Data-driven characterization of multidirectional pedestrian traffic

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Outline

1. Motivation and objective
2. Related research
3. Methodology
4. Empirical analysis
5. Conclusion and future work


JEWLERS
FLOWERS
CANDY
GRILLMEISTER

Background - context

Understanding and predicting of pedestrian traffic

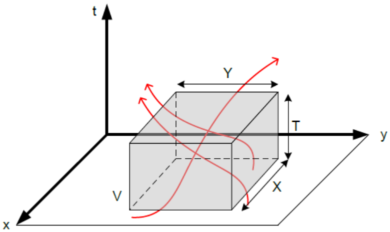
- Convenience and safety for pedestrians
- LOS indicators: based on data or/and models of pedestrian dynamics

Traffic indicators

- **Density**: the number of pedestrians present in an area at a certain time instance [#ped/m^2]
- **Flow**: the number of pedestrians passing a line segment in a unit of time [#ped/ms]
- **Velocity**: the average of the velocities of pedestrians present in an area at a certain time instance / passing a line segment in a unit of time [m/s]

Characterization based on Edie's definitions

General formulation



Density: $k(V) = \dfrac{\sum_i^N t_i}{dx \times dy \times dt}$

Flow: $\vec{q}(V) = \dfrac{\sum_i^N d_i}{dx \times dy \times dt}$

Velocity: $\vec{v}(V) = \dfrac{\vec{q}(V)}{k(V)} = \dfrac{\sum_i^N d_i}{\sum_i t_i}$

[van Wageningen-Kessels et al., 2014], [Saberi and Mahmassani, 2014]

Characterization based on Edie's definitions

Limit conditions

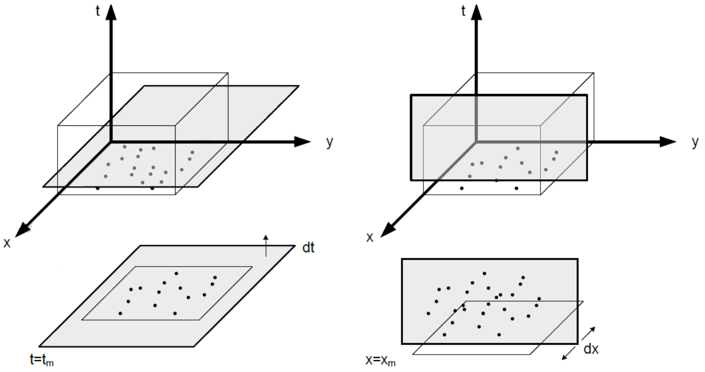
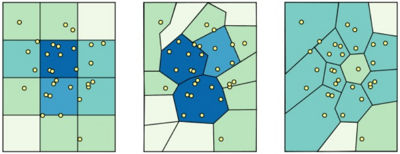


Photo: [Saberi and Mahmassani, 2014]

Characterization based on Edie's definitions

- Results depend on size, shape and the placement of a measurement unit
  - May be highly sensitive to minor changes
- Arbitrary aggregation
  - May generate noise in the data [Openshaw, 1983]
  - May lead to loss of heterogeneity across space

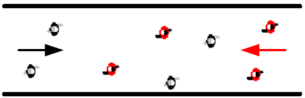
Density indicator



Characterization based on Edie's definitions

- Arbitrary aggregation
  - May lead to loss of heterogeneity across pedestrians
  - Does not comply with multi-directional nature of pedestrian flows
- Extreme case: velocity and flow vectors cancel out when 2 equally sized streams of pedestrians walk with the same speed but in the opposite directions

