Data-driven fundamental models for pedestrian movements

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Congestion

Research challenges

- Understand, describe and predict
- Optimization of current infrastructure and operations
- Efficient planning and management of future pedestrian facilities
**Fundamentals**

**Quantities**
- Density $k$ (ped/m$^2$)
- Speed $v$ (m/s)
- Flow $q$ (ped/m·s)

Daamen (2004), Duives et al. (2015)
Limitations

**Fundamental quantities**
- Highly inspired by vehicular traffic
- Arbitrary spatial and temporal discretization

**Fundamental relationships**
- Deterministic models: equilibrium assumption
- Empirical observations: scattered pattern
Pedestrian flow characterization
Pedestrian flow characterization

Quantities
- Density $k$ (ped/m$^2$)
- Speed $v$ (m/s)
- Flow $q$ (ped/m·s)

Challenges
- Discretization method
- Complex pedestrian movements
- Heterogeneous population
- Multi-directional flows

Daamen (2004), Duives et al. (2015)
Spatial discretization

Grid-based

Range-based

Voronoi-based

Steen and Seyfried (2010), Saberi and Mahmassani (2014), Duives et al. (2015)
Data-driven approach: 3DVoro

Context

Model

- Space-time representation: $\Omega \subseteq \mathbb{R}^3$
- Units: meters and seconds
- $p = (x, y, t) \in \Omega$: physical position $(x, y)$ in space at a specific time $t$
- Assumption: $\Omega$ is convex (obstacle-free and bounded)

Data: trajectories

- Continuous: $\Gamma_i : \{p_i(t) | p_i(t) = (x_i(t), y_i(t), t)\}$
- Discrete (sample): $\Gamma_i : \{p_{is} | p_{is} = (x_{is}, y_{is}, t_s)\}, t_s = [t_0, t_1, ..., t_f]$
3D Voronoi diagram

**Definition**

- Associate \( p \in \Omega \) with the closest \( \Gamma_i \):

\[
\delta_{\Gamma}(p, \Gamma_i) = \begin{cases} 
1, & D(p, \Gamma_i) \leq D(p, \Gamma_j), \forall j \\
0, & \text{otherwise}
\end{cases}
\]

\[
D(p, \Gamma_i) = \min \{d(p, p_i)\}
\]

- Various definitions of \( d(\cdot, \cdot) \) are possible

- Voronoi cell for \( \Gamma_i \):

\[
V_i = p \in |\delta_{\Gamma}(p, \Gamma_i) = 1|
\]
Intersection with a plane

\[ \mathcal{P}_{(a, b, c), p_0} : \text{plane through } p_0 \text{ with normal vector } (a, b, c) \]
Voronoi-based traffic quantities

Consider \((x, y, t) \in \Omega\), and \(i\) such that \((x, y, t) \in V_i\)

\[
\text{Density: } k(x, y, t) = \frac{1}{|V_i \cap P_{(0,0,1),(x,y,t)}|}
\]

\[
\text{Flow: } \bar{q}_{(a,b,0)}(x, y, t) = \frac{1}{|V_i \cap P_{(a,b,0),(x,y,t)}|}
\]

\[
\text{Velocity: } \bar{v}_{(a,b,0)}(x, y, t) = \frac{|V_i \cap P_{(0,0,1),(x,y,t)}|}{|V_i \cap P_{(a,b,0),(x,y,t)}|}
\]

Properties

- Data-driven discretization
- General framework
- Microscopic characterization
- Applicable to continuous and discrete data
3D Voro: Application

Synthetic data
- NOMAD simulation tool (Campanella et al.; 2014)
- Flow composition: uni-directional and bi-directional
- Scenarios: low/high demand, homogenous/heterogeneous population

Analysis
- 3D Voro and XY-T methods
Nature of the results

![Graph showing density and flow over time](image-url)

- Density [ped/m²]
- Flow [ped/ms]
- Time [s]

3DVoro and XY-T comparison.
Robustness to sampling of trajectories

True trajectories

Samples

Interpolated trajectories

Sampling

Interpolation

k, v, q

k, v, q

k, v, q

k, v, q
Robustness to sampling of trajectories

<table>
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<tr>
<th>High sampling frequency</th>
<th>Low sampling frequency</th>
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<td>0.1</td>
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<td>0.3</td>
<td>0.3</td>
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<tr>
<td>0.4</td>
<td>0.4</td>
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- **XY-T**
- **E-3D Voronoi**
- **TT-3D Voronoi**
- **TT-3D Voronoi**
- **TT-3D Voronoi**
- **M-3D Voronoi**

Error: 90% quantile interpolation sample
3DVoro: Main findings

- Data-driven and microscopic discretization
- Well defined, flexible and general
- Smooth transitions in measured characteristics
- Robust to noise in the data
- Robust to sampling of trajectories
Pedestrian flow modeling
Speed-density relationship

Models

Empirical observations

Daamen (2004), Zhang (2012)
What affects the speed of pedestrians?

