

# Density Estimates in Cellular Automata Models of Pedestrian Dynamics

Marek Bukáček, Jana Vacková

Faculty of Nuclear Sciences and Physical Engineering  
Czech Technical University in Prague

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SMPS



# Density expectations

## Standard definition

- $\rho = \frac{N}{A}$
- global version  $A$  covers whole area
- local version:  $A$  is fixed in space, i.e. detector approach
- individual version:  $A$  is defined as pedestrian surroundings

# Density expectations

## Standard definition

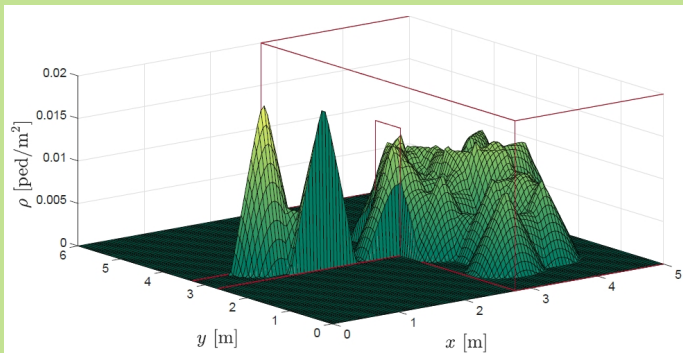
- $\rho = \frac{N}{A}$
- global version  $A$  covers whole area
- local version:  $A$  is fixed in space, i.e. detector approach
- individual version:  $A$  is defined as pedestrian surroundings
- works when particle size is neglectable comparing to size of area
- fulfilled when number of pedestrians is large
- generalization and/or redefinition
- close to fundamental definition (when comparable) ++
- mathematical requirements - roughness, featureless

$$\langle \dot{C} \rangle := \frac{1}{\#T} \sum_{i=2}^{\#T} \frac{|C(t_i) - C(t_{i-1})|}{t_i - t_{i-1}} \quad \max_{t \in \mathbb{R}^+} C(t)$$

# Density definition

## Pedestrian distribution

$$\rho_B = \frac{N}{|B|} = \frac{\int_B \rho(\vec{x}) d\vec{x}}{|B|} = \frac{\int_B \sum_{\alpha=1}^N \rho_{\alpha}(\vec{x}) d\vec{x}}{|B|} = \sum_{\alpha=1}^N \frac{\int_B \rho_{\alpha}(\vec{x}) d\vec{x}}{|B|}$$



## Kernels

- **Point approximation**

$$\rho_\alpha(\mathbf{x}) = \delta_{\mathbf{x}, \mathbf{x}_\alpha}$$

- **Stepwise function** .. cylindrical, Voronoi, Manhattan, ...

$$\rho_\alpha(\mathbf{x}, R) = 1_{A_\alpha(R)}(\mathbf{x}) \frac{1}{|A_\alpha(R)|}$$

- **Conic kernel**

$$\rho_\alpha(\mathbf{x}, R) = \frac{3}{\pi R^3} 1_{A_\alpha(R)}(\mathbf{x}) (R - \|\mathbf{x} - \mathbf{x}_\alpha\|)$$

- **Gaussian kernel** in a symmetric version, i.e. with diagonal covariance matrix

$$\rho_\alpha(\mathbf{x}, R) = \frac{1}{2\pi R^2} \exp \left\{ -\frac{\|\mathbf{x} - \mathbf{x}_\alpha\|^2}{2 R^2} \right\}$$

## Kernels 2

- **Borsalino kernel** from [Krbálek, Krbálková]

$$\rho(\mathbf{x}, R) = \frac{1}{Z} \frac{1}{R} 1_{A_\alpha(R)}(\mathbf{x}) \exp \left\{ \frac{R^2}{\|\mathbf{x} - \mathbf{x}_\alpha\|^2 - R^2} \right\}$$

# Density definition

## Kernels 2

- **Borsalino kernel** from [Krbálek, Krbálková]

$$p(\mathbf{x}, R) = \frac{1}{Z} \frac{1}{R} 1_{A_\alpha(R)}(\mathbf{x}) \exp \left\{ \frac{R^2}{\|\mathbf{x} - \mathbf{x}_\alpha\|^2 - R^2} \right\}$$

