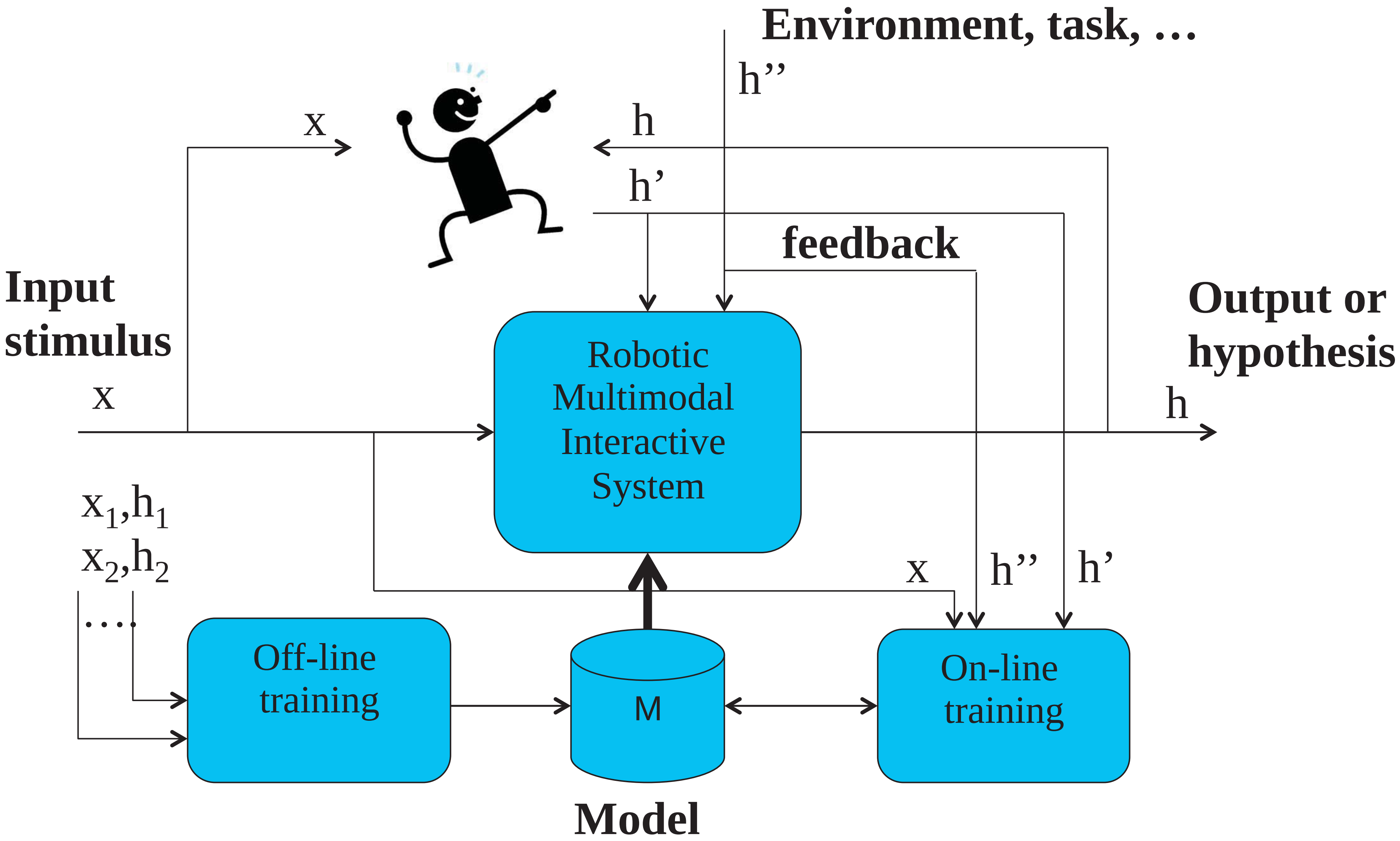
Zone Campus Nord, UPC

Barcelona ROBOT Lab





General Multimodal Scheme



3D MAP BUILDING

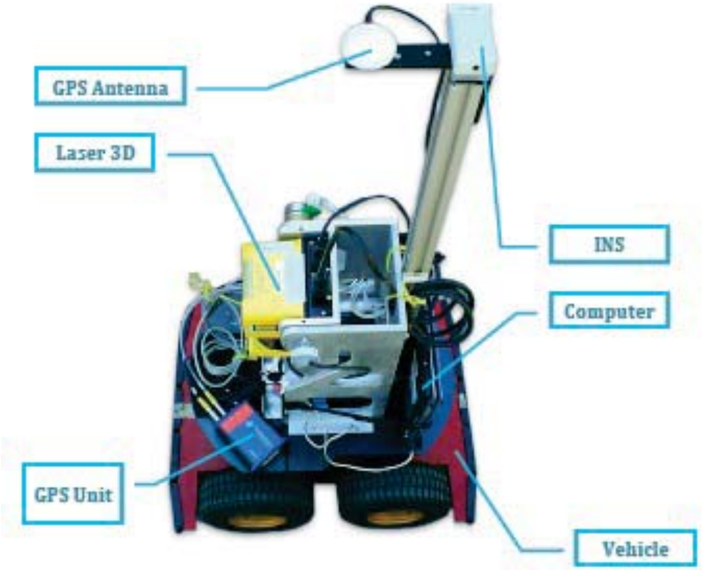
3D Map Building

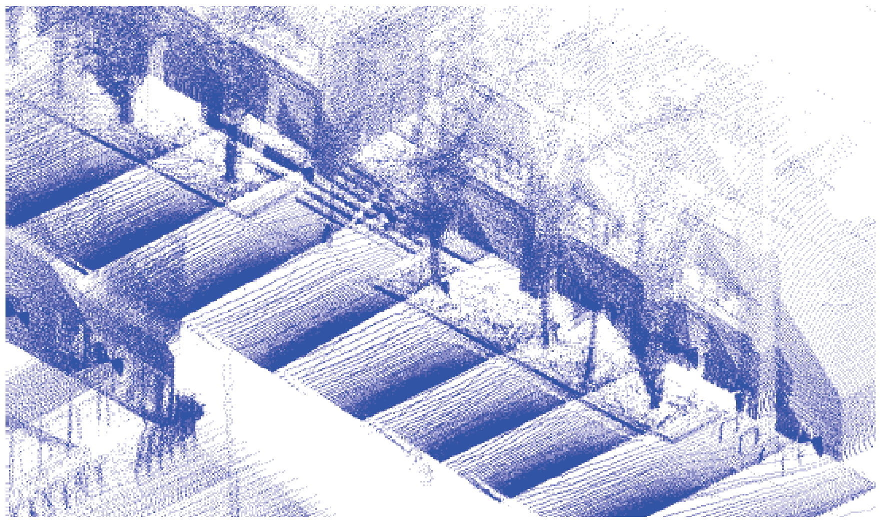
Objective: To build a 3D map of an urban area for navigation purposes.

[Ortega et al, 2009], [Ortega et al, 2009], [Valencia et al, 2009]

Map Building: 3D Sensor

UPC 3D ranger scan

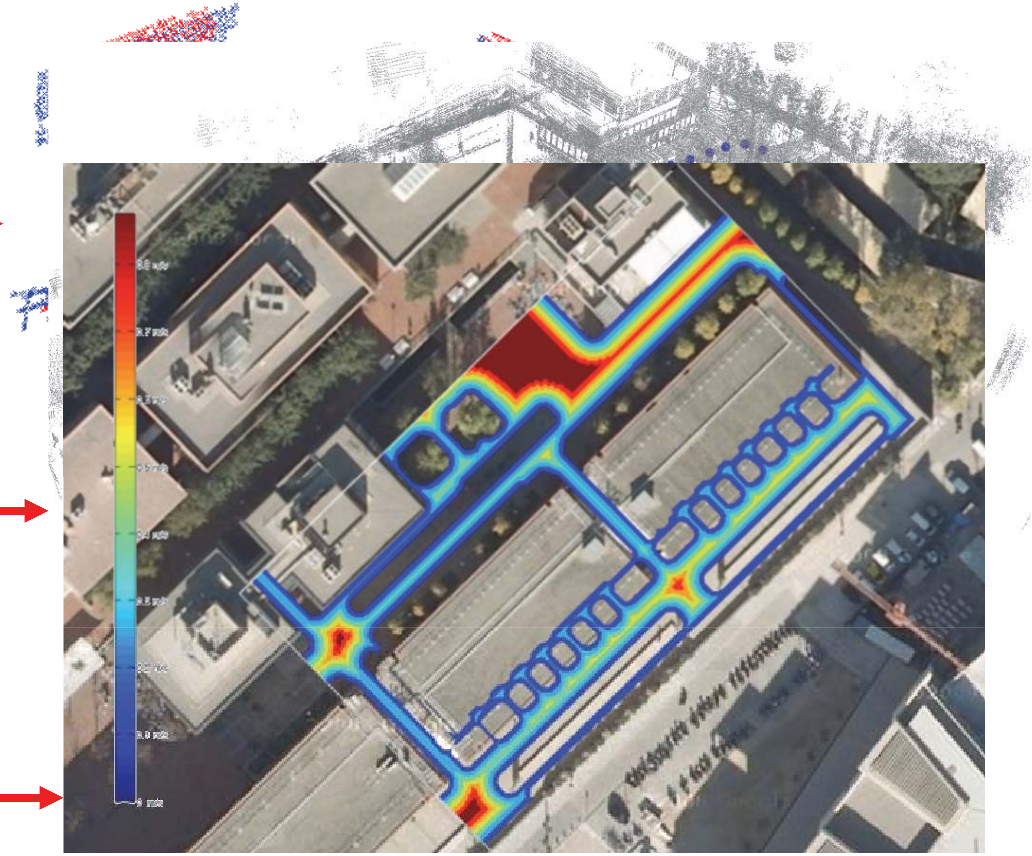




3D Mapping for Service Robots

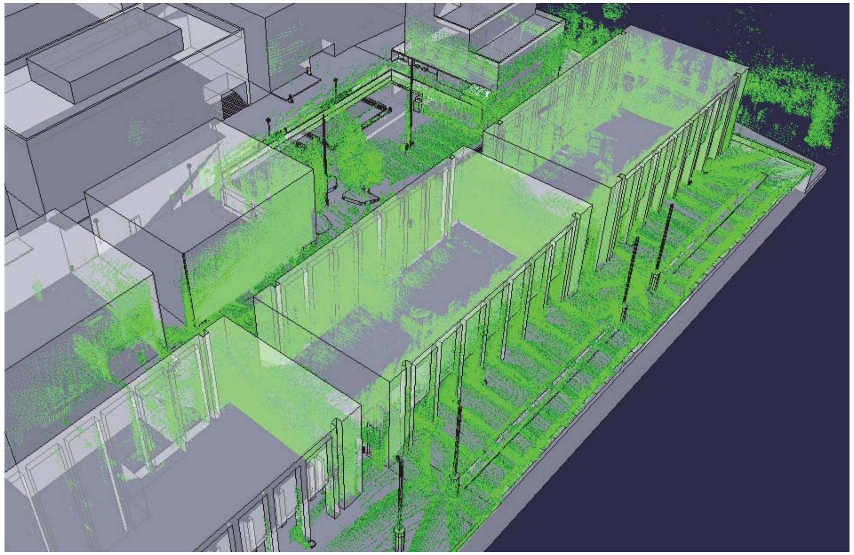
Approach

Data acquisition → ICP alignment → 6DOF SLAM → Traversability map

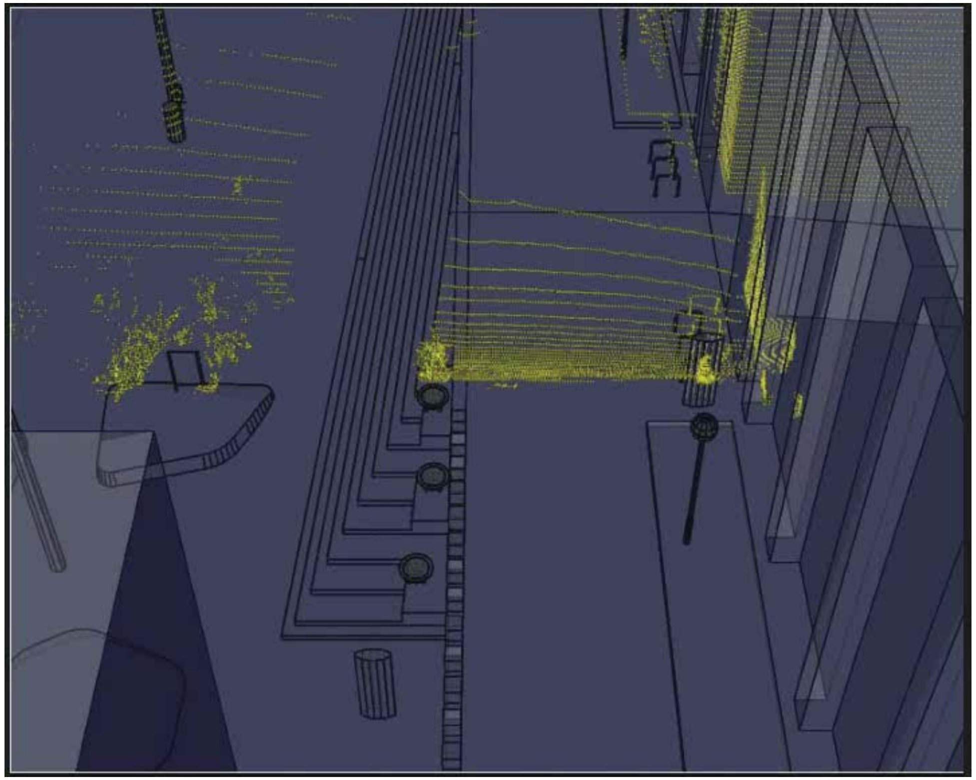


3D Mapping results

- Results are compared to manually built CAD model.
- The CAD model was made using geo-referenced information.

