hEART 2017 - 6th Symposium of the European Association for Research in Transportation

Pedestrian multi-class speed-density relationship: evaluation of integrated and sequential approach

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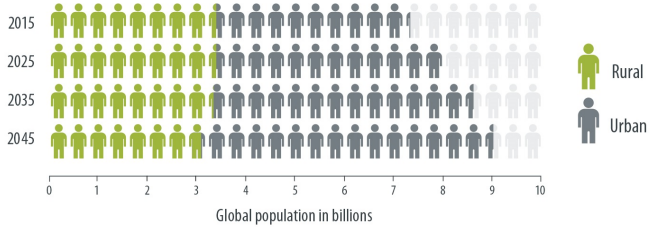
Haifa, September 12, 2017

Urbanization

- 1950: **30%** of the population lives in cities
- 2014: **54%** of the population lives in cities

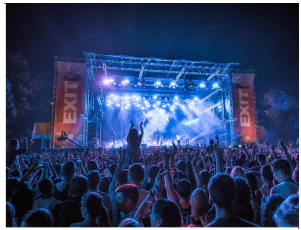
Challenges

- Energy consumption, pollution, climate change
- Increased traffic and congestion



Source: UN World Urbanization Prospects: 2011 Revision

Pedestrian movements: Congestion


Research challenges

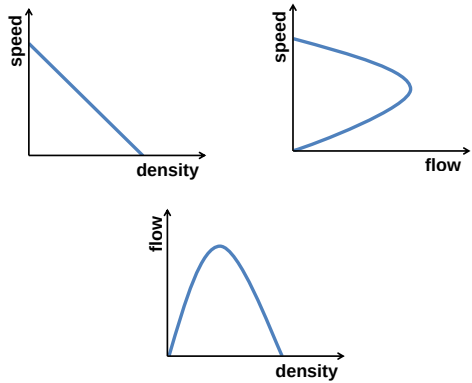
- Understand, describe and predict
- Optimization of current infrastructure and operations
- Efficient planning and management of future pedestrian facilities

Fundamentals

Quantities

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

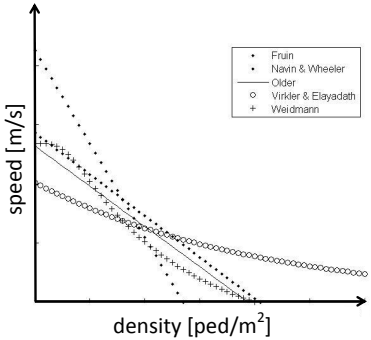
Relationships



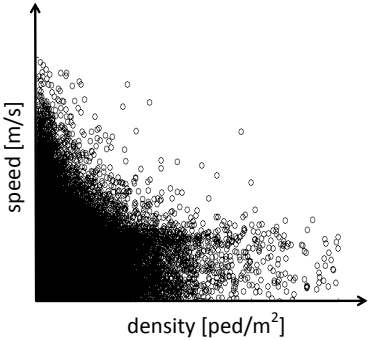
Daamen (2004), Duives et al. (2015)

Speed-density relationship

Models

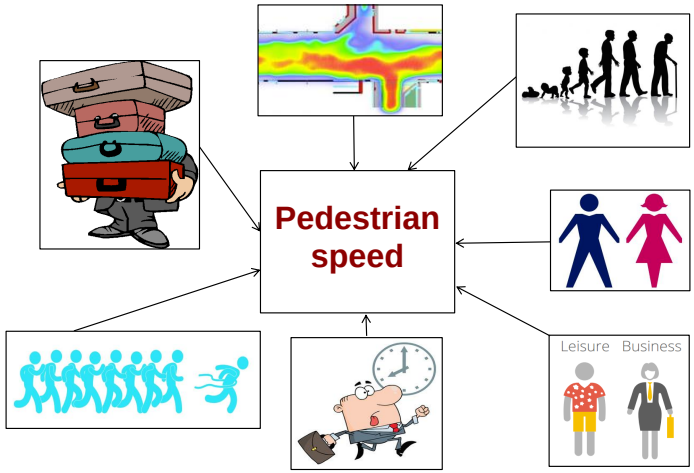


Empirical observations



Daamen (2004), Zhang (2012)

What affects the speed of pedestrians?



