Conference Stochastic Models, Statistics and their Application 2019

Session : Big data and the calibration of mobility simulations

Artificial neural networks predicting pedestrian dynamics in complex buildings

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Simulation of pedestrian dynamics

Artificial neural networks

Corridor and bottleneck experiments

Prediction for the speed

Overview

Simulation of pedestrian dynamics

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Simulation of pedestrian dynamics

- Control of crowd and pedestrian flows in term of safety and performance
 - Large infrastructures (train station, shopping malls) or large events (sport events, festivals)
- Pedestrian dynamics are not straightforward to predict
 - Complex human behaviors including learning and anticipation / Complex multi-agent systems

Simulation of pedestrian dynamics

Control of crowd and pedestrian flows in term of safety and performance

- Large infrastructures (train station, shopping malls) or large events (sport events, festivals)
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 - Complex human behaviors including learning and anticipation / Complex multi-agent systems

Management and control thanks to simulation tools

- Microscopic models inspired from physical, social, psychological or proxemics concepts / Examples are force-based (social force), velocity-based or rule-based
- Models based on few interpretable parameters (desired speed, pedestrian size, ...)

Fundamental diagram

 Phenomenological relationship between the speed (or the flow rate) and the density (or the mean distance spacing)

- Weidmann's model (1992) $W(\bar{s}, v_0, T, \ell) = v_0 \left(1 - \exp\left(\frac{\ell - \bar{s}}{v_0 T}\right)\right)$

Speed/Spacing relationship for the Weidmann's model (1992)



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Models for understanding versus Models for prediction¹



¹See e.g. Saporta, COMPSTAT 2008, pp 315-322 (2008)

Artificial neural networks

- Data-based machine learning approaches for the motion prediction
 - For autonomous driving, motion of robots in crowded environments or pedestrian dynamics in complex geometries²
 - Artificial neural networks (convolutional, LSTM, deep learning, ...)

 $^{^2\}mathsf{See}$ e.g. Alahi et al., 2016; Chen et al., 2017; Das et al., 2015; Ma et al., 2016

Artificial neural networks

- Data-based machine learning approaches for the motion prediction
 - For autonomous driving, motion of robots in crowded environments or pedestrian dynamics in complex geometries²
 - Artificial neural networks (convolutional, LSTM, deep learning, ...)
- Feed-forward neural networks for speed prediction according to the positions of the K nearest neighbors
 - 1. Inputs are the relative positions to the K nearest neighbours (2K inputs)

$$\mathsf{NN}_1 = \mathsf{NN}_1(x_i - x, y_i - y, 1 \le i \le K).$$

Speed prediction according to the relative positions and the mean distance spacing s
_K to the K nearest neighbours (2K + 1 inputs)

$$NN_2 = NN_2(\bar{s}_{\mathcal{K}}, (x_i - x, y_i - y, 1 \le i \le \mathcal{K})).$$

²See e.g. Alahi et al., 2016; Chen et al., 2017; Das et al., 2015; Ma et al., 2016



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Corridor and bottleneck experiments

Corridor

Bottleneck

Speed/Spacing relationship



Mean spacing, m

Experiment	Spacing (m)	Speed (m/s)	ℓ (m)	T (s)	$V_0~({ m m/s})$
Corridor	1.03 ± 0.40	0.35 ± 0.33	0.64	0.85	1.50
Bottleneck	1.14 ± 0.37	0.72 ± 0.34	0.61	0.49	1.64

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Setting the network structures

- Fully connected neurons spread in hidden layers
- Setting the network structures: Optimal number of layers and neurons
 - \rightarrow Tested structures (1)³, (2), (3), (4,2), (5,2), (5,3), (6,3) and (10,4)⁴
- Cross-Validation: Split of the data in training and testing homogeneous datasets
- Training thanks to back-propagation algorithm, minimising the mean squared error

$$\mathsf{MSE} = \frac{1}{N} \sum_{i=1}^{N} (v_i - \tilde{v}_i)^2.$$

 Training and testing in bootstrap loops (50 subsamples) to evaluate the precision of estimation

³One hidden layer with 1 neuron

⁴Two hidden layers with respectivelly 10 and 4 neurons

Network NN_1 based on the relative positions



Network NN_1 based on the relative positions



Network NN₂ based on the relative positions and mean spacing



Network NN₂ based on the relative positions and mean spacing



Prediction for the speed

- Analyse of several combinations of training and testing sets to evaluate the precision and robustness of the predictions
- Tested scenario

- Training set / Testing set
- Notation : C: Corrridor experiment B: Bottleneck experiment

- B/B and C/C.

Single dataset is used for both training and testing

- B/C and C/B. Prediction ability in new situations
- C+B/B, C+B/C and C+B/C+B. Prediction in heterogeneous situations
- Weidmann speed model used as benchmark

Mean squared error

NN1: based on relative positions - NN2: based furthermore on mean distance spacing



Quality of the fit

- Weidmann's model based on $k_0 = 3$ parameters
- Artificial neural networks NN₁ and NN₂ based on $k_1 = 189$ and $k_2 = 88$
- Akaike Information Criterion for the quality of the fit (normal residuals)

$$AIC = 2k + n \ln(MSE) + n(1 + \ln(2\pi))$$



AIC difference

NN1: based on relative positions - NN2: based furthermore on mean distance spacing



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Prediction for the speed

- Significant prediction improvement of pedestrian dynamics (MSE and AIC) with artificial neural networks in cases of heterogeneous scenarios
- ▶ First steps for the modelling of pedestrians behaviors in complex infrastructures/buildings
- Data-based approach for the prediction No modelling of mechanisms governing the pedestrian motion
- Use of mean spacing as input, even if based on pedestrian relative positions already provided, allows improving the prediction and reducing the network complexity

- Training, testing and setting of the network complexity with large experimental datasets⁵
- Prediction of full trajectories in two dimensions and coupling to strategical routing models for simulation in complex scenarios
- Comparison to other parametric models (force-based models) and multi-agent systems

 $^{^{5}}$ ped.fz-juelich.de/database



Many thanks for your attention!