How to account for pedestrian heterogeneity?

- Relaxing the homogeneity assumption of the equilibrium
- Probabilistic modeling approach
  - Pedestrian probabilistic speed-density relationship: PedProb-vk
  - Multi-class speed-density relationship: MC-vk
Multi-class speed-density relationship: MC-vk

Assumptions

- The speed of pedestrians is a random variable
- Population is partitioned into classes
- The speed-density relationship varies across classes
Modeling framework

\[
f_{MC-vk}(v_i|k_i, X_i; \theta_j(k_i), \beta_j) = \sum_{j=1}^{J} f_j(v_i|k_i, j; \theta_j(k_i)) \Pr(j|X_i; \beta_j)
\]

Traffic condition data

Behavioral profile of pedestrians

Class-specific model (CSM)

Class membership model (CMM)

Multi-class speed-density relationship (MC-vk)
Lausanne railway station
Lausanne railway station: Data

- Individual trajectories
- Train timetable
- Infrastructure data
Model specification: Lausanne railway station

Classes: $C_1$ and $C_2$

Class-specific model (CSM)

- Rayleigh model:
  \[ f_j(v_i|k_i, j; \mu_j(k_i)) = \frac{v_i}{2\mu_j^2(k_i)/\pi} \exp\left(-\frac{v_i^2}{4\mu_j^2(k_i)/\pi}\right) \]

- Mean: $\mu_j(k_i) = v_{f,j} - \gamma_j k_i$

Class membership model (CMM)

- Fitness function:
  \[ U_{i,j} = V_{i,j} + \varepsilon_{i,j} = CSC_j + \beta_j X_i + \varepsilon_{i,j} \]

- Logit model:
  \[ \Pr(j|X_i; \beta_j) = \frac{e^{V_{i,j}}}{\sum_{j=1}^2 e^{V_{i,j}}} \]

- Explanatory variables
  - Pedestrian type
  - Time period
  - OD distance
  - Time to departure
Class-specific behavior

\[ \text{average speed [m/s]} \]

- \(C_1\): less sensitive to congestion
- \(C_2\): more sensitive to congestion

\[ \text{density [ped/m}^2\text{]} \]
Class profiling

![Class profiling graphs](image)

- **Class sharing**
  - Class 1: $C_1$
  - Class 2: $C_2$

- **Pedestrian type sharing**
  - AP
  - DP
  - TP
  - NP

- **Average time to departure**
  - $C_1$
  - $C_2$

- **Average OD distance**
  - $C_1$
  - $C_2$
Comparison with deterministic models

![Graph showing comparison between different models.](image)

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<td>$4.81e^{-03}$</td>
<td>$3.63e^{-03}$</td>
<td>$3.95e^{-03}$</td>
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<td>$7.69e^{-01}$</td>
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Scenario analysis: train timetable modification

- Instrument for policy making and daily operations
- Impact of different scenarios on the movement behavior and LoS
- Augmentation by posterior analysis

![Graph showing reduction of time to departure and share percentage](image)
MC-vk: Main findings

- Probabilistic approach to account for heterogeneity
- Conceptually insightful
- Parsimonious, flexible and fairly general
- Superior compared to the deterministic approaches
- Suitable for forecasting analysis
Conclusion
Main contributions

- Utilization of data potential
- Data-driven discretization and characterization
- Probabilistic models for speed-density relationship
- Application on different case studies and practical guidelines
Future directions

Models

- Characterization: anisotropy and presence of obstacles
- Speed-density relationships: anisotropy and dynamics

Applications

- Level-of-service analysis
- Planning, design and optimization
- Simulation and management of pedestrian traffic

Data

- Different behavioral situations and types of infrastructure
- Real sites, new collection technologies
Thank you

Workshop on Transportation Network and Management:  
**Data-driven fundamental models for pedestrian movements**  
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References II