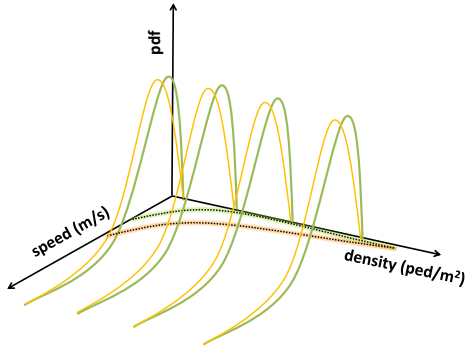
Weidmann (1993), Daamen (2004)

Modeling framework

Objective: Accounting for pedestrian heterogeneity
Approach: Probabilistic multi-class speed-density relationship

Assumptions

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

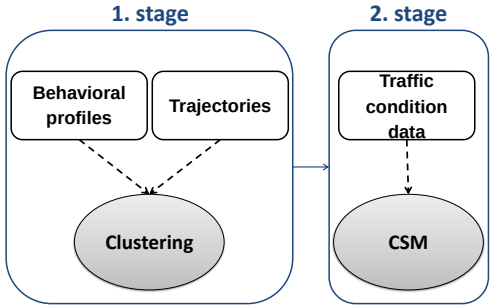


Model specifications

Probabilistic multi-class speed-density relationship

- Sequential (two-stage) approach
  - Population segmentation and movement behavior modeled sequentially
- Integrated approach
  - Population segmentation and movement behavior modeled simultaneously

Sequential approach



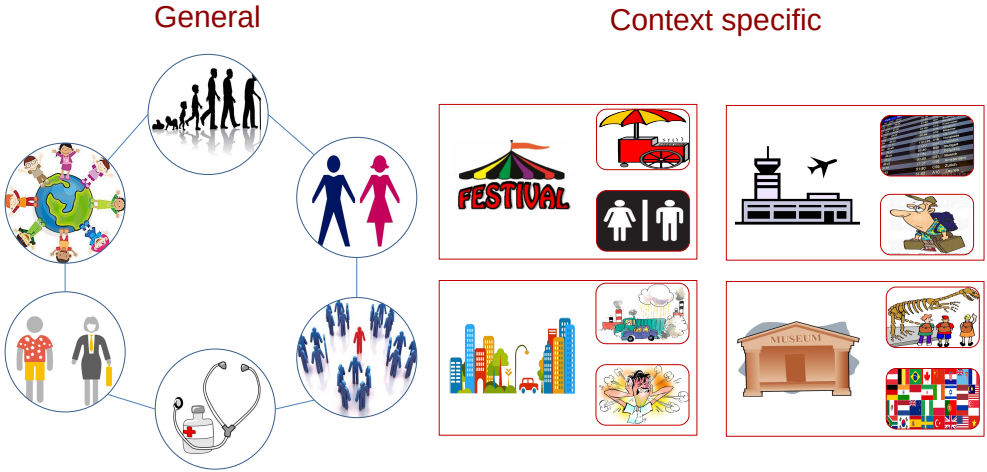
Population segmentation: clustering

- Similarity measures: feature-based, shape-based
- Algorithm: K-means clustering

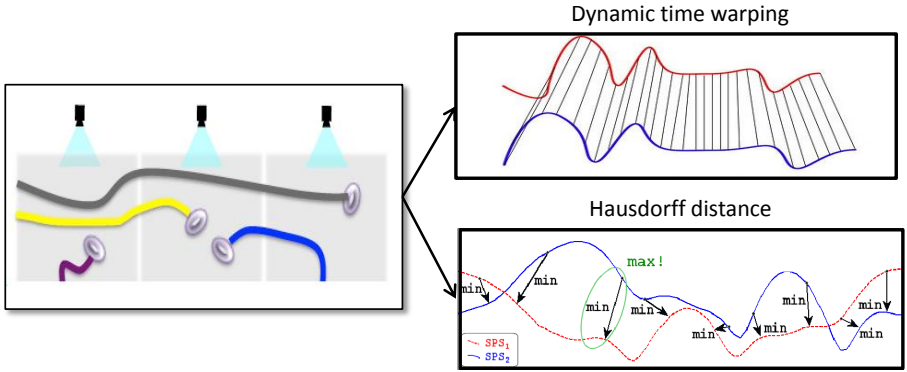
Class-specific model (CSM)