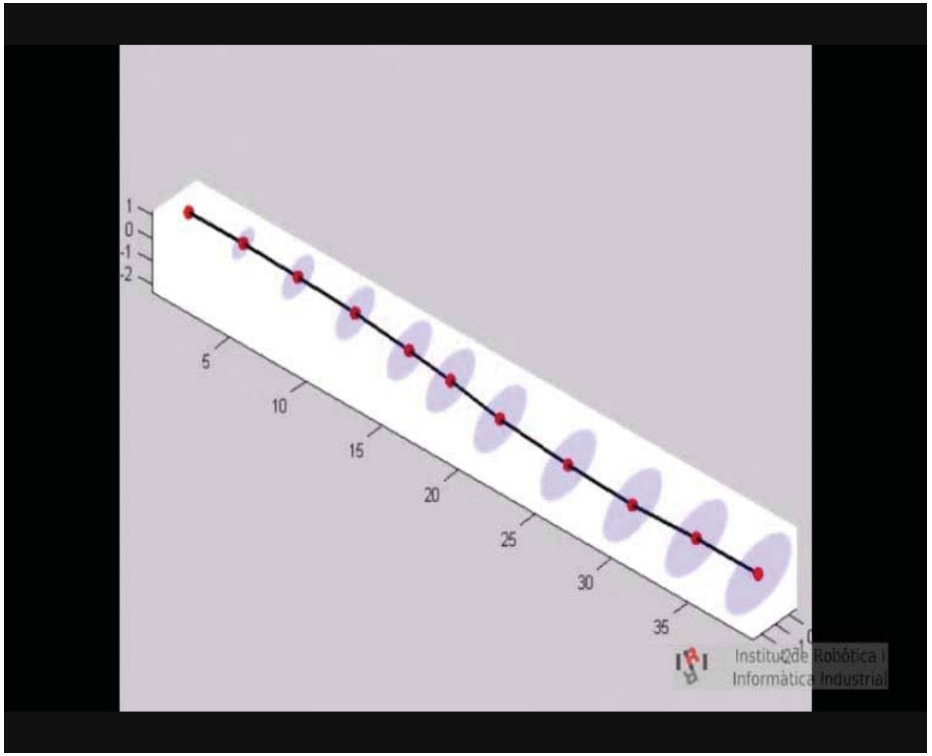


The final 3D model

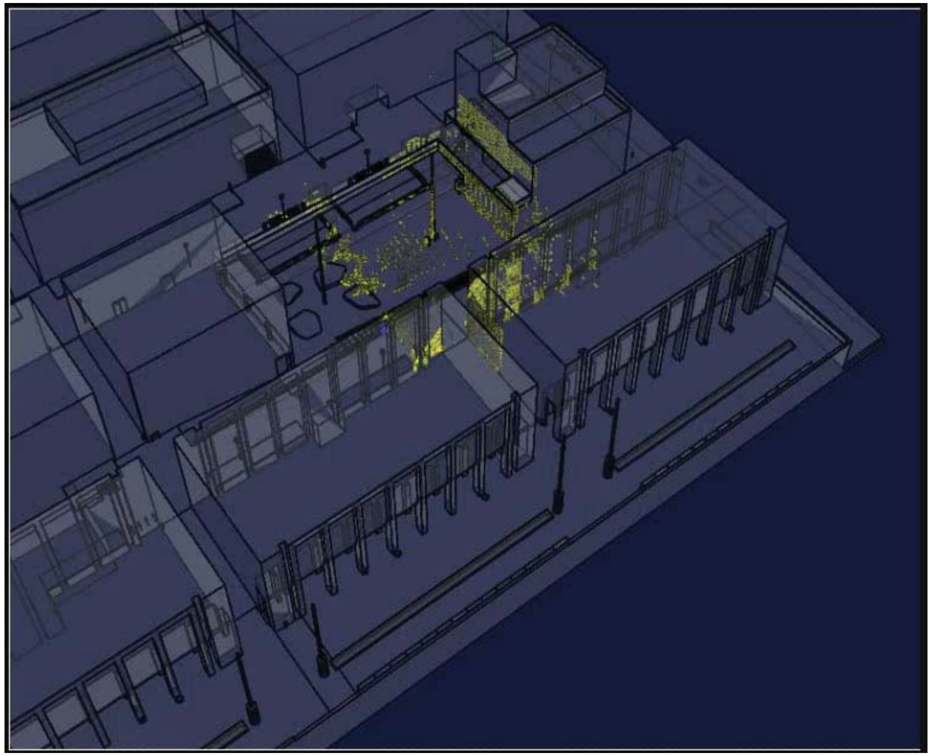


Detail view of the 3D model

3D Mapping results

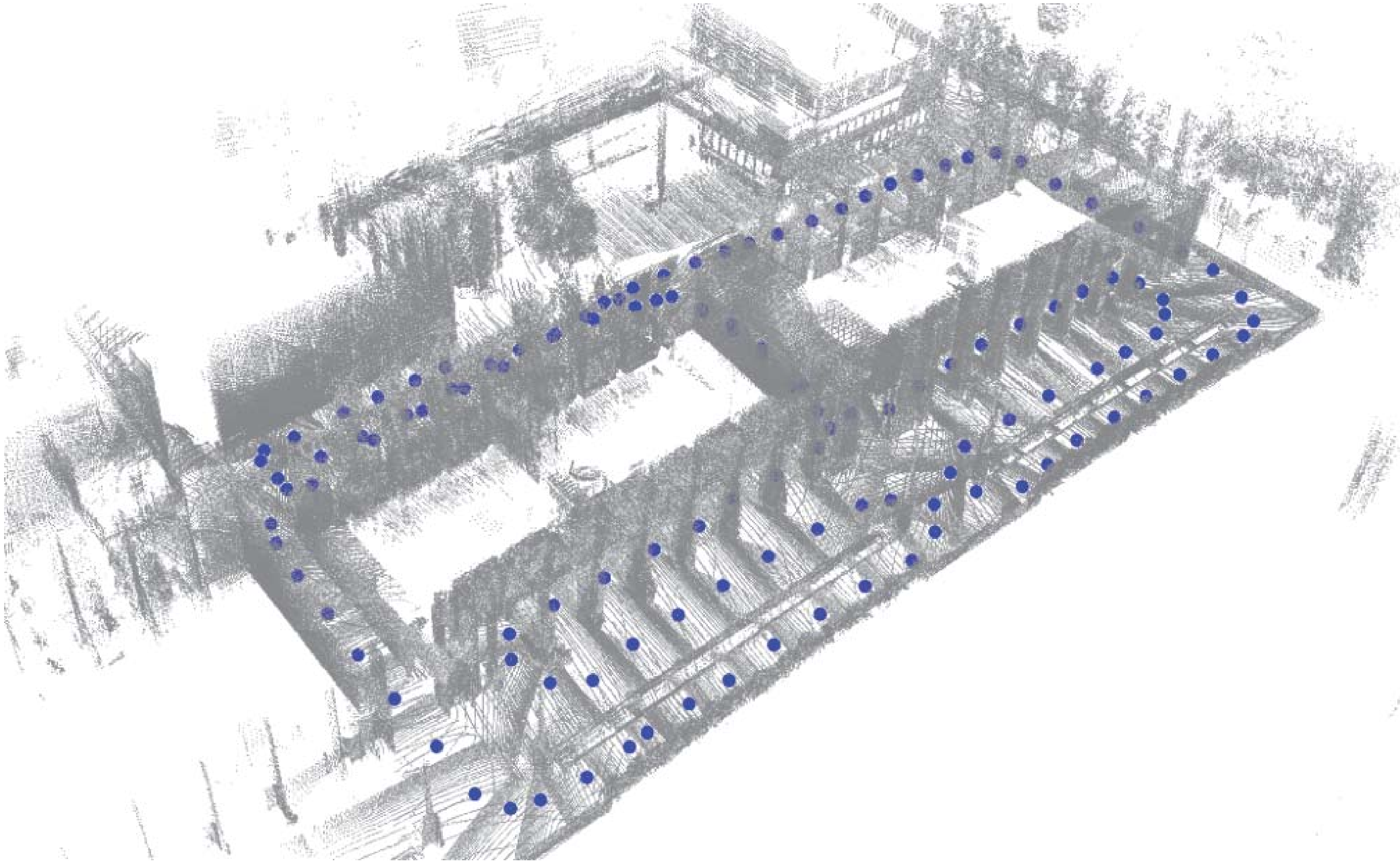


Looking solutions to close the loop



Generated model superimposed on the CAD model

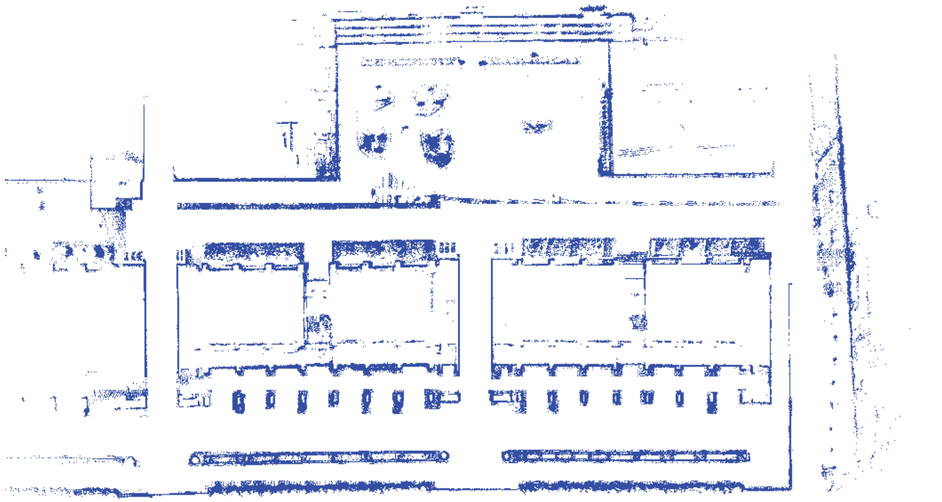
2D Path on the 3D Map



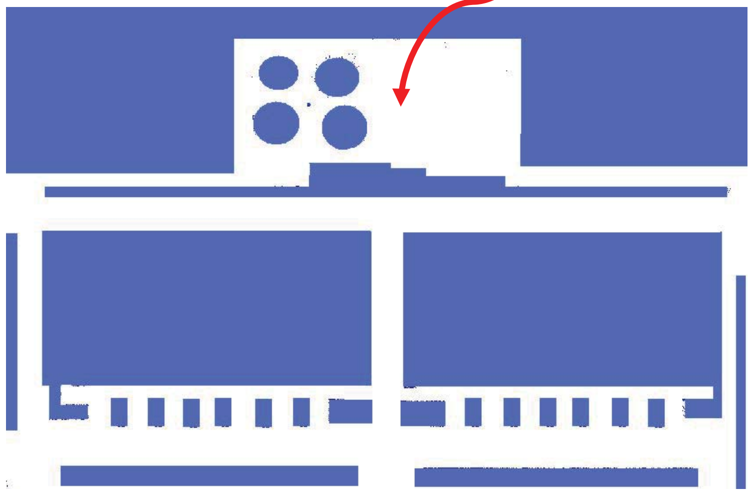
The path obtained on the 3D Map

Traversability Map

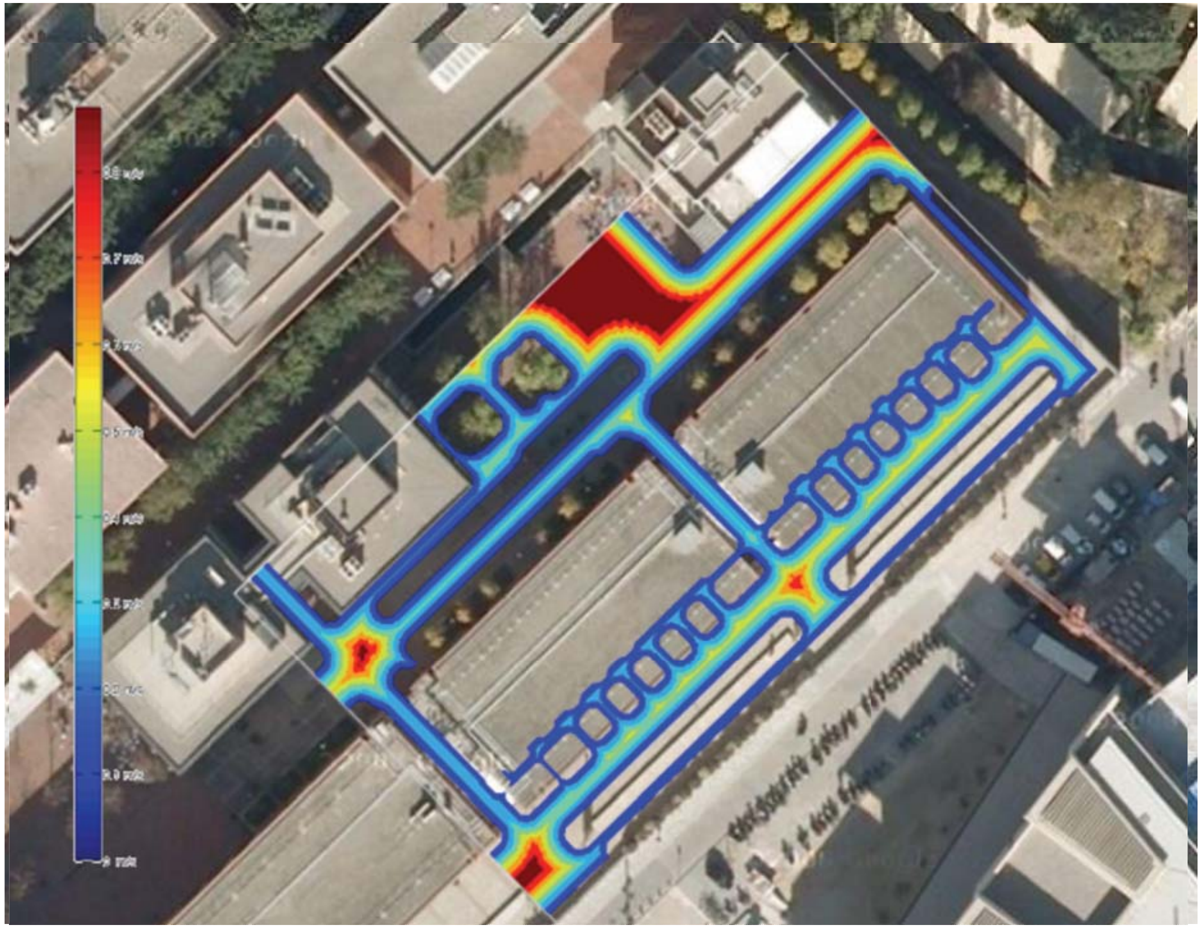
- 2D layer at the robot's frontal lase height



Grid map



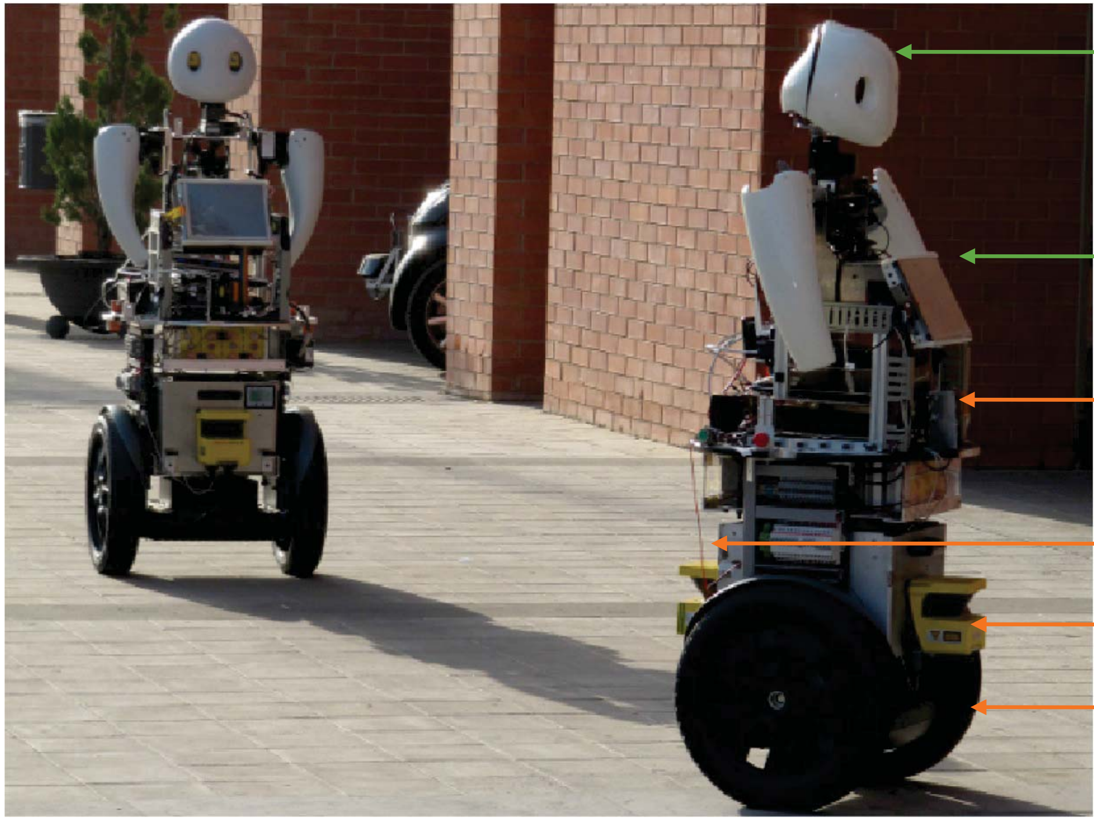
Traversability Map



ROBOT NAVIGATION

Robot Navigation

Objective: Autonomous navigation in urban areas avoiding obstacles.



Bumblebee Stereo Camera

Touch Screen

Front Vertical Hokuyo Laser Scanner

Back Horizontal Leuze Laser Scanner

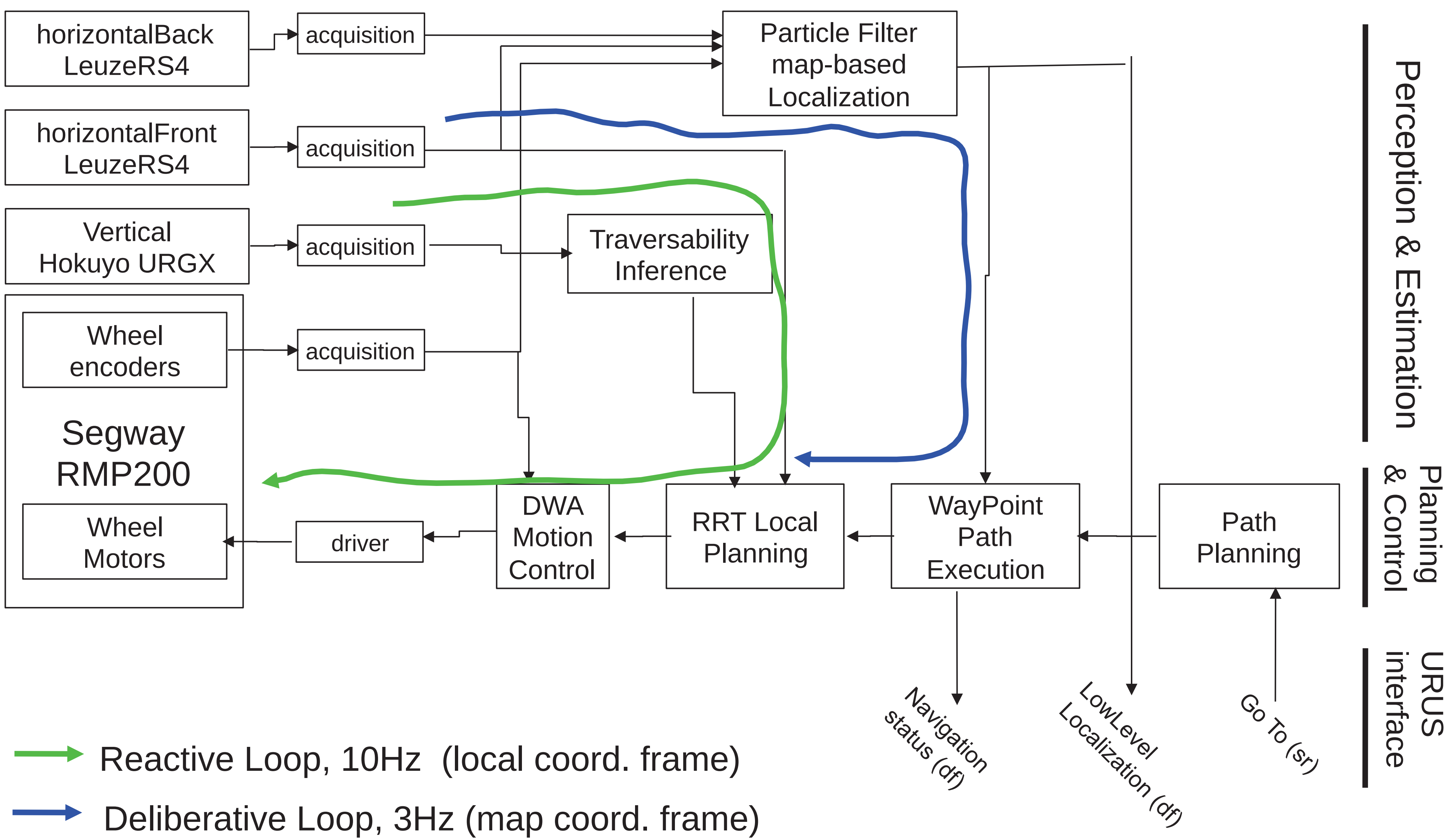
Front Horizontal Leuze Laser Scanner

Wheel encoders (2D odometry)

[Corominas, Mirats, Sanfeliu, 2008]
[Corominas et al, 2010]
[Sanfeliu et. al., 2010] [Trulls et al., 2011]

HRI sensors
Navigation Sensors

Autonomous Navigation Framework



Reactive Loop, 10Hz (local coord. frame)

Deliberative Loop, 3Hz (map coord. frame)

Obstacle Avoidance Diagram

Inputs:

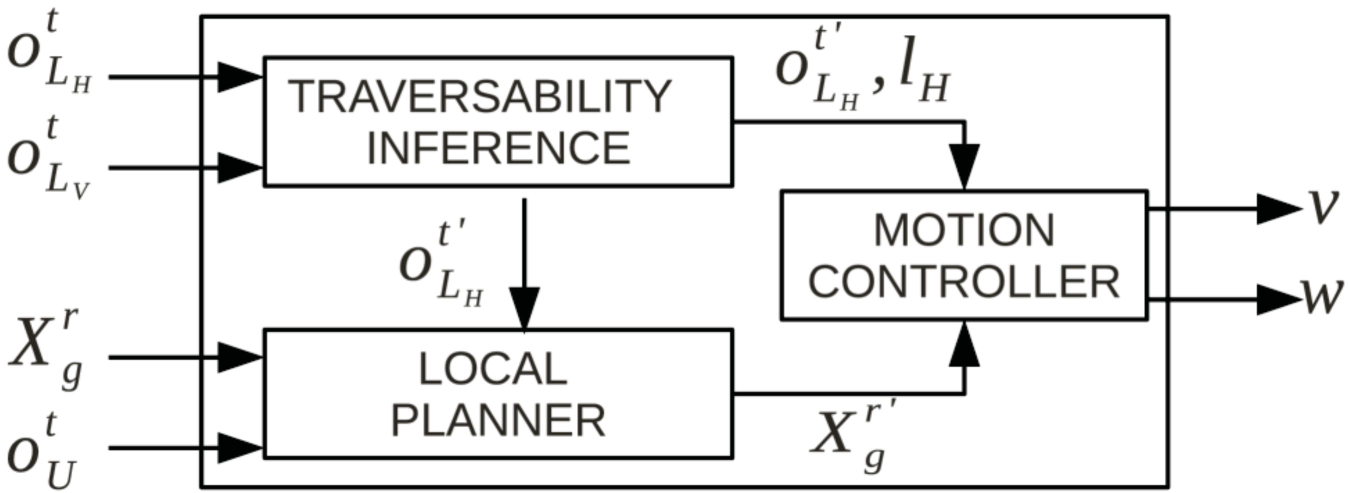
Outputs:

Front horizontal Laser

Front vertical Laser

Goal position in local frame

Odometry data



Platform commands

FREE Goal position in local frame

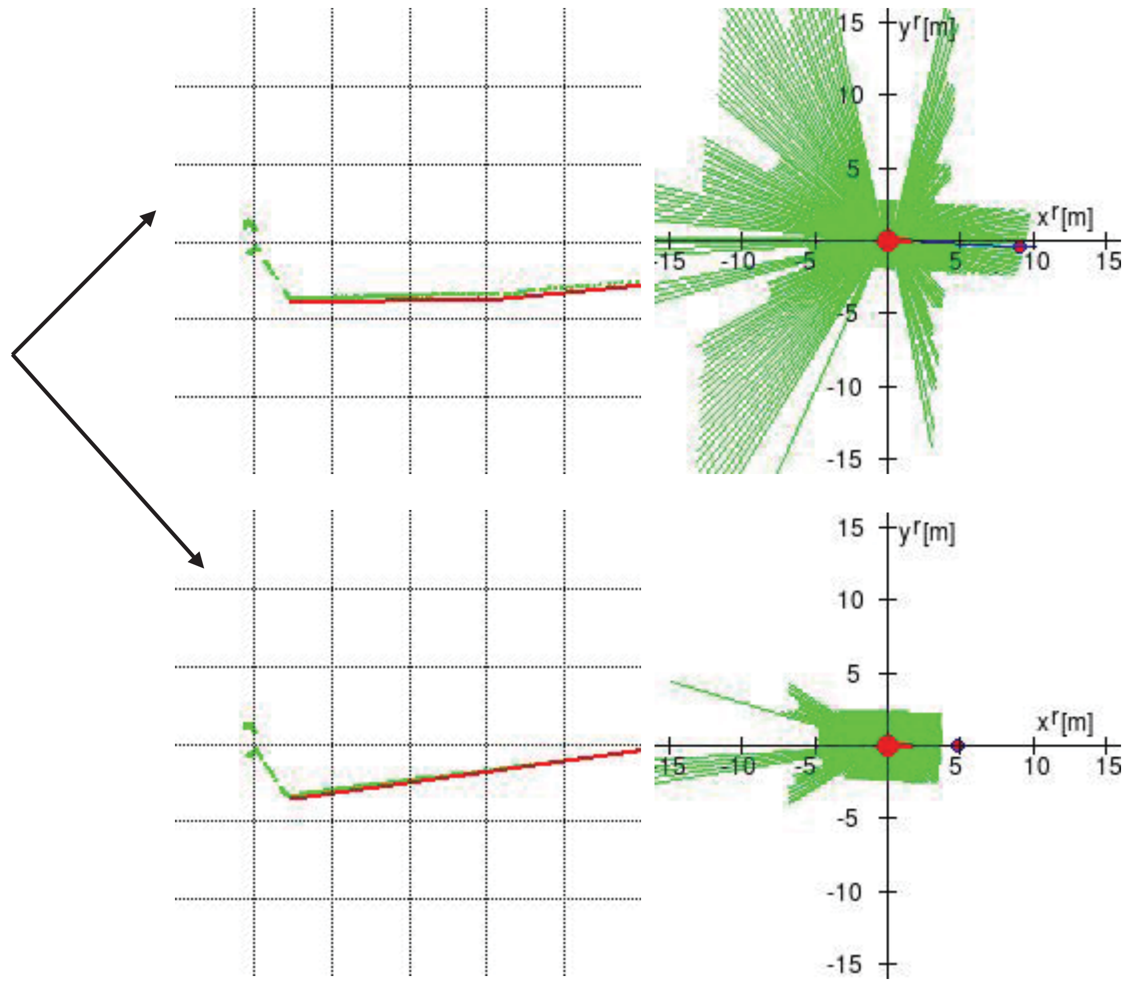
Traversability Inference

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

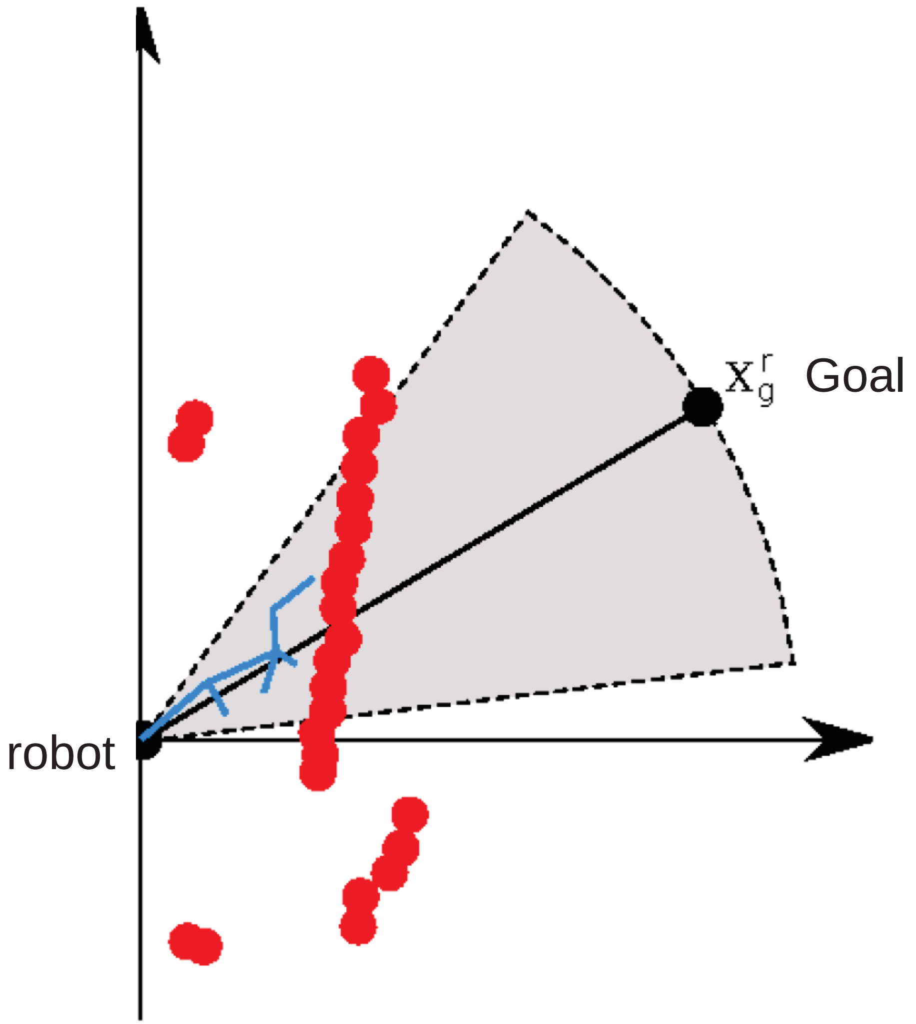
- Extraction of vertical regression line from vertical laser data to detect ramps

