ICRA26 **Workshop on Pedestrian Behaviour Prediction**

Vienna, Austria, June 1st, 2026

Proactive Autonomous Navigation in Human Populated Environment

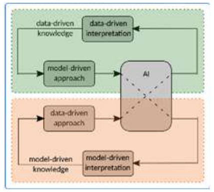
Philippe Martinet

Director of Research
ACENTAURI team
Inria Sophia-Antipolis

Inria ACENTAURI

ACENTAURI: **A**rtifi**C**ial int**E**lligence and efficie**NT A**lgorithms for a**U**tonomous **R**obot**I**cs

Created in May 2021, https://team.inria.fr/acentauri



Goal : study **intelligent, collaborative, mobile** and **autonomous** robots.

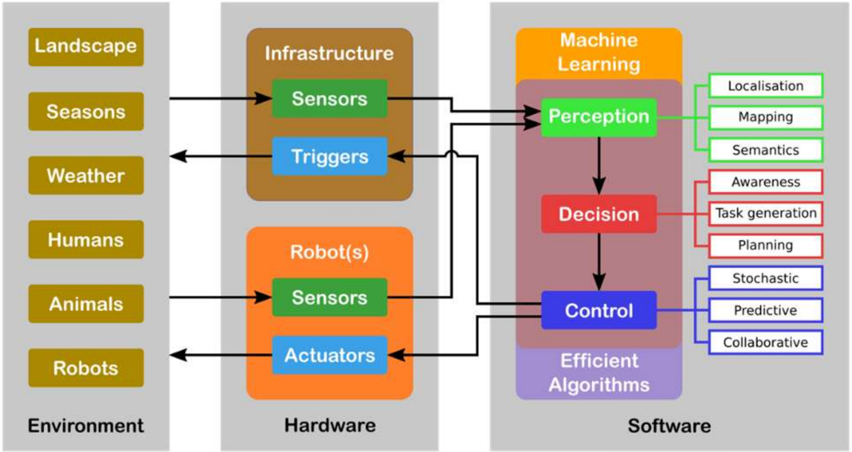
- Develop **real-time perception of complex and dynamic environments** in order to build large scale semantic representations that can be shared to other robots
- Develop **intelligent robots** able to (i) decide their actions in real-time (ii) manage uncertainty (iii) predict in real-time the future states (iv) acquire new capacities
- Develop **autonomous collaborative robots** able to accomplish complex task taking high-level cognitive-based decisions without human intervention
- Develop **efficient optimization methods and algorithms** to process large amount of data and solve hard problems in robotic perception, decision and control.

Research Axes:

- **A**: Augmented spatio-temporal **perception** of complex environments
- **B**: Situation awareness for **decision** and planning
- **C**: Advanced multi-sensor **control** of autonomous multi-robot systems

Applications field

- Transportation of people and goods with autonomous connected vehicles
- Environment monitoring with a collaborative robotic system



Autonomous Navigation in Dynamic and Human Populated Environments

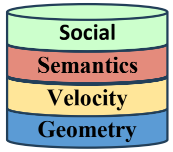
Where I want to go?

Defining the goal and a task in a representation (Map)

Where I am and in which situation I am?

Localization and situational awareness

What is the good representation for the dynamic environment?



Multi layer description of the dynamic environment

What the different agents will do next?

Prediction in presence of the hidden dimension of human

How to decide? Is it possible to acquire new knowledge and being proactive?

Vehicle-Human interaction model, Social force model, Proactive navigation

Autonomous Navigation in Dynamic and Human Populated Environments

Shared space in Inner city Sonnenfelsplatz, Graz, Austria

- Navigation in close interaction with pedestrians.
- Non structured environment
- No priority rules
- Low speed limit

Crowdbot: Safe Robot Navigation in Dense Crowds

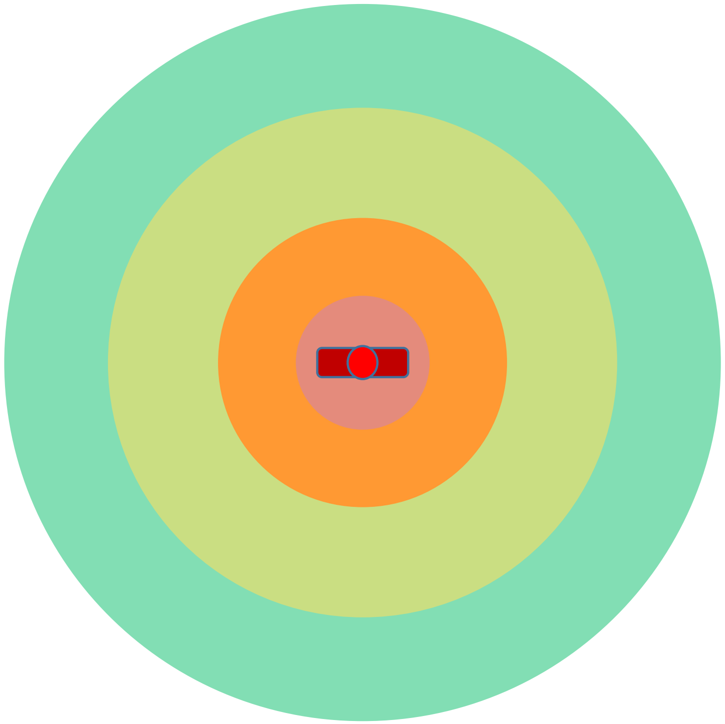
- Navigation in close interaction with pedestrians.
- Structured and encumbered environment
- No a priori traffic rules
- Social cooperability

PPMP: Powered Personal Mobility Platforms PLEV: Personal Light Electrical Vehicle






Space around humans



[1] The Hidden Dimension: Hall, Edward T., 1966

Intimate Space
embracing, touching or whispering

Personal Space
interactions among good friends or family

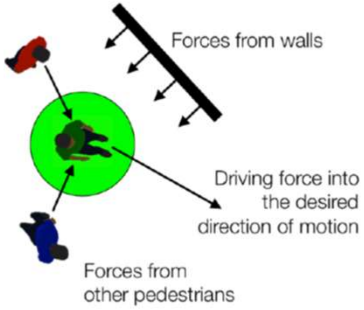
Social Space
interactions among acquaintances

Public Space
public speaking

Social Force Model

Attraction $\mathbf{f}_i^0 = m_i \frac{v_i^0(t)e_i^0 - \mathbf{v}_i(t)}{\tau_i}$

Force applied on the pedestrian in the SFM: [12] $\mathbf{f}_i = \mathbf{f}_i^0 + \mathbf{f}_i^e$ Repulsion



f_i Total force applied on pedestrian i

f_i^0 Driving force towards the goal applied on pedestrian i

f_i^e Sum of the interaction force applied on pedestrian i

$$f_i^e = \sum_{j(\neq i)} f_{ij} + \sum_{o\in O} f_{io}$$

$f_{ij} = A_i e^{(r_{ij}-dij)/B_i} n_{ij}$

$f_{io} = A_o e^{(r_i-dio)/B_o} n_{io}$

f_{ij} Interaction force between pedestrian i and pedestrian j

f_{io} Interaction force between pedestrian i and obstacle o

Headed Social Force Model (HSFM) [13]

Force input

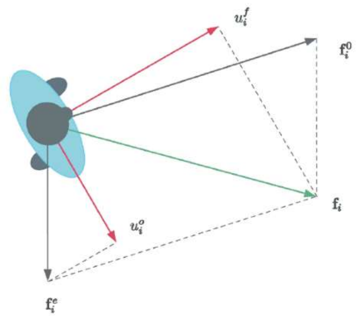
$u_i^f = \left(\mathbf{f}_i^0 + \mathbf{f}_i^e\right)^\top \mathbf{r}_i^f$ Projection along the forward direction

$u_i^o = k^o \left(\mathbf{f}_i^e\right)^\top \mathbf{r}_i^o - k^d v_i^o$ Projection along the orthogonal direction

Torque input

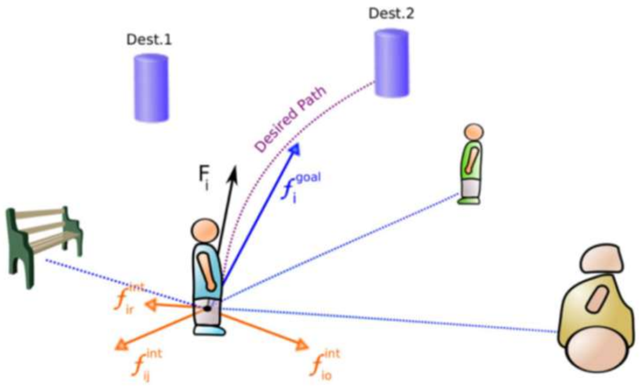
$u_i^\theta = -k^\theta\left(\theta_i - \theta_i^0\right) - k^\omega \omega_i$ Torque about the vertical axis which drives the dynamics of the pedestrian's heading

$$\mathbf{R}(\theta_i) = \begin{bmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{bmatrix} \doteq [\mathbf{r}_i^f \ \mathbf{r}_i^o]$$



Force decomposition in the HSFM [11]

Extended Social Force Model (ESFM) [14]



$$\mathbf{f}_i^e = \sum_{j(\neq i)\in N} \mathbf{f}_{ij}^{int} + \sum_{o\in O} \mathbf{f}_{io}^{int} + \sum_{R} \mathbf{f}_{ir}^{int}$$

Pedestrian Obstacle Robot

[12] D. Helbing, I. Farkas, and T. Vicsek (2000). "Simulating Dynamic Features of Escape Panic". In: Nature

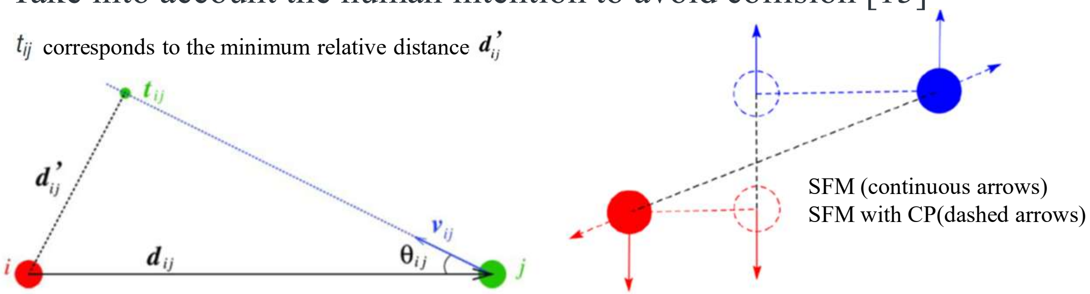
[13] F. Farina et al. (2017). "Walking Ahead: The Headed Social Force Model". In: PLOS ONE

[14] G. Ferrer et al. (2017). "Robot social-aware navigation framework to accompany people walking side-by-side". In: Autonomous Robots

Extended Headed Social Force Model (EHSFM) with Collision Prediction (CP)

Take into account the human intention to avoid collision [15]

t_{ij} corresponds to the minimum relative distance $\boldsymbol{d}'_{ij}$



(a) Definition of t_{ij} (b) Description of the interaction force

$$t_i = \min_j \{t_{ij}\} \quad \boldsymbol{f}_{ij}^{int}(\{d_{ij}\}, \{v_{ij}\}, v_i) = A_s \frac{v_i}{t_i} e^{-d_{ij}/B_s} \frac{\boldsymbol{d}'_{ij}(t_i)}{d'_{ij}(t_i)}$$

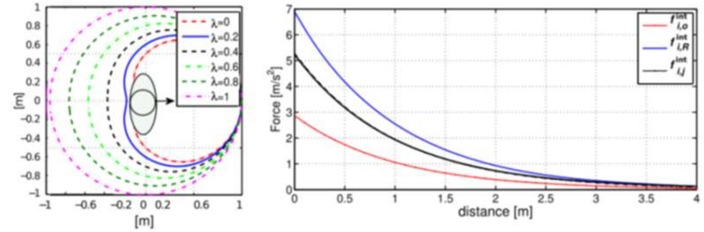
[15] F. Zanlungo, T. Ikeda, and T. Kanda (2011). ***"Social force model with explicit collision prediction"***. *In: EPL (Europhysics Letters)*

Range of view [16]

$$w_{\psi_{ij}} = \left(\lambda + (1-\lambda)\frac{1+\cos(\psi_{ij})}{2}\right)$$

$$\text{with } \cos(\psi_{ij}) = \overrightarrow{e_i} \cdot \overrightarrow{n_{ij}}$$

$$\boldsymbol{f}_i = \boldsymbol{f}_i^0 + w_{\psi_{ij}} * \boldsymbol{f}_i^e$$



[16] G. Ferrer et al. (2017). ***"Robot social-aware navigation framework to accompany people walking side-by-side"***. *In: Autonomous Robots*

Add evaluation of different kinds of people:

- Degree of participation
- Group behavior

Degree of participation $\sigma \in (0,1]$

$$\boldsymbol{f}_i^e = \sum_{j(\neq i)\in N} \boldsymbol{f}_{ij}^{par} + \sum_{o\in O} \boldsymbol{f}_{io} + \sum_{r\in R} \boldsymbol{f}_{ir}$$