- Class-specific speed-density relationship: $f_j(v_i|k_i, j; \theta_j(k_i))$

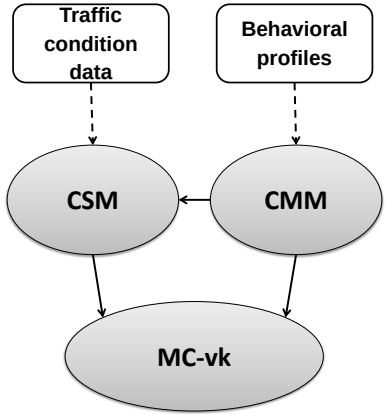
Feature-based clustering



Shape-based clustering



Integrated approach



Population segmentation:

- Class membership model (CMM): $\Pr(j|X_i;\beta_j)$
- Fitness function: $U_{i,j} = V_{i,j} + \varepsilon_{i,j} = CSC_j + \beta_j X_i + \varepsilon_{i,j}$

Class-specific model (CSM)

- Class-specific speed-density relationship: $f_j(v_i|k_i,j;\theta_j(k_i))$

Multi-class speed-density (MC-vk)

$$\sum_{j=1}^{J} \underbrace{f_j(v_i|k_i,j;\theta_j(k_i))}_{\text{CSM}} \underbrace{\Pr(j|X_i;\beta_j)}_{\text{CMM}}$$

Application

Case study: Lausanne railway station

Data sets

Pedestrian type	Period	Walking pattern	Time to departure	OD distance
Arriving	Peak	Group		
Departing	Off-peak	Alone		
Transferring				
Non-passengers				

Two-stage approach

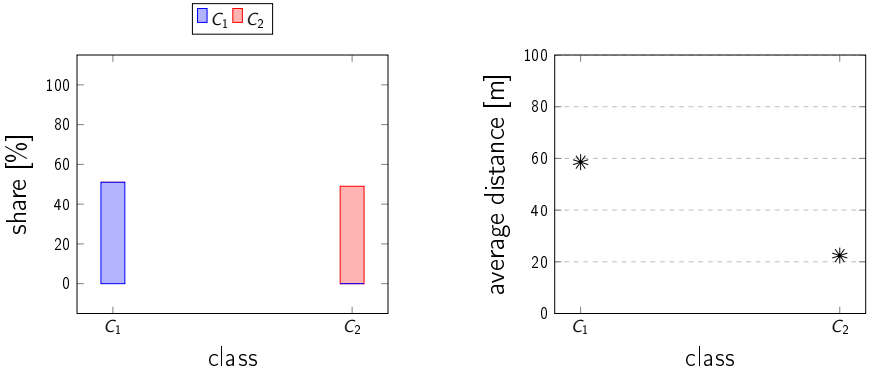
Clustering: Performance analysis

Clustering	R^2	CH	DI	DB	Score
Feature-based					
Pedestrian type	433	1	3.23	5.83	443.06
Peak - Pedestrian type	515	58.1	3.77	1	578.33
OD distance	60.8	101	8.27	2.94	**173.01**
Time spent	176	6.41	3.03	3.09	188.53
Shape-based					
DTW	1	52.2	42	69.3	164.5
HD	28.3	24.6	12.1	4.65	**69.65**

R^2: R-squared, CH: Calinski-Harabasz, DI: Dunn index, DB: Davies-Bouldin

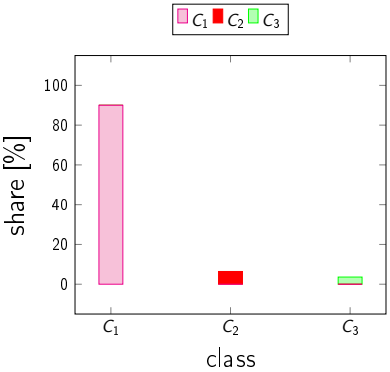
DTW: Dynamic time warping, HD: Hausdorff distance

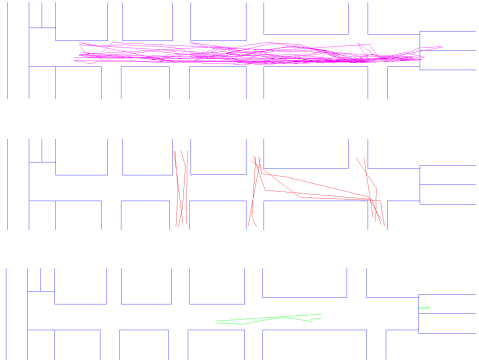
Class profiling: OD distance



C_1: pedestrians walking longer distances
C_2: pedestrians walking shorter distances