## Min dist

- scaled inverse value of appropriate distance

$$p(\vec{x}) = \frac{c_{md}}{\text{dist}(\vec{x})}$$

- different ranges

$$\text{dist}(\vec{x}) := D(\vec{x}) := \min_{\{\alpha \in N: \angle(\vec{x}_\alpha, \vec{s}_x) \leq \frac{\pi}{3}\}} \|\vec{x} - \vec{x}_\alpha\|$$

- different distances

$$\text{dist}(\vec{x}) := D(\vec{x})^2$$

# Density definition

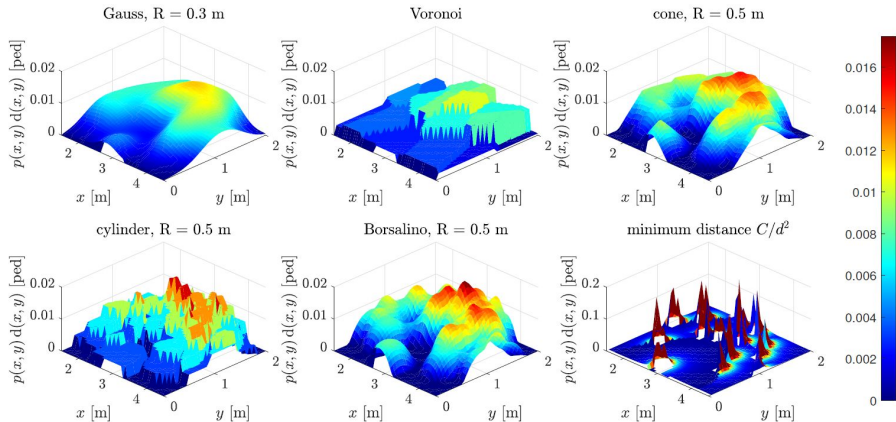
## Existing methods

- Voronoi method
- weighted pedestrians based on distance to detector/pedestrian
- weighted pedestrians based on time presence in detector
- minimum distance based estimates

Ref.	Year	Dim	Kernel	Details
Daamen, Hoogendoorn, and Bovy (2005); Daamen and Hoogendoorn (2007)	2005	2	-	density defined using travel times
Helbing et al. (2006)	2006	1	-	smooth particle count
Helbing, Johansson, and Al-Abideen (2007)	2007	2	exponential	weighted pedestrian contribution
Johansson et al. (2008); Johansson (2009)	2008	2	exponential	local density using weights
Krisp et al. (2009)	2009	2	Gauss	tool for visual choice of bandwidth
Steffen and Seyfried (2010)	2010	2	Voronoi	the concept used here
Schadschneider, Chowdhury, and Nishinari (2010); Schadschneider et al. (2018)	2010	2	exponential	concept of weighting pedestrian
Schadschneider and Seyfried (2011)	2011	2	-	no consensus for the estimates
Liddle et al. (2011)	2011	2	Voronoi	stabilization of the result
Tipakornkiat, Kim, and Limanond (2011)	2011	1	-	density at sidewalks (crossing lines)
Zhang et al. (2011)	2011	2	Voronoi	comparing of few methods
Plaue et al. (2012); Plaue, Bärwolff, and Schwandt (2014)	2012	2	Gauss	bandwidth depends on time
Fan (2013); Fan, Herty, and Seibold (2013)	2013	2	Gauss	density of vehicular streams
Tordeux et al. (2015)	2015	1	Voronoi, Gauss	comparing of few methods
Duives, Daamen, and Hoogendoorn (2015)	2015	2	Voronoi, exp.	comparing of few methods
Krbálek and Krbálkova (2018)	2018	1	Borsalino	smooth particle count
Mollier et al. (2019)	2019	2	Gauss	opt. bandwidth for vehicles Fan (2013)
Bukáček and Vacková (2019)	2019	2	Cone	individual density study
Hillebrand, Hoogeveen, and Geraerts (2020)	2020	2	Voronoi, Gauss	comparing of few methods
Vacková and Bukáček (2020)	2020	2	Cone	application of individual density