Vert. laser

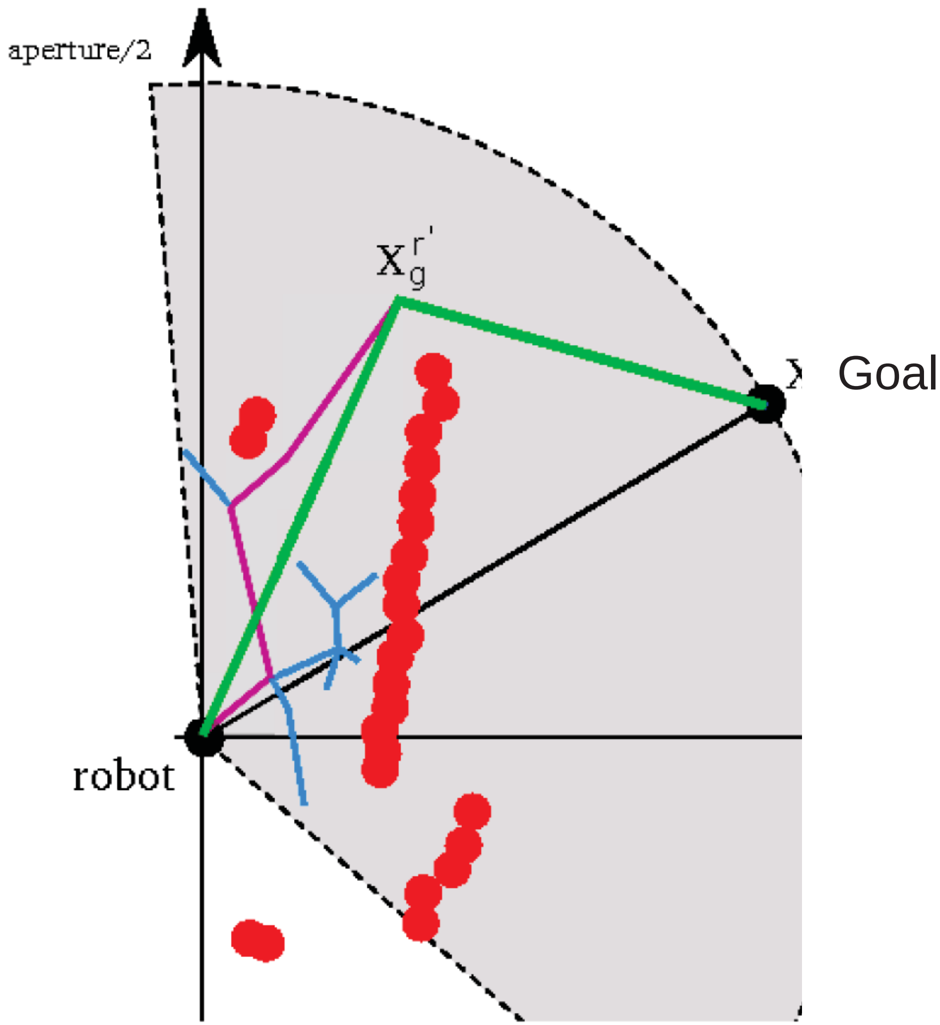
Hori. laser



Local Planner

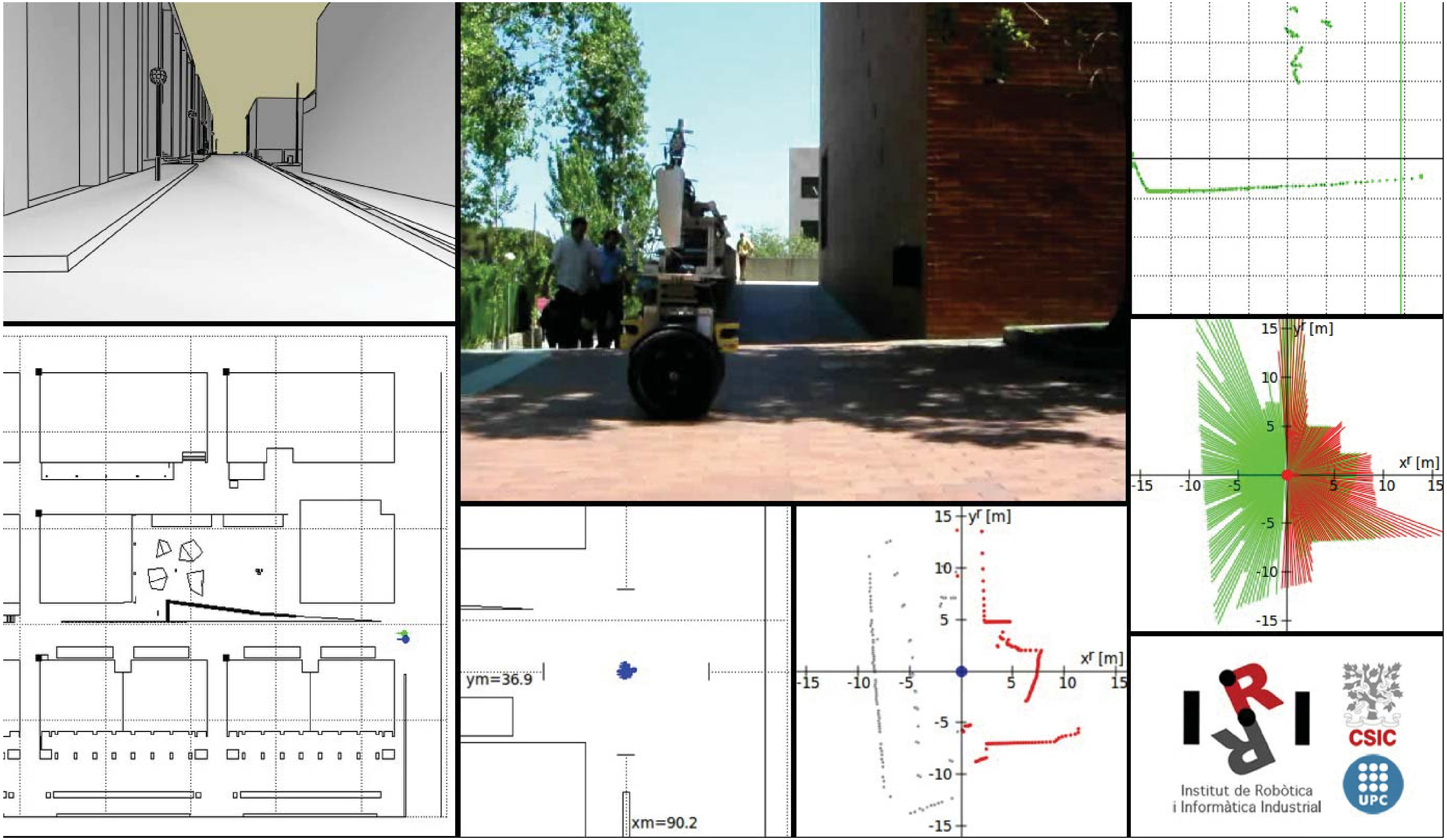


Initial situation. First path tentative



Final situation. Path found

Navigation Results



Videos_pruebas\Tibi_Navegando_BRL_2010_WMV V9_002.wmv

ROBOT NAVIGATION BEING AWARE OF PEOPLE

Robot Navigation Being Aware of People

Objective: Autonomous navigation in urban areas in crowded sites. The robots have to deal with the motion of people and being aware of them.

Approach: One way to solve this topic is using Extended Social Force Model. Idea:

$$F_i = f_i^{goal} + F_i^{\text{int}} \quad \text{where } f_i = m_i \frac{dv_i(t)}{dt}$$

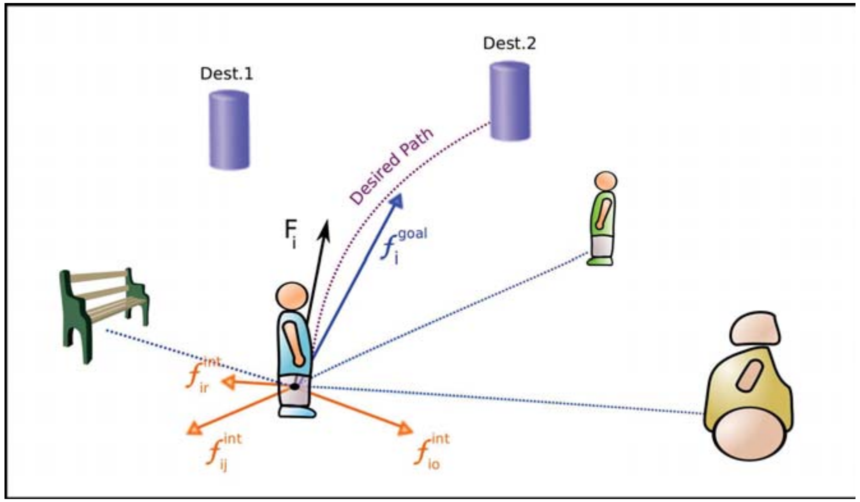
where

$$F_i^{\text{int}} = \sum_{j \in P} f_{i,j}^{\text{int}} + \sum_{o \in O} f_{i,o}^{\text{int}} + f_{i,r}^{\text{int}}$$

where P set of people and O set of obstacles

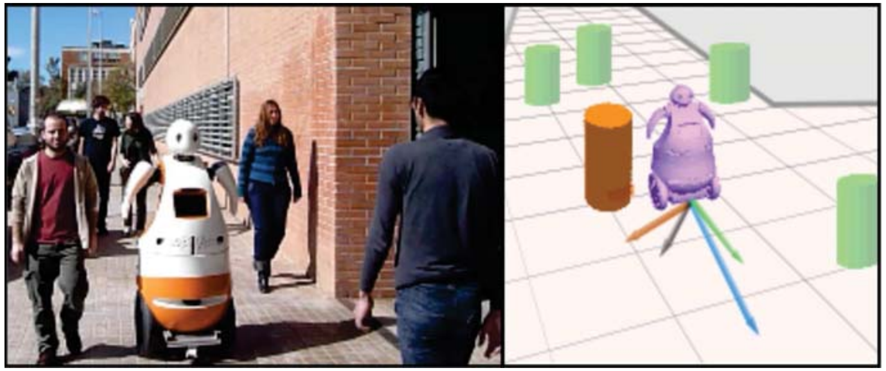
$$f_i^{goal} = k_i(v_i^0 - v_i)$$

$$f_{i,q}^{\text{int}} = A_q \, e^{(d_q - d_{i,q})/B_q} \frac{\vec{d}_{i,q}}{d_{i,q}}$$

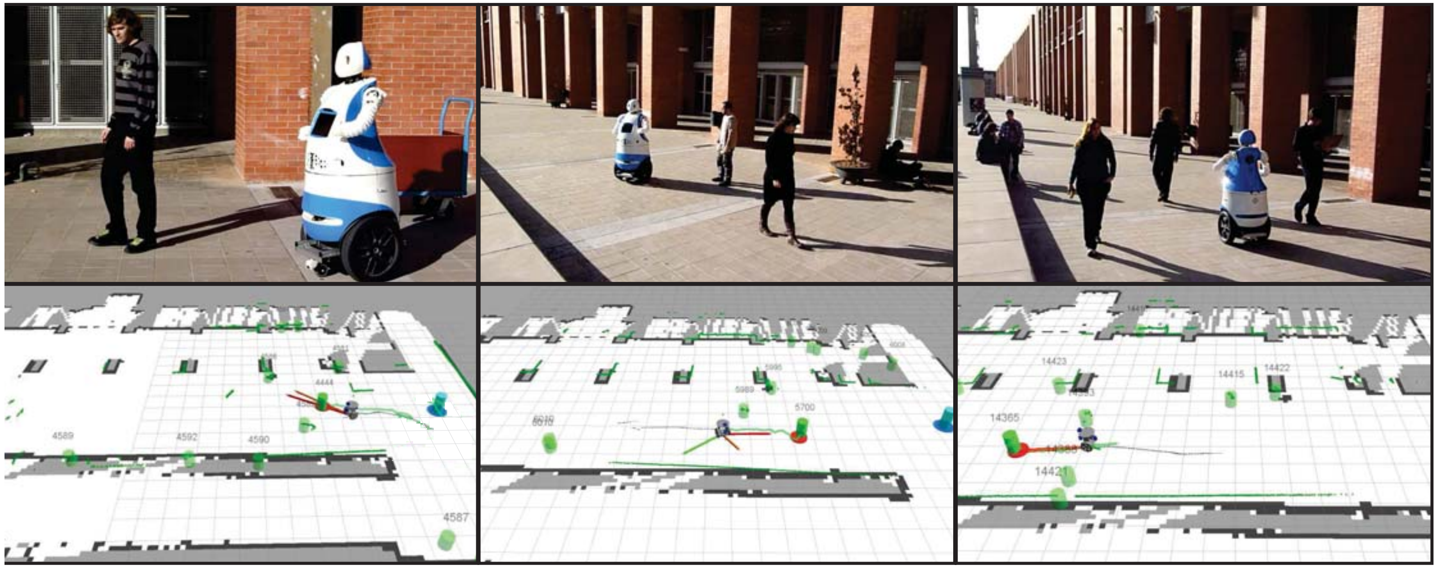


[Ferrer, Garrell, Sanfeliu, 2013]

Results



Navigation with Social Force Model



Some results on social aware navigation

Videos

Navigation with Social Force Model

BEHAVIOR ESTIMATION OF HUMAN MOTION

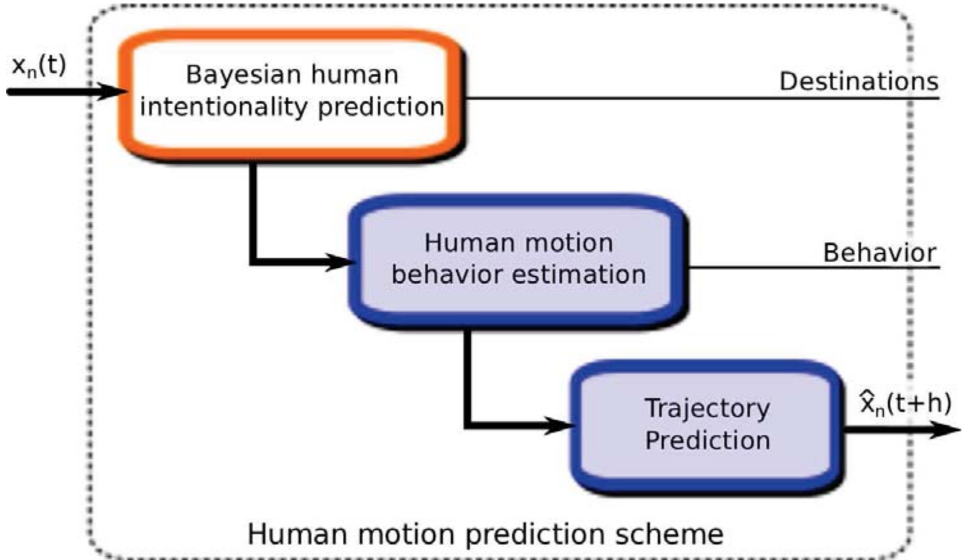
Behavior Estimation of Human Motion

Objective: Learn human motion behaviors.

We have to learn the human motion parameters of each person: *aware, balanced and unaware.*

Approach:

We want to estimate the human motion behaviors $B=\{B_1, B_2, \ldots\}$ than means to learn a set of parameters $\theta_l=\{k_l,q_l,b_l,\lambda_l,d_l\}$, which define the interaction force in SFM, for each behavior. We use human motion prediction.



[Ferrer, Sanfeliu, 2013]

Behavior Estimation of Human Motion

Approach:

The set of behaviors corresponding to one target is defined as

$B_n = \{B_{n,q}, \forall q \neq n\}$ as the set of parameters that describe the interactions of the nth target and its surrounding targets

$$f_n^{\text{int}}(B_n) = \sum_{q \in Q} f_{n,q}^{\text{int}}(B_{n,q})$$

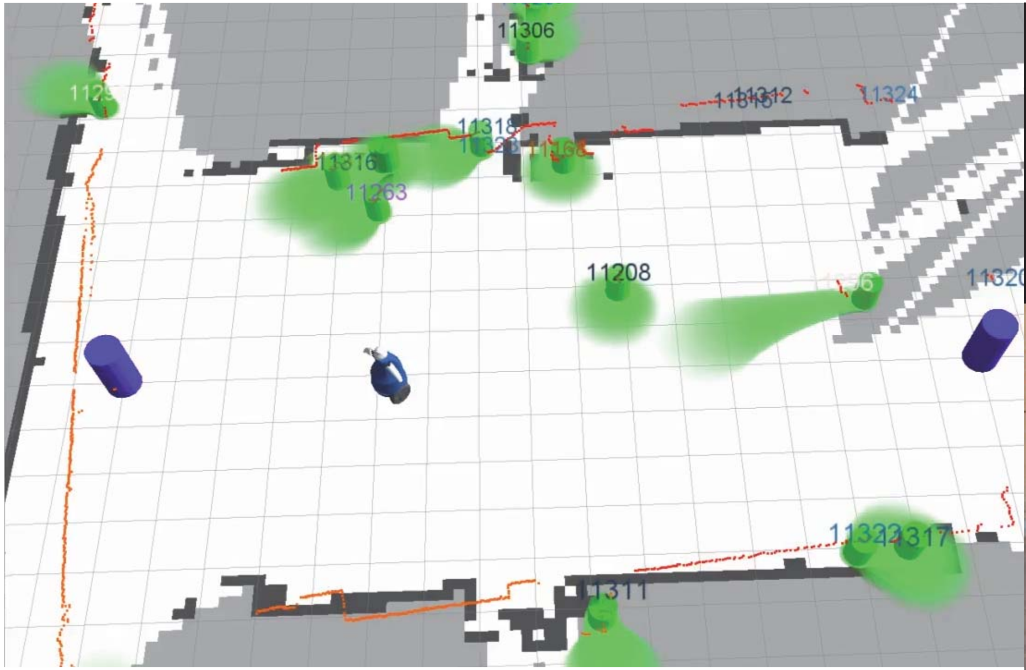
The estimated force of interaction is formulated as

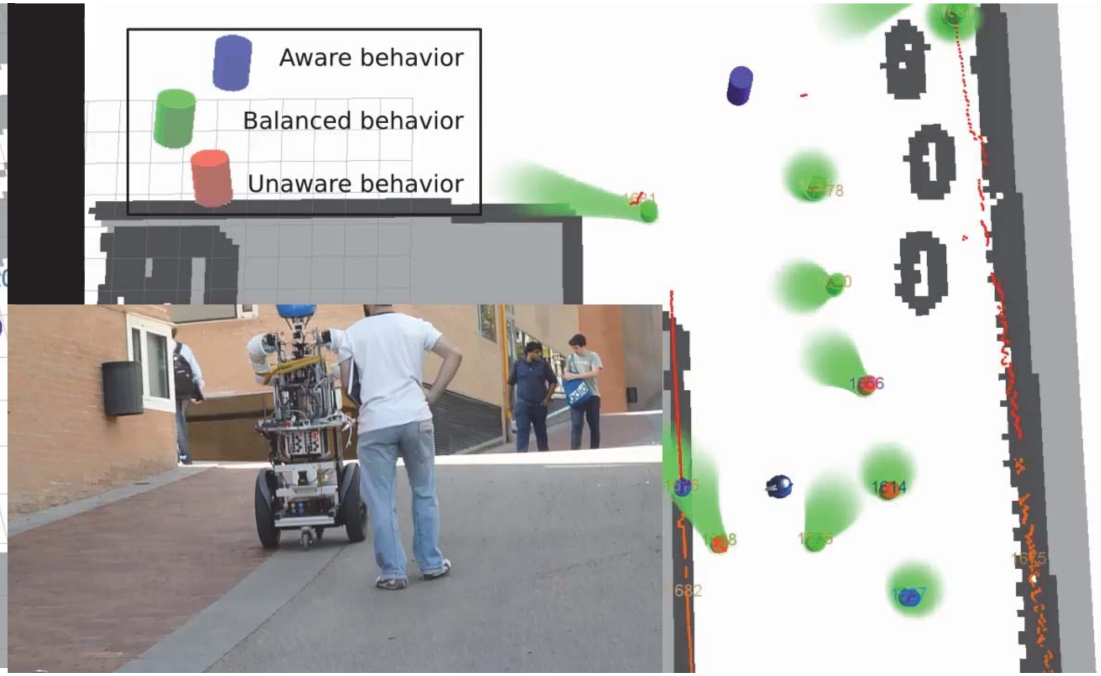
$$f_{obs}^{\text{int}} = f_{obs} - f_n^{goal}(D_n) - f_{n,q}^{\text{int}}(B_{n,q})$$

and we have to find the parameters that minimize

$$\widehat{\theta}_{n,q} = \operatorname{argmin}(\| f_{obs}^{\text{int}} - f_{n,q}^{\text{int}}(\theta) \|)$$