Class profiling: HD





C_1: main stream
C_2: minor stream
C_3: incomplete trajectories

Class-specific model

Rayleigh distribution

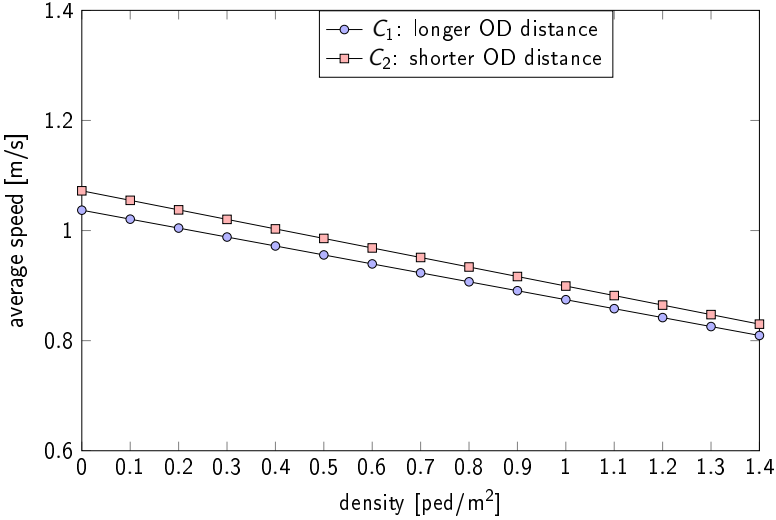
$$f_j(v_i|k_i, j, \mu_j(k_i)) = \frac{v_i}{2\mu_j^2(k_i)/\pi} \exp(-\frac{v_i^2}{4\mu_j^2(k_i)/\pi})$$

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

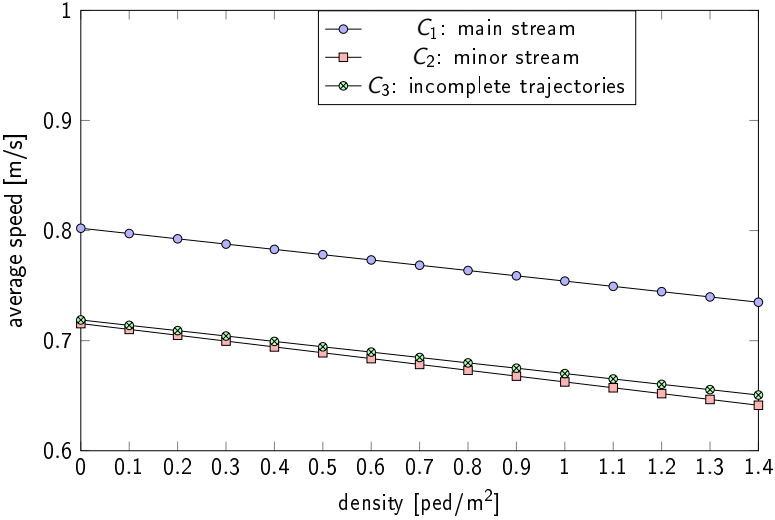
Alternative specifications

- Weibull, Log-normal, Exponential
- Lower performance (BIC)

Class-specific behavior: OD distance



Class-specific behavior: HD



Integrated approach

MC-vk: Model specification

Two classes: class C_1 and class C_2

CMM: Logit model

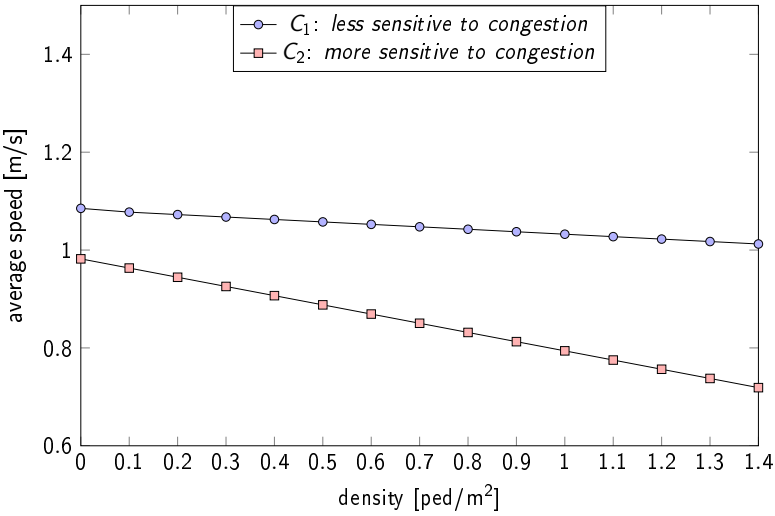
$$\Pr(j|X_i;\beta_j) = \frac{e^{V_{i,j}}}{\sum_{j=1}^{2} e^{V_{i,j}}}$$