Velocity and flow indicators

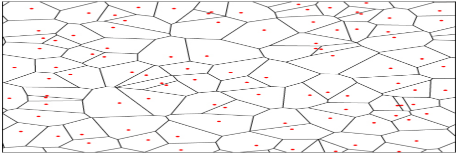


Voronoi-based spatial discretization

- A personal region A_i is asigned to each pedestrian i
- Each point $p = (x, y)$ in the personal region is closer to i positioned at $p_i = (x_i, y_i)$ than to any other pedestrian, with respect of the Euclidean distance

$$A_i = \{p | d_E(p, p_i) \leq d_E(p, p_j), \forall j\}$$

- Pedestrian flows: [Steffen and Seyfried, 2010]



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Data-driven discretization framework

Pedestrian trajectories

- The trajectory of pedestrian i is a curve in space and time
$$p_i = (x_i, y_i, t_i)$$
- 3D Voronoi diagrams associated with trajectories
- Each trajectory Γ_i is associated with a 3D Voronoi 'tube' V_i
- A point $p = (x, y, t)$ belongs to the set V_i if
$$d(p, \Gamma_i) \leq d(p, \Gamma_j), \forall j$$
$$d(p, \Gamma_i) = min\{d_*(p, p_i) | p_i \in \Gamma_i\}$$
- $d_*(p, p_i)$ - spatio-temporal assignment rule

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Data-driven discretization framework

Sample of points

- The trajectory is described as a finite collection of triplets
$$p_{is} = (x_{is}, y_{is}, t_s), t_s = [t_0, t_1, ..., t_f]$$
- 3D Voronoi diagrams associated with the points $p_{is} = (x_{is}, y_{is}, t_s)$
- Each point p_{is} is associated with a 3D Voronoi cell V_{is}
- A point $p = (x, y, t)$ belongs to the set V_{is} if
$$d_*(p, p_{is}) \leq d_*(p, p_{js}), \forall j$$
- $d_*(p, p_{is})$ - spatio-temporal assignment rule

Spatio-temporal assignment rules

Naive distance

$$d_N(p, p_i) = \begin{cases} \sqrt{(p-p_i)^T(p-p_i)}, & \Delta t = 0 \\ \infty, & otherwise \end{cases}$$

Distance To Interaction (DTI)

$$d_{DTI}(p, p_i) = \begin{cases} \sqrt{(p-p_i)^T(p-p_i)}, & \Delta t = 0 \\ \frac{(p-p_i(t_i+\Delta t))\vec{v_i}(t_i)}{\|(\vec{v_i}(t_i))\|}, & otherwise \end{cases}$$

$p = (x, y, t), \; p_i = (x_i, y_i, t_i), \; \Delta t = t - t_i$

Spatio-temporal assignment rules

Time-Transform distance (TT)

$$d_{TT}(p, p_i) = \sqrt{(x - x_i)^2 + (y - y_i)^2} + \alpha(t - t_i)$$

α is a conversion constant expressed in meters per second

Mahalanobis distance

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

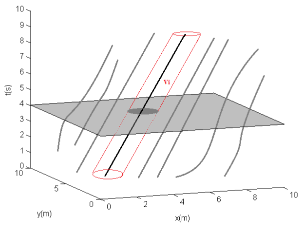
- M_i - symmetric, positive-definite matrix that defines how distances are measured from the perspective of pedestrian i

$p = (x, y, t)$, $p_i = (x_i, y_i, t_i)$

Voronoi-based traffic indicators

The set of all points in V_i corresponding to a specific time t

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



Density indicator

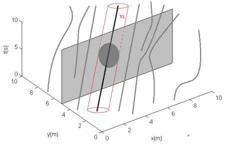
$$k_i = \frac{1}{V_i(t)}$$

Voronoi-based traffic indicators

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

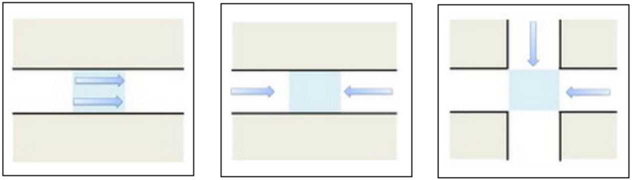
$$\vec{q}_i = \begin{pmatrix} \frac{1}{V_i(x)} \\ \frac{1}{V_i(y)} \end{pmatrix}$$

