Human Motion Prediction for Navigation of a Mobile Robot

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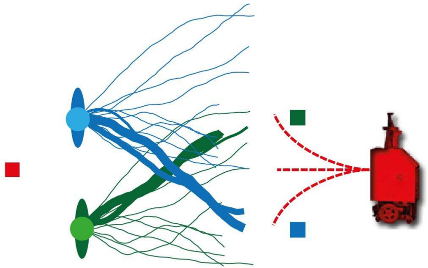
IURO-Project: Interactive Urban Robot

Motivation and Goals

Motivation: Why do we need human motion prediction?

- Collision Avoidance
- Learning and Imitation of human behavior
- Improve path planning

Goal: Estimate most probable trajectory for humans



State of the Art & Contributions

State of the Art:

- Use of a static environment model (Bennewitz, 2004)
- Constant velocity model (Dee and Hogg, 2008)
- Our approach $\Leftrightarrow$ **Chung and Huang , 2010**

Contributions:

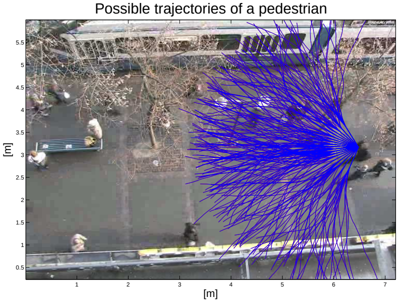
- Inclusion of the goal information for each human
- Decrease of the prediction error
- Solution for special cases

General Overview

- The idea is to generate all possible way-points for a human:
  $\Rightarrow$ **Pedestrian Ego-Graph**

- Rank each way-point according to cost functions estimated from human trajectories
  $\Rightarrow$ **Cost Function**

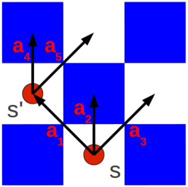
- Learning the cost functions



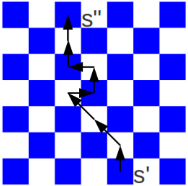
- Estimate the most probable trajectory to reach a predefined goal $\Rightarrow$ **Optimal trajectory**

Markov Decision Process

- Markov Decision Process (MDP): $M = (S, A, P^a_{ss'}, \gamma, R^a_{ss'})$
  - S = Set of states
  - A = Set of actions
  - $P^a_{ss'}$ = Transition probability
  - $R^a_{ss'}$ = Reward function
  - λ = Discount factor $\in (0, 1)$



- Policy : $\pi : S \rightarrow A$



Most likely trajectory

- Value function V over the policy π:

$$V^{\pi}(s_0) = R_{s_0 s_1} + \lambda R_{s_1 s_2} + \lambda^2 R_{s_2 s_3} + \ldots + \lambda^t R_{s_t s_{t+1}}$$

where $R_{s_i s_j}$ is the reward function from the state s_i to s_j

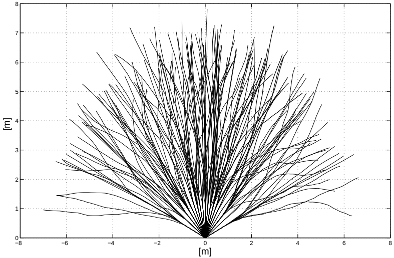
- Optimal policy π^*:

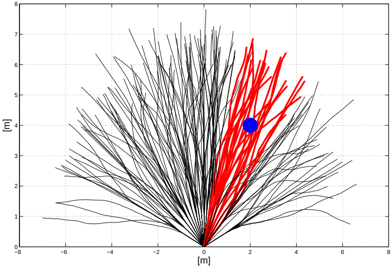
$$V^{\pi^*}(s_0) = \min_j \quad V^{\pi_j}(s_0)$$

- Description of two variables:
  1. π Policy
  2. $R^a_{ss'}$ Reward function

Pedestrian Ego-Graph (PEG)

- Set of trajectories obtained with different cluster-algorithms
- Each trajectory is a policy π of the MDP
- Every pedestrian is oriented to a goal $\Rightarrow$ Reduction of the PEG



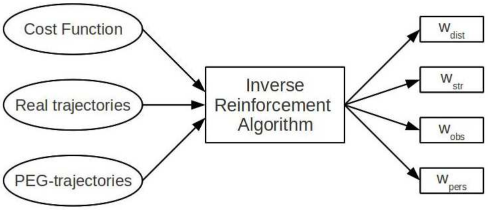


Cost function

The cost function represents the reward function R of the MDP and are based on social forces [4]:

$$C_{tot}(s_i) = w_{dist}C_{dist}(s_i) + w_{str}C_{str}(s_i) + w_{obs}C_{obs}(s_i) + w_{pers}C_{pers}(s_i)$$

- Estimation of cost-weightings: $w_i = \{w_{dist}, w_{str}, w_{obs}, w_{pers}\}$