$$U_{i,j} = V_{i,j} + \varepsilon_{i,j} = CSC_j + \beta_j X_i + \varepsilon_{i,j}$$
$$V_{i,1} = CSC_1 + \beta_{DP,1} DP_i + \beta_{TP,1} TP_i + \beta_{NP,1} NP_i$$
$$V_{i,2} = \beta_{TTD,2} TTD_i + \beta_{PP,2} PP_i + \beta_{OD,2} OD_i$$

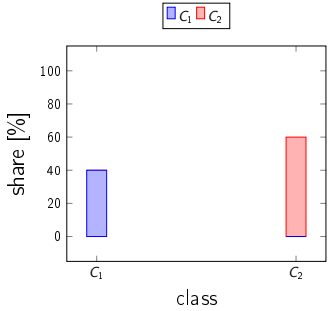
CSM: Rayleigh distribution

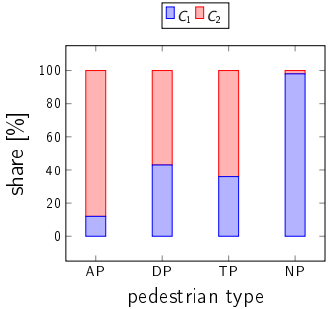
$$f_j(v_i|k_i, j, \mu_j(k_i)) = \frac{v_i}{2\mu_j^2(k_i)/\pi} \exp\left(-\frac{v_i^2}{4\mu_j^2(k_i)/\pi}\right)$$
$$\mu_j(k_i) = v_{f,j} - \gamma_j k_i$$

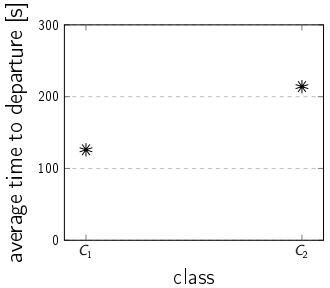
Class-specific behavior

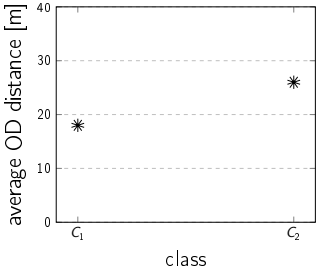


Class profiling



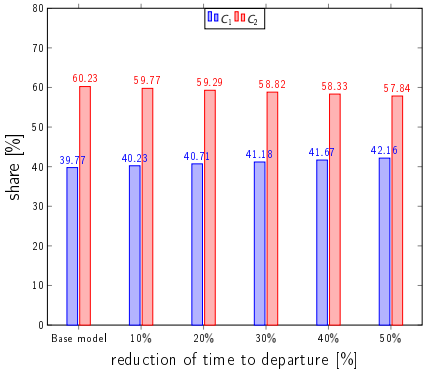






Scenario analysis: train timetable modification

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



Comparison of two-stage and integrated approach

Cohesion: how closely related observations in a cluster are
Separation: how distinct a cluster is from other clusters

Approach	Avg cohesion	Avg separation	Score
Integrated	0.242 (1)	0.258 (1.67)	2.67
Two-stage: HD	0.423 (1.75)	0.431 (1)	2.75
Two-stage: OD	0.242 (1)	0.243 (1.77)	2.77

Conclusion

Main findings

- Probabilistic multi-class models for pedestrian movements
  - Account for population heterogeneity
  - Integrated and two-stage approach
  - Insightful, flexible and fairly general
- Two-stage approach
  - Shape-based clustering better suited to discover behavior of interest
  - Imprecise parameter estimates due to potentially small sample sizes
  - Segmentation may introduce errors in the second stage
- Integrated approach
  - Avoids measurement errors
  - Uses the behavior of interest to define segmentation
  - Suitable for forecasting analysis

Future directions

- Additional criteria for the evaluation of the approaches
- Other feature-based and shape-based similarity measures
- Accounting for dynamics

Thank you

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References I

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