Group Behavior

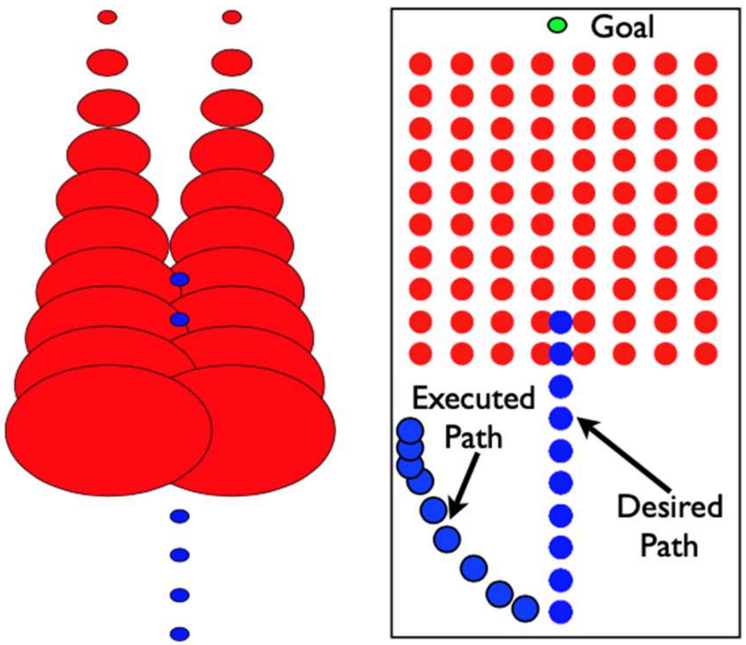
Spring force between each member in a subgroup

$$f_{gr} = k_1(d_{gr} - l_{gr})$$

$$\text{with } k_1 = \begin{cases} \kappa \dfrac{\cos\left(\frac{\angle \overrightarrow{e_i}, \overrightarrow{e_j}}{2}\right)}{l_{gr} * \|v_i - v_j\|^2} & \text{if } d_{gr} < d_0^{gr} \\ 0 & \text{otherwise} \end{cases}$$

$$f_i = f_i^0 + f_i^e + f_i^{gr}$$

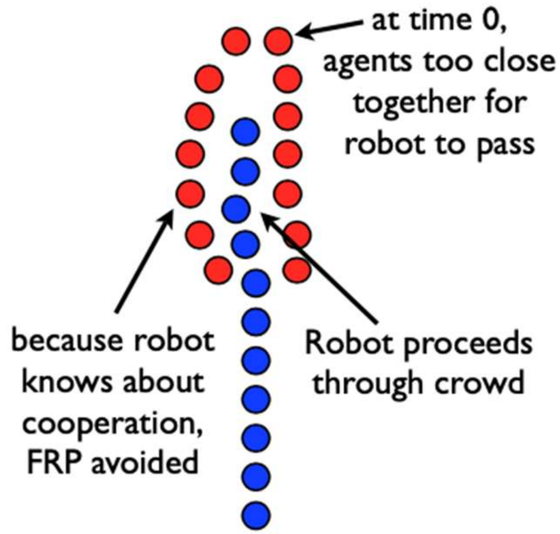
Freezing Robot Problem (FRP)



Freezing Robot Problem due to uncertainty and no collaboration [9]

[9] - P. Trautman and A. Krause, "Unfreezing the robot: Navigation in dense, interacting crowds," 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2010, pp. 797-803, doi: 10.1109/IROS.2010.5654369.

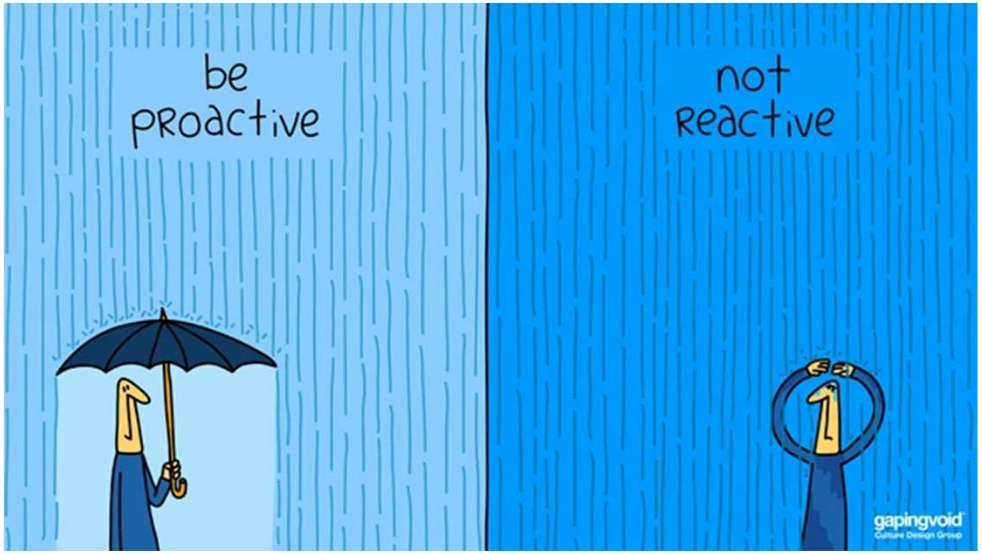
How is solved the FRP?



Freezing Robot Problem solved considering the collaboration between human robot[10]

[10] - P. Trautman and A. Krause, "Unfreezing the robot: Navigation in dense, interacting crowds," 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2010, pp. 797-803, doi: 10.1109/IROS.2010.5654369.

Reactive vs Proactive



	Reactive	**Proactive**
Collision avoidance	🙂	🙂
Freezing Robot	☹️	🙂
Anticipation skill	😐	🙂
Legible motion	☹️	🙂

Reactive	Stimuli → Reaction → New Stimuli
Proactive	Anticipated Stimuli → Proaction → Stimuli

"While the static environment does not provide any navigable solution, proactions can produce the emergence of a dynamic navigable solution to avoid the robot to be frozen. " P. Martinet

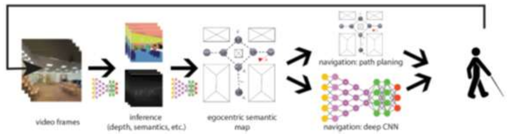
Our work

Robot-Human interaction

MOBIDEEP project
Crowdbot project

Uncertainty-Aware Collaborative Navigation in Crowded Environment (Emmanuel Alao)

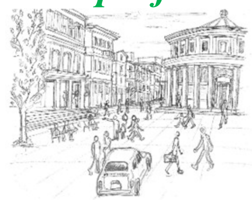
Autonomous navigation in human populated environment (Enrico Fiaché)



AV-Human interaction

HIANIC project

Proactive, Cooperative and Social Navigation Framework (Maria Kabtoul)



AV-PLEV interaction

ANNAPOLIS project

Multi-Risk-Aware Autonomous Navigation under Uncertainty induced by Personal Light Electric Vehicles (Emmanuel Alao)

Content

Introduction

Robot-Human interaction

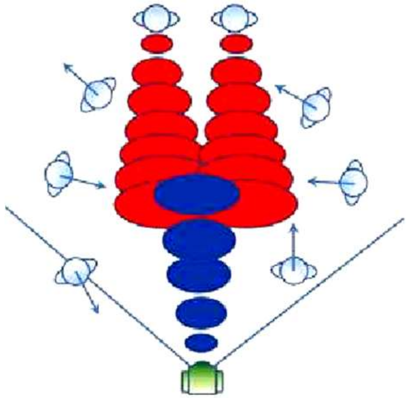
AV-Human interaction

AV-PLEV interaction

Conclusion and future prospects

Uncertainty-Aware Collaborative Navigation in Crowded Environment

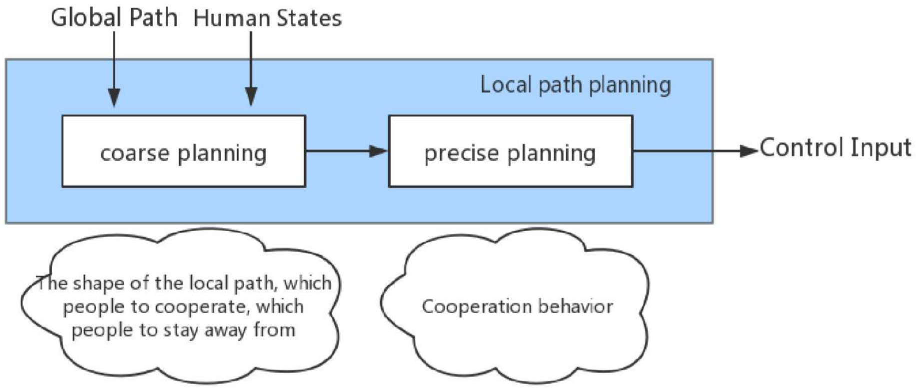
- **The main goal**
  - avoid *Freezing Robot Problem - FRP*.
- *Freezing Robot Problem – FRP* **:**
  - Occurs, when agents in a crowd are modeled independently of each other
  - Leading to a *massive uncertainty*
  - Robot is frozen in one place, thinking that every possibly predicted path leads to a collision
- **Problem definition:**
  - study and development of *uncertainties-aware*
    - collaborative navigation strategies
      - promote *socially accepted pro-active control actions*
        - *future time horizon*
          - uncertainties in the prediction of human locomotion.
- **Implication:**
  - robot must be *aware* of *uncertainties* in the dynamics of the robot and pedestrians
  - *uncertainties* in the perceived *position*, *velocity* and *other states* of the humans in the crowd
  - Performance in Real-time



Uncertainty explosion due to uncorrected prediction. *Freezing Robot Problem – FRP*

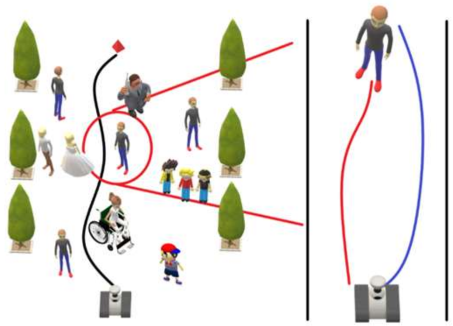
Uncertainty-Aware Collaborative Navigation in Crowded Environment

Advancement in Robot Perception[17]



- [18] proposed Cooperative Model Predictive Control(CMPC) Local planner for co-navigation between the human and the robot.

- **Limitations**
  - **Perfect knowledge of pedestrian state**
  - **MPC not in Robot Frame**
  - **Not real-time**

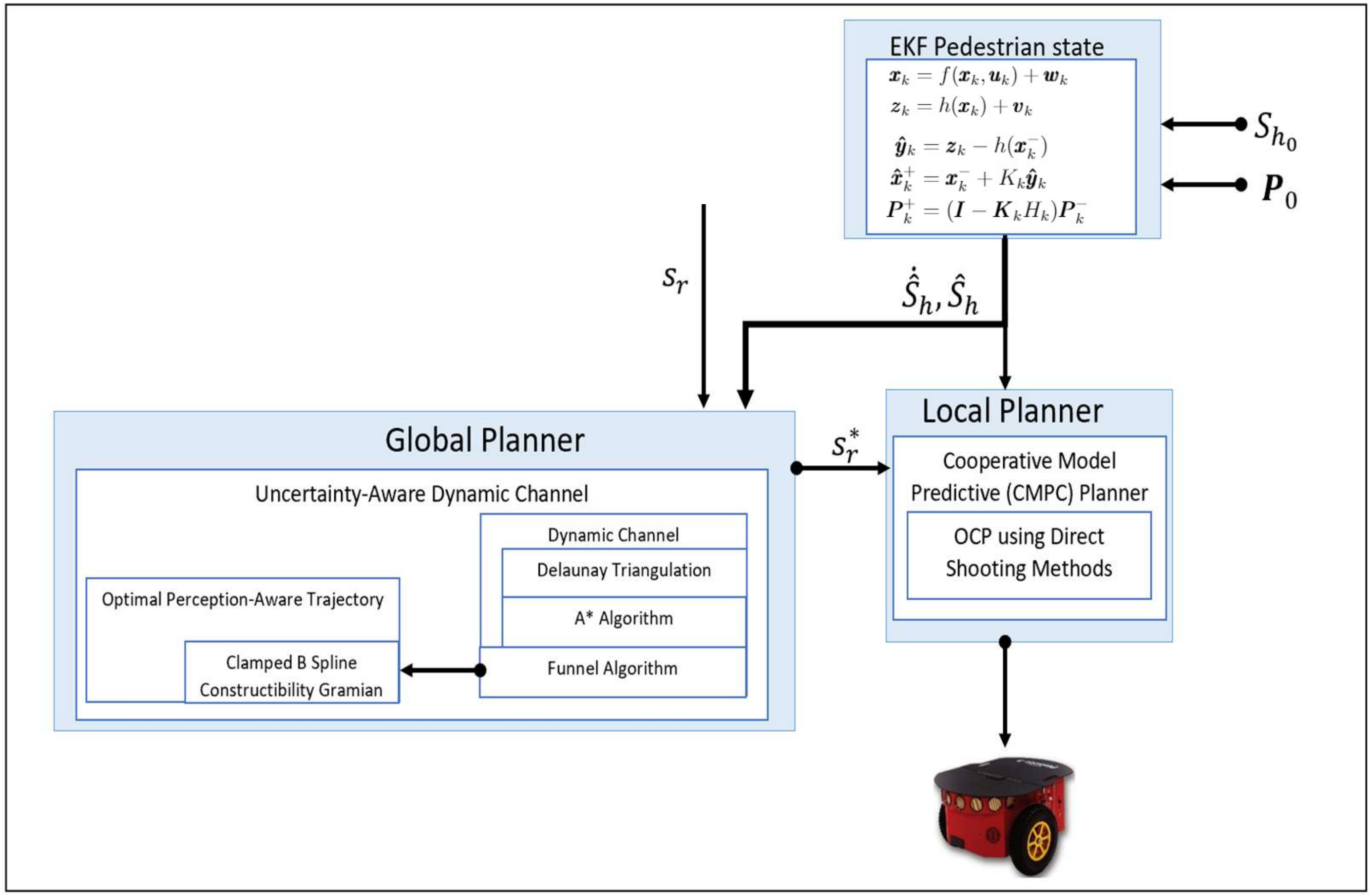


Two steps of the path planning[18]

[17] Towards Data Science "https://towardsdatascience.com/pedestrian-tracking-in-real-time-using-yolov3-33439125efdf"
[18] W. Jin, "Proactive-cooperative navigation in crowded environments for autonomous robots,"

