Mobility Assistance and Human Aware Navigation

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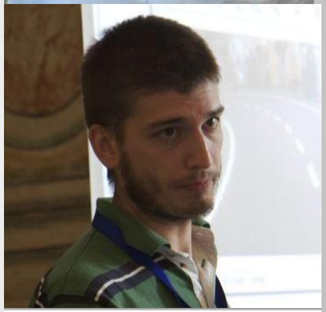
Motivation and Problem

- Transport of people with reduced mobility using a robotic wheelchair in dynamic environments

- Navigation must take into account :
  - Partial and uncertain knowledge of the environment ;
  - Prediction of agents' behavior ;
  - Comfort and safety ;
  - Social conventions.

Mobility Assistance and Human Aware Navigation: 3 topics

- Autonomous navigation in dynamic and human populated environments *(Jorge Rios-Martinez)*



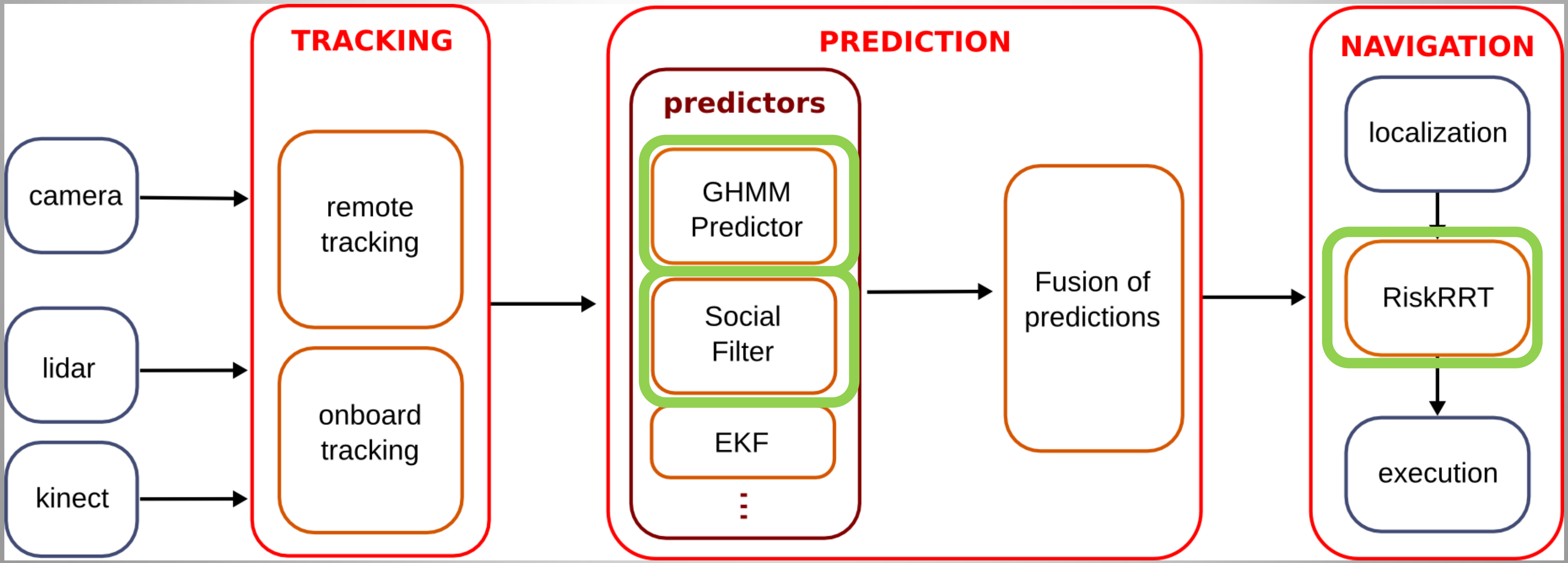
- Navigation using a leader *(Procopio Stein)*

- Human-Robot interface and User intentions understanding *(Arturo Escobedo)*

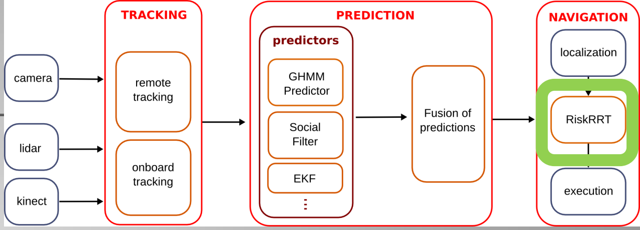
Topic 1: Autonomous navigation in dynamic and human populated environments

Proposed solution :

- Integrated motion-planning and mid-term motion prediction ;
- Interaction detection for socially acceptable robot-motion.



Navigation : RiskRRT *[Fulgenzi 2009]*



Based on the classic RRT framework [2], it takes into account uncertainty of environment sensing and prediction:

- Static obstacles are represented by an occupancy grid.
- Dynamic obstacles are represented by an estimated position and a velocity.
- Prediction of motion for dynamic obstacles is implemented using motion patterns.

Nodes of the tree contain not only position but also a feasible speed for the robot at that time.

The best plan is returned according to a time threshold.

[1] C. Fulgenzi, A. Spalanzani, and C. Laugier, “Probabilistic motion planning among moving obstacles following typical motion patterns”, in IEEE/RSJ International Conference on Intelligent Robots and Systems, 2009.
[2] S. LaValle and J. Kuffner, J.J., “Randomized kinodynamic planning,” Robotics and Automation, 1999.

