Human Motion Prediction for Navigation of a Mobile Robot

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Master Thesis

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http://www.dei.unipd.it/
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IURO-Project: Interactive Urban Robot

Introduction

Approach

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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 ⇔ 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:
  ⇒ Pedestrian Ego-Graph

• Rank each way-point according to cost functions estimated from human trajectories
  ⇒ Cost Function

• Learning the cost functions

• Estimate the most probable trajectory to reach a predefined goal
  ⇒ Optimal trajectory
Markov Decision Process

• Markov Decision Process (MDP): $M = (S, A, P_{ss'}, \gamma, R_{ss'})$
  ▶ $S$ = Set of states
  ▶ $A$ = Set of actions
  ▶ $P_{ss'}^a$ = Transition probability
  ▶ $R_{ss'}^a$ = Reward function
  ▶ $\lambda$ = Discount factor $\in (0, 1)$

• Policy: $\pi : S \rightarrow A$
Most likely trajectory

• Value function $V$ over the policy $\pi$:

$$V^\pi(s_0) = R_{s_0s_1} + \lambda R_{s_1s_2} + \lambda^2 R_{s_2s_3} + ... + \lambda^t R_{s_ts_{t+1}}$$

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

• Optimal policy $\pi^*$:

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

• Description of two variables:

1. $\pi$ Policy
2. $R^\alpha_{ss'}$ Reward function
Pedestrian Ego-Graph (PEG)

- Set of trajectories obtained with different cluster-algorithms
- Each trajectory is a policy $\pi$ 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

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

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

- $C_{\text{pers}}$: Cost function based on the Personal space model:

$$C_{\text{pers}}(s^k_i) = \sum_j C_{jk} = \sum_j \exp(-0.5(s^j_i - s^k_i)^t \Sigma^{-1}(s^j_i - s^k_i))$$

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

Pedestrian ego-graph

Reduced PEG

Set of most probable trajectories

Most probable trajectory
Conclusions

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

- Reduction of the prediction error

<table>
<thead>
<tr>
<th>Pred. Error</th>
<th>1 [m]</th>
<th>2 [m]</th>
<th>3 [m]</th>
<th>4 [m]</th>
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<tbody>
<tr>
<td>CV</td>
<td>0.037</td>
<td>0.122</td>
<td>0.221</td>
<td>0.363</td>
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<tr>
<td>LTA [2]</td>
<td>0.054</td>
<td>0.128</td>
<td>0.212</td>
<td>0.285</td>
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<tr>
<td>SBCM [1]</td>
<td>0.030</td>
<td>0.074</td>
<td>0.100</td>
<td>0.105</td>
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<tr>
<td>OURs</td>
<td>0.031</td>
<td>0.072</td>
<td>0.097</td>
<td>0.099</td>
</tr>
</tbody>
</table>

- 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


Hannah Dee, and David Hogg ”Detecting inexplicable behavior “, 2008.