Comparing Neural Network and Knowledge-Based Approaches for Crowd Dynamics

Group C

Technical University of Munich

Machine Learning in Crowd Modeling and Simulation
March 2, 2024

Presentation Overview

Introduction

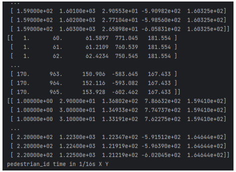
- Mainly based on 2 papers:
  - Example 7: *Prediction of Pedestrian Dynamics in Complex Architectures with Artificial Neural Networks*
  - Example 8: *Review of Pedestrian Trajectory Prediction Methods: Comparing Deep Learning and Knowledge-based Approaches*
- High level goal:
  - **Implement** neural network and knowledge-based methods
  - **Test** and **compare** on simple scenarios

Difference between neural and knowledge-based approach

	Knowledge-based	**Deep learning**
Semantics	Model	Algorithm
	Parameter	Coefficient
	Calibration	Training
	Validation	Testing
Methodology	Differential equation systems or cellular automata	Neural network, mostly RNN, LSTM, CNN, GAN
Inputs	System actual state (e.g., pedestrian relative positions, velocities, etc. at time t)	Past trajectories discretised over the time interval $[t-T, t]$, $T \approx 2$–4 s

Dataset introduction

- Dokumentation von Versuchen zur Personenstromdynamik - report for Project Hermes, Bergische Universität Wuppertal
- data is structured in a csv table : pedestrian id, time, x, y, z
- we remove the z coordinate as it is constant for each pedestrian
- different pedestrians have their speeds measured at different time spans (they are released gradually)
- the time is measured in 1/16s the position in cm, origin is chosen arbitrarily

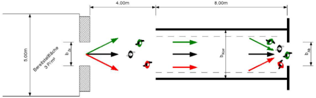


```
 ...
 [ 1.59000e+02  1.60100e+03  2.90553e+01 -5.90982e+02  1.60325e+02]
 [ 1.59000e+02  1.60200e+03  2.77104e+01 -5.98560e+02  1.60325e+02]
 [ 1.59000e+02  1.60300e+03  2.65898e+01 -6.05831e+02  1.60325e+02]]
[[   1.       60.        61.5897  771.045   181.554 ]
 [   1.       61.        61.2109  760.539   181.554 ]
 [   1.       62.        62.4234  750.545   181.554 ]
 ...
 [ 170.      963.       150.906  -583.645   167.433 ]
 [ 170.      964.       152.116  -593.082   167.433 ]
 [ 170.      965.       153.928  -602.462   167.433 ]]
[[ 1.00000e+00  2.90000e+01  1.36802e+02  7.86632e+02  1.59410e+02]
 [ 1.00000e+00  3.00000e+01  1.34933e+02  7.74737e+02  1.59410e+02]
 [ 1.00000e+00  3.10000e+01  1.33191e+02  7.62275e+02  1.59410e+02]
 ...
 [ 2.20000e+02  1.22300e+03  1.22347e+02 -5.91512e+02  1.64644e+02]
 [ 2.20000e+02  1.22400e+03  1.21919e+02 -5.96390e+02  1.64644e+02]
 [ 2.20000e+02  1.22500e+03  1.21219e+02 -6.02045e+02  1.64644e+02]]
pedestrian_id time in 1/16s X Y
```

(a) Numpy data dump

Dataset exploration

- UO - unidirektional offen
- one directional bottlenecked corridor scenario, the width of the corridor was 1.8 m, the width of the bottleneck was varied 0.7, 0.95 1.2 and 1.8m



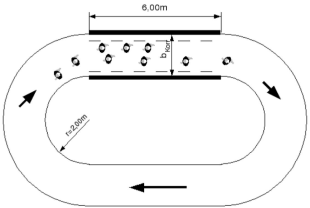
(b) experiment diagram

UO-180-180-180	1,8	1,8	1,8	200	1:29
UO-145-180-180	2×0,72	1,8	1,8	150	1:17
UO-110-180-180	0,5+0,6	1,8	1,8	100	0:59
UO-070-180-180	0,7	1,8	1,8	100	1:19
UO-060-180-180	0,6	1,8	1,8	50	0:56
UO-050-180-180	0,5	1,8	1,8	50	1:00
UO-180-180-120	1,8	1,8	1,2	150	1:19
UO-180-180-095	1,8	1,8	0,95	150	1:38
UO-180-180-070	1,8	1,8	0,7	150	1:38

(c) experiment table

Dataset exploration

- UG - unidirektional geschlossen
- one directional track oval shaped track scenario
- number of pedestrians was varied - 15, 30, 60, 85, 95, 110, 140, 230
- track was 1.8m wide, measurement area was 6m long, inner diameter was 2 m
- pedestrians took time to start moving was high density (85+ people)



(d) experiment diagram

Versuch.	b_{Korr} [m]	N	ρ	Zeit [min]
UG-180-015	1,8	15	0,25	1:49
UG-180-030	1,8	30	0,50	1:38
UG-180-60	1,8	60	1,00	1:50
UG-180-085	1,8	85	1,50	2:01
UG-180-110	1,8	110	2,00	3:19
UG-180-140	1,8	140	2,50	2:17
UG-180-170	1,8	170	3,00	2:03
UG-180-230	1,8	230	4,00	3:26
UG-180-110-2	1,8	110	2,00	3:23