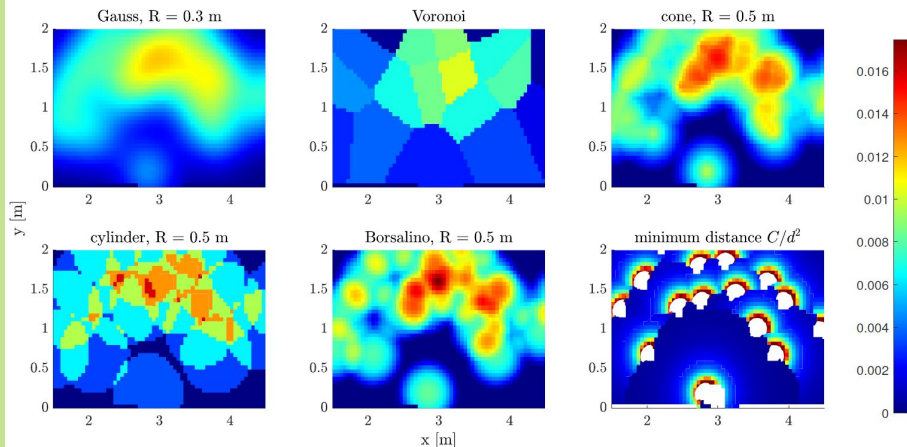


## Illustration of distributions



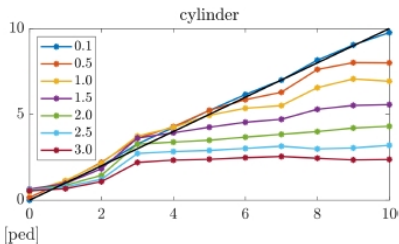
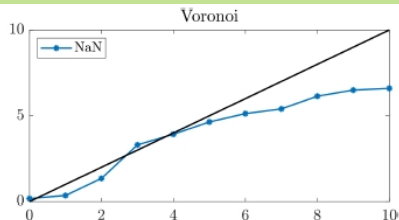
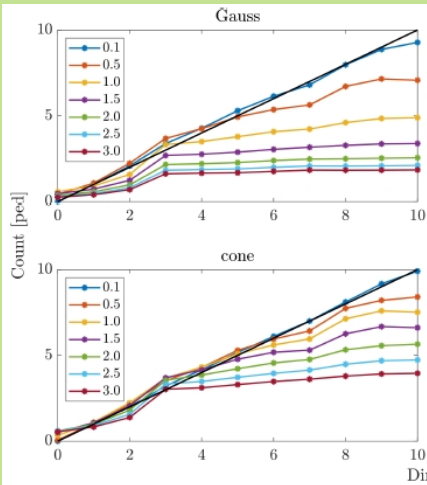
# Density definition

## Illustration of distributions

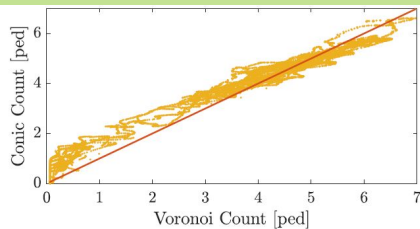
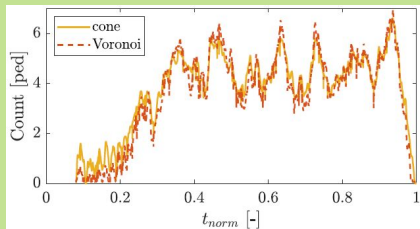