Uncertainty-Aware Collaborative Navigation in Crowded Environment

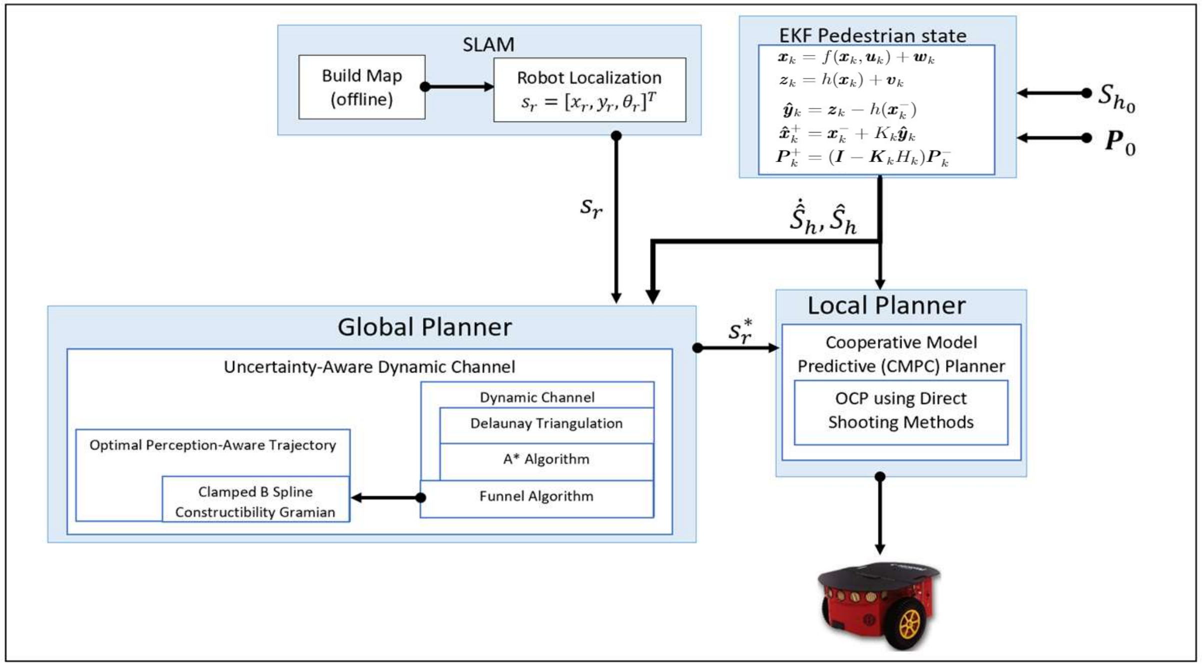
- To develop a dynamic model for estimating the pedestrian’s states.
- To develop an uncertainty-aware dynamic path through the crowd
- To develop an uncertainty-aware NMPC planner for autonomous navigation
- Real-time simulation and experimentation of the planner

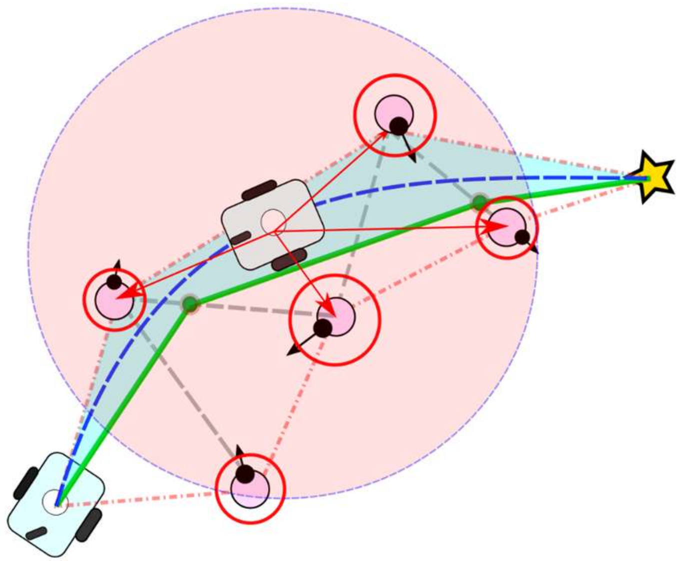


Global Architecture

Uncertainty-Aware Collaborative Navigation in Crowded Environment

❑ Global Architecture



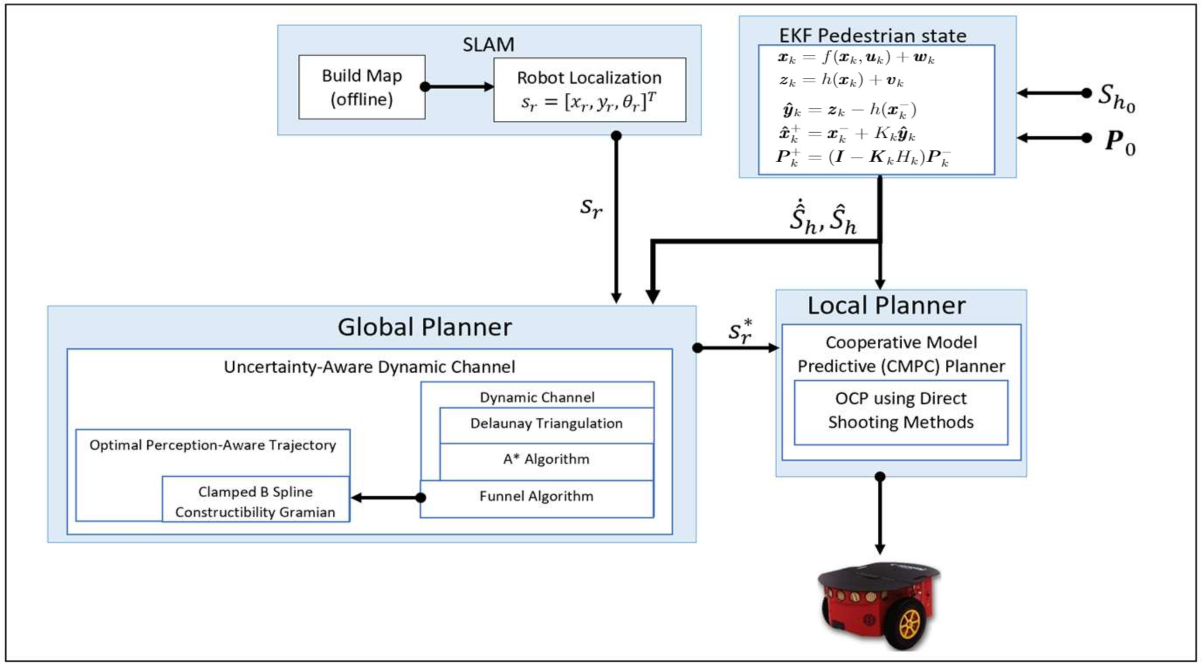


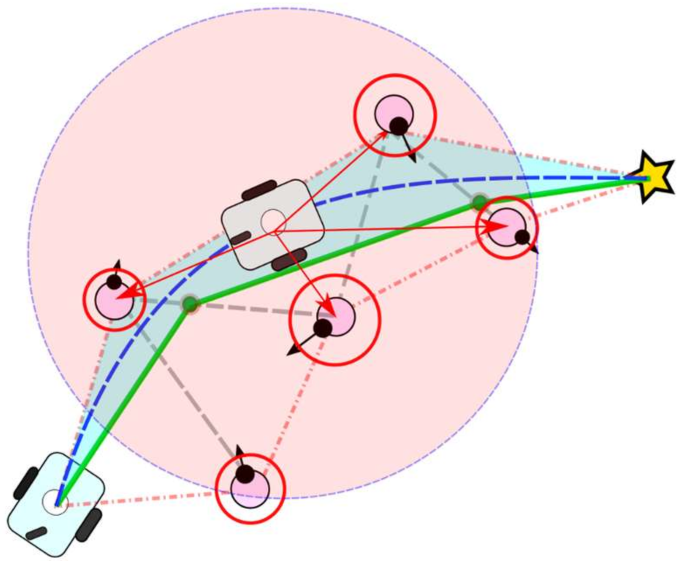
1) Pedestrian State Estimation
2) Dynamic Channel
3) NMPC planner
4) Results and Experimentation

❑ Robot relies on sensors (LiDAR, camera) placed on the robot

Uncertainty-Aware Collaborative Navigation in Crowded Environment

❑ Global Architecture





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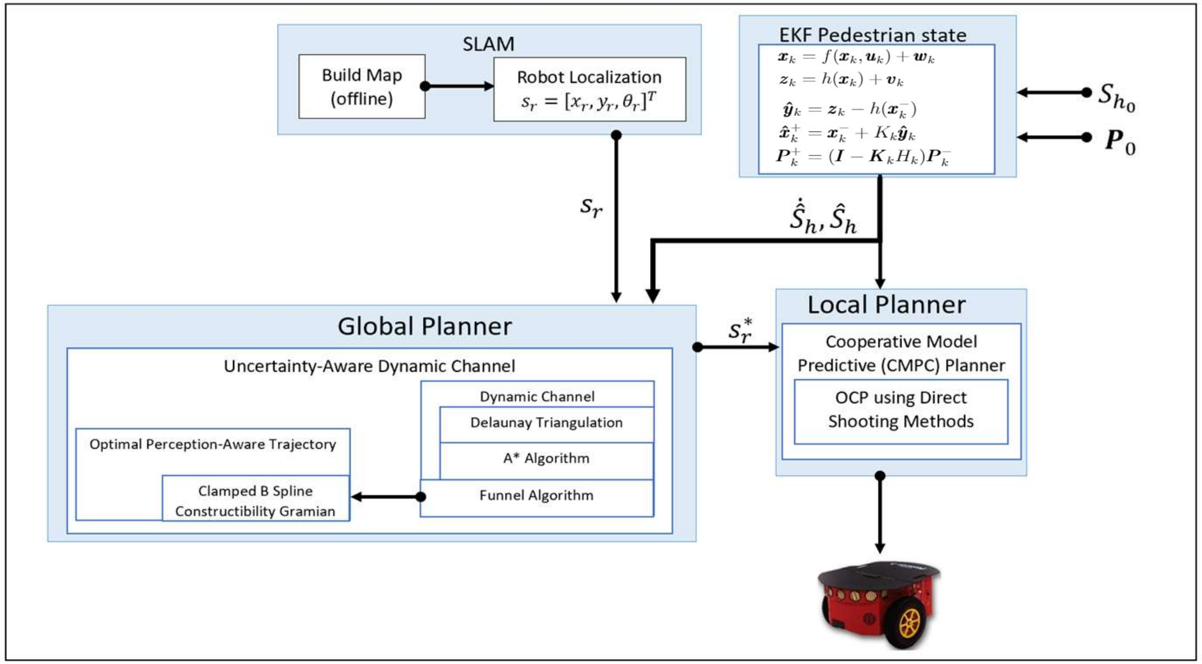
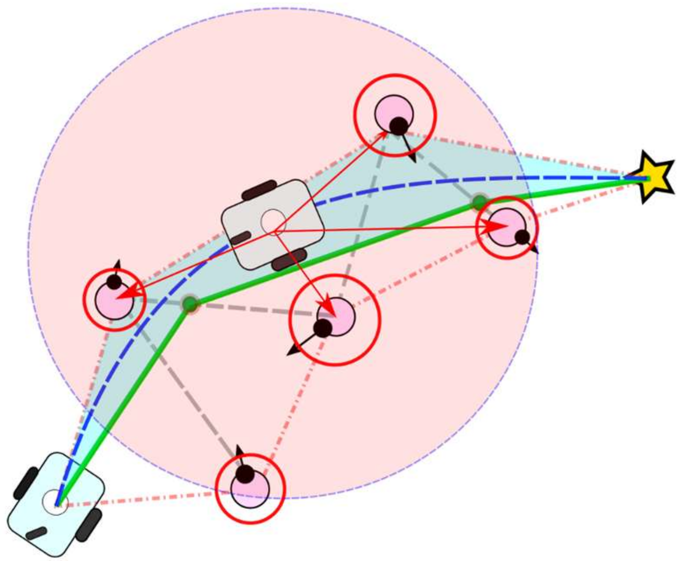
Uncertainty-Aware Collaborative Navigation in Crowded Environment

❑ Global Architecture





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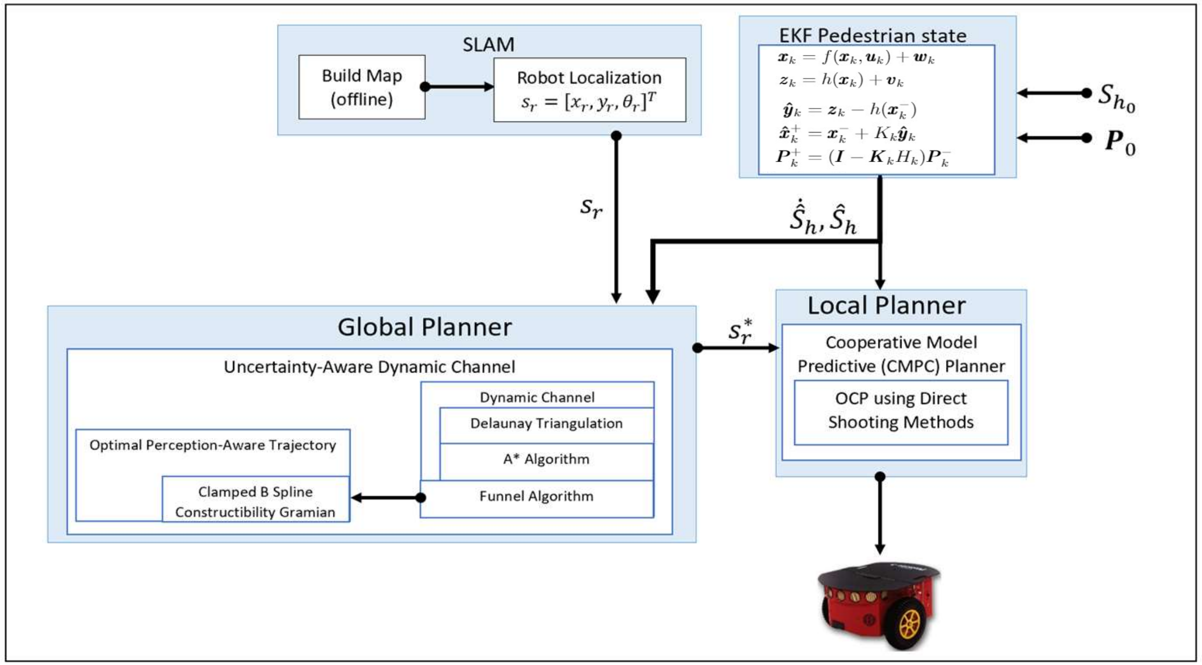
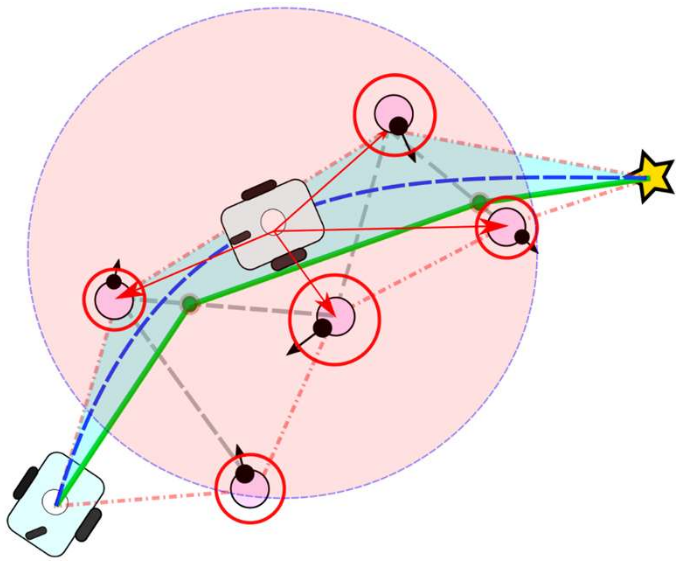
Uncertainty-Aware Collaborative Navigation in Crowded Environment