RiskRRT planner: Risk of collision

The algorithm relies on the Risk of collision (collP):

$$collP = Pcs + (1 - Pcs) * Pcd$$

Pcs= Prob. of Coll. w/ static objects.
Pcd= Prob. of Coll. w/ dynamic objects.

and the weight function (W)

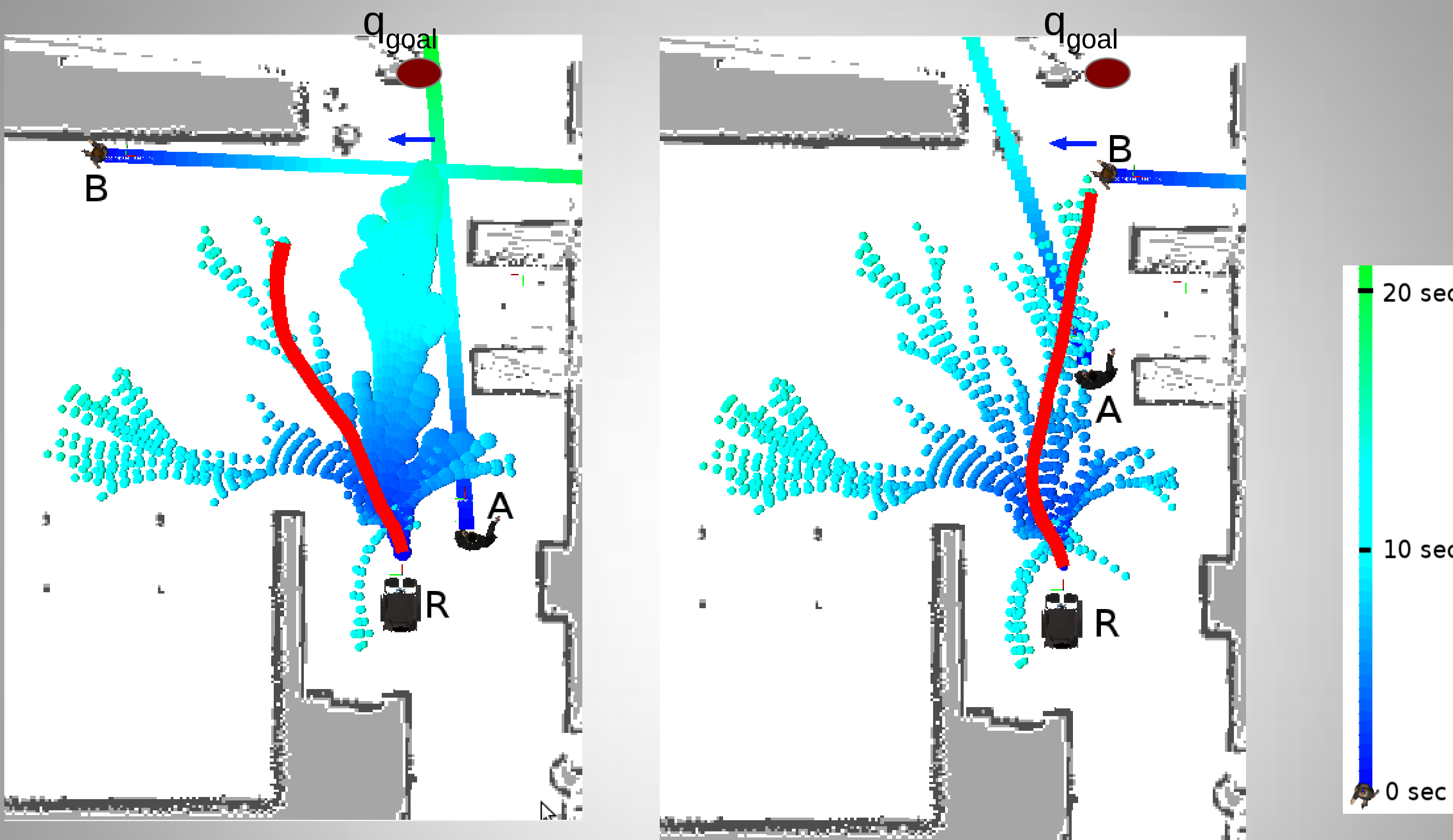
$$W = f(w\_collP, d)$$

d = distance to goal
w_collP = the worst collP among previous nodes in the same branch.

calculated on each node, to choose the best path.

Best path is the partial branch that finishes in the node with minimum W.