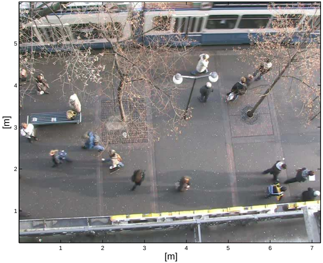


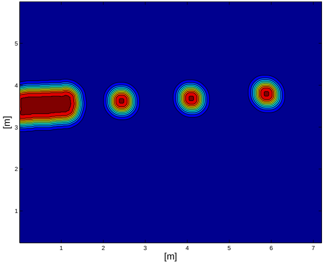
Static Obstacle: Distance Map

- C_{obs}: Static obstacles

$$C_{obs}(s_i) = \exp(-0.5\frac{dist(s_i)^2}{\sigma_d^2})\exp(-0.5\frac{dist(s_i)^2}{\sigma_w^2})$$

Comfortable distance: $\sigma_d = 0.361[m]$ [2]
Radius of influence: $\sigma_w = 2.088[m]$ [2]





Dynamic obstacle: Pedestrians

- C_{pres}: Cost function based on the Personal space model:

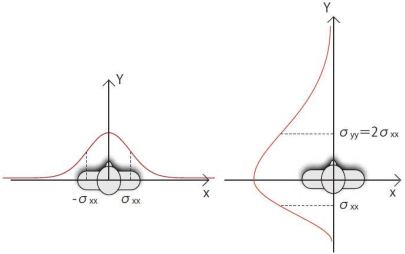
$$C_{pers}(s_i^k) = \sum_j C_{jk} = \sum_j exp(-0.5(s_i^j - s_i^k)^t \Sigma^{-1} (s_i^j - s_i^k))$$

The variable $\Sigma = \Sigma_f$ if the pedestrian k is in front of j and $\Sigma = \Sigma_s$ if the pedestrian is on the side.

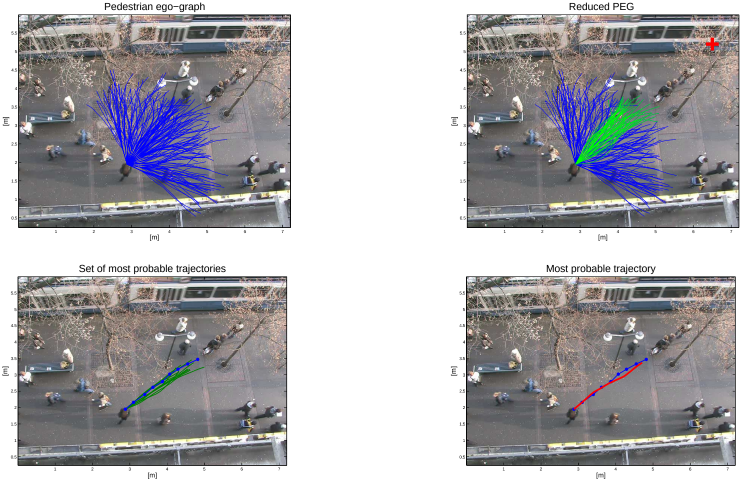
$$\Sigma_f = \begin{pmatrix} \sigma_{xx}^2 & 0 \\ 0 & 4\sigma_{xx}^2 \end{pmatrix}$$

$$\Sigma_s = \begin{pmatrix} \sigma_{xx}^2 & 0 \\ 0 & \sigma_{xx}^2 \end{pmatrix}$$

$\sigma_{xx} = 0.369[m]$ from [3]



Simulation: Prediction Algorithm



Conclusions

The results are obtained by comparing the estimated trajectories with a real dataset [2]

- Reduction of the prediction error

Pred. Error	*1 [m]*	*2 [m]*	*3 [m]*	*4 [m]*
CV	0.037	0.122	0.221	0.363
LTA [2]	0.054	0.128	0.212	0.285
SBCM [1]	**0.030**	0.074	0.100	0.105
OURs	0.031	**0.072**	**0.097**	**0.099**

- CV : Constant velocity model
- LTA: Linear trajectory avoidance [2]
- SBCM: Spatial behavior cognition model [1]

- Reduction of the computational effort
- Solution special cases

Future Work

- Detect pedestrian walking in groups
  - The prediction is erroneous
  - Pedestrian in a group break the standard human behavior

- Train the model on different classes
  - Human behavior changes with different environments
  - Sidewalk, open space, crossing ...

Literature

- [1] Shu-Yun Chung and Han-Pang Huang *“A Mobile Robot that Understands Pedestrian Spatial Behaviors“*,2010.
- [2] S.Pellegrini,A.Ess,K.Schindler,L. van Gool *“You’ll Never Walk Alone: Modeling Social Behavior for Multi-target Tracking“*,2009.
- [3] Thositaka Amaoka, Hamid Laga, Suguru Saito, and Masayuki Nakajima *‘Personal Space Modeling for Human-Computer Interaction“*,2009.
- [4] K Lewin *“Field Theory in Social science “*,1951.
- Hannah Dee, and David Hogg *”Detecting inexplicable behavior ”*,2008.