Velocity indicator

$$\vec{v}_i = \frac{\vec{q}_i}{k_i}$$

Empirical analysis

Scenarios



- Synthetic pedestrian trajectories
- Voronoi-based characterization for trajectories with d_N, d_{TT}, d_M, d_{DTI}

Properties of 3D Voronoi-based characterization

✓ Discretization is performed at the level of an individual: suitable for multi-directional flow composition

- Reproduces different simulated settings with uniform and non-uniform movement
- Preserves heterogeneity across pedestrians and space
- Discretization is adjusted to the reality of the flow: leads to smooth transitions in measured traffic characteristics

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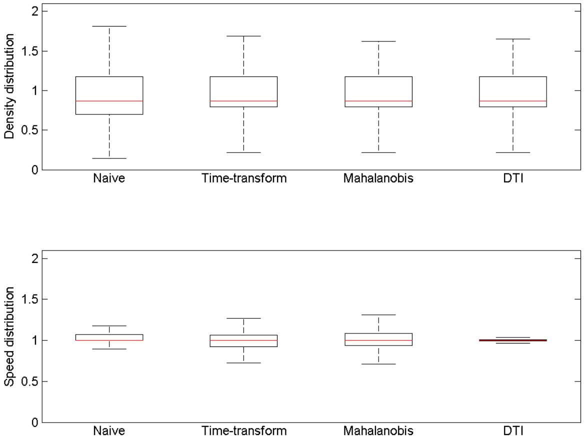
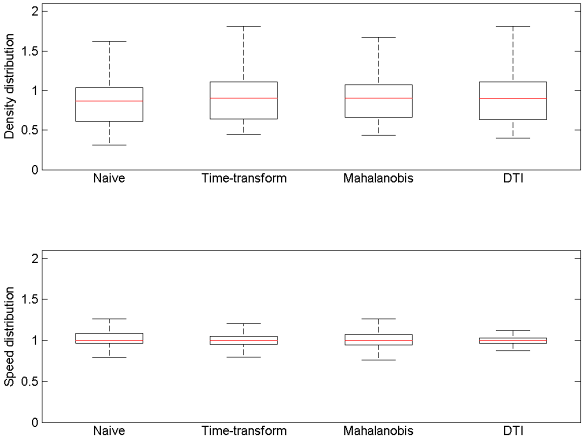
Unidirectional non-uniform straight-line movement



Bidirectional non-uniform straight-line movement



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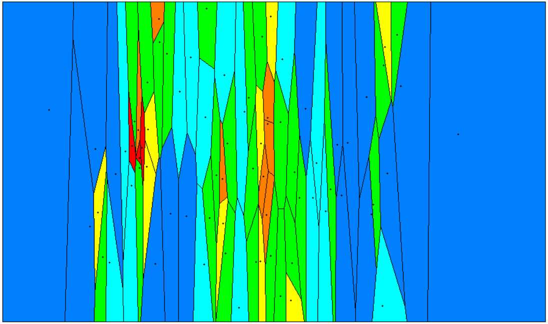
3D Voronoi-based characterization - density map



	LOS	Pedestrian density
blue	A	< 0.179 [ped/m^2]
cyan	B	< 0.270
green	C	< 0.455
yellow	D	< 0.714
orange	E	< 1.333
red	F	≥ 1.333

Table: Pedestrian walkway LoS density threshold values according to NCHRP (in SI units).