RiskRRT planner: illustration



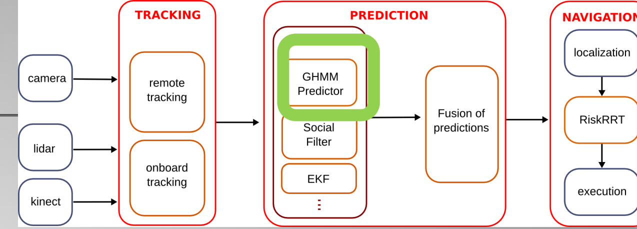
t *t + 10*

A, B two pedestrians

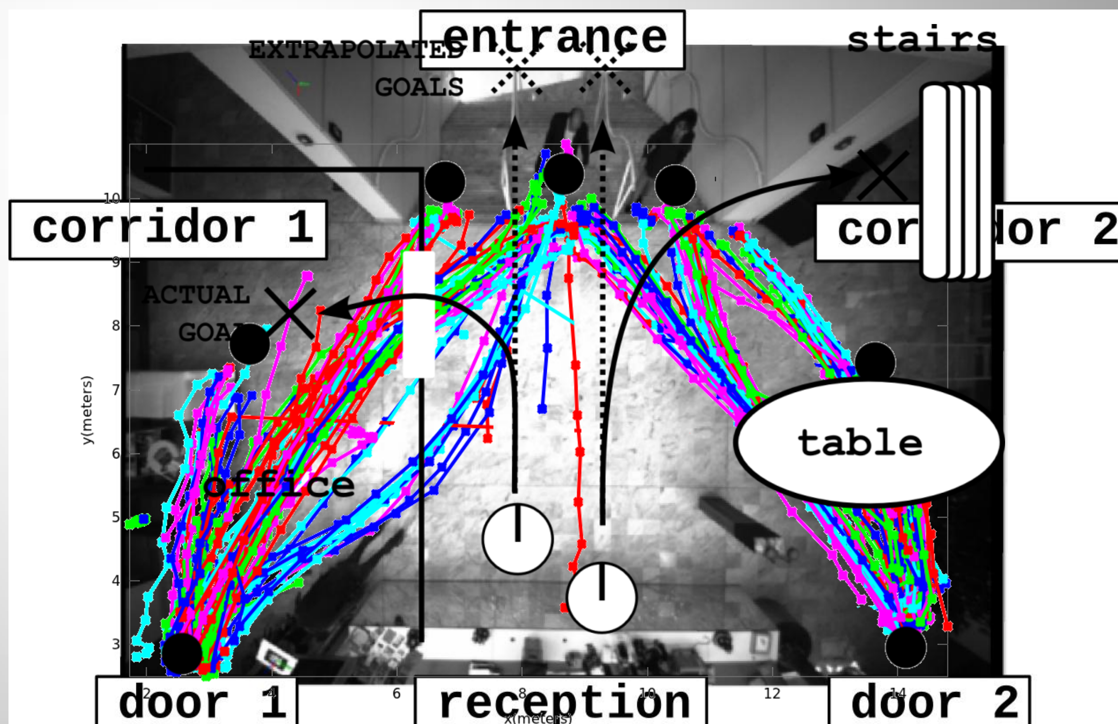
q_{goal} Goal of Robot R

Size of nodes is Risk of collision

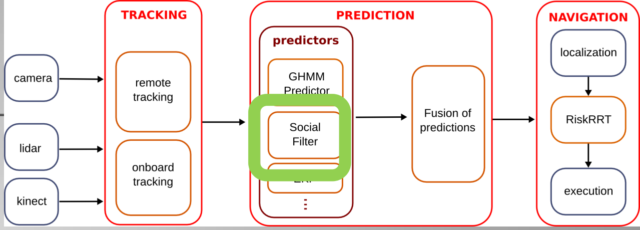
Trajectory prediction



- Humans do not move at random, instead they follow typical paths
- Modeling typical paths:
  - Gaussian Processes [Tay 2007, Ellis 2009, Kim 2011]
  - Growing Hidden Markov Models [Vasquez 2009]



Human management of space



- Personal Space [3]

Zone around the human body that people feel is “their space”. In that zone others cannot intrude without arousing discomfort.

- O-Space [4]

Groups can establish a joint or shared area which only participants have permitted access to it, they protect it and others tend to respect it.

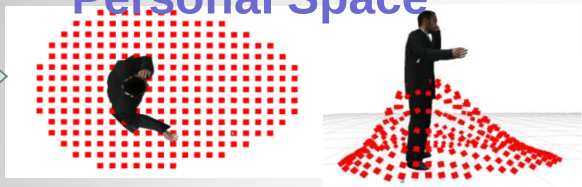
Disturbance to these spaces causes discomfort to people

[3] Hayduk, L. A. (1978). Personal space: An evaluative and orienting overview. Psychological Bulletin .
[4] Kendon, A. (2010). Spacing and orientation in co-present interaction. In Development of Multimodal Interfaces: Active Listening and Synchrony, volume 5967 of Lecture Notes in Computer Science .

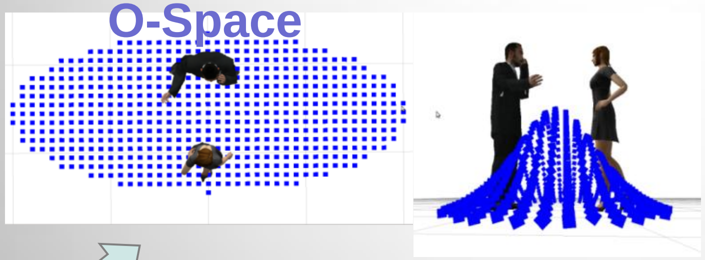
The Social Filter

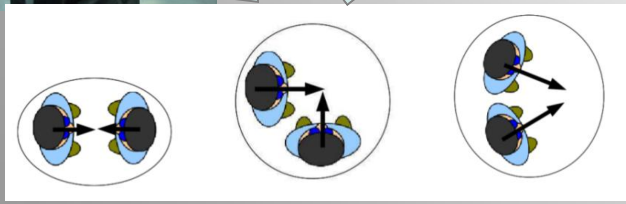
From the models of social conventions, a Risk of disturbance is included as part of the Risk of Collision in the RiskRRT algorithm.