Results





Learning human motion behaviors

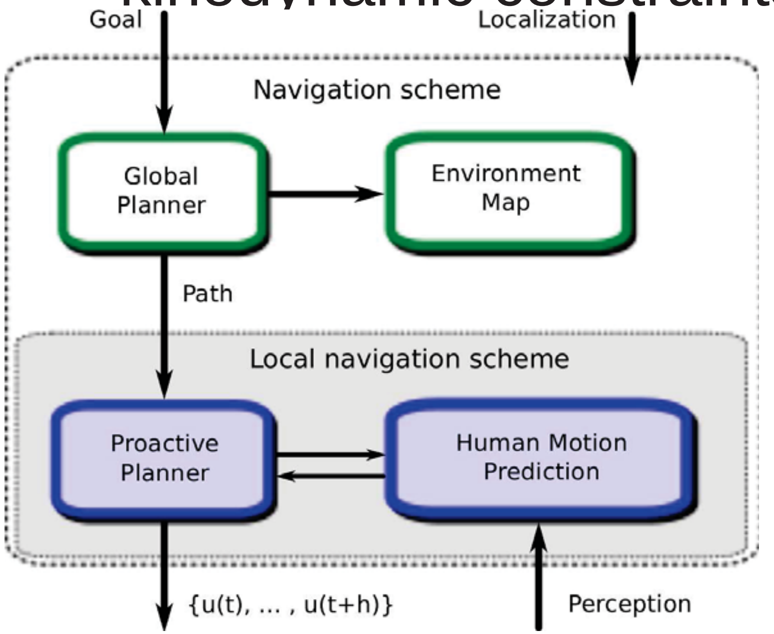
Testing human motion behaviors

PROACTIVE KINODYNAMIC PLANNING FOR ROBOT NAVIGATION

Proactive Kinodynamic Planning for Robot Navigation

Objective: Extend the navigation taken into account prediction of all people movements

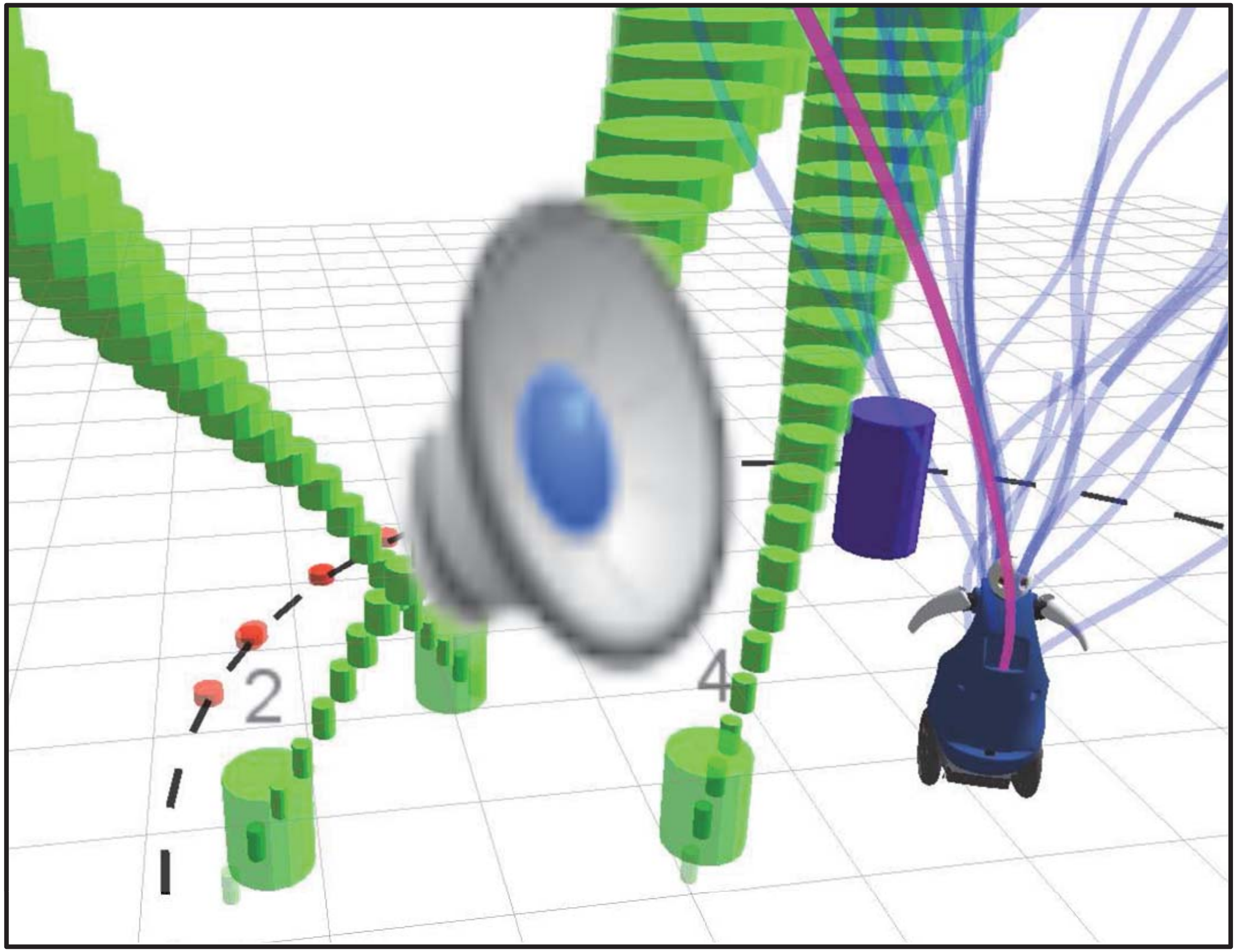
Approach: a planner that predicts human motion and minimizes its impact on all those nearby pedestrians. A cost-based navigation path is calculated while satisfying both dynamic and nonholonomic constraints, also referred as kinodynamic constraints.



- A kinodynamic solution is calculated.
- Proactive planning in which planning uses prediction information, and prediction is dependent on the plath Calculated.
- Prior requirement: a global planner provides a valid global path.
- At each iteration, the planner provides a locally valid path.
- The path computed minimizes the perturbations on the scene, according to a cost function.

[Ferrer, Sanfeliu, 2014]

Results

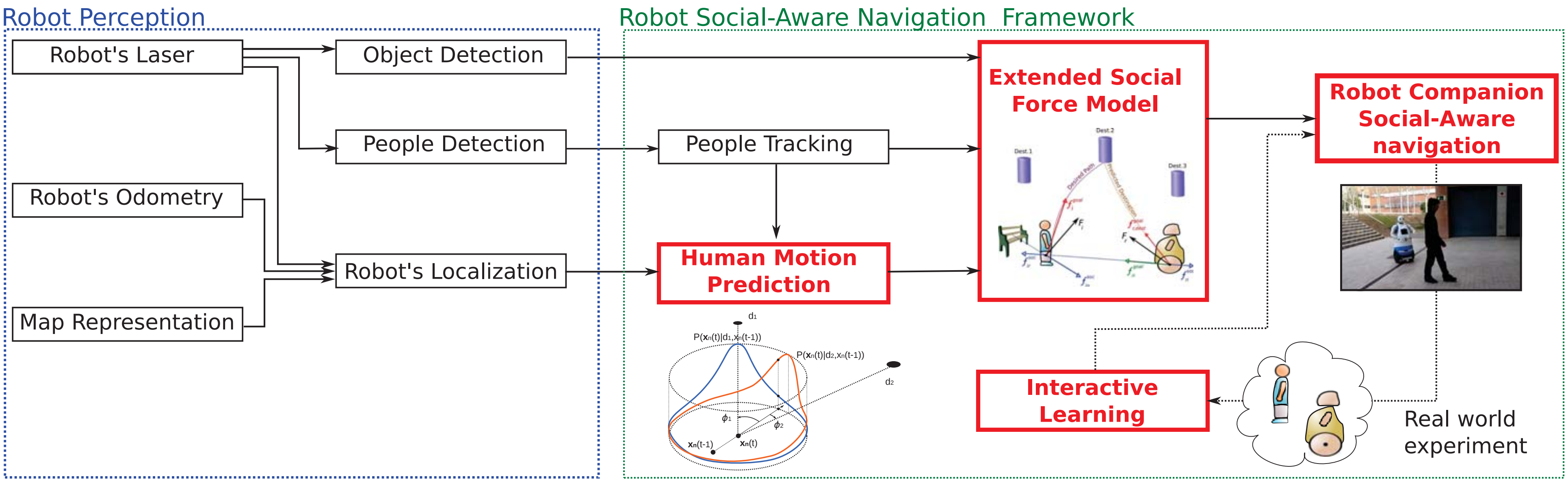


Advanced navigation using Proactive Kinodynamic planning

GUIDING AND ACCOMPANY PEOPLE

Objective:

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



General diagram

[Garrell, Sanfeliu, 2012]
[Garrell, Villamizar, Moreno-Noguer, Sanfeliu, 2012]
[Garrell, Villamizar, Huerta, Sanfeliu, 2013]

Simulation Results

Simulations

Real Life Experiment Results

Guiding using social forces

Guiding people

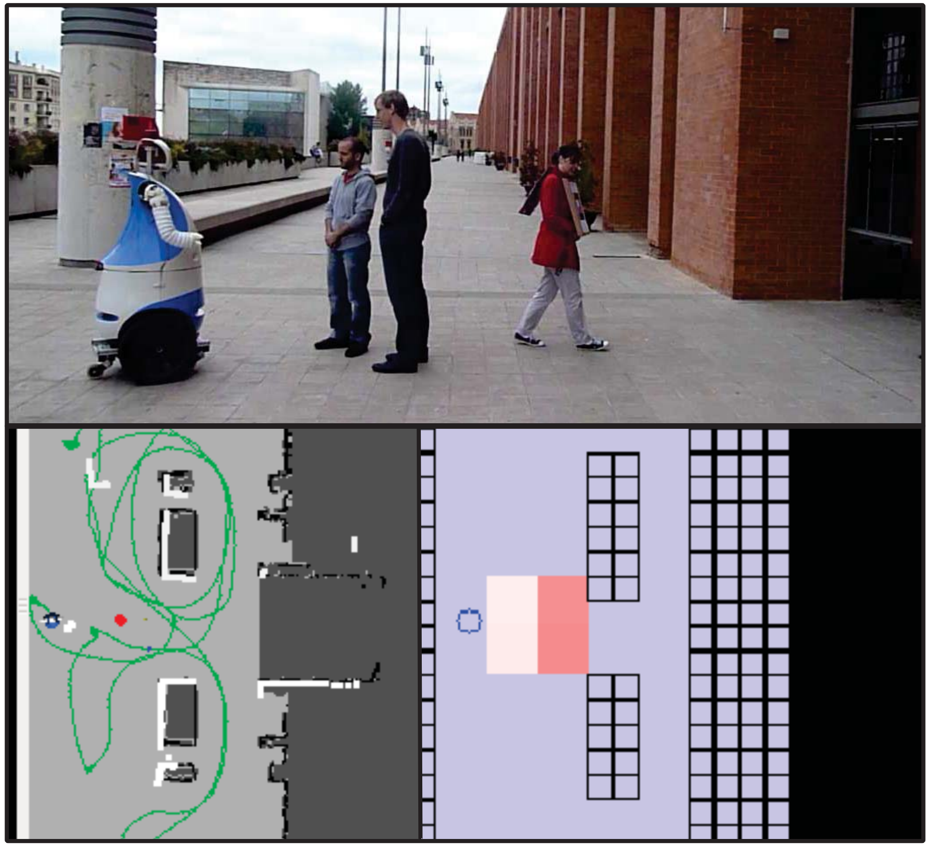
Dabo Accompanying People (teleoperated)

LOOKING AND FOLLOWING PEOPLE

Looking and Following a Person

Objective: The robot has to find a person that hides in the environment.

Dabo performs the find-and-follow task with a mobile target (person)



Real scenario

Dabo trajectory

[Goldhoorn, Sanfeliu, Alquezar, 2013]
[Goldhoorn, Garrell, Sanfeliu, 2014] Submitted

Looking and Following a Person

Approach:

It is based on POMDP.

- This model contains a set of states (*S*) which in our case are defined as the position of the person and the robot (s_{robot}, s_{person})

- The robot can do an action of the set A (the robot can move in the eight directions o stay in the same place)

- Instead of knowing the exact state, an observation of the state is done

- In the find-and-follow problem observations are equal to states, but the person position (s_{person}) has a special value *hidden* when he is not visible.

- The POMDP model computes the probability $T=P(s'! s,a)$ to going from one state to another one with an action *a* and the observation $Z=P(o! s',a)$. The reward function *R* is used to guide the learning process indicating which are the best actions to do in which states, the policy. Our reward function, $-d_{rp}$, is decreasing when the person robot distance is decreasing.

- Instead of knowing the full state, a probability of being in each possible state is stored, the belief.

Looking and Following a Person

Approach:

- The starting belief b_0 is given
- The belief is updated using the observation and the probability functions
- The best action to execute for each belief state is calculated by computing the value function:

$$Q(a,b) = \sum_{s' \in S} b(s)R(s,a) + \gamma \sum_{o \in O} P(o|b,a)V(b')$$

$$\text{where } V(b) = \max_{a \in A} Q(b,a)$$

- Finding the exact solution is intractable, therefore approximations methods are used.
- In our case we use the POMCP (Montecarlo simulations to generate a policy)

Adaptive CR-POMCP

Approach:

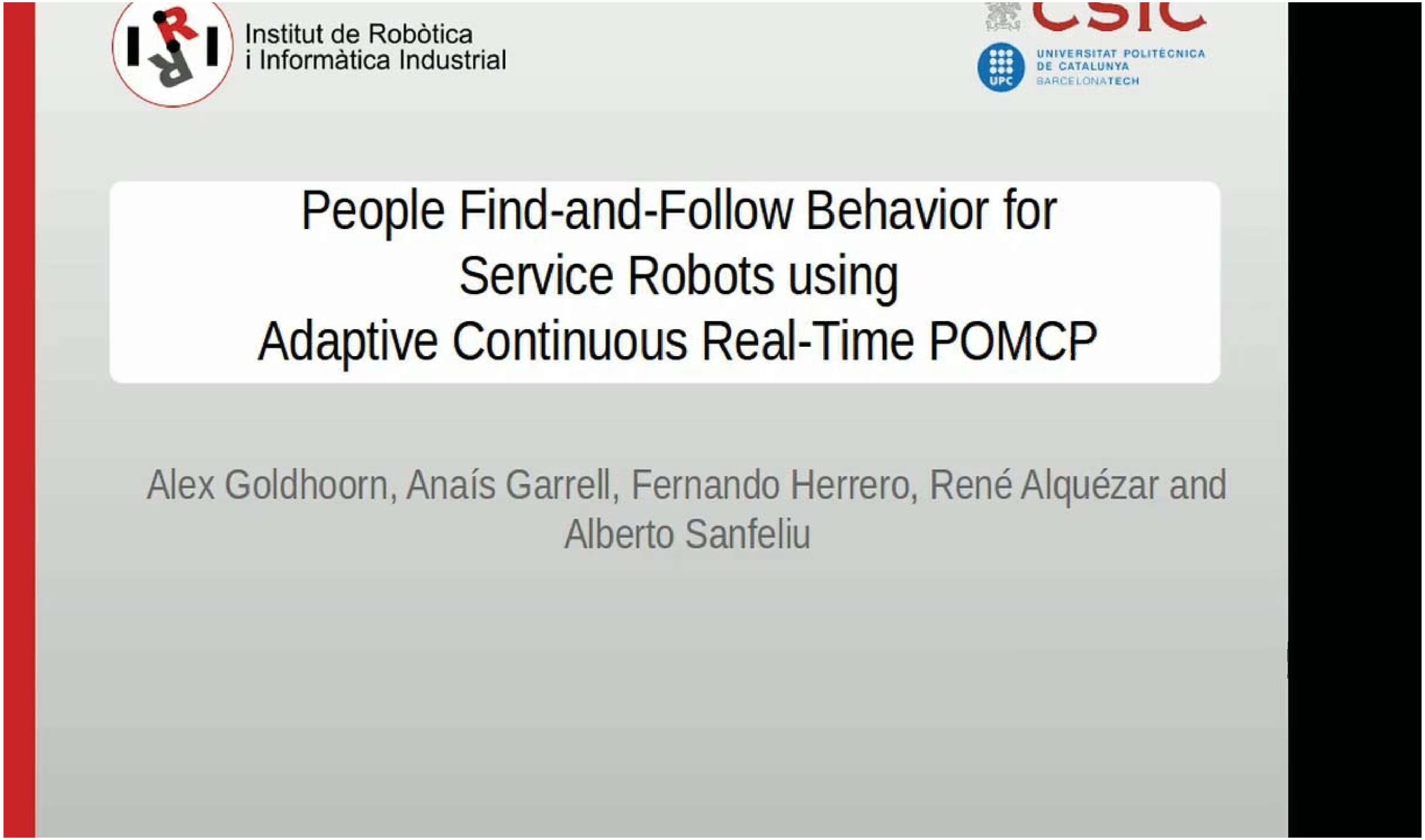
The Adaptive CR-POMCP follower which takes into account:

- Works in continuous space
- Uses the CR-POMCP
- When the person is visible uses the Heuristic Follower

Algorithm 1 The POMCP planner. Retrieving children nodes is noted as *Node*[a] (for action a for example).

```
function SIMNODE(Node,s,depth)
    if depth > d_max then return 0
    else
        a ← argmax_a Node[a].V + c·sqrt( log(Node.N) / Node[a].N )
        if depth = 1 then Node.B = Node.B ∪ {s}
        (s', o, r_immediate) ← G(s, a)
        if s' is not final and not Node[a][o] exists and
                                Node[a][o].N ≥ e_count then
            Add Node[a][o]
        end if
        if s' is not final then
            if Node[a][o] exists  then
                r_delayed ← SIMNODE(Node[a][o],s',depth+1)
            else
                r_delayed ← ROLLOUT(s',depth+1)
            end if
        else
            r_delayed ← 0
        end if
        r_total ← r_immediate + γ r_delayed
        Node[a].N ← Node[a].N + 1
        Node[a].V ← Node[a].V + (r − Node[a].V) / N
        Node.N ← Node.N + 1
        Node.V ← Node.V + (r − Node.V) / N
        return r
    end if
end function
function ROLLOUT(s,depth)
    if depth > d_max then return 0
    else
        a ~ π_rollout()
        (s', o, r) ← G(s, a)
        return r + γ ROLLOUT(s',depth+1)
    end if
end function
```

Simulations and Real Life Experiments



Real life experiments of Dabo performs the find-and-follow task with a mobile target (person)

ROBOT LEARNING FACES AND OBJECTS

Robot Learning Faces and Objects

Objective:

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]