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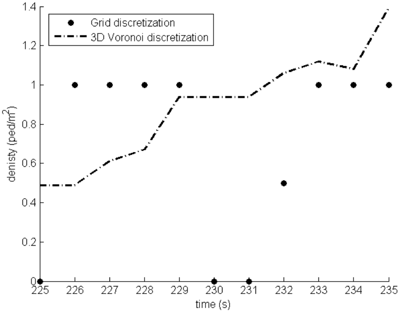
3D Voronoi-based characterization vs. grid-based method

Density sequences



Robustness to the sampling rate

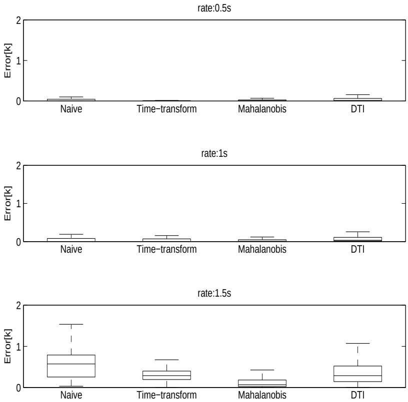
- Sample of points from synthetic pedestrian trajectories obtained using different sampling rate
- Voronoi-based characterization for points with d_N, d_{TT}, d_M, d_{DTI}

Numerical analysis

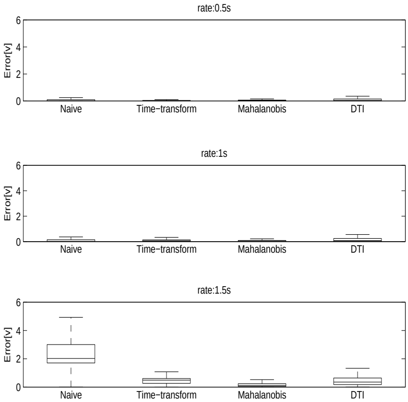
- Statistics of interests: distribution of k and v errors for 1000 randomly sampled points