❑ Global Architecture





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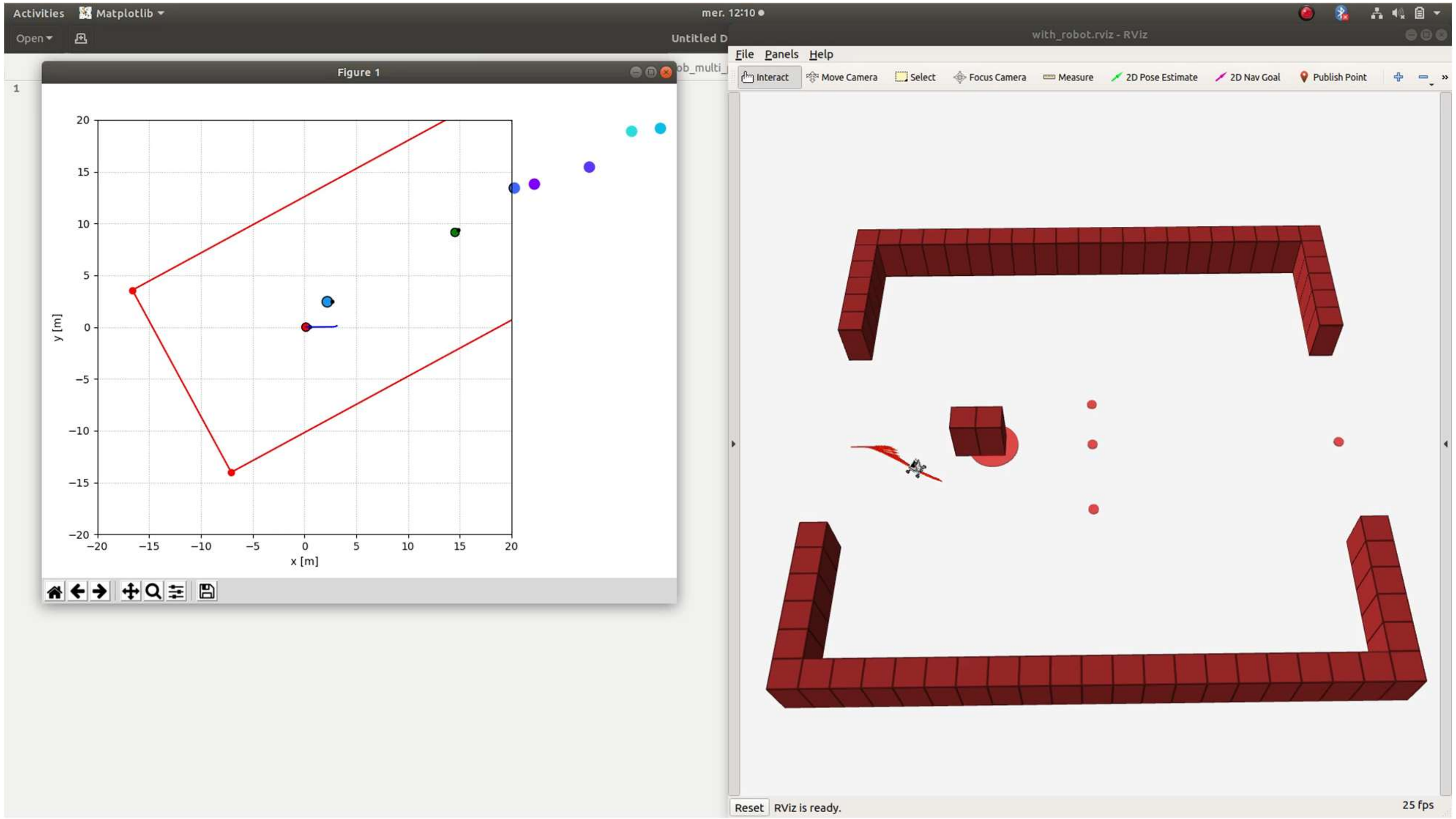
Uncertainty-Aware Collaborative Navigation in Crowded Environment

- **Simulation in Spaciss/Pedsim**

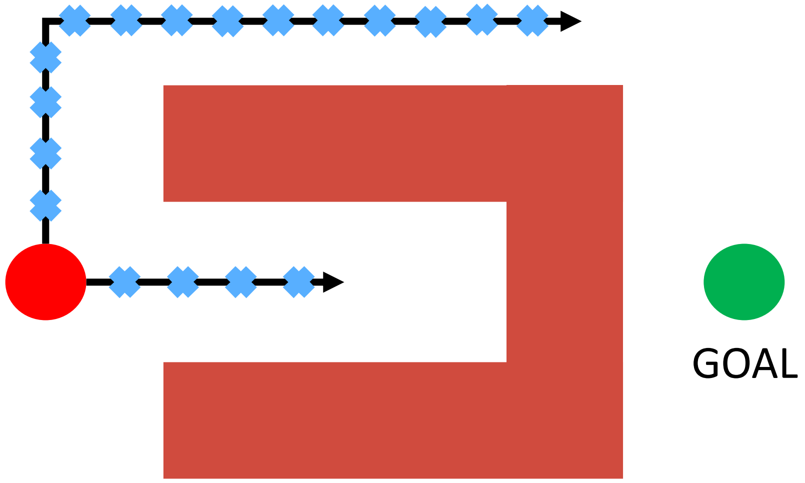


Uncertainty-Aware Collaborative Navigation in Crowded Environment

- ❑ **Experimentation**
  - ▪ **Obstacles**
  - ▪ **Pedestrian and Obstacles**

❑ **Most objectives were achieved, the robot can proactively avoid collision with obstacles and NMPC was able to run at an average rate of 25 Hz**

Model Predictive Control



$$\min_{\boldsymbol{u}} c(\boldsymbol{x},\boldsymbol{u}) = \min_{\boldsymbol{u}} \left(\sum_{k=0}^{N_P} ||\boldsymbol{x}_k - \boldsymbol{x}^*||_{\boldsymbol{Q}}^2 + \sum_{k=0}^{N_P-1} ||\boldsymbol{u}_k - \boldsymbol{u}_{k-1}||_{\boldsymbol{R}}^2 \right)$$

$$\text{subject to:} \quad \boldsymbol{x}_{k+1} - \boldsymbol{f}_d(\boldsymbol{x}_k,\boldsymbol{u}_k) = 0, \quad k = 0,\dots,N_P - 1$$
$$\boldsymbol{x}_k \in \mathcal{X}, \quad k = 0,\dots,N_P$$
$$\boldsymbol{u}_k \in \mathcal{U}, \quad k = 0,\dots,N_P - 1$$

The MPC is strongly influenced by the choice of the prediction horizon

[16] – E. Fiasché et al. ''Towards autonomous robot navigation in human populated environments using an universal sfm and parametrized mpc'', IROS 2023

Parametrized Model Predictive Control

$$\boldsymbol{u} = \boldsymbol{\pi}(\boldsymbol{\eta}), \quad \boldsymbol{\pi} : \mathbb{R}^{N_\eta} \rightarrow \mathbb{R}^{N_p}$$

Existing parameterizations

- Linear Parameterization (LERP or ZOH)

$$\boldsymbol{u} = \boldsymbol{\Pi}\boldsymbol{\eta}$$

Too simple -> leading to collisions

- B-Spline parameterization

$$\boldsymbol{u}(t) = \sum_{i=-1}^{N+1} \boldsymbol{\eta}_i, \boldsymbol{B}_{i,3}(t)$$

Computationally expensive -> leading to collisions

Contribution

Thin Plate Spline Radial Basis Function (TPS-RBFs)

$$\boldsymbol{u}(t) = \sum_{j=0}^{N_b} \omega_j \varphi\left(\|\boldsymbol{t} - c_j\|\right)$$

$$\varphi(r) = r^2 \log(r)$$

- Smooth and continuous control trajectories
- Compact parameterization

[16] – E. Fiasché et al. ‘‘Towards autonomous robot navigation in human populated environments using an universal sfm and parametrized mpc’’, IROS 2023

Papers

W. Jin, P. Salaris, P. Martinet, “**Proactive-Cooperative Navigation in Human-Like Environment for Autonomous Robots**”, 17th International Conference on Informatics in Control, Automation and Robotics, ICINCO20, pp. , Paris, France, July 7-9th, 2020

E. Alao, P. Martinet, “**Uncertainty-aware Navigation in Crowded Environment**”, 2022 IEEE/RSJ International Conference on Control, Automation, Robotics and Vision (ICARCV22), Singapore, Singapore, December 11-13th, 2022

F. Fusco, G. Allibert, O. Kermorgant, P. Martinet, “**Investigating the Performances of Control Parameterizations for Nonlinear Model Predictive Control**”, 2022 IEEE/RSJ International Conference on Control, Automation, Robotics and Vision (ICARCV22), Singapore, Singapore, December 11-13th, 2022

F. Fusco, G. Allibert, O. Kermorgant, P. Martinet, “**Benchmarking Nonlinear Model Predictive Control with Input Parameterizations**”, 26th International Conference on Methods and Models in Automation and Robotics (MMAR22), Miedzyzdroje, Poland from 22-25 August, 2022

E. Fiasché, P. Martinet, E. Malis, “**Towards autonomous robot navigation in human populated environments using an Universal SFM and parametrized MPC**”, 2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS23), Detroit, USA, October 1-5th, 2023

Content

Autonomous Navigation in Dynamic and Human Populated Environments

What are the main challenges?

Understanding human behavior around vehicles or robots

Understanding human driven devices behaviors

Characterize the behaviors

Prediction of future behaviors over one horizon

Estimation of the cooperability of human

Avoid the freezing robot problem

Producing legible motion (respect social rules)

Succeed to find solution in a limited time

Our work

Propose a model for vehicle human interaction

Develop a longitudinal and lateral controller

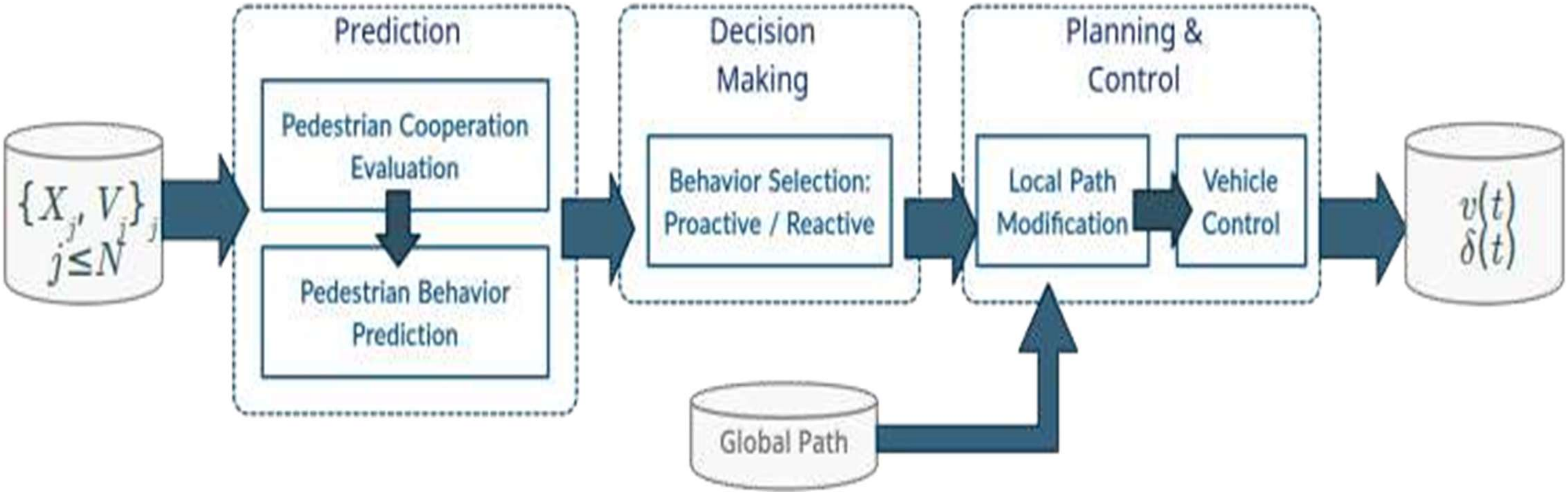
Build a global architecture for proactive navigation

