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Data-driven characterization of pedestrian flows

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Introduction



Methodology

- Discretization framework
- Definitions of the indicators









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- 3 Empirical analysis







Pedestrian traffic

Importance

• Understanding, reproducing and forecasting phenomena that characterize pedestrian traffic is necessary in order to provide services related to pedestrian safety and convenience.

Indicators

- Density (ped/m^2) , speed (m/s) and flow (m/ped/s)
- Used to observe and to model the flows of pedestrians
- Consistent and unified approach to the definitions of the indicators is missing





Comparison of the approaches

Properties

- P1: Consistency of the results in measurement and modeling
- P2: Compliance with multi-directional nature of pedestrian flows

P3: Preserved heterogeneity of pedestrians

 $P_{\rm 4}$: Independence of arbitrarily chosen space and time intervals over which the variables are defined

 $P_{\rm 5}$: Applicability to pedestrian trajectories described analytically or as a sample of points

Method	P_1	P2	P_3	P ₄	P_5
Edie (1963)	~	×	×	×	×
Jabari et al. (2014)	~	X	~	✓	×
van Wageningen-Kessels et al. (2014)	~	X	X	×	×
Helbing et al. (2007)	~	×	×	×	×
Steffen and Seyfried (2010)	X	~	~	partialy	×





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- 3 Empirical analysis
- 4 Conclusion and future work





Pedestrian trajectories

• The trajectory of pedestrian i is a curve in space and time

$$\Gamma_i : \{p_i(t) | p_i(t) = (x_i(t), y_i(t), t)\}$$

- 3D Voronoi diagrams associated with trajectories
- Each trajectory Γ_i is associated with a 3D Voronoi 'tube' V_i

$$V_i = \{p|\min\{d_*(p, p_i)|p_i \in \Gamma_i\} \le \min\{d_*(p, p_j)|p_j \in \Gamma_j\}, \forall j\}$$

• $d_*(p, p_i)$ - spatio-temporal assignment rule





Sample of points

• The trajectory is described as a finite collection of triplets

$$\Gamma_i : \{p_{is} | p_{is} = (x_{is}, y_{is}, t_s)\}, t_s = [t_0, t_1, ..., t_f]$$

- 3D Voronoi diagrams associated with the points
- Sequences of 3D Voronoi cells V_{is} are assigned to the sequence of points for each pedestrian

$$V_i = \{V_{is}|V_{is} = \{p|d_*(p,p_{is}) \leq d_*(p,p_{js})\}, orall j\}$$

• $d_*(p, p_{is})$ - spatio-temporal assignment rule





Naive assignment rule

$$d_N(p,p_i) = \left\{ egin{array}{c} \sqrt{(p-p_i)^T(p-p_i)}, & \Delta t = 0 \ \infty, & otherwise \end{array}
ight.$$

Time-Transform assignment rules

$$d_{TT_1}(p, p_i) = \sqrt{(x - x_i)^2 + (y - y_i)^2 + \alpha^2 (t - t_i)^2}$$
$$d_{TT_2}(p, p_i) = \sqrt{(x - x_i)^2 + (y - y_i)^2} + \alpha_i(t_i)|(t - t_i)|$$
$$d_{TT_3}(p, p_i) = \sqrt{(x - x_i)^2 + (y - y_i)^2 + \alpha_i^2(t_i)(t - t_i)^2}$$

lpha and $lpha_i$ - conversion constants expressed in meters per second





Predictive assignment rule

$$d_{P}(p, p_{i}) = \begin{cases} \sqrt{(x_{i} + (t - t_{i})v_{i}^{x}(t_{i}) - x)^{2} + (y_{i} + (t - t_{i})v_{i}^{y}(t_{i}) - y)^{2}}, & t - t_{i} \geq 0 \\ \infty, & otherwise, \end{cases}$$

 $v_i^x(t_i), v_i^y(t_i)$ - the speed of pedestrian *i* at t_i in x and y directions $(x_i + (t - t_i)v_i^x(t_i), y_i + (t - t_i)v_i^y(t_i))$ - the anticipated position of the pedestrian at time t

Mahalanobis assignment rule

$$d_M(p,p_i) = \sqrt{(p-p_i)^T M_i(p-p_i)}$$

 M_i - symmetric, positive-definite matrix that defines how distances are measured from the perspective of pedestrian i





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$$V_i(t) = \{(x(t), y(t), t) \in V_i\} \sim [m^2]$$



Density indicator

$$k(x,y,t) = rac{1}{|V_i(t)|}, ext{ for } x,y \in V_i(t)$$





The set of all points in V_i corresponding to a given location x and y

$$V_i(x) = \{(x, y, t) \in V_i\} \sim [ms]$$

 $V_i(y) = \{(x, y, t) \in V_i\} \sim [ms]$



Flow indicator

$$ec{q}(x,y,t) = \left(egin{array}{c} q^x(x,y,t)\ q^y(x,y,t) \end{array}
ight) = \left(egin{array}{c} rac{1}{|V_i(x)|}\ rac{1}{|V_i(y)|} \end{array}
ight)$$