Personal Space

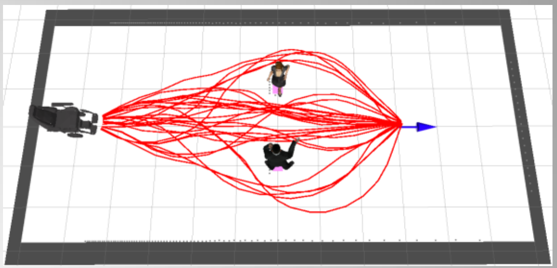


O-Space

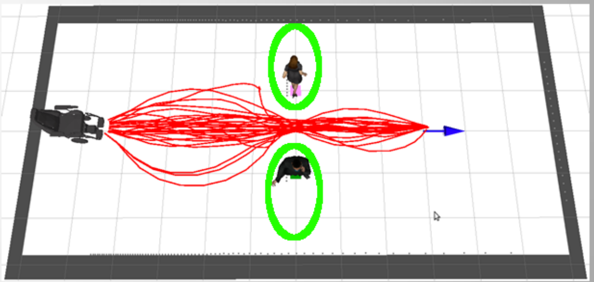




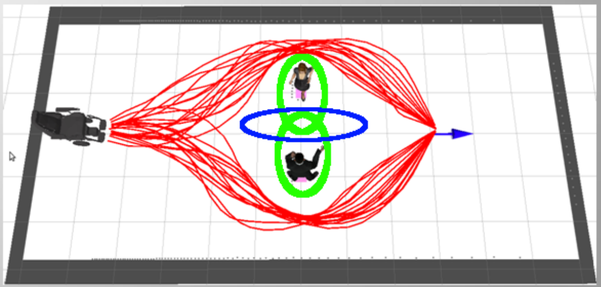
- Planning without Social Filter



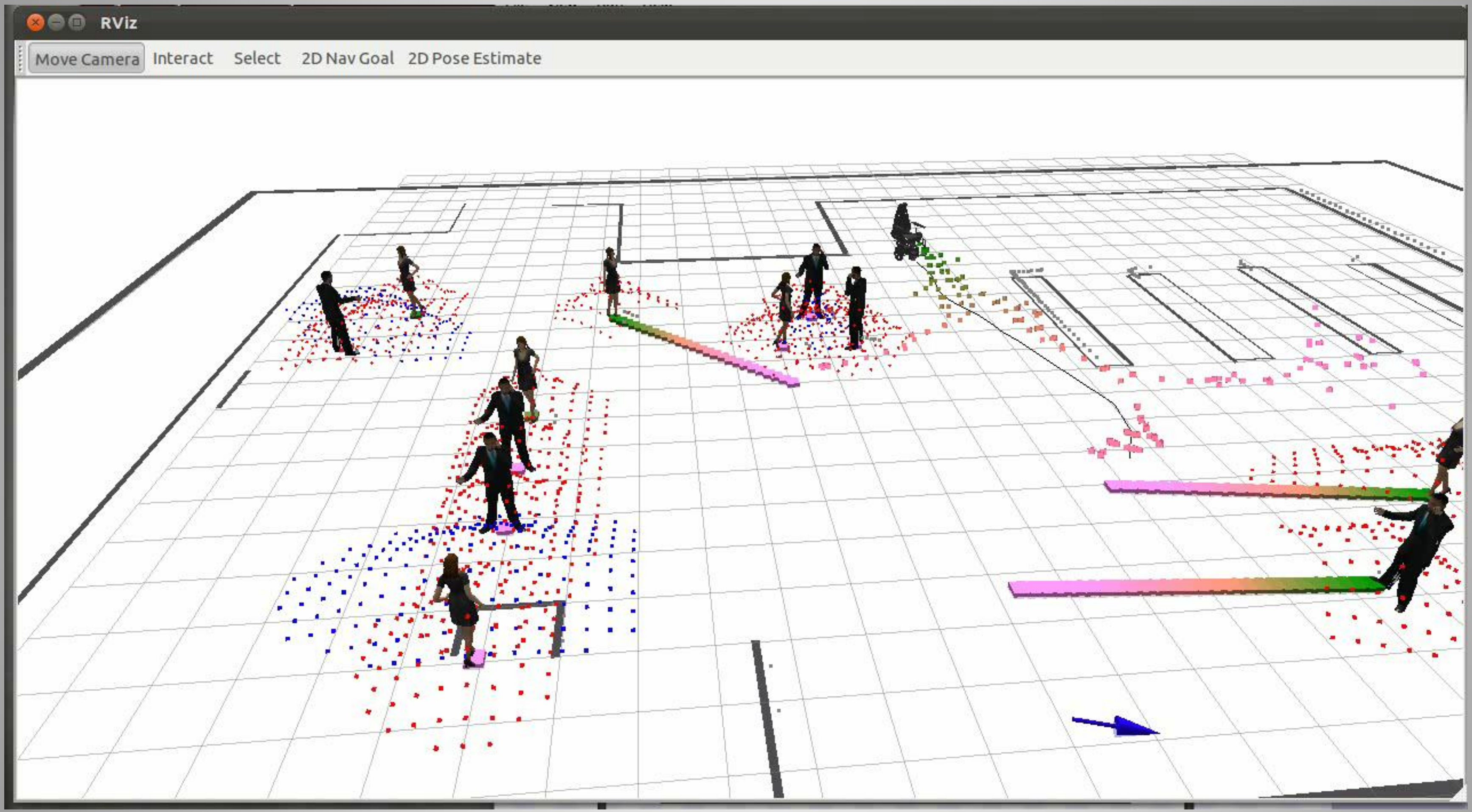
- Planning with Social Filter back to back