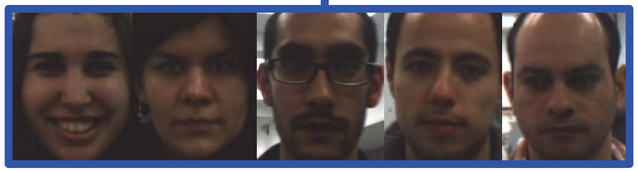
Objective

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



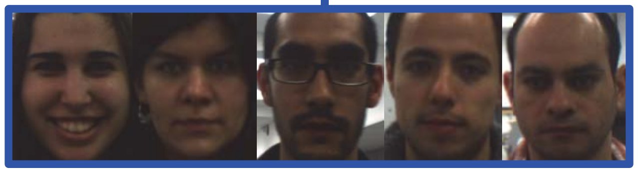
Faces

Objective

Robot TIBI learns to recognize faces and objects using human assistance

Face Recognition

Object Recognition

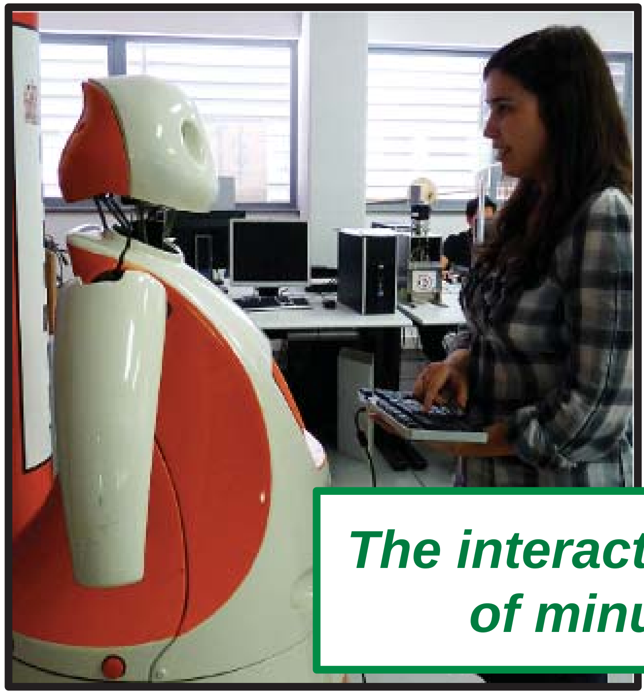


Faces

3D Objects

Objective

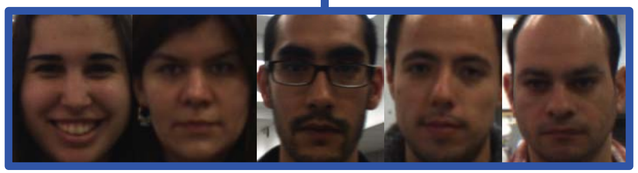
Robot TIBI learns to recognize faces and objects using human assistance