Perform simulation

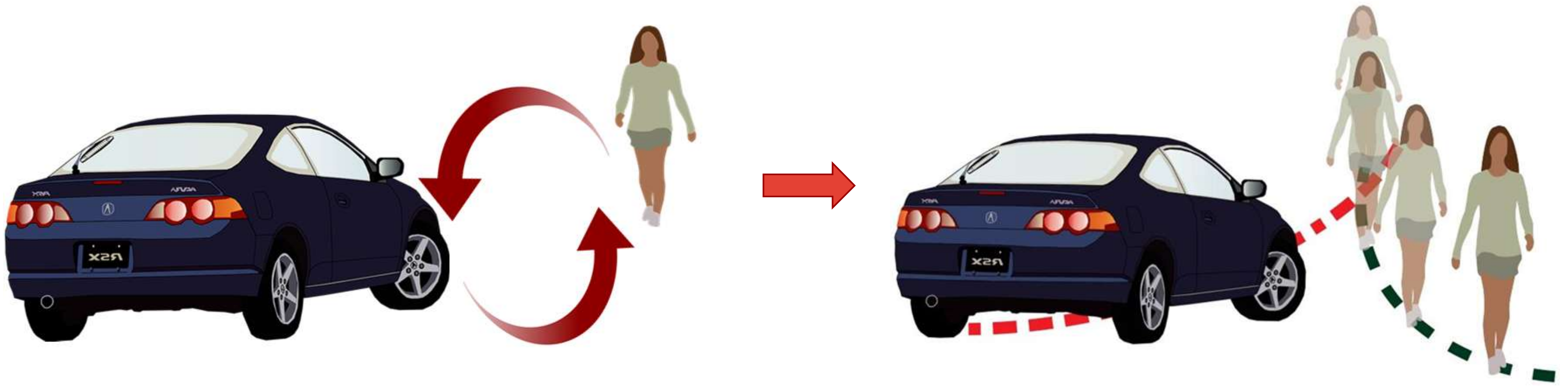
Develop real experimentation

PhD Maria Kabtoul

Proactive, Cooperative and Social Navigation Framework in Hianic project



Pedestrian Behavioral Modeling

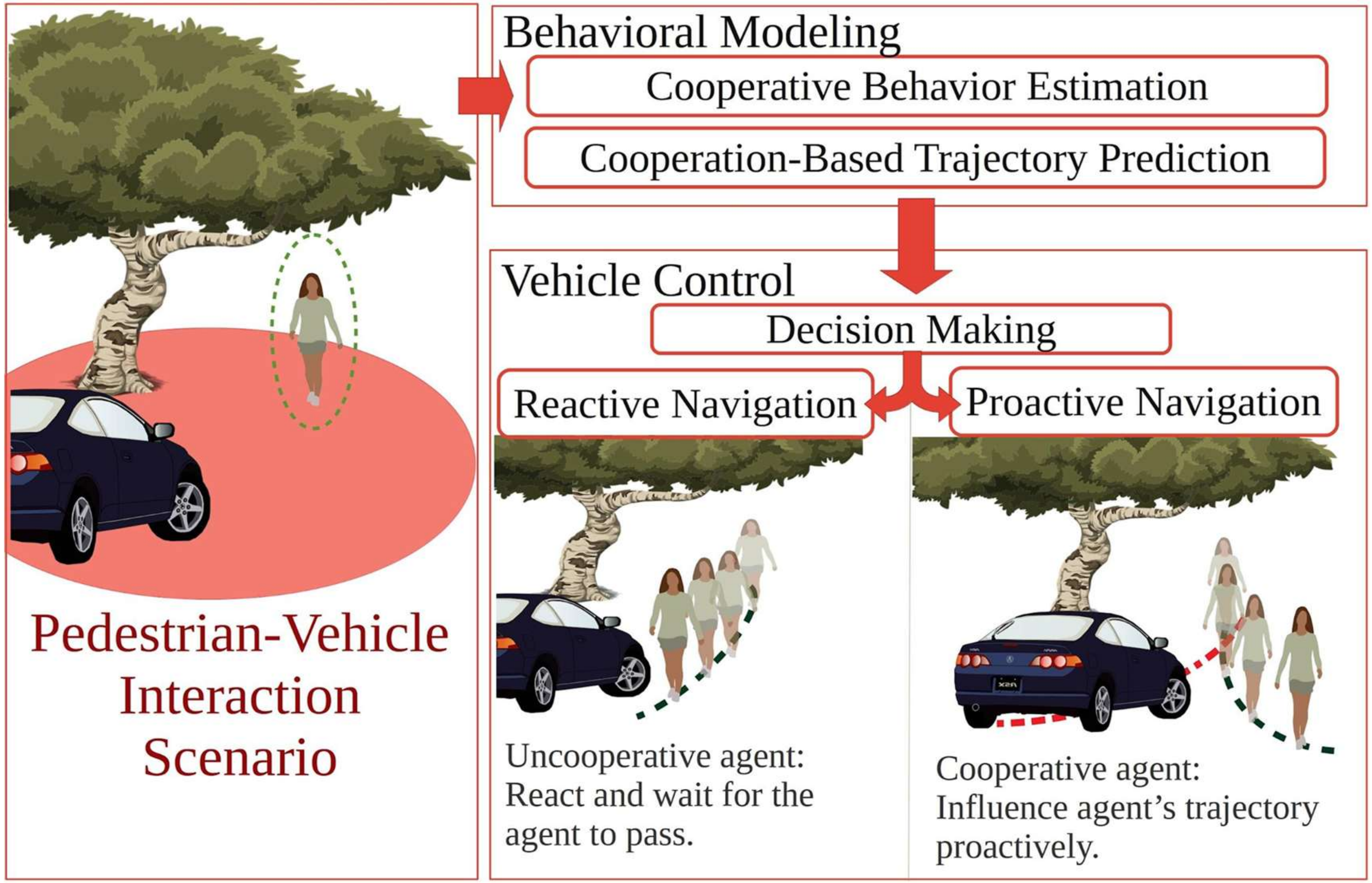


Understand the pedestrian's reaction and intention.
Produce legible trajectories.

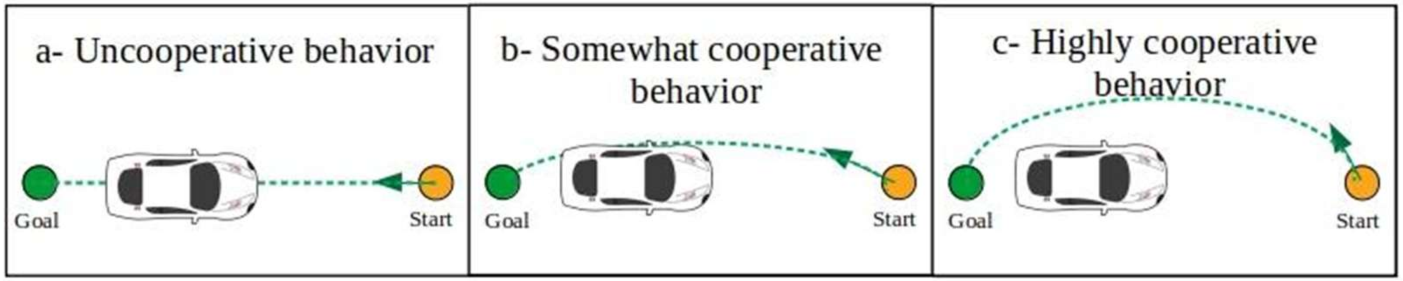
A cooperative task

Propose Model

*[1] M. Kabtoul, A. Spanlanzani, P. Martinet, **"Towards proactive navigation: A Pedestrian-Vehicle Cooperation Based Behavioural Model"**, IEEE International Conference on Robotic and automation, ICRA 2020, pp. , Paris, France, June 1-5th, 2020*

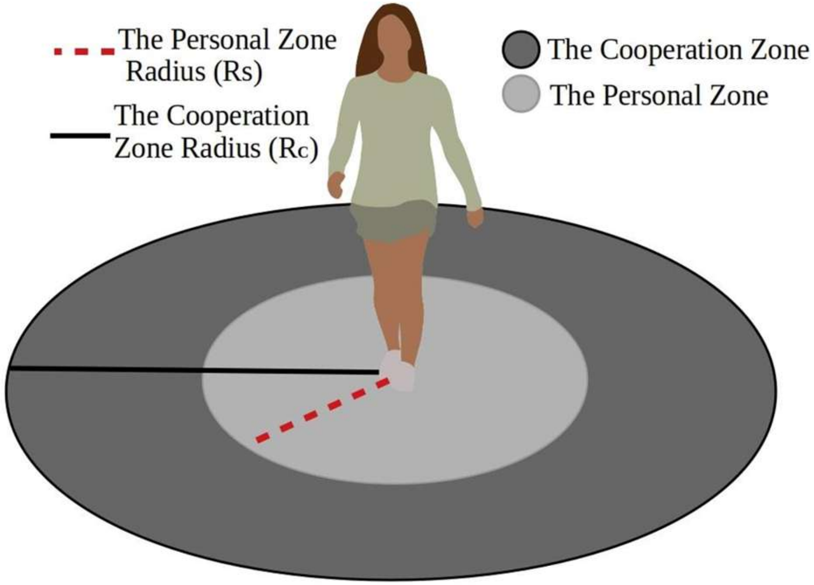


Pedestrian's Cooperation Modeling



Two zones due to the specific dimensions and social constraints of a vehicle

- A zone for pedestrians' influence. [2]
- A zone for vehicle's influence.



Example: we might be comfortable while another individual passes a meter behind us, but might feel differently towards a vehicle!

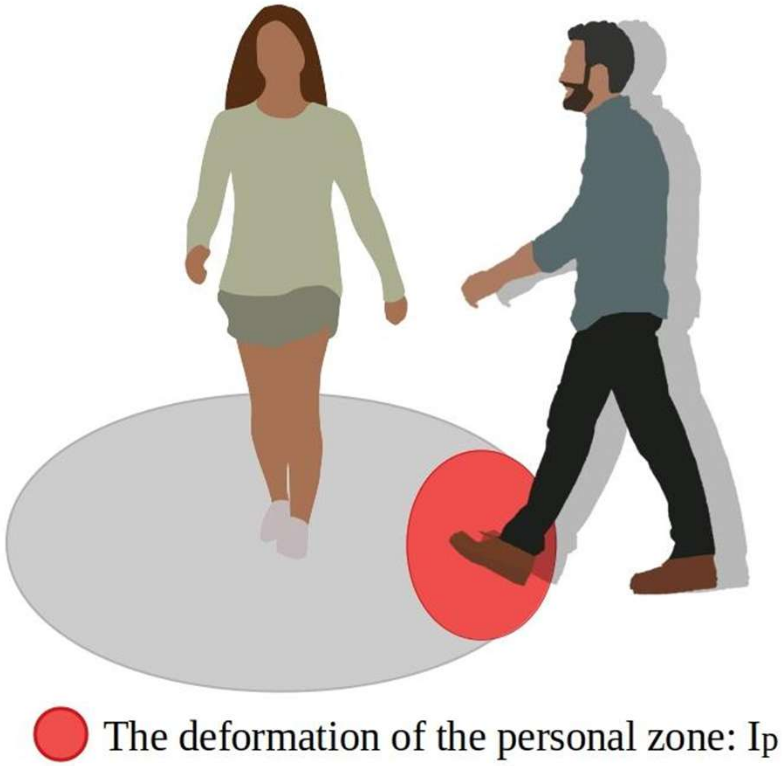
[2] J. Rios-Martinez, A. Spalanzani, and C. Laugier, "From proxemics theory to socially-aware navigation: A survey," International Journal of Social Robotics, vol. 7, pp. 137–153, Apr. 2014.

Proactive, Cooperative and Social Navigation Framework in Hianic project

A space measured based on the concept of the deformable virtual zone (DVZ). [3]

Used to drive a motion:

- minimize Ip: avoidance.
- increase Ip: join an activity.



[3] R. Zapata, P. Lépinay, and P. Thompson, "Reactive behaviors of fast mobile robots," Journal of Robotic Systems, vol. 11, no. 1, pp.13–20, 1994.

The cooperation Factor Model (CF) $CF(t) \in [0,1]$

CF is a function of:

1. Personal parameters:
   - The mean longitudinal velocity of the agent ($m.s^{-1}$)
   - The agent's goal.

2. Space parameters:
   - Density of the space surrounding the agent
   - Deformation of the personal zone.

3. Vehicle's influence:
   - Probability of collision between the pedestrian and the vehicle.

$$CF_a(t) = f_c(P^a_{cf}(t))$$

$$f_c : \quad [0,1]^{4\times 1} \rightarrow [0,1]$$
$$P^a_{cf} \longmapsto AP^a_{cf} + B$$

$A \in \mathbb{R}^{1\times 4}$, $B \in \mathbb{R}$, and the cooperation parameters of agent a (P^a_{cf}) are the following:

$$P^a_{cf}(t) = \left[\mathbb{P}_{[a,veh]}(t), \mathcal{D}^a(t), I^a_P(t), \frac{V^a_m(t)}{V_{Pmax}}\right]^T$$

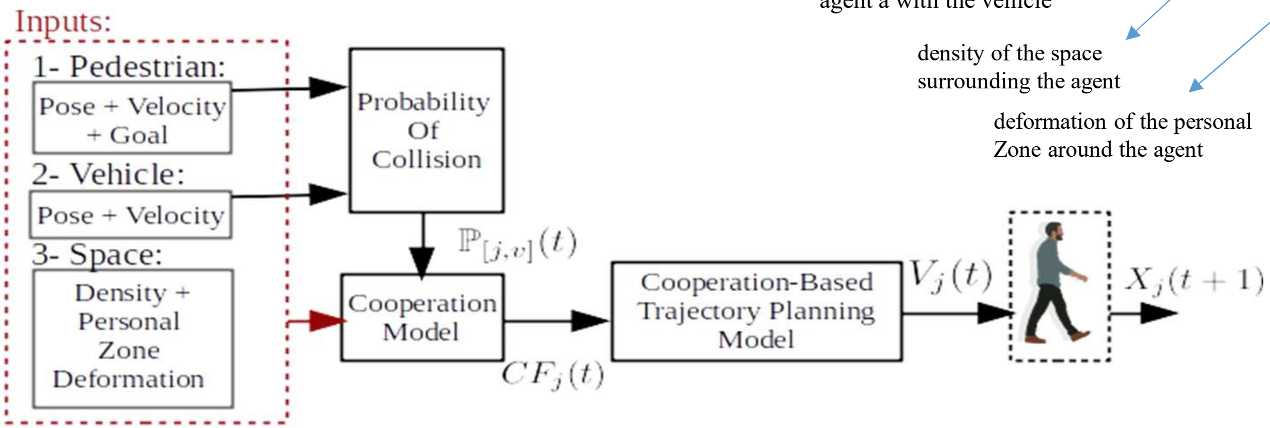
probability of collision of agent a with the vehicle

density of the space surrounding the agent

deformation of the personal Zone around the agent

maximum allowed velocity of a pedestrian in the shared space

mean velocity of the agent ($m.s^{-1}$)



The cooperation Factor Model (CF) $CF(t) \in [0,1]$

The pedestrian trajectory model parameters:

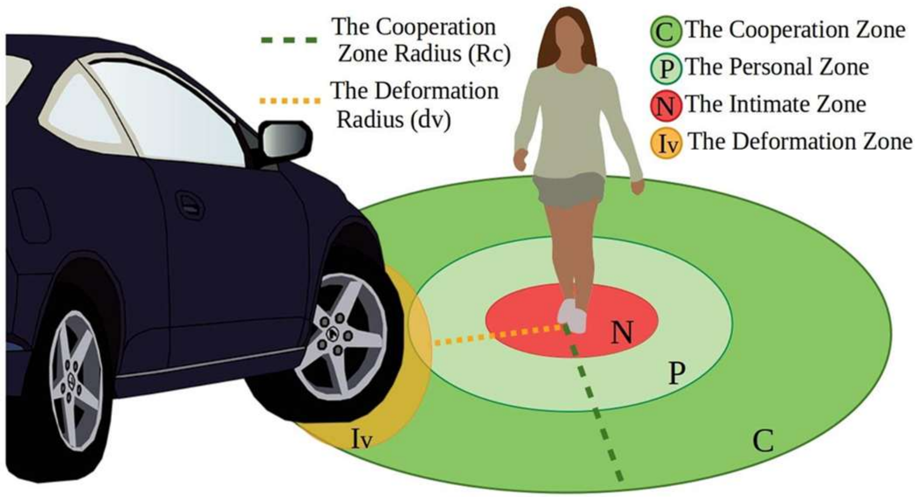
Vehicle Influence

$$P_m(t) = \begin{bmatrix} CF_a(t).I_V(t) \\ CF_a(t).\Theta_V(t) \\ [1 - CF_a(t)].\Theta^a_{goal}(t) \\ [1 - CF_a(t)].D^a_{goal}(t) \\ \dot{CF}_a(t) \\ I^a_P(t) \\ \theta^a_P(t) \end{bmatrix}$$

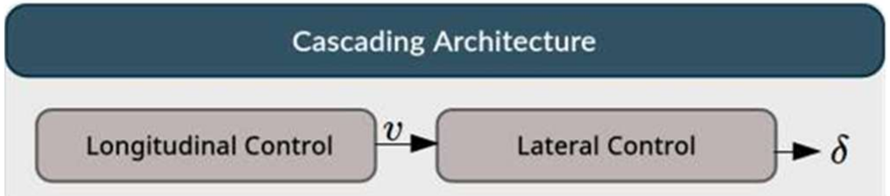
Destination Influence

Pedestrians Influence

The deformation of the personal zone: Ip

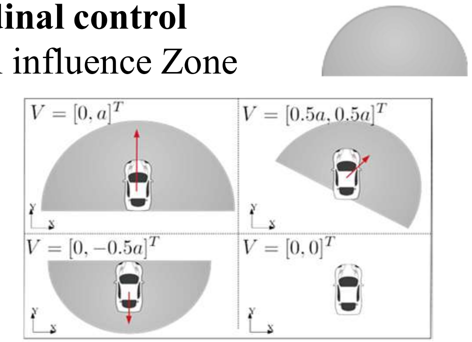


Control



*[5] M. Kabtoul, A. Spanlanzani, P. Martinet, **"Proactive Longitudinal Velocity Control In Pedestrians-Vehicle Interaction Scenarios** ", 2020 IEEE 23rd International Conference on Intelligent Transportation Systems, ITSC 2020, pp. , September 20-23th, 2020*

Longitudinal control
Define an influence Zone



Find the longitudinal control which maximizes the pedestrians cooperation, while ensuring the safety constraints for all the pedestrians in the influence zone:

$$J = \frac{1}{M} \sum_{j=1}^{M} \alpha_1 \left(1 - CF_j(t)\right) - \alpha_2 SI_j(t)$$

Number of pedestrians in the influence zone

The Cooperation Factor

The safety Index

Lateral Control

- Find the local steering control in a pedestrian populated environment (human-like steering)
- Avoid the freezing of the vehicle in dense scenarios (proactive)
- Maintain the agents safety (collision avoidance)

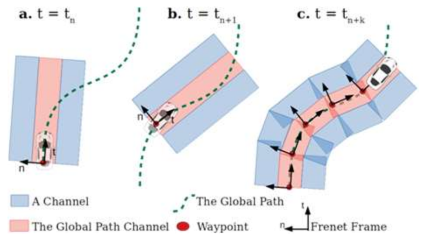
$$w_C(t) = \beta_0 \left[w_{fuzzy}(t) + \beta_1 w_{local}(t) + \beta_2 w_{global(t)}\right]$$

The cost of disturbing the pedestrians in the selected channel

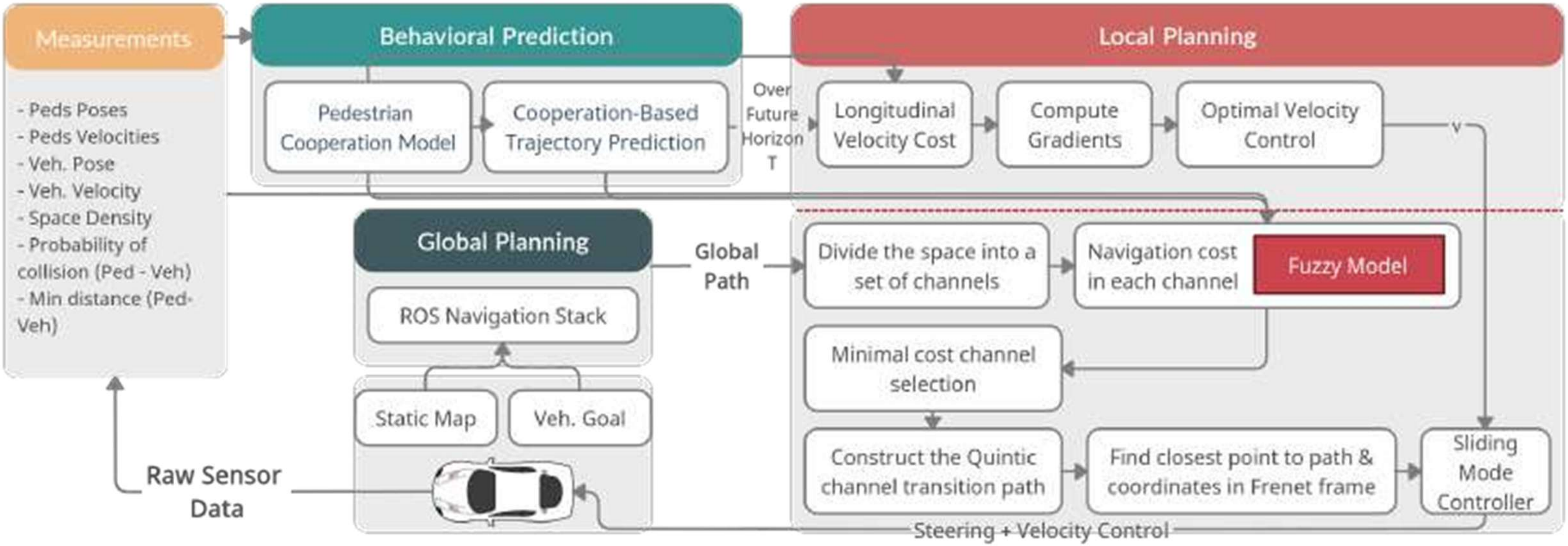
The cost of going from the current location to the goal channel

The cost of going back to the global path from the selected channel

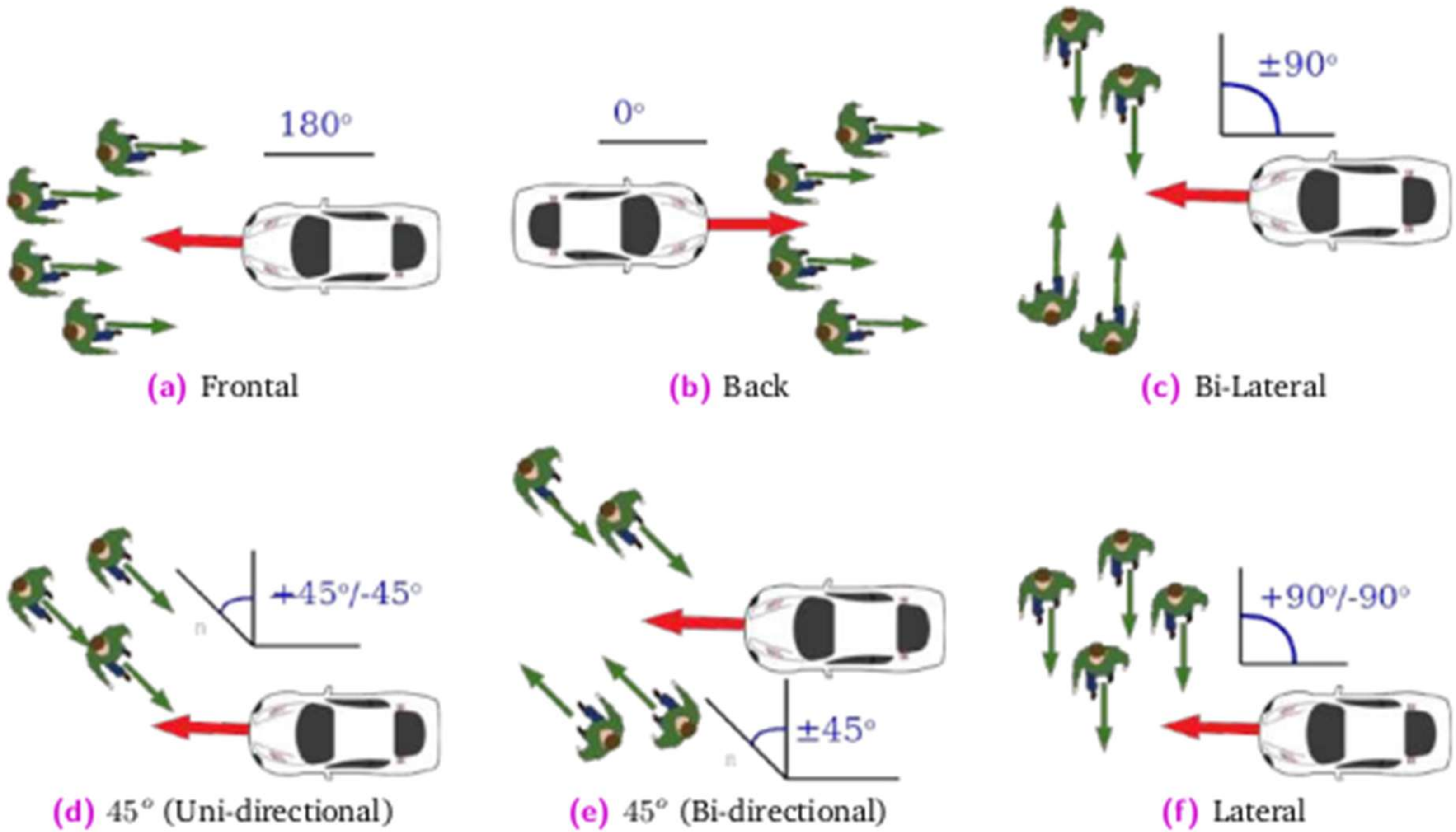
1. **Dynamic channel based decision making:**
   - Divide the space into a set of channels
   - Find the best channel: (lower density, more cooperative agents, closer to the global path).
2. **Planning**: find the steering between channels that ensures:
   - Natural driving pattern.
   - Legible trajectory.