viz a viz: interaction zone



Navigation using social conventions and prediction



Topic 2: Navigation using a leader

take advantage of moving agents during navigation in dynamic environments

Innorobo 2012

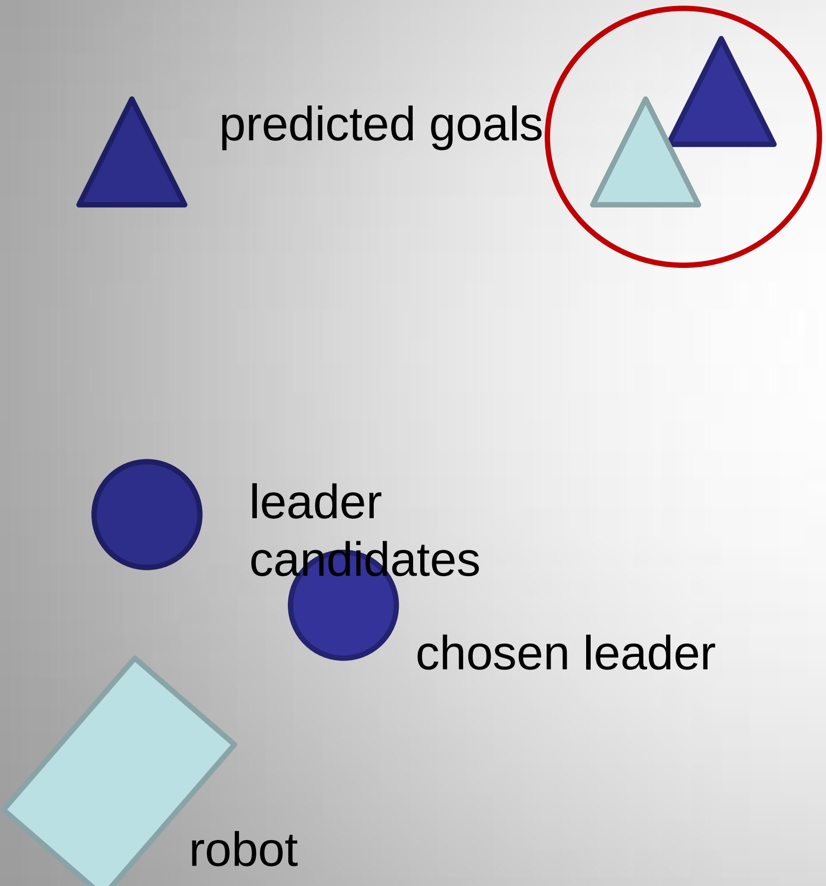
Main advantages:

- *Reduce computational requirements*
- *Escape Freezing Robot Problem*
- *Better acceptance by humans*
- *Avoid undetected obstacles (spilled coffee)*

Algorithm for selecting and following a leader

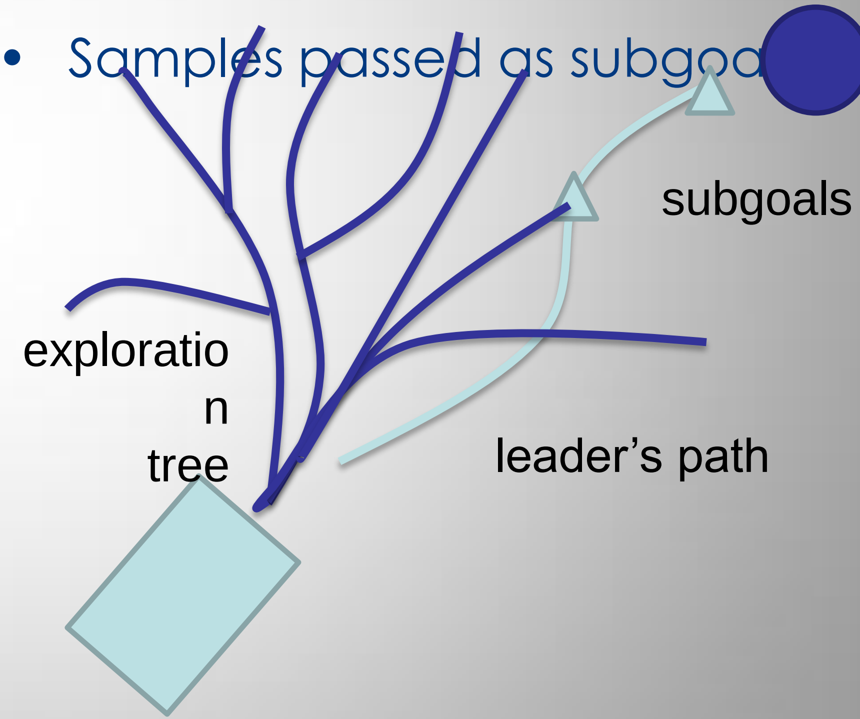
Leader Selection

- Goal similarity



Leader Following

- RiskRRT algorithm [Fulgenzi 2008]
- Leader path tracked
- Samples passed as subgoals



Experiments

REAL DATA + SIMULATION

- GHMM trained with real data
- Simulated Robot
- Fiducial markers were worn as hats
- Overhanging camera + wide angle lens
- People moved among interest points

- **Two types** of tests were conducted:
  - **leader detection and following**
  - **leader following among people**