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

Face Recognition

Object Recognition



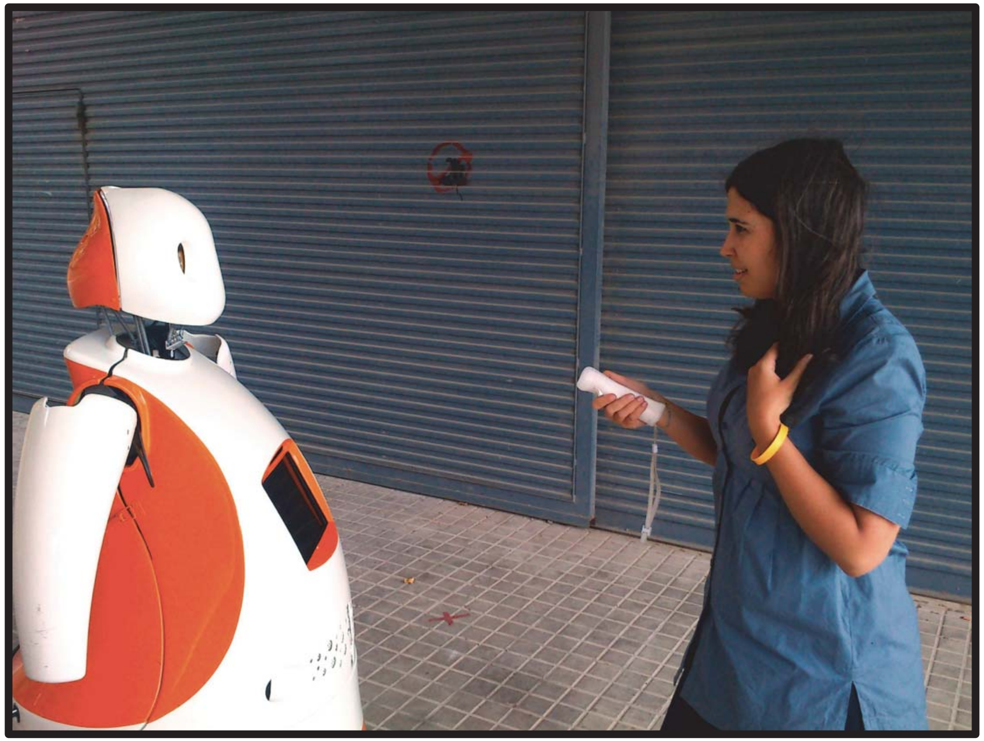
Faces

3D Objects

Approach

Online Human-Assisted Learning

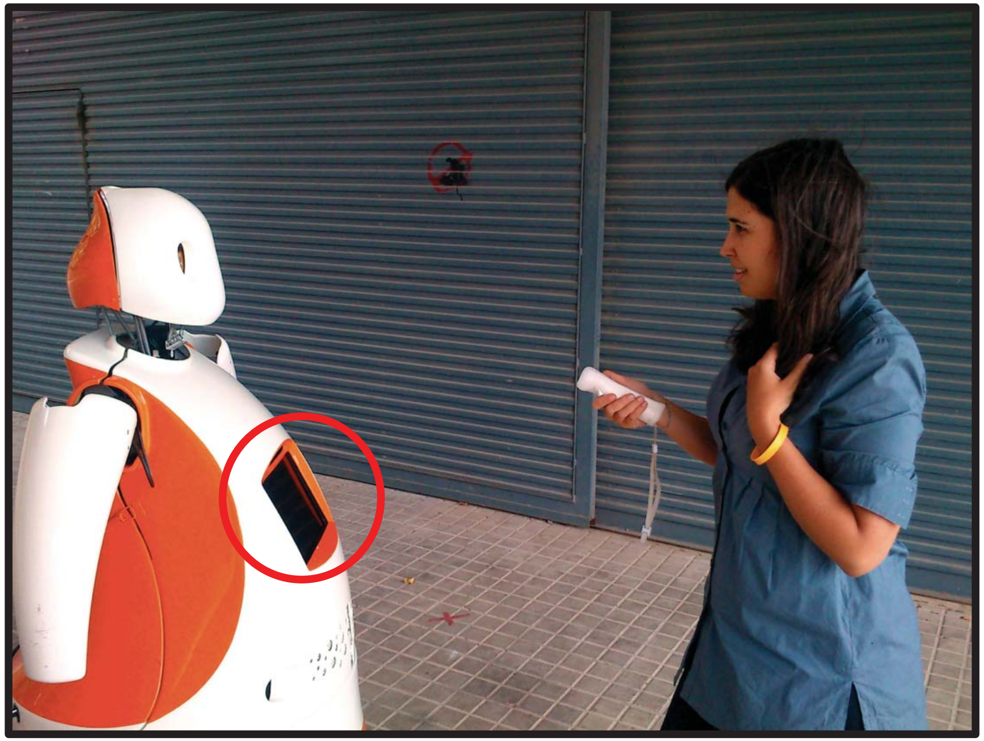
Human-Robot Interaction



Approach

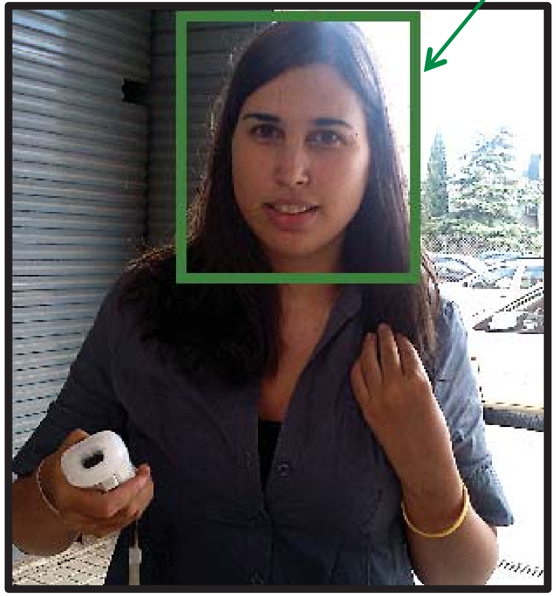
Online Human-Assisted Learning

Human-Robot Interaction



Robot Camera

hypothesis



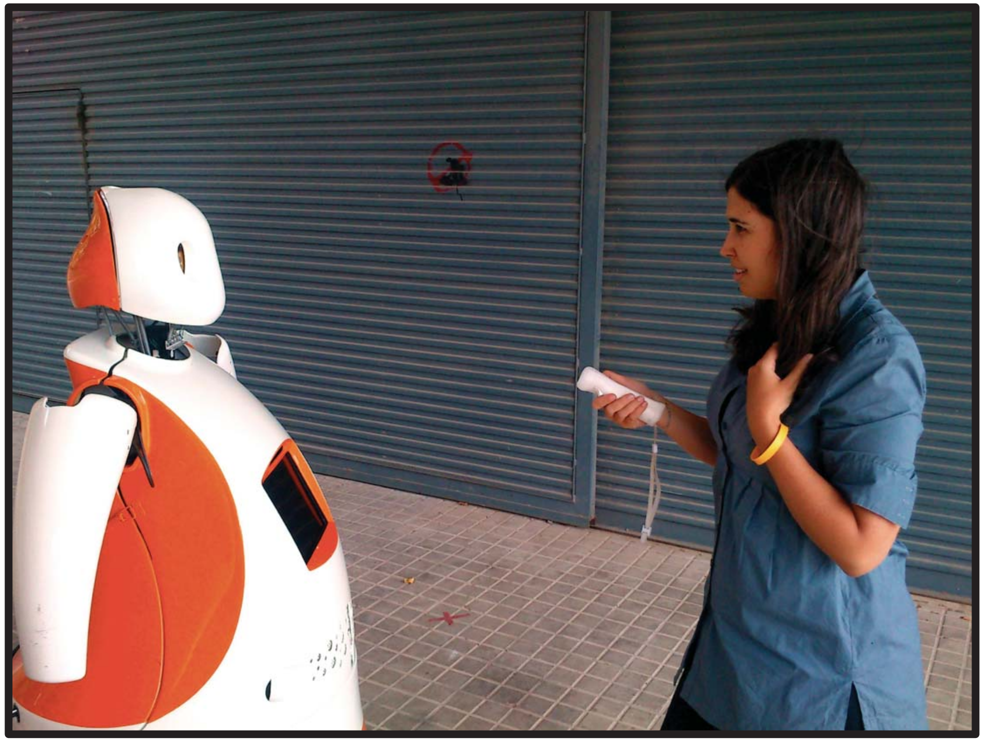
Recognition Results

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

Approach

Online Human-Assisted Learning

Human-Robot Interaction



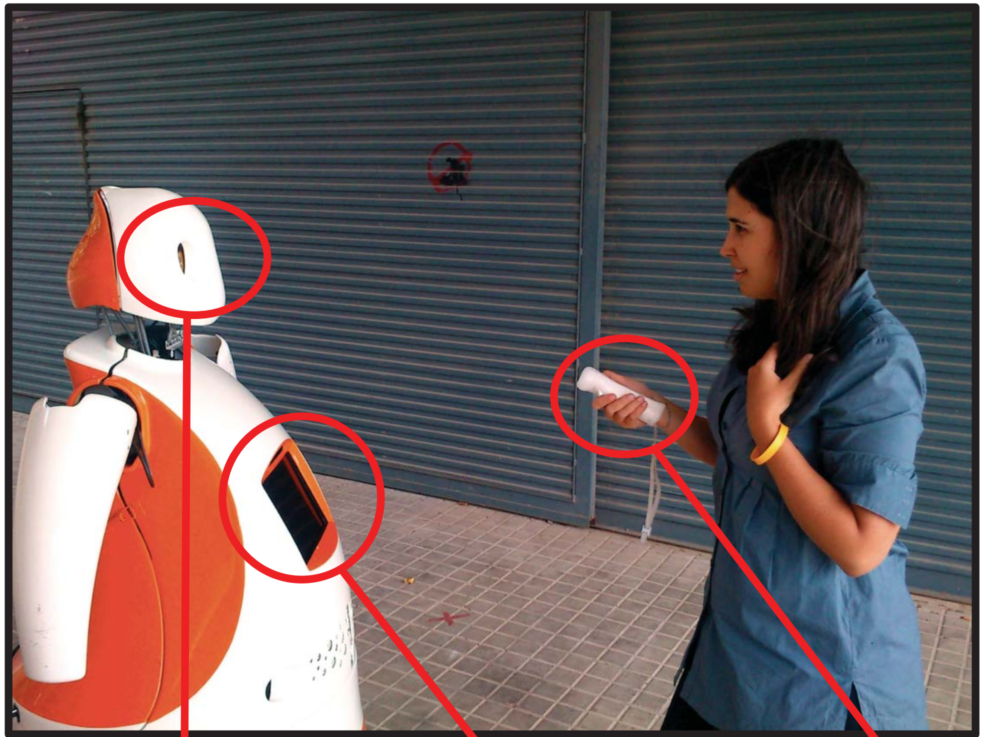
Difficult Cases

***Human-Assisted Learning:* The visual system requires the human intervention**

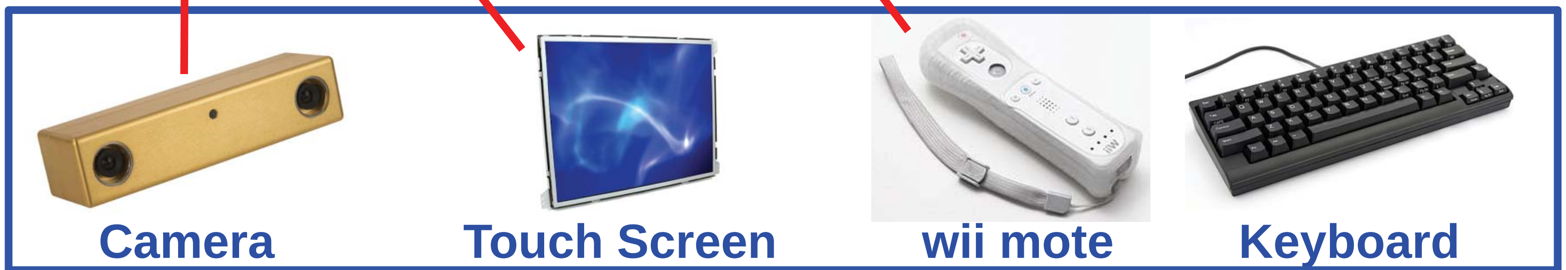
Approach

Online Human-Assisted Learning

Human-Robot Interaction



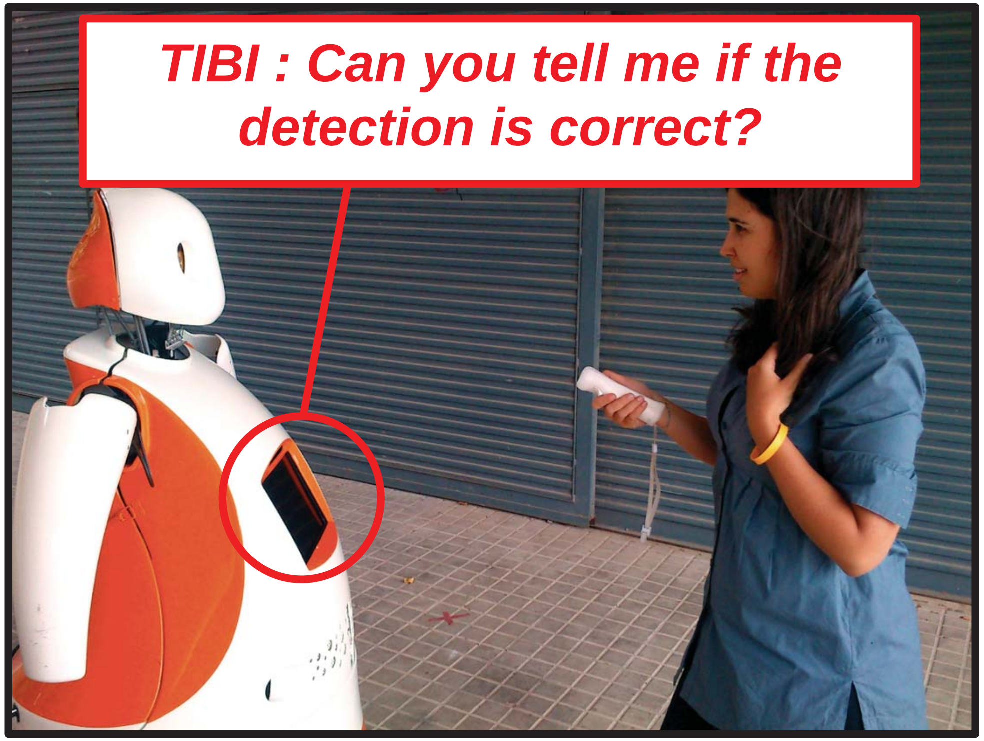
Difficult Cases



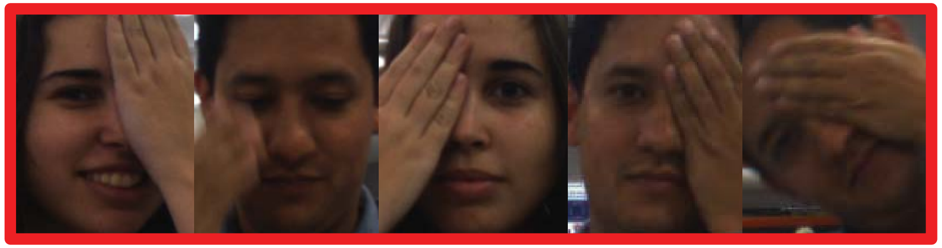
Approach

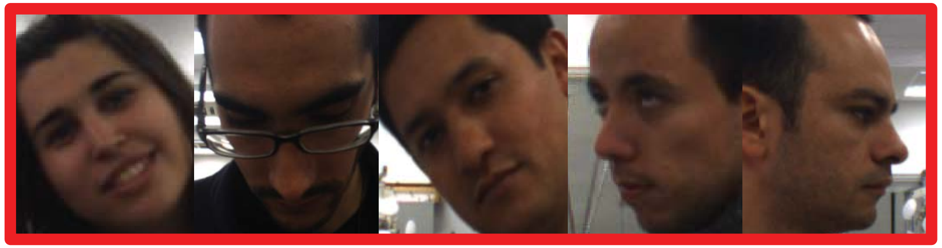
Online Human-Assisted Learning

Human-Robot Interaction



Difficult Cases





Camera

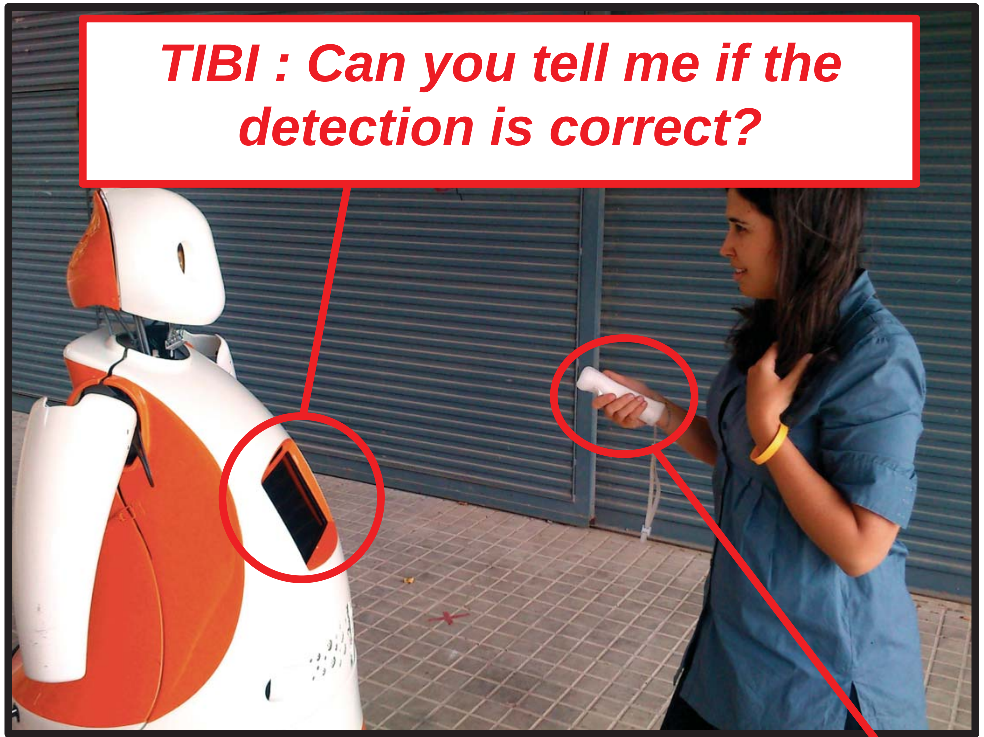
Touch Screen

wii mote

Keyboard

Online Human-Assisted Learning

Human-Robot Interaction



Difficult Cases

Camera

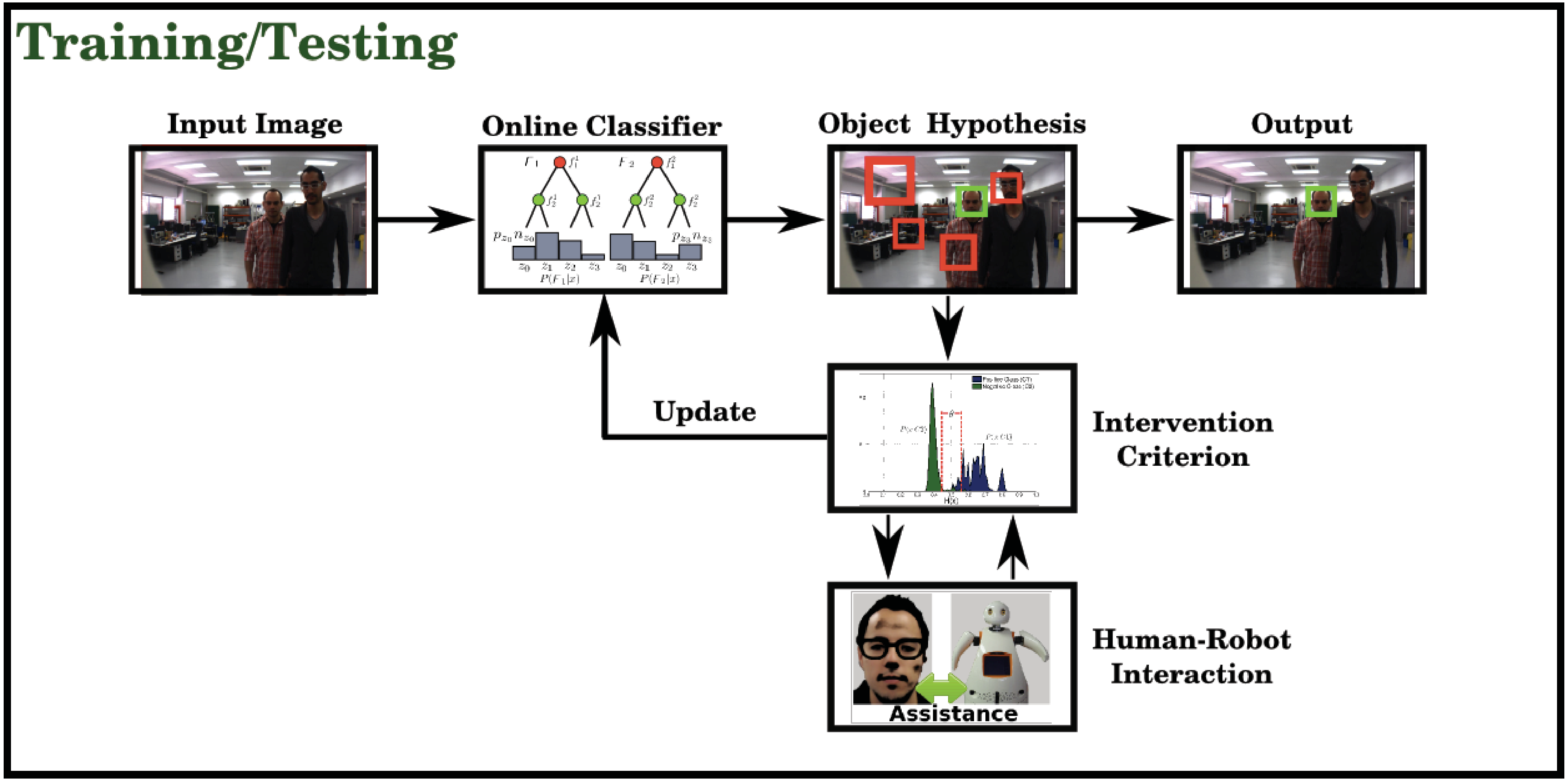
Touch Screen

wii mote

Keyboard

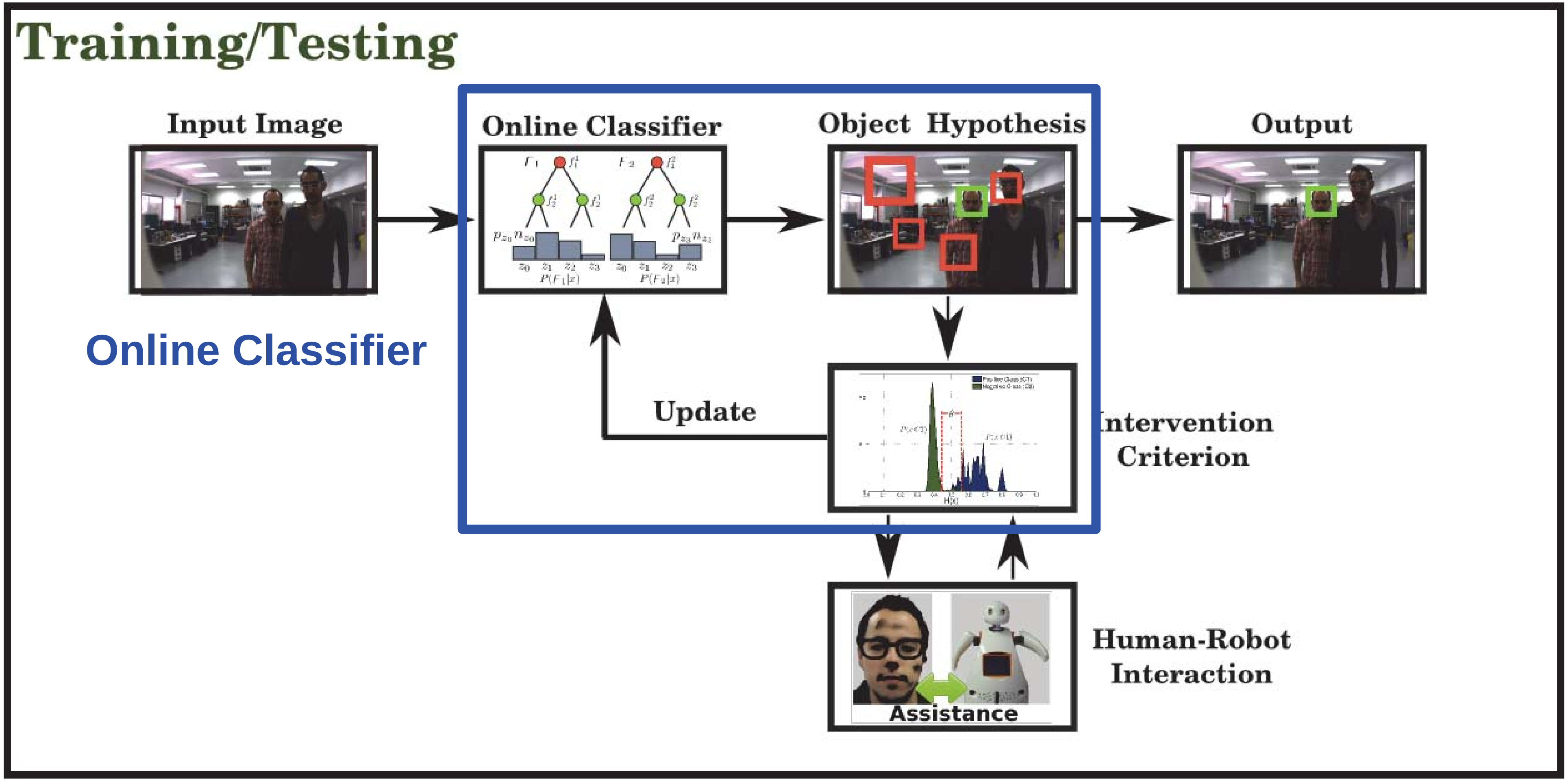
Approach

Online Human-Assisted Learning using Random Ferns



Approach

Online Human-Assisted Learning using Random Ferns



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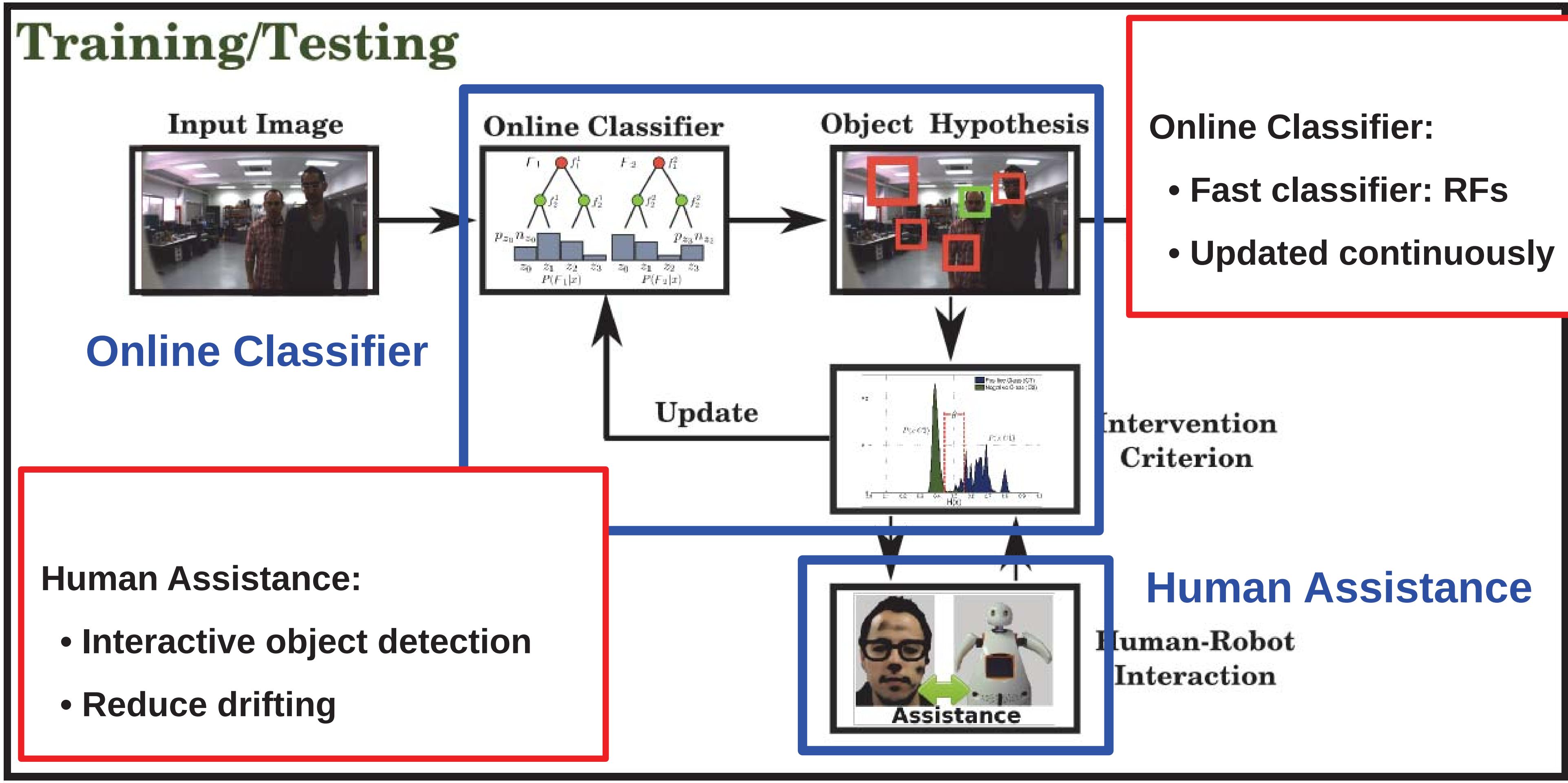
Approach

Online Human-Assisted Learning using Random Ferns

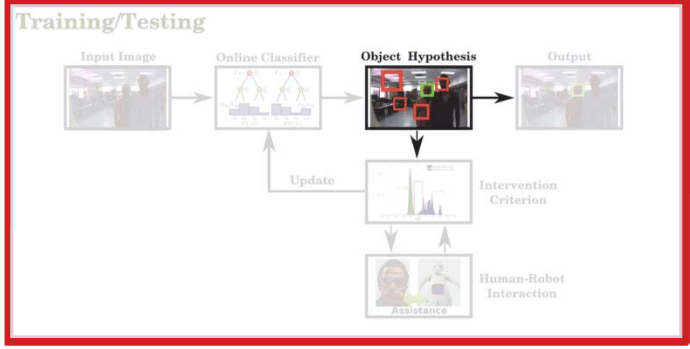


Online Classifier:

- Fast classifier: RFs
- Updated continuously

Human Assistance:

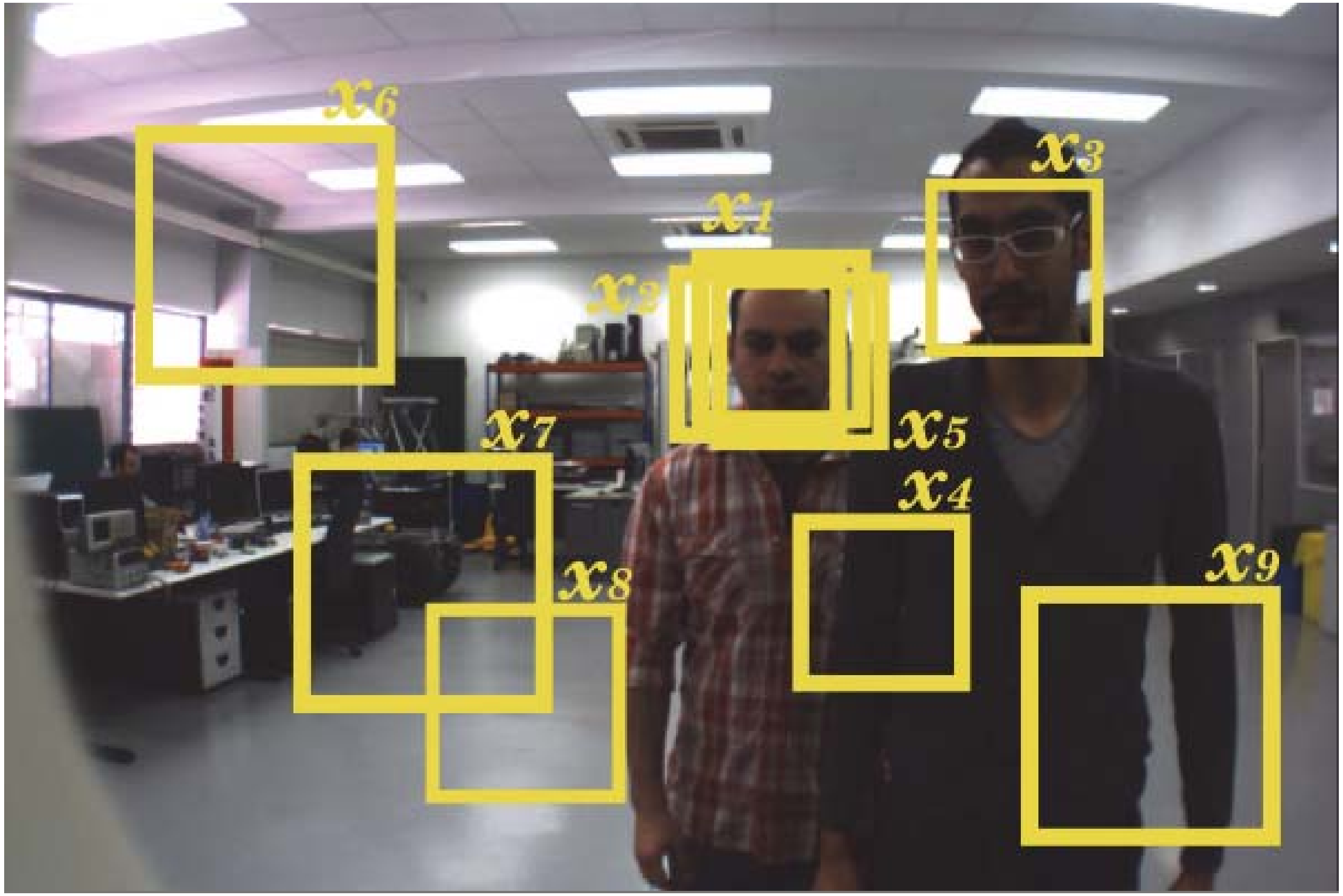
- Interactive object detection
- Reduce drifting

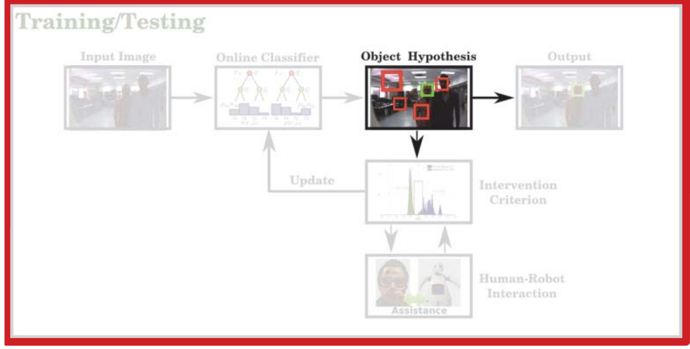


Approach

Object Hypothesis

- Object hypotheses: detections given by the classifier

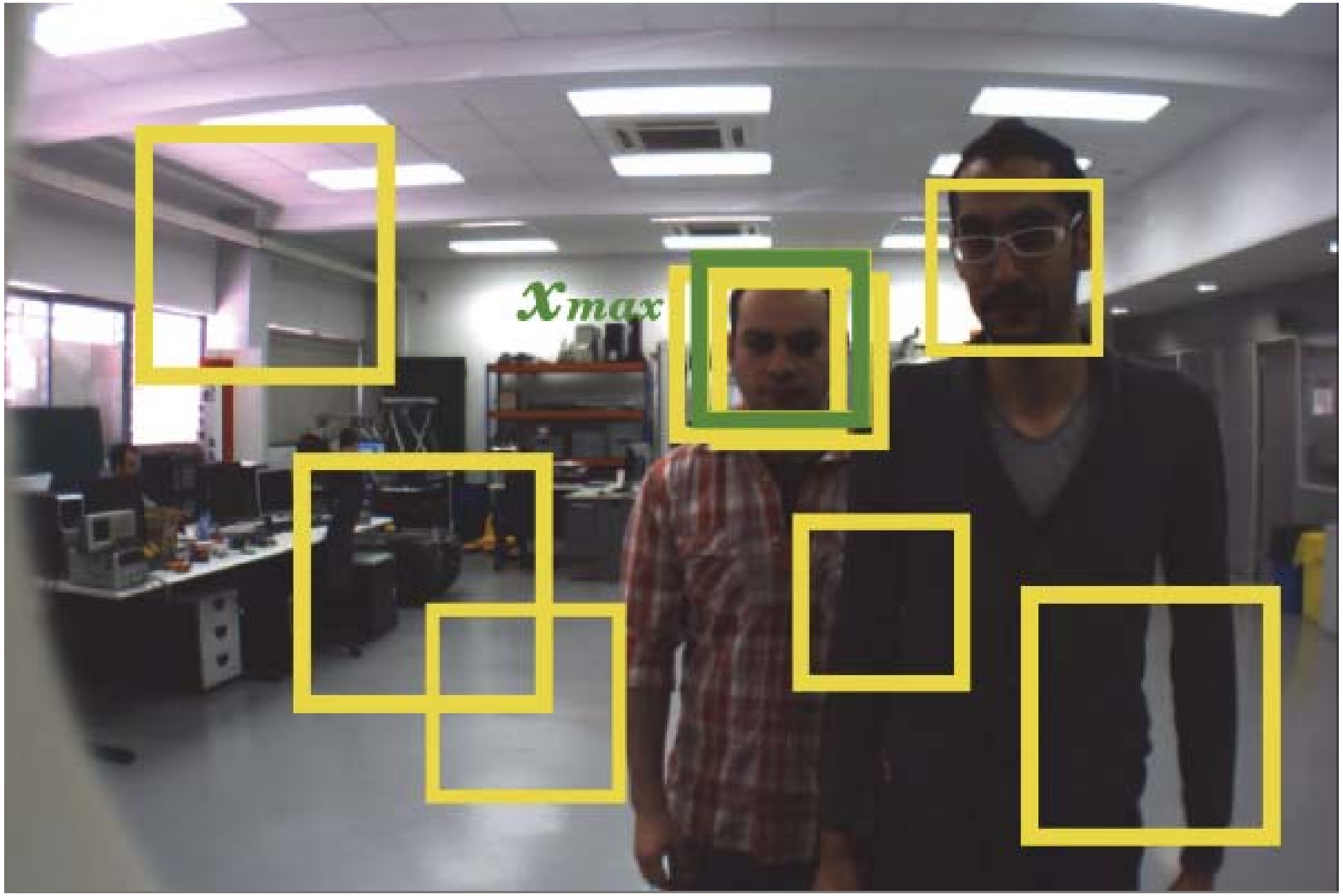


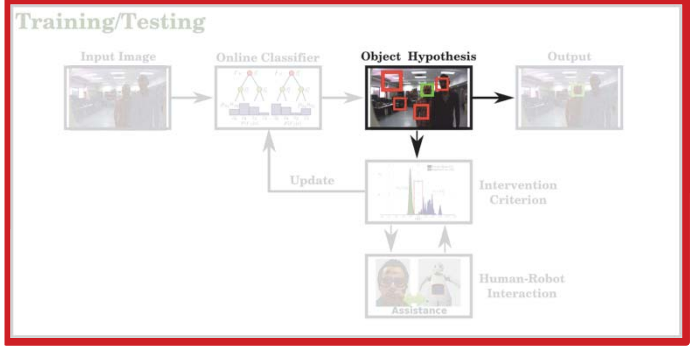


Approach

Object Hypothesis

- Object candidate: highest-confidence hypothesis (detection)