Implementation Under ROS



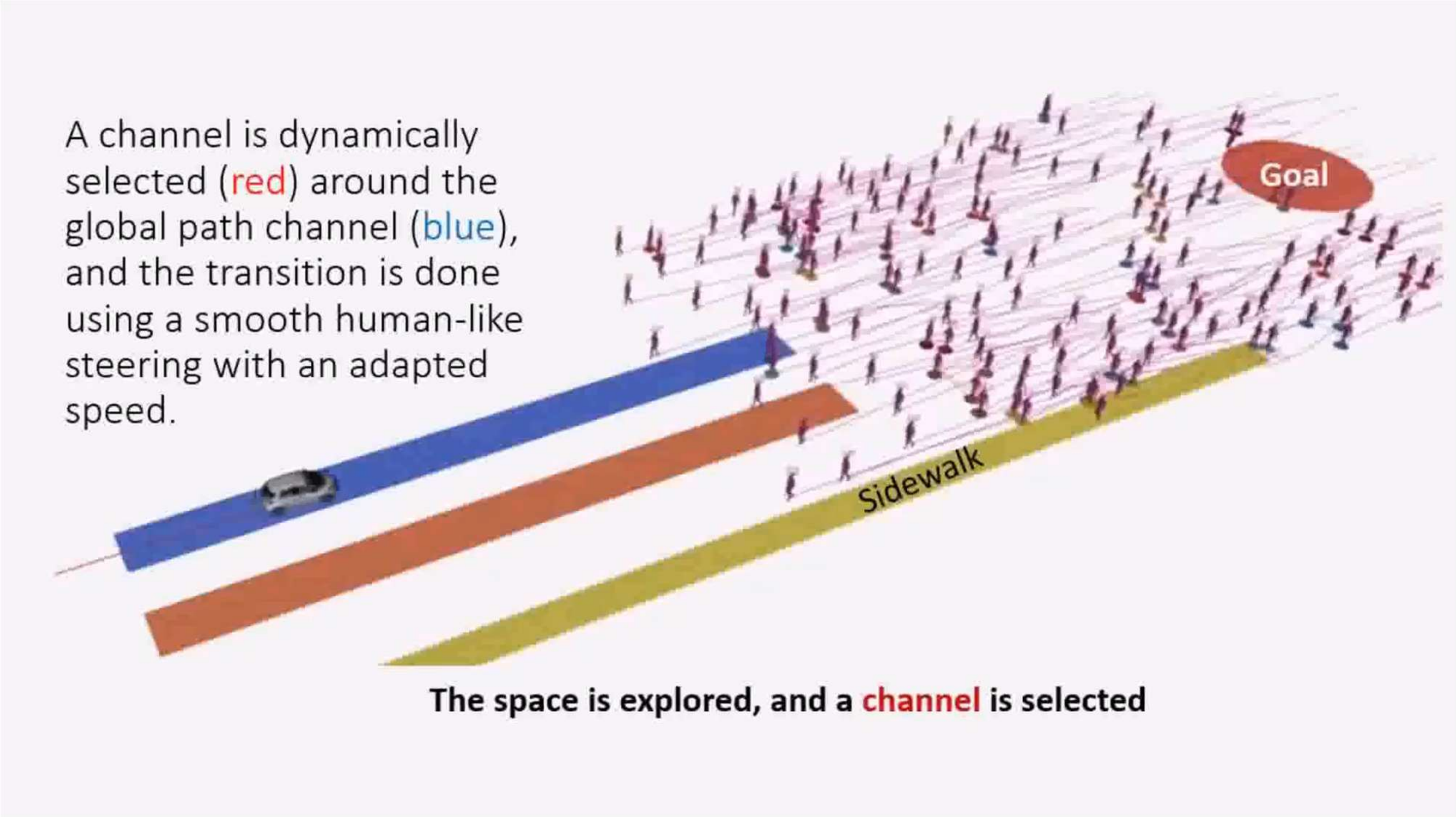
Testing Scenarios



Simulation Results in Frontal Crossing

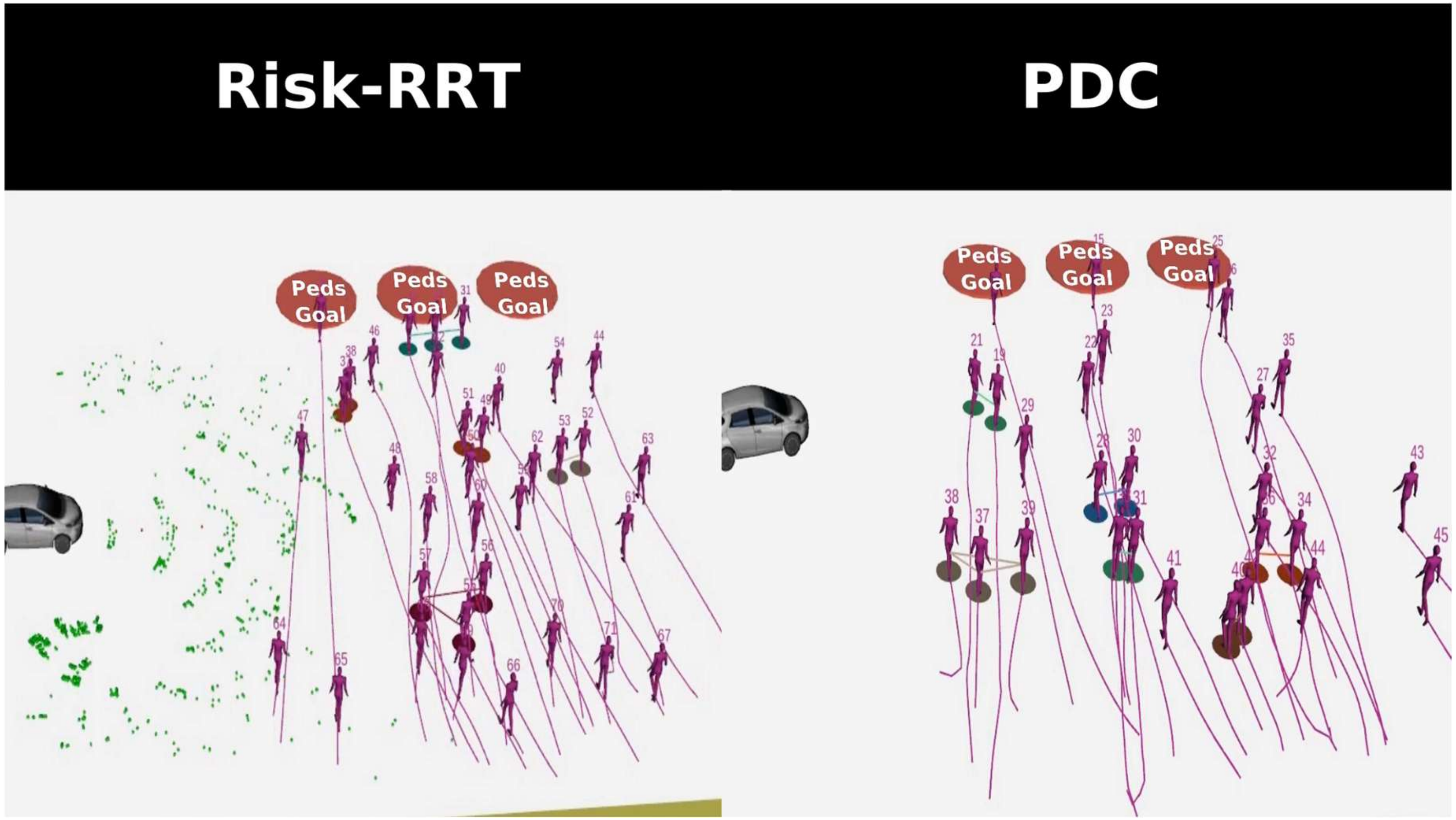
SPACiSS Simulator [6]

*[6] Prédhumeau, M. "**Simulating Realistic Pedestrian Behaviors in the Context of Autonomous Vehicles in Shared Spaces**: Doctoral Consortium". AAMAS, 2021.*



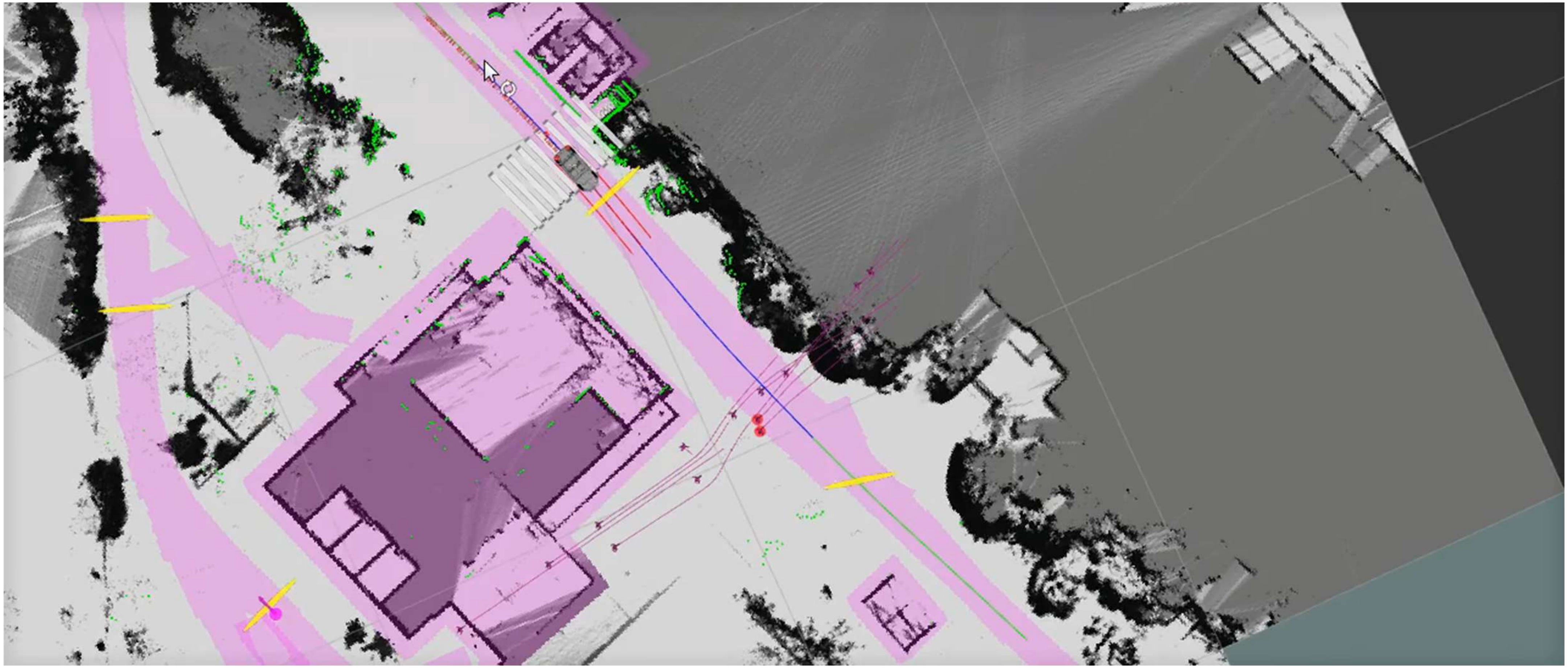
Simulation Results in Lateral Crossing Comparison with risk-RRT [7]

[7] Fulgenzi, C., Spalanzani, A., Laugier, C., and Tay, C. ***Risk based motion planning and navigation in uncertain dynamic environment****. Research Report. Oct. 2010, p. 14.*



Results in Lateral Crossing

ICARS



Papers

M. Kabtoul, A. Spanlanzani, P. Martinet, “**Proactive Longitudinal Velocity Control In Pedestrians-Vehicle Interaction Scenarios**”, 2020 IEEE 23rd International Conference on Intelligent Transportation Systems, ITSC 2020, pp. , September 20-23th, 2020

M. Kabtoul, A. Spanlanzani, P. Martinet, “**Towards proactive navigation: A Pedestrian-Vehicle Cooperation Based Behavioural Model**”, IEEE International Conference on Robotic and automation, ICRA 2020, pp. , Paris, France, June 1-5th, 2020

M. Kabtoul, A. Spalanzani, P. Martinet,“ **Proactive And Smooth Maneuvering For Navigation Around Pedestrians**”, IEEE International Conference on Robotics and Automation (ICRA), Philadelphia (PA), USA, pp., May 23-27th, 2022

M. Kabtoul, M. Predumeau, A. Spalanzani, J. Dugdale, P. Martinet, “ **How To Evaluate the Navigation of Autonomous Vehicles Around Pedestrians?**”, in IEEE Transaction on Intelligent Transportation System, vol. 25, N°3, pp. 2311-2321, 2023

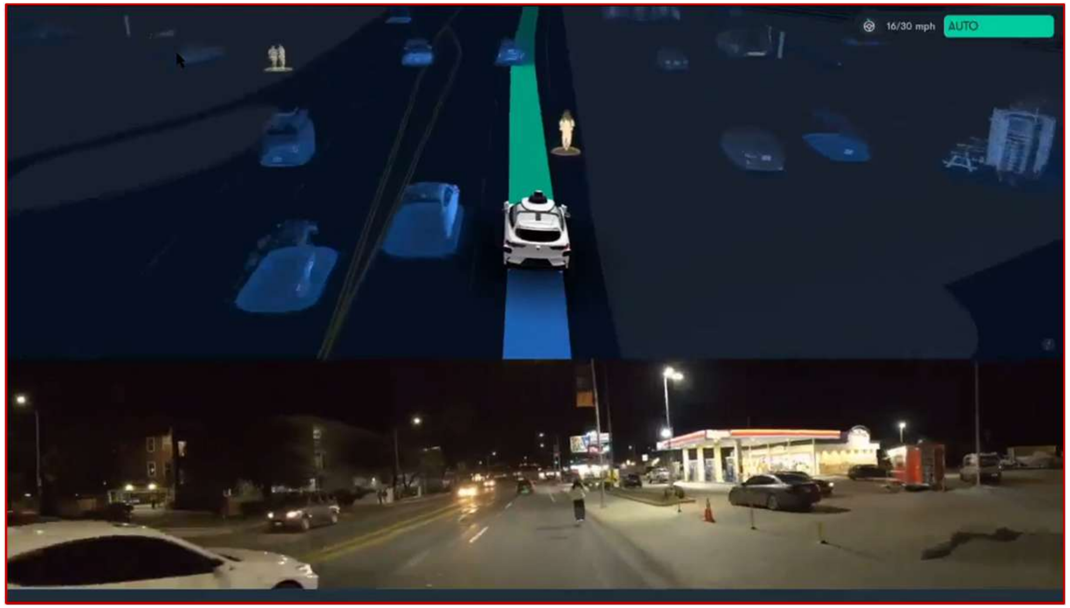
Content

Motivation

Annapolis project (22-26)

PhD Emmanuel Alao (22-25)

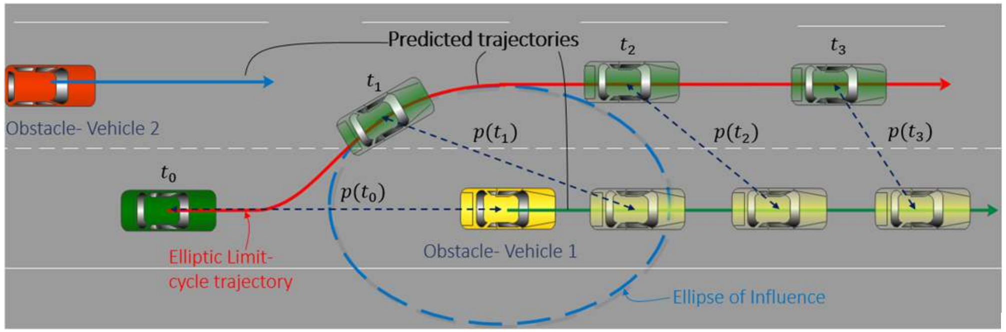
In an urban environment, the intentions and the actual future motions of the surrounding pedestrians (observed and hidden ones) and/or **PLEV** (Personal Light Electric Vehicle) are never perfectly known. Only a prediction of their motion are estimated with uncertainty.