# Kernel types - point approximation

## Point approximation vs cone



## Voronoi vs cone

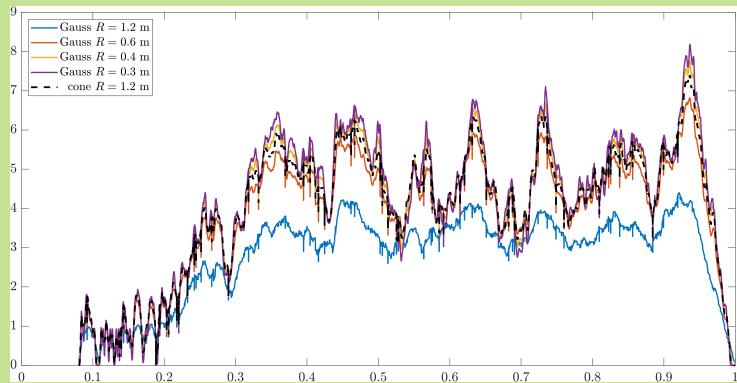


# Kernel types - Gauss

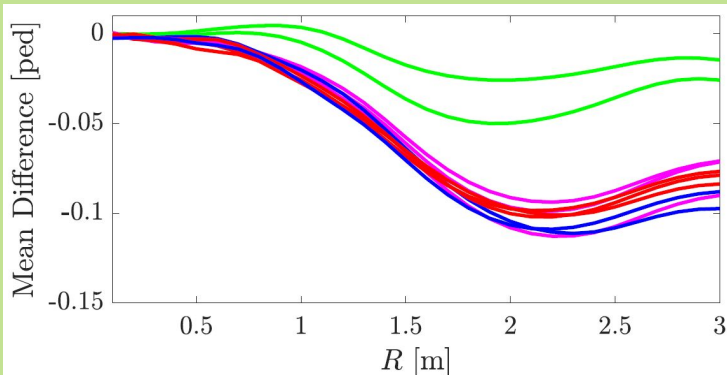
## Mass recalculation

$$\int_{A_R} p(\mathbf{x}, \sigma) d\mathbf{x} = \int_{A_{k\sigma}} p(\mathbf{x}, \sigma) d\mathbf{x} = \int_0^{\frac{k^2}{2}} e^{-t} dt$$