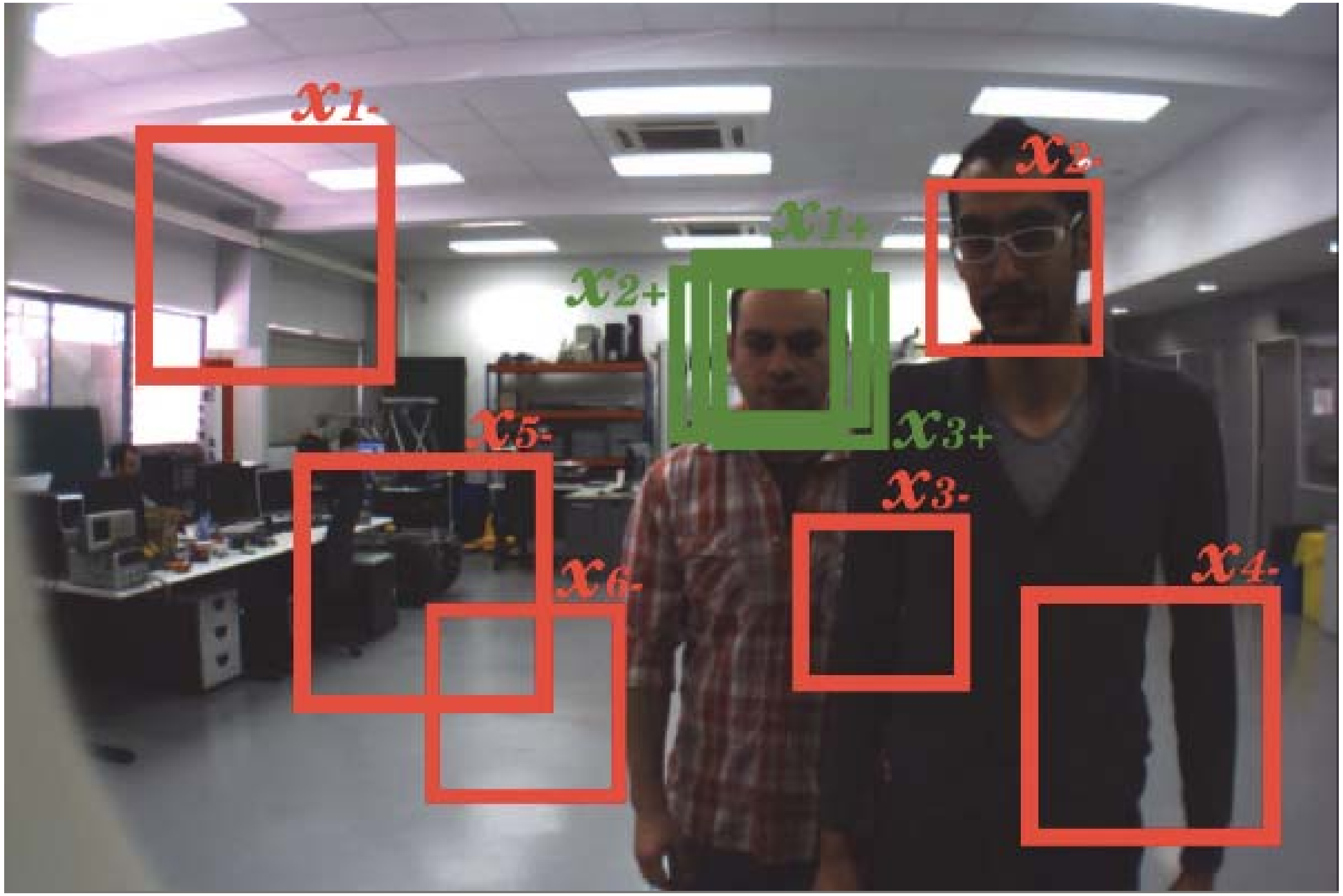




Approach

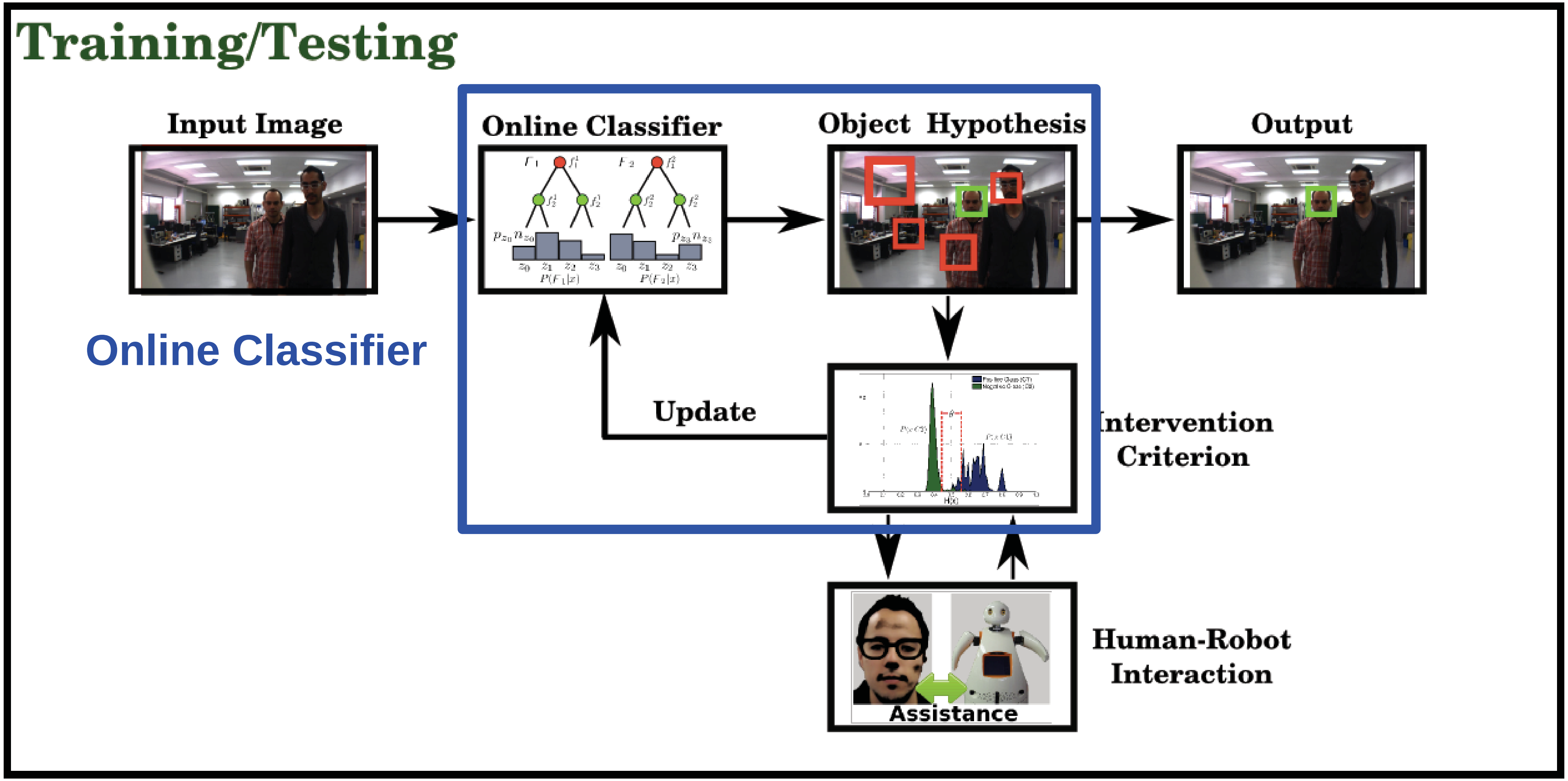
Object Hypothesis

- New samples: positive and negative samples



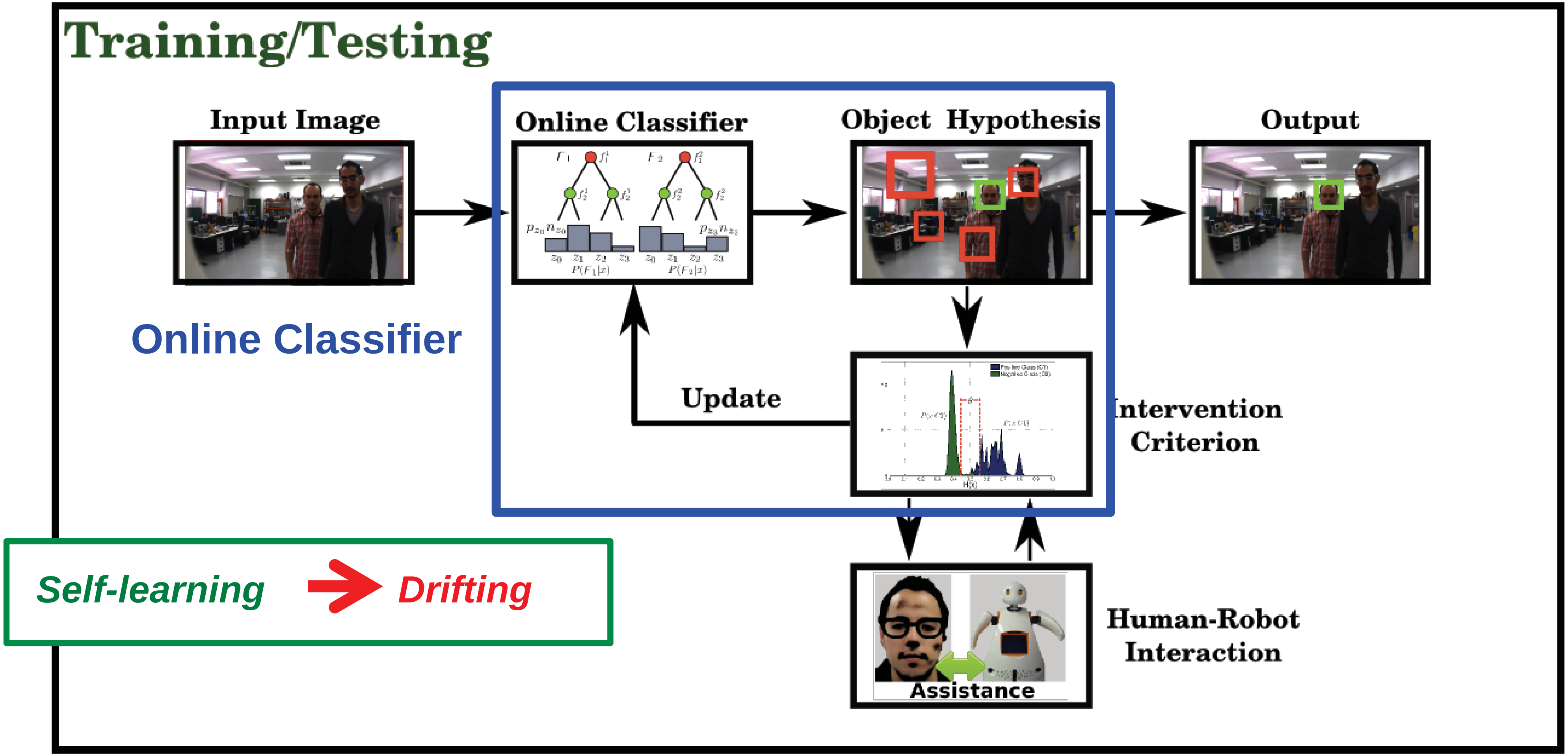
Approach

Online Human-Assisted Learning using Random Ferns

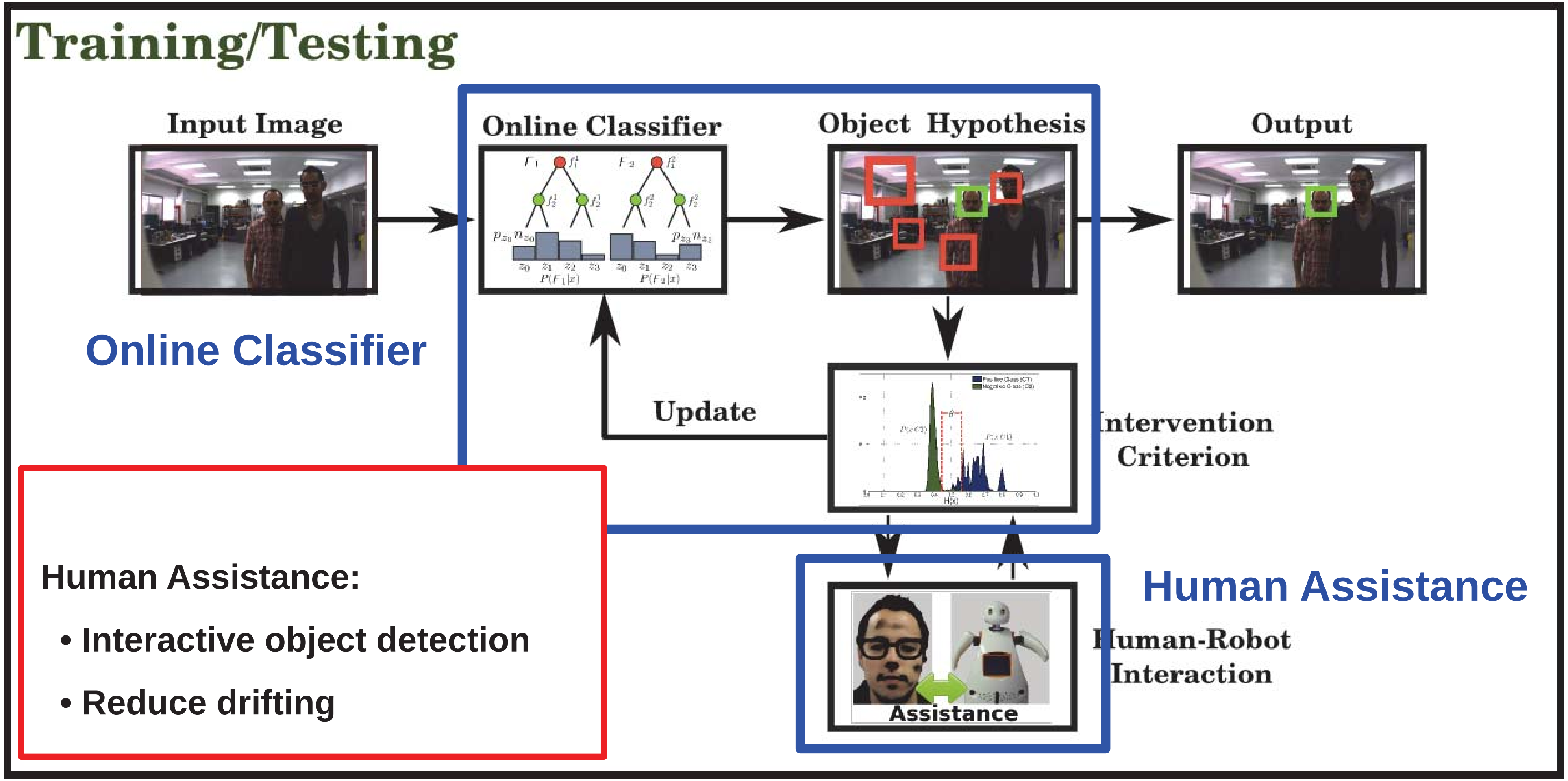


Approach

Online Human-Assisted Learning using Random Ferns



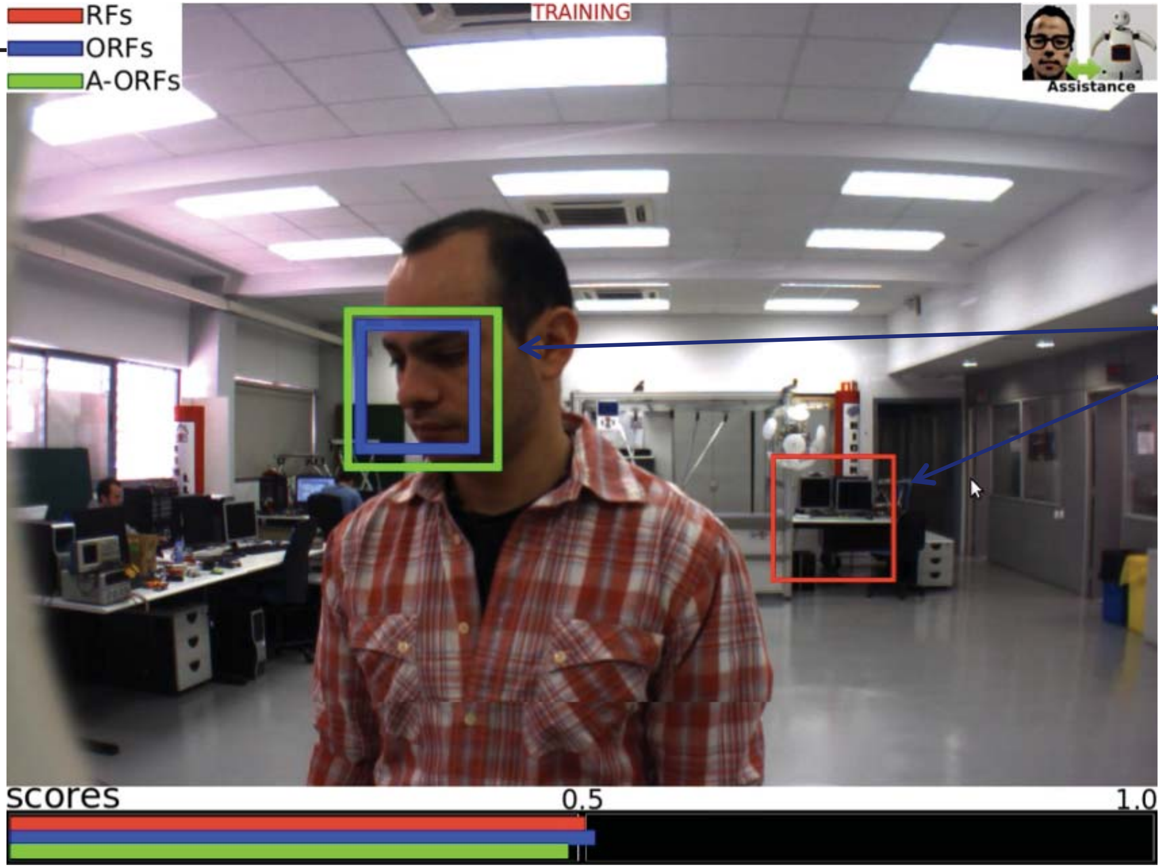
Online Human-Assisted Learning using Random Ferns