Unidirectional uniform straight-line movement

Density indicator

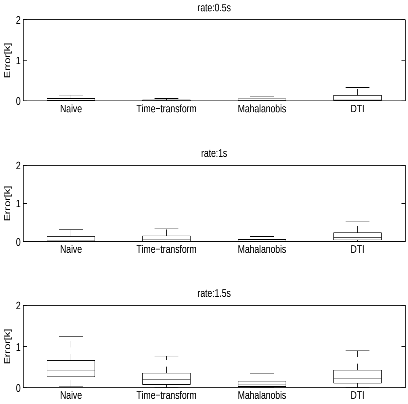


Speed indicator

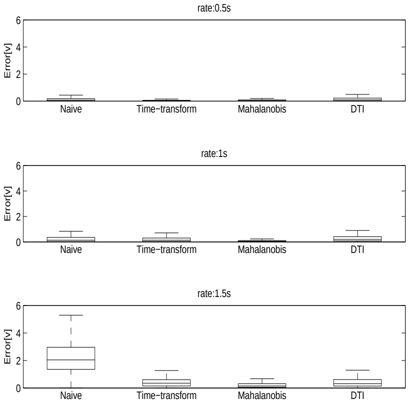


Unidirectional non-uniform straight-line movement

Density indicator

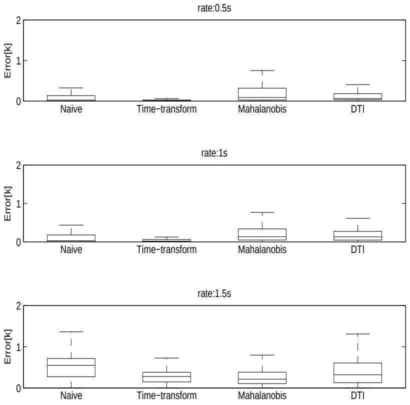


Speed indicator

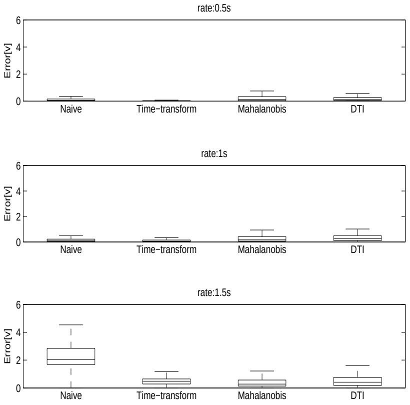


Unidirectional non-uniform zig-zag movement

Density indicator

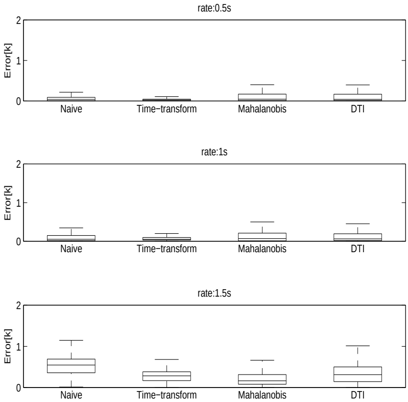


Speed indicator

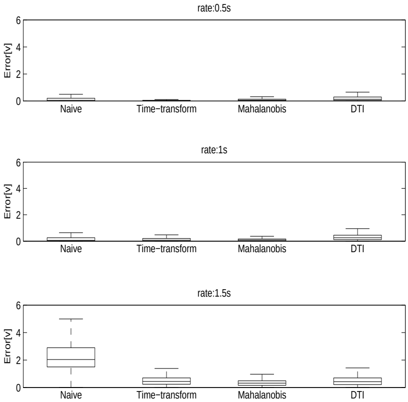


Bidirectional uniform straight-line movement

Density indicator

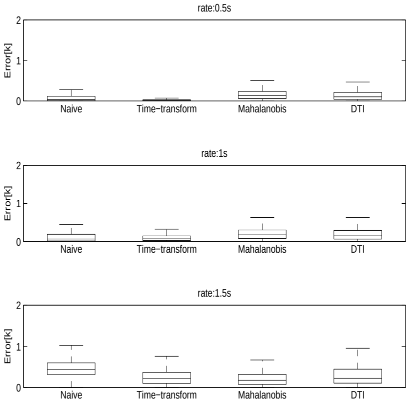


Speed indicator

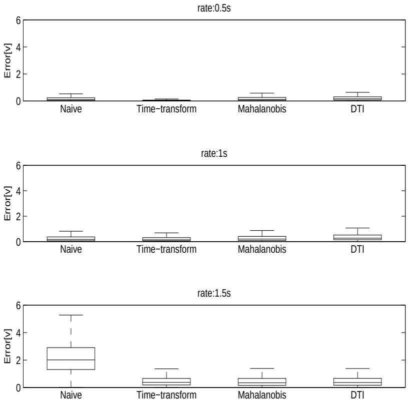


Bidirectional non-uniform straight-line movement

Density indicator

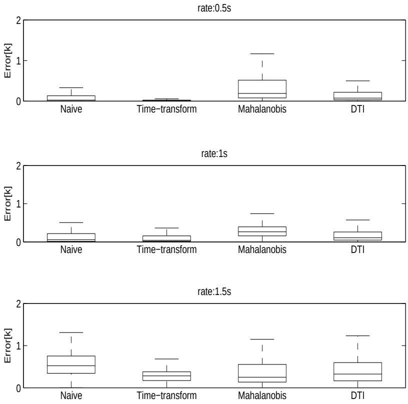


Speed indicator

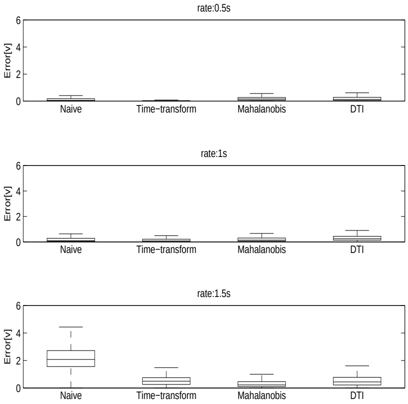


Bidirectional non-uniform zig-zag movement

Density indicator

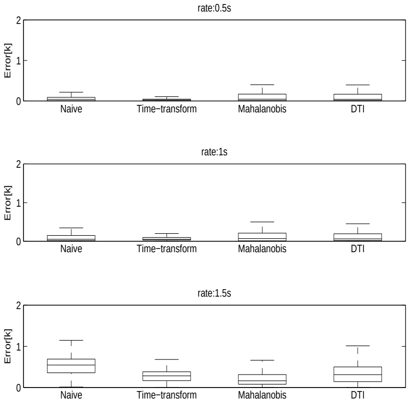


Speed indicator

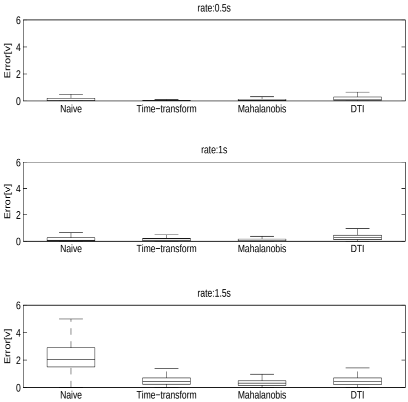


Crossing uniform straight-line movement

Density indicator



Speed indicator



Conclusions

- Pedestrian-oriented flow characterization: Edie's definitions adapted through a data-driven discretization
- Suitable for multi-directional flow composition
- Reproduces different simulated settings with uniform and non-uniform movement
- Preserves heterogeneity across pedestrians and space
- Leads to smooth transitions in measured traffic characteristics