Experiments: real data + sim

leader **detection and following**

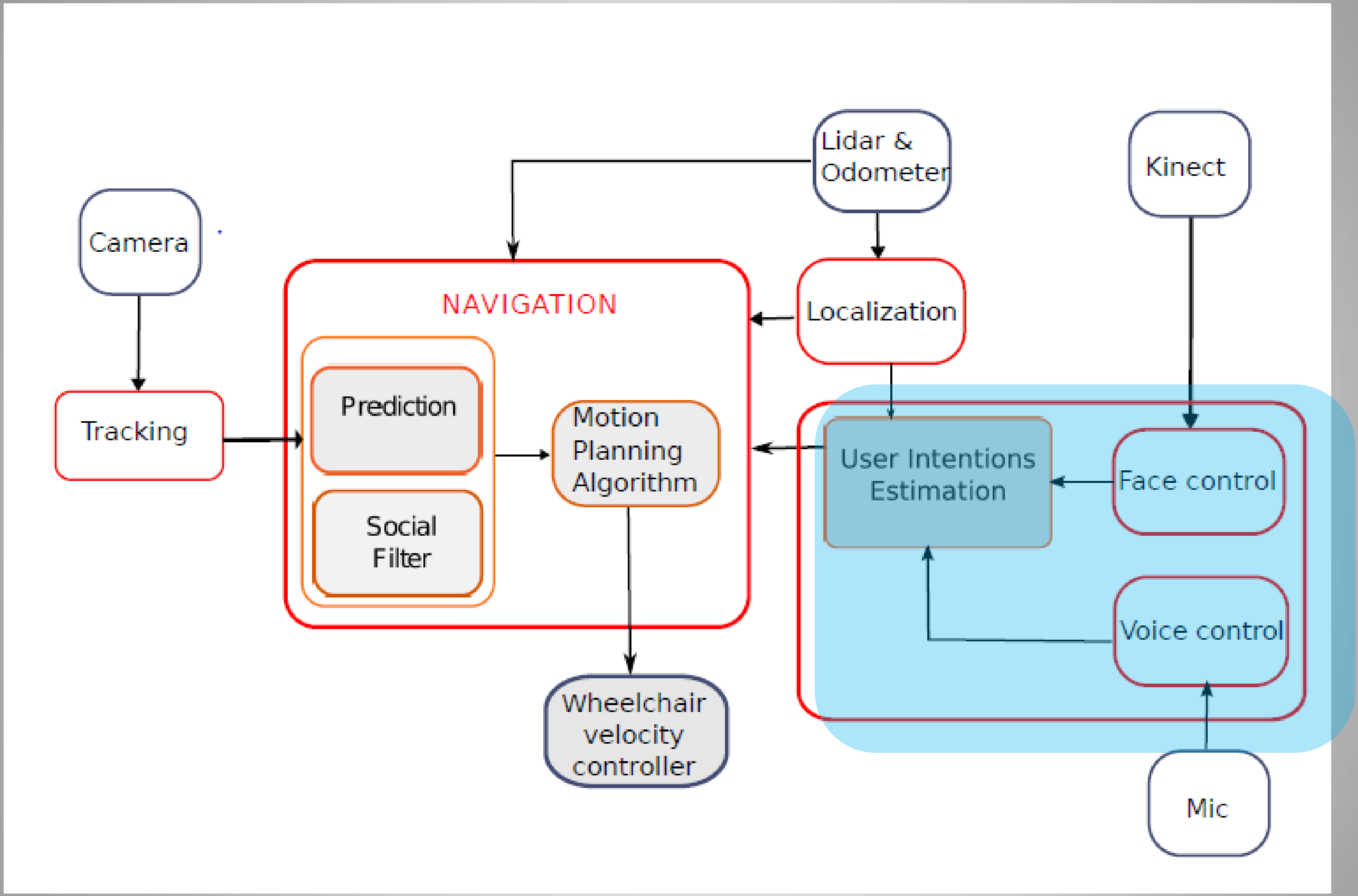
leader **following among people**

people naturally give room for the leader to pass.
the robot benefits from this space

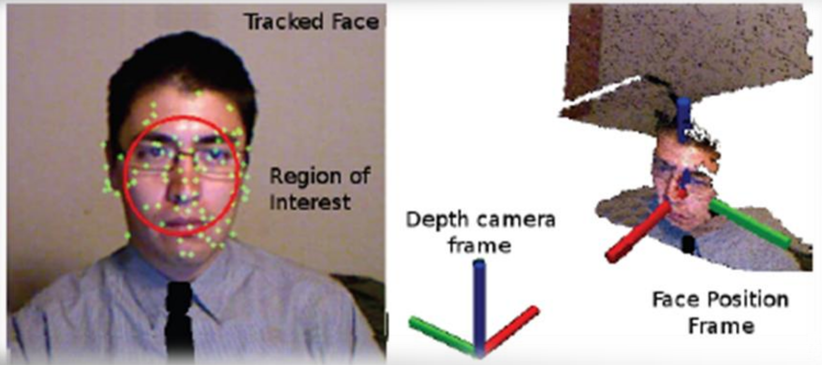
Experiments

- Goal: **Leader following** to escape **frozen** situations;
- Reduction of 25% in time spent to reach goal, when following a leader.

Topic 3: Understanding the user intention

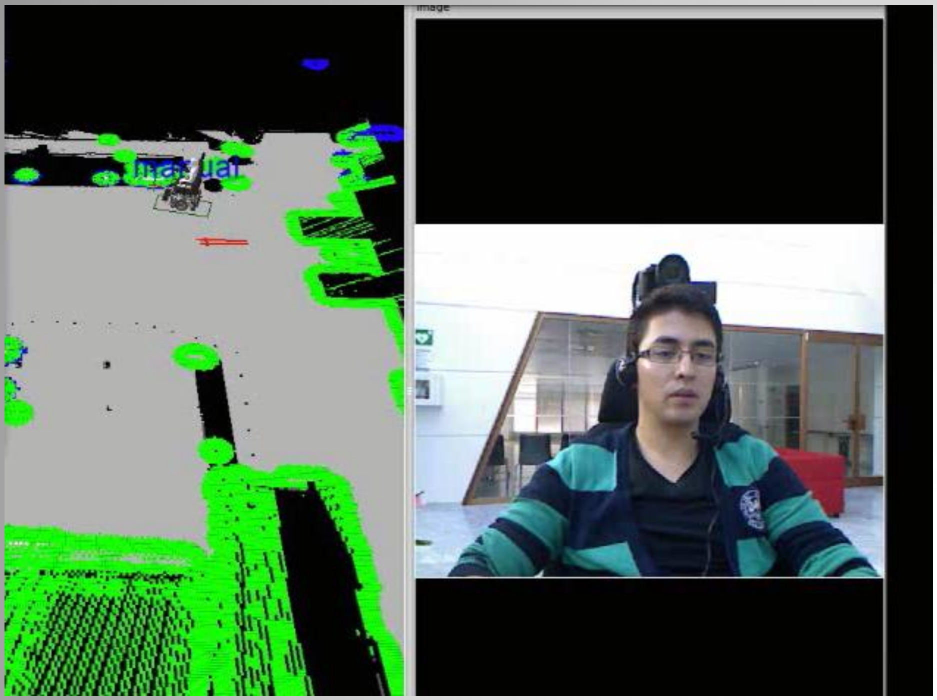


Human-Robot interface: Face Control



- Face pose estimation using random regression forests [Fanelli 2011]
- Angular speed proportional to face heading angle
- Linear speed remains constant (limitation)