(e) experiment table

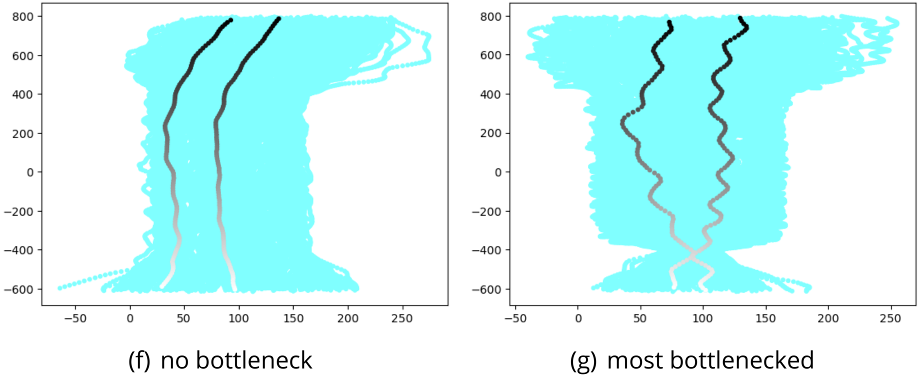
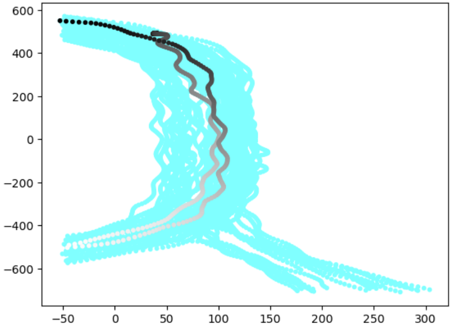
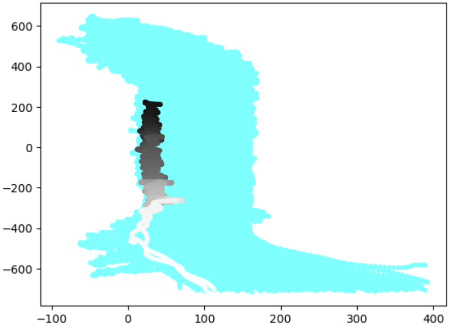


Figure: unidirektional geschlossen pedestrian trajectories (the trajectories of two chosen pedestrians progress black to white)



(a) fewest people



(b) most people

Figure: unidirektional ofnnen pedestrian trajectories (the trajectories of two chosen pedestrians progress black to white)

Implementation of knowledge-based model

- Microscopic speed-based model (Weidmann, 1993)
- A non-linear function of mean spacing with three parameters

$$W(\bar{s}_K, v_0, T, l) = v_0 \left(1 - e^{\frac{l - \bar{s}_K}{v_0 T}}\right)$$

$$\bar{s}_K = \frac{1}{K} \sum_i \sqrt{(x - x_i)^2 + (y - y_i)^2}$$

- Where
  - $\bar{s}_K$ is mean Euclidean spacing to K closest neighbours
  - T is following time gap with neighbours
  - v_0 is pedestrian speed in free situation
  - l physical size of pedestrian in stopped situation

Implementation of neural network

- Feed-forward multi-layer perceptron
- Fully connected hidden layers h with sigmoid activation function
- Input:
  - x, y positions
  - v, u velocities
  - $\bar{s}_K$ mean distance spacing
- Output: Prediction of pedestrian speed

Implementation of neural network

The four neural networks with different inputs.

- Relative positions to K closest neighbors.
  $NN_1 = NN_1(x_i - x, y_i - y, 1 \leq i \leq K)$
- Relative positions and velocities to K closest neighbors.
  $NN_2 = NN_2(x_i - x, y_i - y, v_i - v, u_i - u, 1 \leq i \leq K)$
- Relative positions with mean distance spacing $\bar{s}_K$
  $NN_3 = NN_3(\bar{s}_K, (x_i - x, y_i - y, 1 \leq i \leq K))$
- Relative positions and velocities with mean distance spacing $\bar{s}_K$
  $NN_4 = NN_4(\bar{s}_K, (x_i - x, y_i - y, v_i - v, u_i - u, 1 \leq i \leq K))$

Comparison between approaches

- Metrics for testing
  - Average Displacement Error (ADE)
  - Final Displacement Error (FDE)
- Testing method
  - Use testing set to evaluate
  - Comparing predictions using metrics
- Expected results
  - DL outperforms KB
  - KB outperforms DL (insufficient data)

Comparison between approaches

- Benefits:
  - DL: High accuracy, complex interaction learning.
  - KB: Theoretical clarity, effective in crowds.
- Drawbacks:
  - DL: Needs large data, lacks interpretability.
  - KB: Limited to average behavior, less flexible.
- Challenges:
  - DL: Generalization, model complexity.
  - KB: Adapting to new scenarios, bias in models.

Conclusion and Future work

- Both DL and KB have their strengths and limitations
- Future work
  - Hybrid Approach
  - DL Expansion
  - Robustness, Input Variables

Thank you for your attention!

References

Tordeux et al. (2020)
Prediction of pedestrian dynamics in complex architectures with artificial neural networks
Journal of intelligent transportation systems Vol 24, 556-568. Taylor & Francis.

Korbmacher et al. (2022)
Review of pedestrian trajectory prediction methods: Comparing deep learning and knowledge-based approaches
IEEE Transactions on Intelligent Transportation Systems IEEE.

Weidmann (1993)
Transporttechnik der Fussgaenger - Transporttechnische Eigenschaften des Fussgarngerverkehrs, Literaturauswertung
IVT Schriftenreihe Vol 90. ETH Zurich.