- Sampled data: 3D Voronoi diagrams with Time-Transform distance perform the best
  - Reproduces different simulated settings
  - Robust with respect to the sampling rate

Future directions

- Additional spatio-temporal assignment rules will be tested
- More numerical analysis based on synthetic and real-world data (case study: Lausanne train station)
- Stream-based definitions of indicators and their interaction [Nikolić and Bierlaire, 2014]

Thank you for your attention

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Mahalanobis distance

Directions of interest

$$p_{is} = (x_{is}, y_{is}, t_s),\ v_i(t_s) = \frac{1}{t_{(s+1)} - t_s} \begin{pmatrix} x_{i(s+1)} - x_{is} \\ y_{i(s+1)} - y_{is} \\ 1 \end{pmatrix}$$

$$d^1(t_s) = \frac{v_i(t_s)}{||v_i(t_s)||},\ ||d^1(t_s)|| = 1$$

$$d^2(t_s) = \begin{pmatrix} d_x^1(t_s) \\ d_y^2(t_s) \\ 0 \end{pmatrix},\ d^1(t_s)^T d^2(t_s) = 0,\ ||d^2(t_s)|| = 1$$

$$d^3(t_s) = \begin{pmatrix} 0 \\ 0 \\ t_{(s+1)} - t_s \end{pmatrix},\ ||d^3(t_s)|| = t_{(s+1)} - t_s$$

Mahalanobis distance

Change of coordinates

$$S_1(t_s,\delta) = p_{is} + (t_{(s+1)} - t_s)v_i(t_s) + \delta d^1(t_s)$$

$$S_2(t_s,\delta) = p_{is} - (t_{(s+1)} - t_s)v_i(t_s) - \delta d^1(t_s)$$

$$S_3(t_s,\delta) = p_{is} + \delta d^2(t_s)$$

$$S_4(t_s,\delta) = p_{is} - \delta d^2(t_s)$$

$$S_5(t_s,\delta) = p_{is} + \delta d^3(t_s)$$

$$S_6(t_s,\delta) = p_{is} - \delta d^3(t_s)$$

$$d_M = \sqrt{(S_j(t_s,\delta) - p_{is})^T M_{is}(S_j(t_s,\delta) - p_{is})} = \delta, j = 1,..,6$$