Adding a new modality: Face Control + Voice Recognition



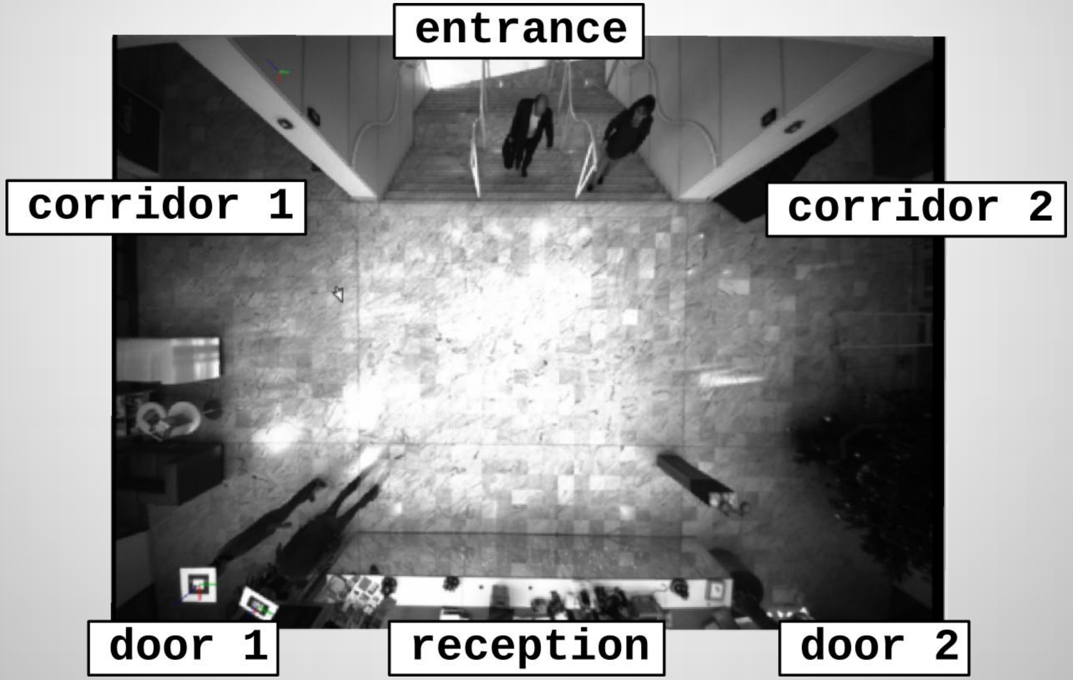
- Some simple voice commands are employed to improve usability.
  (Go, Back, Brake, Faster, Slower).
- Linear speed can be adjusted by the user.
- Voice recognition -> pocketsphinx (Carnegie Mellon University).

Main Drawbacks

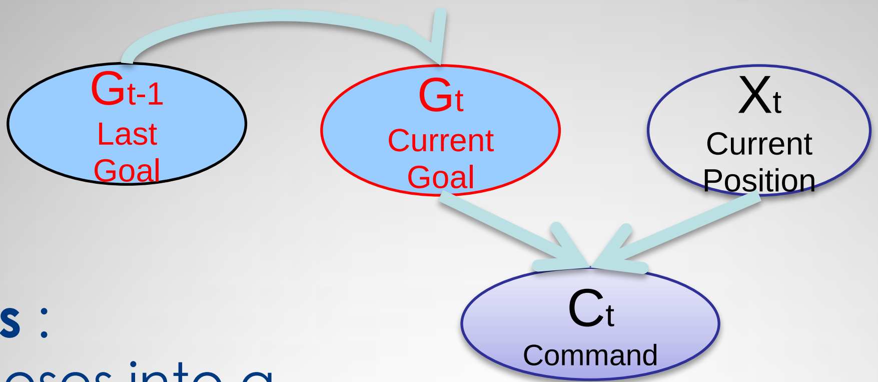
- Fatigue due to prolonged focusing while driving.
- Unwanted movements when the user moves the head without really aiming to control the wheelchair.

User Intention Estimation FROM FACE POSITION.

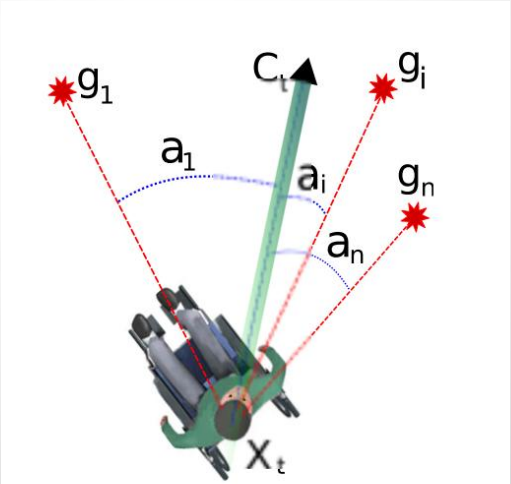
Idea: Use of contextual information (important places in the environment), user habits, and orders from a face tracking system to infere the user's desired destination.