Training Step

Description

Human Assistance



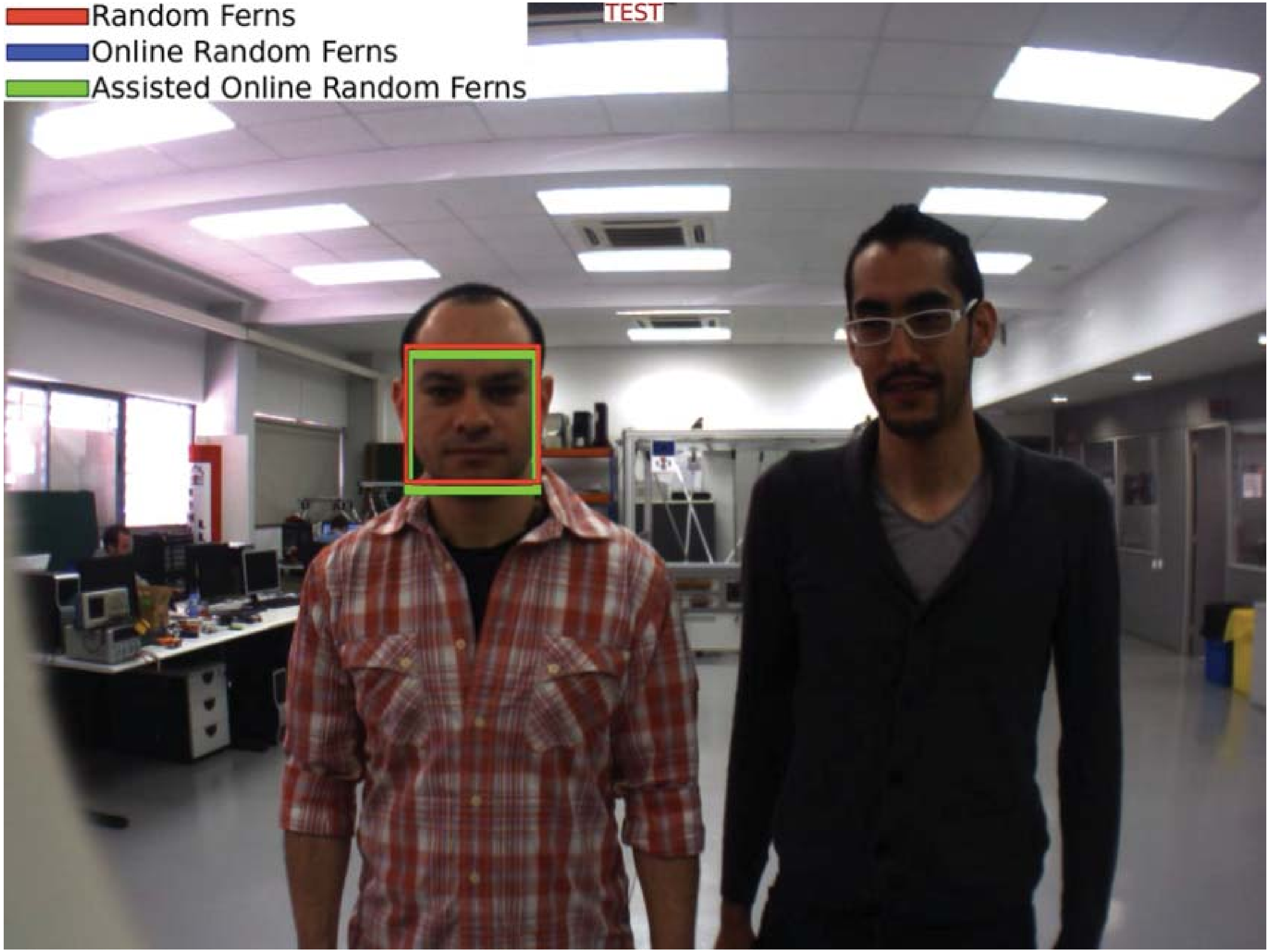
Detections

Recognition Scores

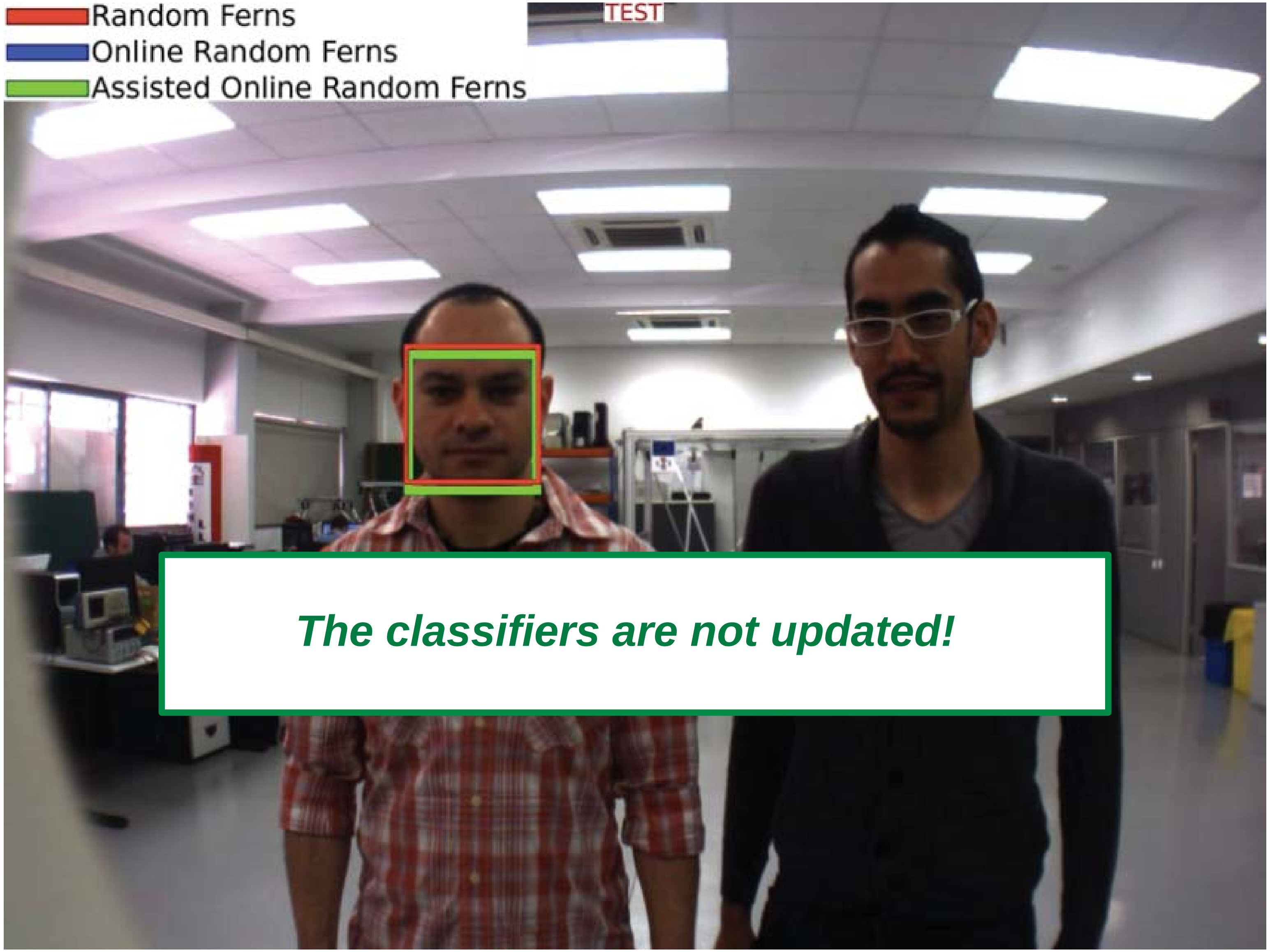
RFs: Offline Random Ferns
ORFs: Online Random Ferns
A-ORFs: Online Human-Assisted Random Ferns

Training Step

Testing Step

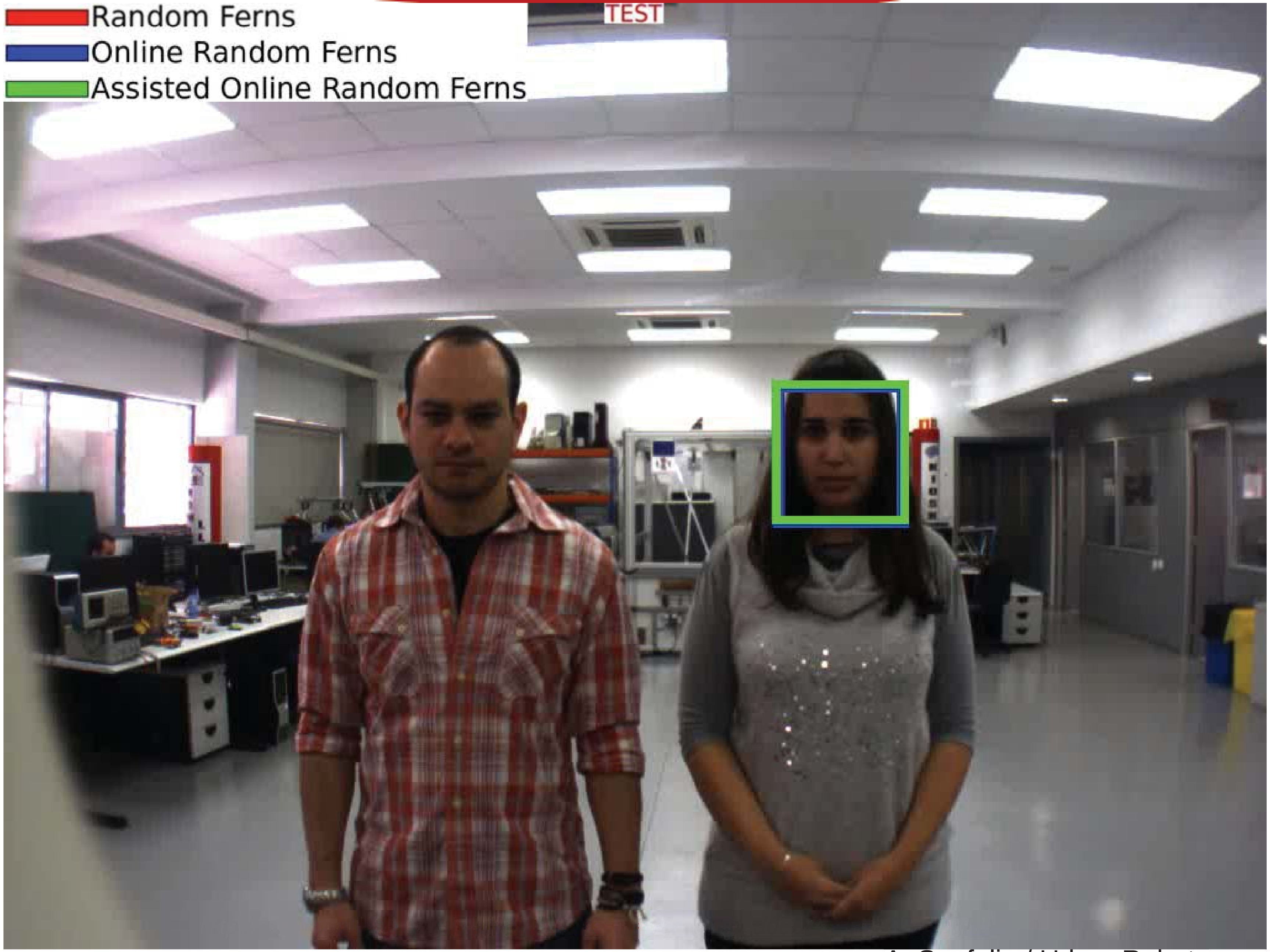


Testing Step



The classifiers are not updated!

Testing Step

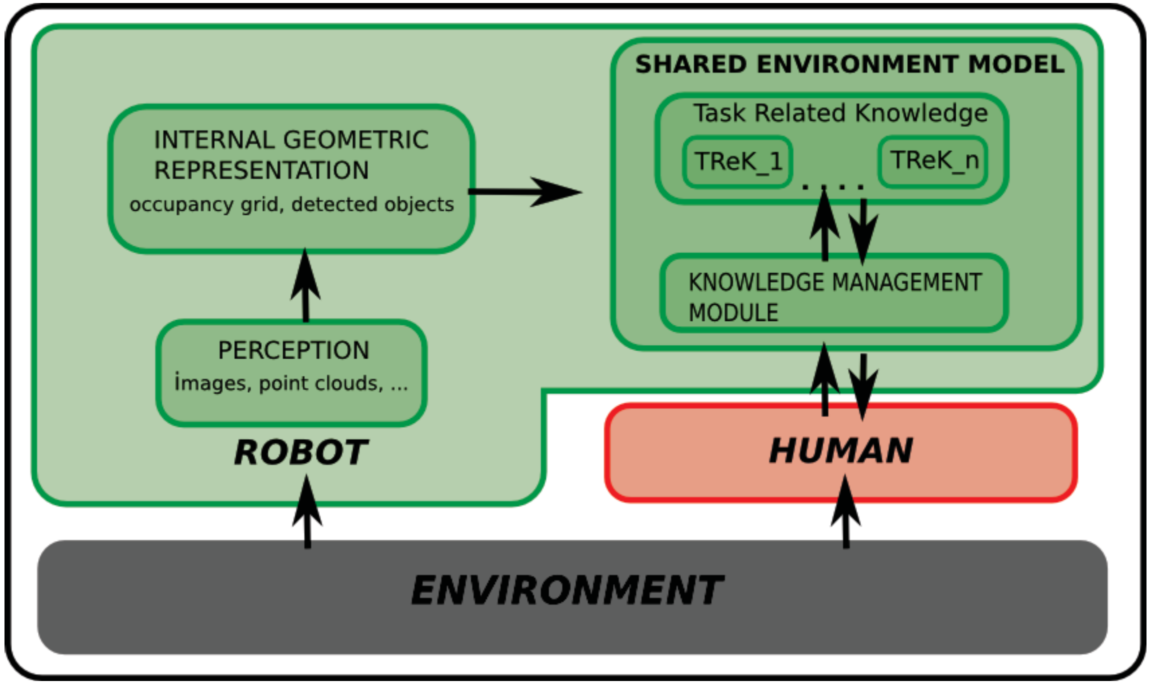


Results with Objects

HUMAN-ROBOT TASK COLLABORATION

Human-Robot Task Collaboration

Objective: Design models for Human-Robot task collaboration.

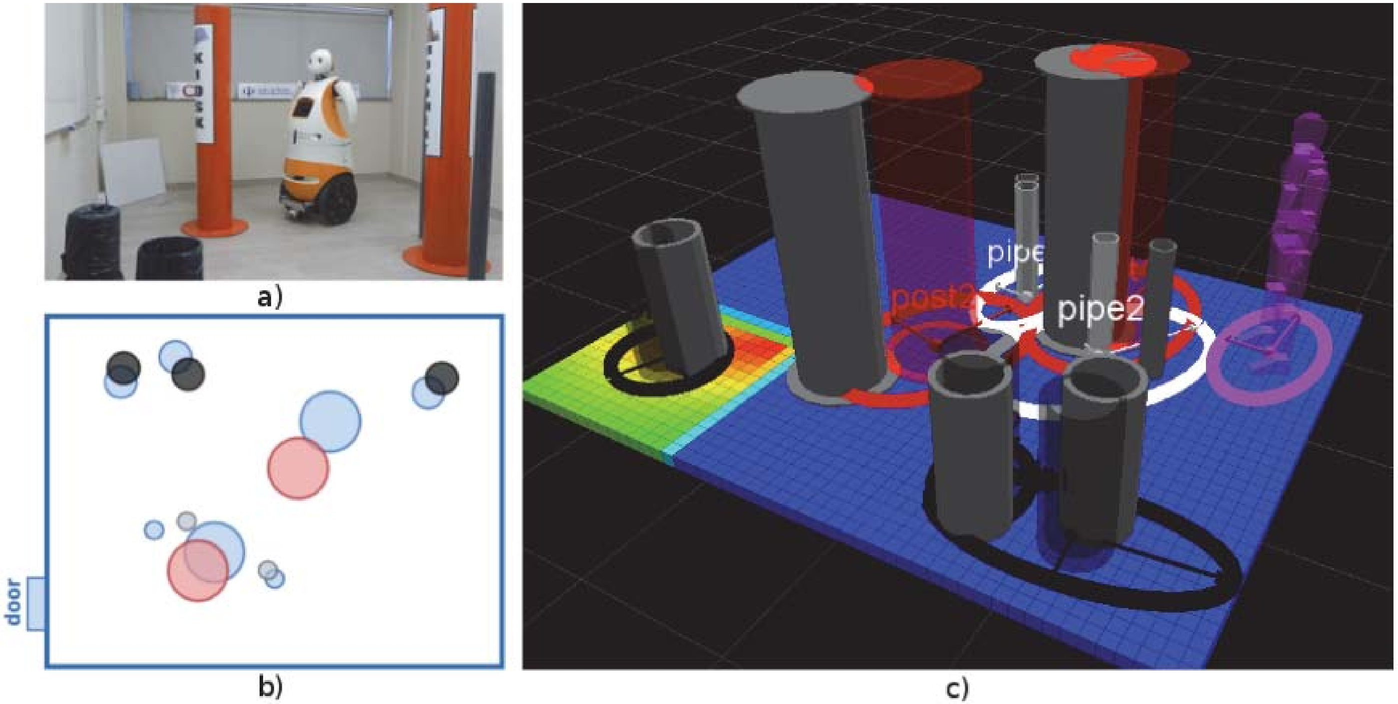


General Scheme

[Retamino and Sanfeliu, 2013]

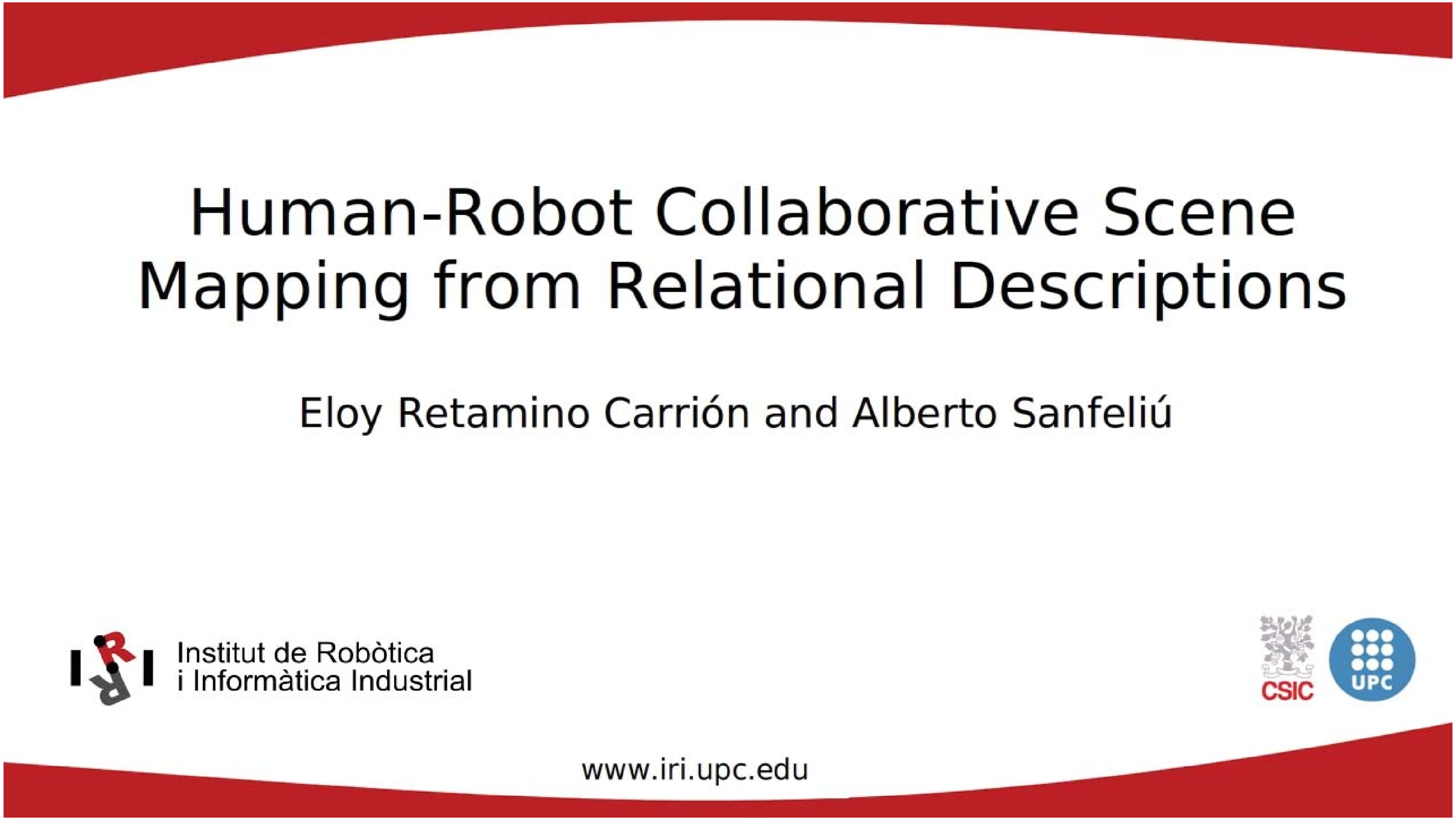
Human-Robot Task Collaboration for Scene Mapping

Objective: Build a through Human-Robot collaboration



Map building

Human Robot Collaboration for Scene Mapping



AERIAL ROBOTICS FOR EMERGENCY SITUATIONS

Aerial Robotics Cooperative Assembly System (ARCAS)

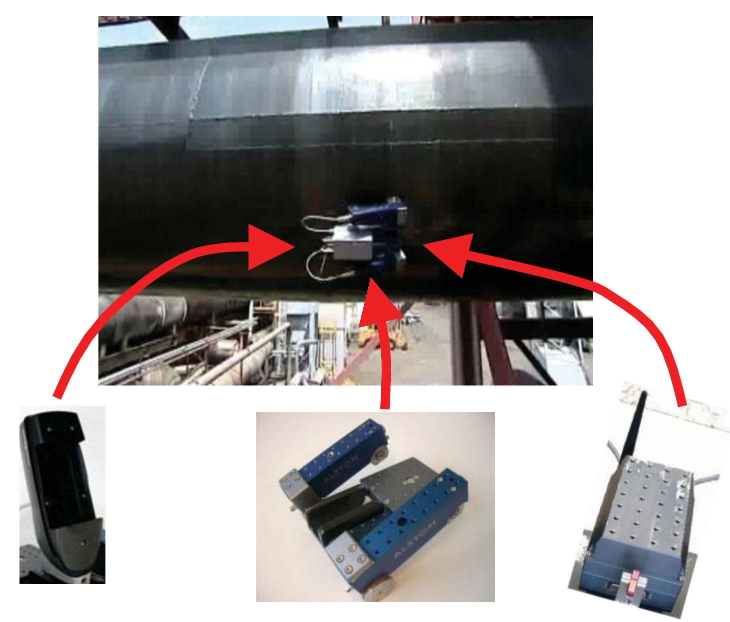
ARCAS Objectives:

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

http//:www.arcas.es

Application Scenarios

Flying + Manipulation + Perception + Multi-robot Cooperation



Project Objectives

Project objectives

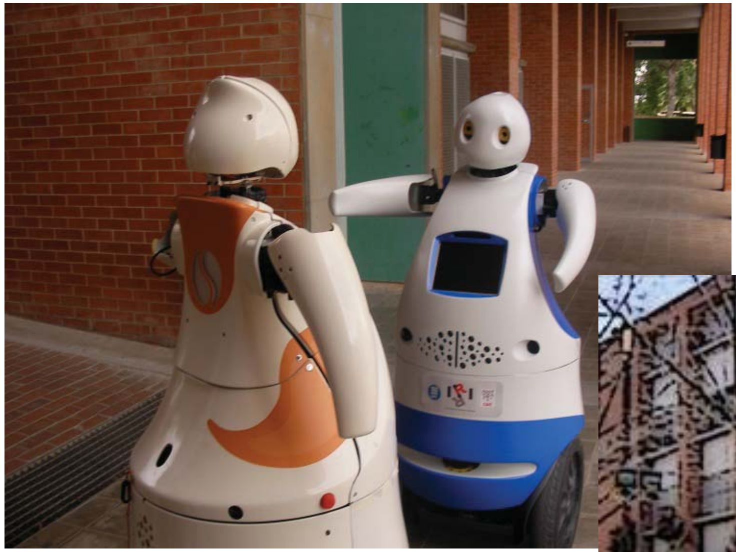
Project Achievements 2^{nd} Year

Project achievements 2^{nd} Year

URBAN ROBOTCS RELATED EUROPEAN AND NATIONAL PROJECTS

Robots Collaborating with People in Every Day Tasks Projects

FP6 URUS (2006-2009); UBROB (2007-2010); RobTaskCoop (2010-2014), Robot-Int-Coop (2014-2017)



Conclusions

- Urban robots are going to play an important role in our lives and they require the design of new architectures, models and methods
- Robots must deal with uncertainty in perception and robot actuation problems in real life tasks
- Robots must include learning and adaptive modes to solve real life tasks
- Human in the loop scheme allows to improve robot perception and action

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Urban Robotics: First Steps

How long we will take to unleash robots in cities?