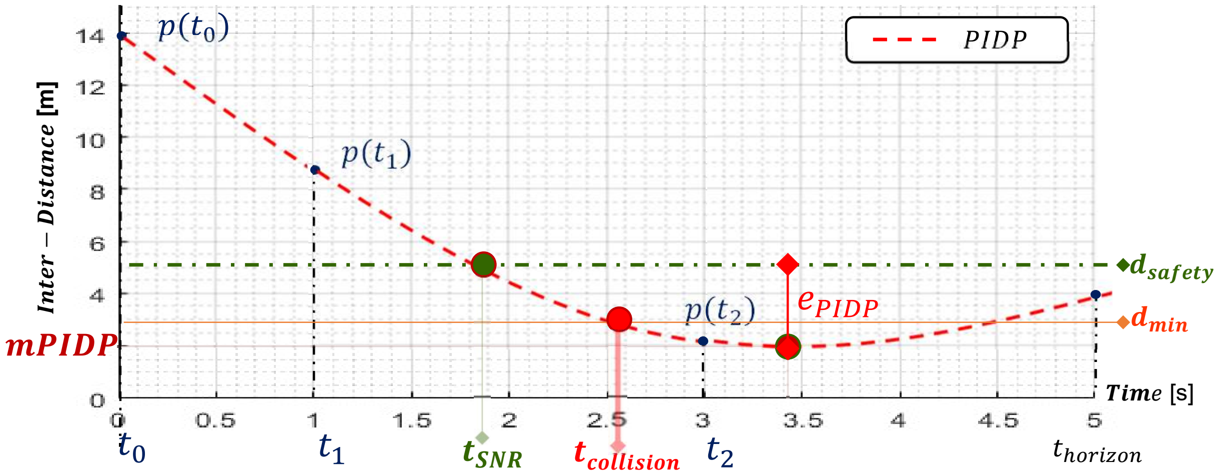


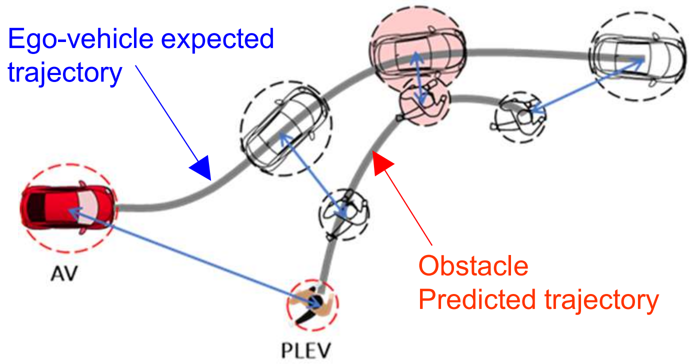
Waymo® showing possible collision with PLEV

→ **How to ensure safe and efficient motion of an autonomous vehicle without being overly conservative?**

The concept of Predictive Inter-Distance Profile (PIDP)







$t_{Collision}$: Time To Collision

$mPIDP$: Minimum of PIDP

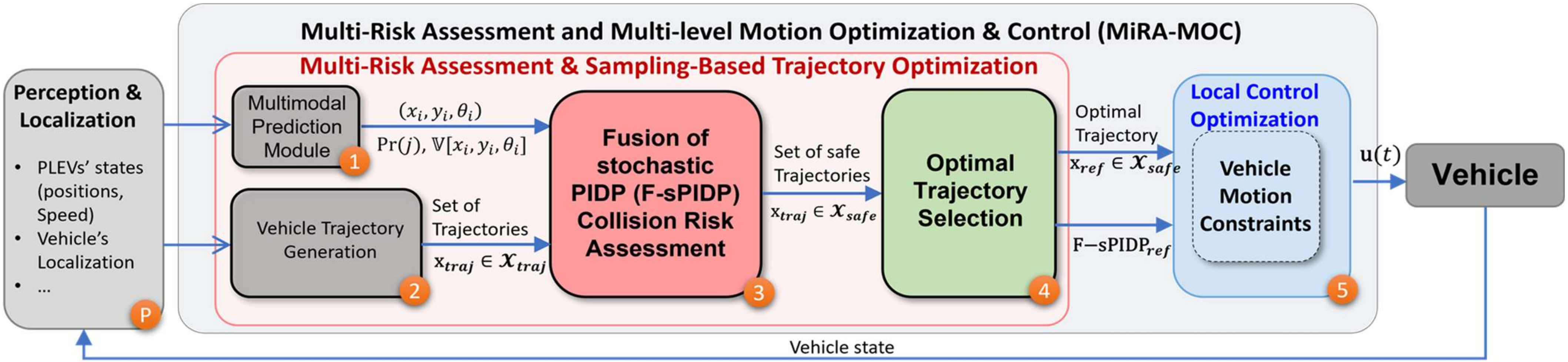
$e_{PIDP} = d_{safety} - mPIDP$

t_{SNR} : First time “Safety Not Respected”

Strengths:
- ✓ Generic & Independent of the path geometry
- ✓ Spatio-temporal metrics
- ✓ Flexible and contain several features for risk assessment

[14] D. Iberraken, L. Adouane and D. Denis, “Safe Autonomous Overtaking Maneuver based on Inter-Vehicular Distance Prediction and Multi-Level Bayesian Decision-Making”, ITSC 2018, USA.

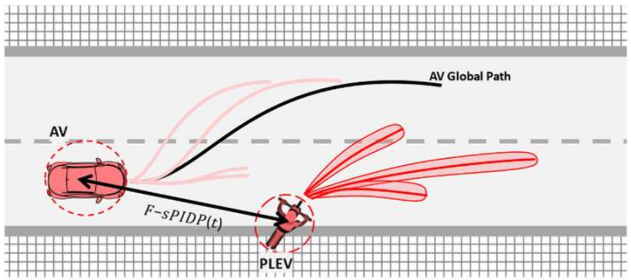
MiRA-MOC: Multi-Risk Assessment and Multi-level Motion Optimization & Control



Risk Assessment – Predictive Inter-Distance Profile (PIDP)

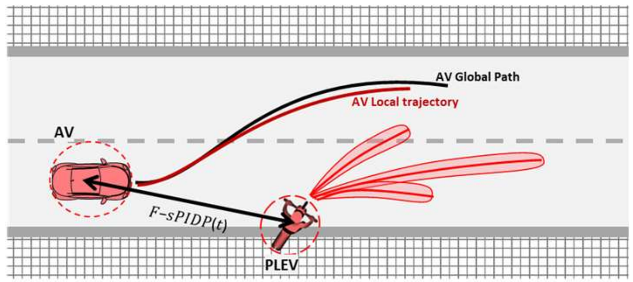
1. Sampling-based Optimal Trajectory Selection:

- Compute trajectory samples
- Selected Safe and Optimal Global Path using Fusion of stochastic PIDP (F-sPIDP)



2. Local Trajectory Optimization:

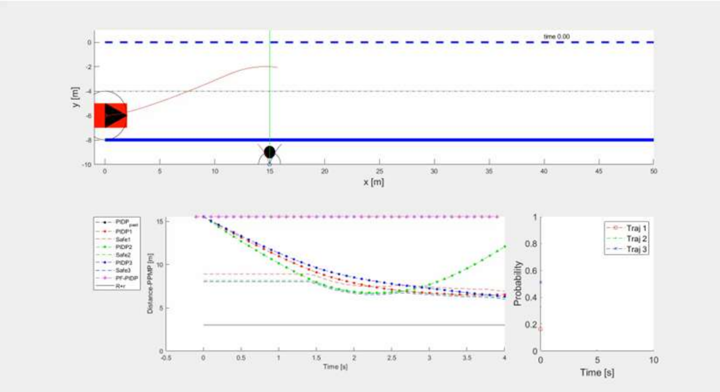
- Compute Local trajectory respecting vehicle kinematic constraints and motion uncertainties obtained from F-sPIDP

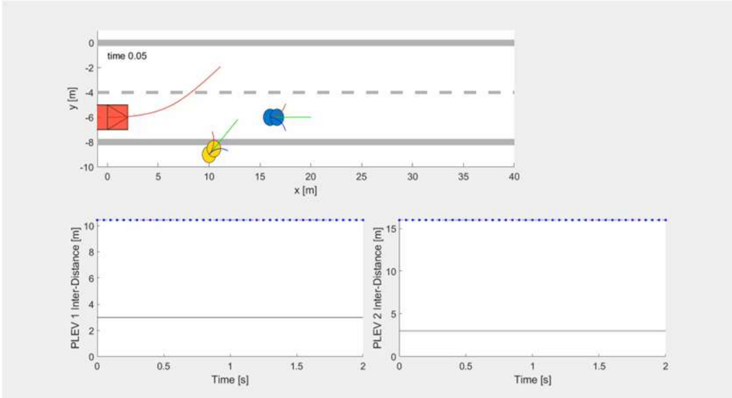


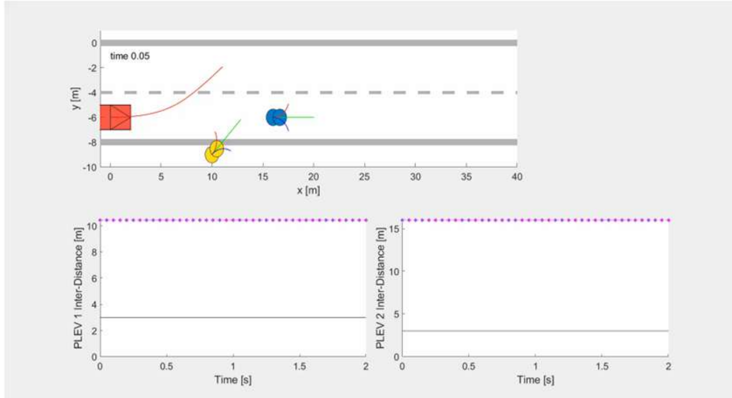
Main results

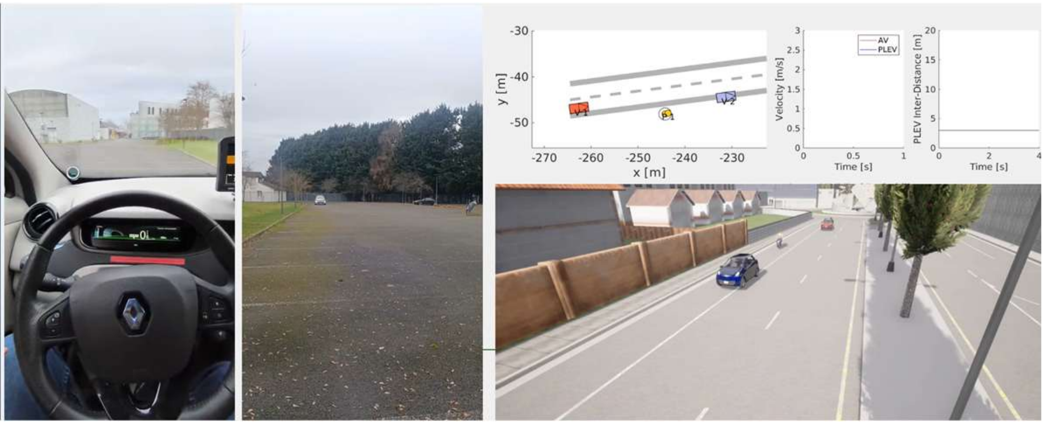
Emmanuel Alao *(PhD 22-25)*

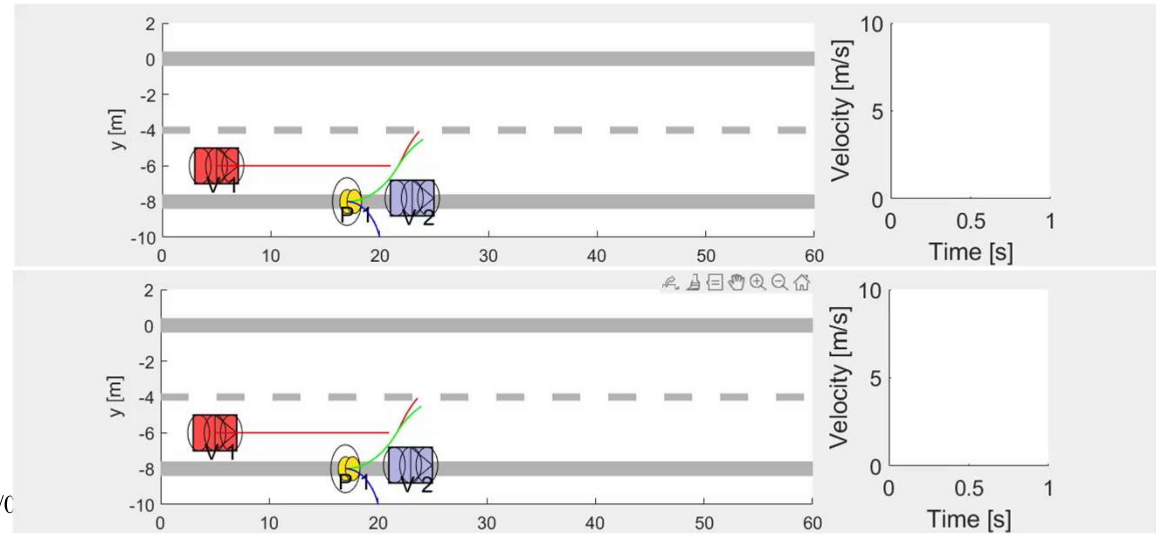
Simulation and real experiments











Papers

E. Alao, L. Adouane, P. Martinet, “**Reliable Risk Assessment and Management using Probabilistic Fusion of Predictive Inter-Distance Profile for Urban Autonomous Driving**“, European Control Conference (ECC), Stockholm, Sweeden, June 25-28th, 2024

E. Alao, L. Adouane, P. Martinet, “**Multi-Risk Assessment and Management in the Presence of Personal Light Electric Vehicles**“, International Conference on Informatics in Control, Automation and Robotics (ICINCO), Porto, Portugal, 18-20 Oct. 2024, 2024. ***Best student Paper***.

E. Alao, L. Adouane, P. Martinet, “**Hybrid Optimization Method for Safe Autonomous Navigation under Uncertainty**“, IFAC Intelligent Autonomous Vehicles Symposium (IFAC IAV 2025), Phoenix, Arizona, USA, 2025.

E. Alao, L. Adouane, P. Martinet, “**Stochastic and Safe Multi-Risk Fusion for Autonomous Navigation in the presence of PLEVs**“, IEEE Intelligent Vehicles Symposium (IV 2025), Cluj-Napoca, Romania, 2025.

E. Alao, L. Adouane, P. Martinet, “**Multi-Level Optimization for Safe Predictive Control of Autonomous Vehicles to Avoid Uncertain Multimodal PLEVs**”, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS25), Hangzhou, China, October 19-25, 2025

E. Alao, L. Adouane, P. Martinet, “**Multi-Priority-Based Strategy for Risk Assessment and Management in the Presence of Multiple Personal Light Electric Vehicles**“, in Springer Nature Computer Science, Vol. , N°13, pp., 2025

Content

Introduction

Robot-Human interaction

AV-Human interaction

AV-PLEV interaction

Conclusion and future prospects

Conclusion and future prospects

Belief in proactive navigation

- Vehicle/Robot human interaction (HVI/RHI) model (either Data/Model/Hybrid driven)
- Estimate the parameters, refine them online
- Proactive navigation strategy (based on channel, Dynamic channel, influence zone, …)
- Advanced control techniques (MPC, MPPI)
- Reliable and realistic enough human behavior simulator
- Evaluation in real world

There is a lack in vehicle/robot to humans communications that must be addressed….Autonomous vehicle/robot must be understood by human on their intention possibly better than human do!!