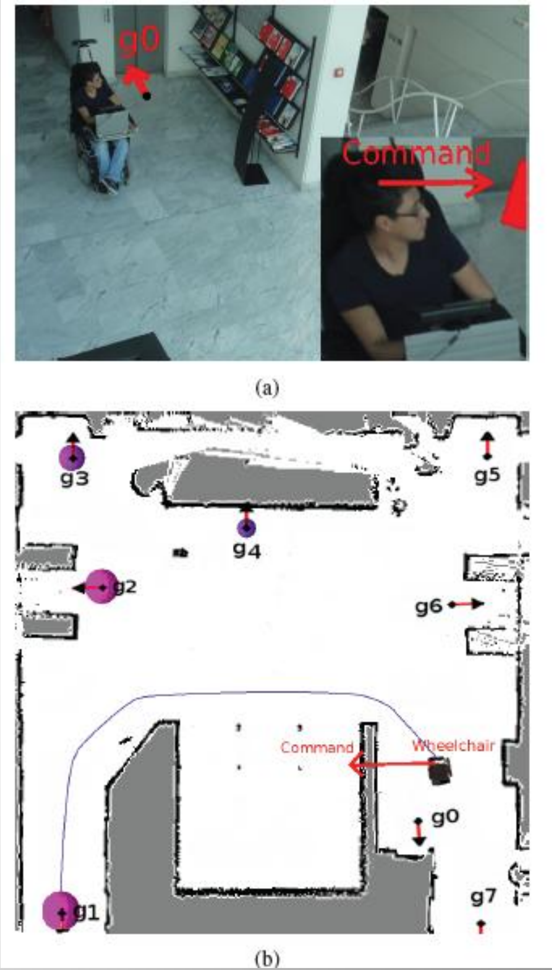


User intention: bayesian network model



- **User intentions** : topological poses into a predefined map
- **Estimate the user's intended goal G** from the **current position X**, the **user command C** and the **prior knowledge of the environment**





USER INTENTION Bayesian MODEL

$$P(G_t^i|C_tX_t) = \eta P(C_t|X_t\ G_t^i)\sum_j P(G_t^i|G_{t-1}^j)\,P(G_{t-1}^j|C_{t-1}X_{t-1})$$

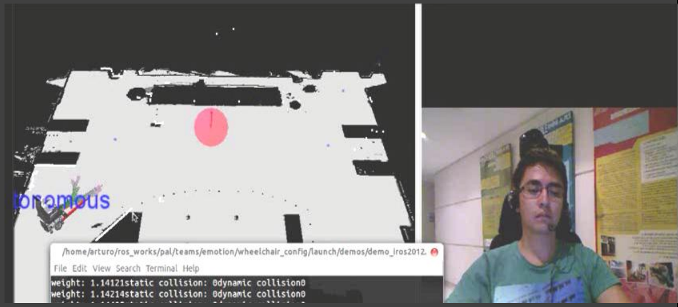
$P(G_t^i|C_tX_t)$: Current probability for the Goal (i) to be the intended destination.

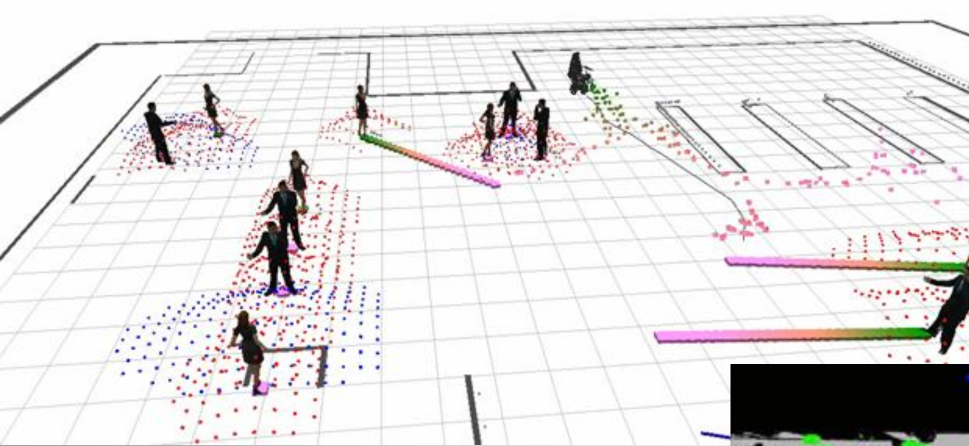
$P(C_t|X_t\ G_t^i)$: User model, Probability of pointing in the direction of the goal.

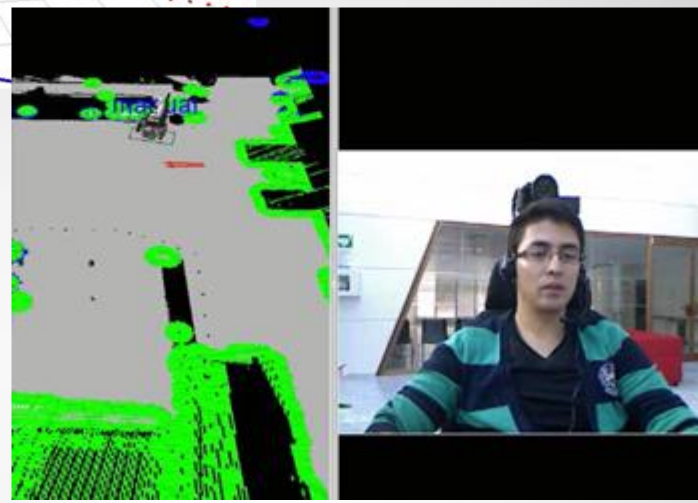
$P(G_t^i|G_{t-1}^j)$: Probability of changing the previous estimated goal.

$P(G_{t-1}^j|C_{t-1}X_{t-1})$: Previous Estimated Probability

η: Proportionality Constant







THANK YOU FOR YOUR ATTENTION !

50 commandes

- Trouve moi la sortie
- Trouve moi le banc
- Fais-moi passer le passage piéton
- Passe la porte
- Prend le couloir
- Donne moi l'escalier
- Continue – avance
- Trouve le passage