Velocity indicator

$$\vec{v}(x,y,t) = \begin{pmatrix} \frac{q^x(x,y,t)}{k(x,y,t)} \\ \frac{q^y(x,y,t)}{k(x,y,t)} \end{pmatrix} = \begin{pmatrix} \frac{|V_i(t)|}{|V_i(x)|} \\ \frac{|V_i(t)|}{|V_i(y)|} \end{pmatrix}$$

Introduction

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Synthetic data





- NOMAD simulation tool [Campanella, 2010]
- Population is assumed to be (approximately) homogenous in terms of walking speed
- Demand: 1.2 pedestrians/second





Robustness with respect to the aggregation

- 100 sets of pedestrian trajectories synthesized for the described setting
- Indicators calculated for each set via 3D Voro and the standard Edie's method
- Hypothesis: the obtained distributions of the indicators represent the same population

Kruskal-Wallis test

Method	V-d _N	V-d _{TT}	V-d _{TT2}	V-d _{TT}	V-d _P	V-d _M	Edie
<i>p</i> -value	1	1	1	1	1	1	5.28e ⁻¹³





Robustness with respect to the sampling frequency

- The samples of points from the synthetic trajectories obtained using different sampling frequencies
- Indicators calculated via
 - 1. 3D Voro applied to the trajectories obtained using the interpolation of the points
 - 2. 3D Voro applied directly to the samples
- Comparison of the indicators at 1000 randomly selected points to the corresponding values obtained utilizing true trajectories





High sampling frequency: $3.33s^{-1}$

Mathod	Mean		Mode		Med	lian	90% quantile	
Method	IT	SoP	IT	SoP	IT	SoP	IT	SoP
3D Voro-d _N	$1.82e^{-0.2}$	/	0	/	0	/	$4.37e^{-0.2}$	/
3D Voro-d _{TT1}	$2.12e^{-0.2}$	$2.00e^{-0.2}$	0	0	0	$8.10e^{-0.4}$	$1.02e^{-0.2}$	$1.08e^{-0.2}$
3D Voro-d _{TT2}	$4.57e^{-0.2}$	$5.47e^{-0.2}$	0	0	$1.00e^{-0.4}$	$5.05e^{-0.3}$	$1.82e^{-0.2}$	6.83e ⁻⁰²
3D Voro-d _{TT3}	$5.61e^{-0.2}$	$8.60e^{-0.2}$	0	0	$4.30e^{-04}$	$1.33e^{-0.2}$	$1.78e^{-0.2}$	9.83e ⁻⁰²
3D Voro-d _P	$9.44e^{-0.2}$	$1.31e^{-01}$	0	0	$1.25e^{-0.3}$	1.33e ⁻⁰²	$1.95e^{-0.2}$	$1.20e^{-01}$
3D Voro-d _M	$3.47e^{-0.2}$	8.57e ⁻⁰²	0	0	$8.80e^{-04}$	$2.09e^{-0.2}$	$1.80e^{-0.2}$	$1.28e^{-01}$
Edie	$1.05e^{-01}$	/	$2.50e^{-0.2}$	/	$5.00e^{-0.2}$	/	$2.38e^{-01}$	/

Low sampling frequency: $0.5s^{-1}$

Method	Mean		Mode		Median		90% quantile	
	IT	SoP	IT	SoP	IT	SoP	IT	SoP
3D Voro-d _N	1.78e ⁻⁰¹	/	0	/	$1.32e^{-01}$	/	$3.51e^{-01}$	/
3D Voro-d _{TT1}	4.23e ⁻⁰¹	3.85e ⁻⁰¹	$1.25e^{-0.2}$	$2.83e^{-0.3}$	$1.11e^{-01}$	$8.54e^{-0.02}$	4.79e ⁻⁰¹	$4.14e^{-01}$
3D Voro-d _{TT2}	$2.29e^{-01}$	$1.90e^{-01}$	$1.27e^{-0.2}$	$2.83e^{-0.3}$	$1.24e^{-01}$	8.75e ⁻⁰²	$4.54e^{-01}$	3.95e ⁻⁰¹
3D Voro-d _{TT3}	$2.77e^{-01}$	$2.49e^{-0.2}$	$1.73e^{-0.2}$	$4.36e^{-0.3}$	$1.32e^{-01}$	8.82e ⁻⁰²	$4.70e^{-01}$	4.38e ⁻⁰¹
3D Voro-d _P	$2.79e^{-01}$	2.73e ⁻⁰¹	$1.88e^{-0.2}$	$2.05e^{-0.2}$	$1.23e^{-01}$	$9.51e^{-0.02}$	4.71e ⁻⁰¹	$3.99e^{-01}$
3D Voro-d _M	$2.46e^{-01}$	2.73e ⁻⁰¹	3.37e ⁻⁰²	$6.38e^{-0.2}$	$1.43e^{-01}$	$1.00e^{-01}$	$4.99e^{-01}$	$4.66e^{-01}$
Edie	6.37e ⁻⁰¹	/	1.13e ⁻⁰¹	/	5.63e ⁻⁰¹	/	1.19	/





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Conclusion and future work

Conclusion

- A novel approach: data-driven discretization via 3D Voronoi diagrams
- Features number of desired properties
- Superior to existing methods
 - Robustness with respect to the aggregation
 - Robustness with respect to the sampling frequency

Future work

- Analysis of the performance for different scenarios
- Weighted assignment rules





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