## Gauss vs cone

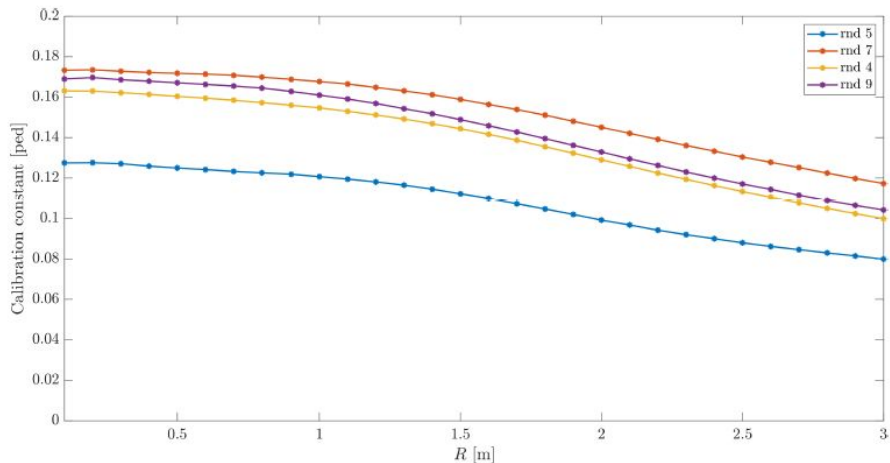


## Borsalino vs cone



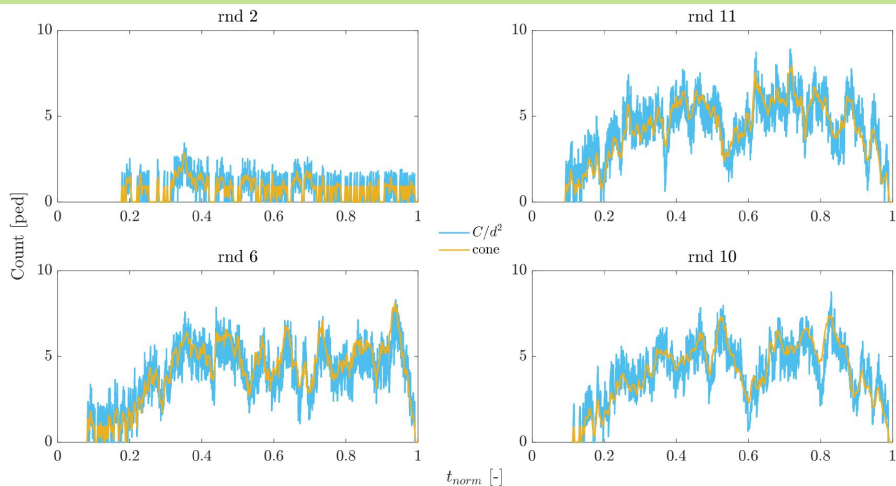
# Kernel types - minimal distance

## Minimal distance calibration



# Kernel types - minimal distance

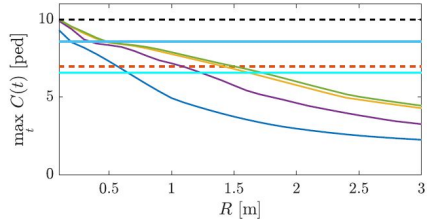
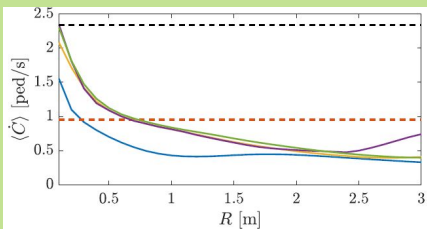
## Minimal distance vs cone





# Comparison

## Roughness, featureless

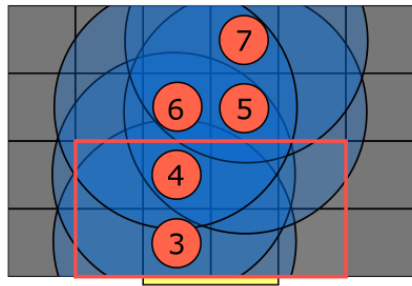
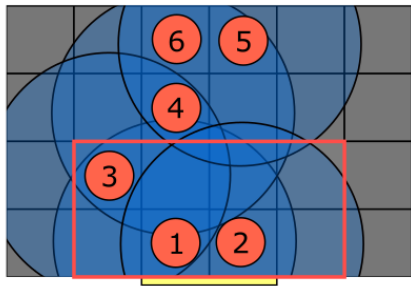


— Gauss — Voronoi — cone — cylinder — Borsalino —  $C/d^2$  —  $C/d$  - - - Dirac

## Mean occupancy

Mean ped. count [ped]		Training data for Min. distance				Testing data for Min. distance				
Method	R [m]	Rnd 5	Rnd 7	Rnd 4	Rnd 9	Rnd 2	Rnd 11	Rnd 6	Rnd 10	
NP	Voronoi	-	0.77	4.03	2.81	3.40	0.27	3.69	3.63	3.58
	Point approximation	-	1.51	4.29	3.34	3.80	0.68	4.18	4.05	4.01
	Minimum distance $1/d$	-	1.52	4.27	3.72	3.95	0.85	4.22	4.11	4.12
	Minimum distance $1/d^2$	-	1.46	4.21	3.49	3.82	0.73	4.12	4.04	4.00
P1	Conic kernel	0.3	1.59	4.49	3.48	3.99	0.73	4.35	4.26	4.21
	Cylindrical kernel	0.3	1.58	4.48	3.47	3.98	0.73	4.33	4.25	4.20
	Borsalino kernel	0.3	1.59	4.49	3.49	3.99	0.73	4.35	4.27	4.22
	Gaussian kernel	0.1	1.59	4.49	3.49	3.99	0.73	4.35	4.27	4.22
P2	Conic kernel	0.9	1.59	4.43	3.39	3.91	0.77	4.24	4.15	4.10
	Cylindrical kernel	0.9	1.60	4.37	3.33	3.84	0.81	4.15	4.07	4.00
	Borsalino kernel	0.9	1.59	4.44	3.40	3.93	0.76	4.26	4.16	4.12
	Gaussian kernel	0.3	1.58	4.44	3.41	3.93	0.75	4.27	4.18	4.13
P3	Conic kernel	1.5	1.52	4.19	3.17	3.65	0.78	3.94	3.89	3.81
	Cylindrical kernel	1.5	1.39	3.87	2.88	3.32	0.74	3.58	3.54	3.46
	Borsalino kernel	1.5	1.55	4.26	3.23	3.71	0.80	4.01	3.95	3.87
	Gaussian kernel	0.5	1.54	4.30	3.27	3.76	0.77	4.07	4.00	3.93

## Case study



- assuming inflow 1.5 ped/T
- by standard def. alternating 2 and 3 peds in detector
- using appropriate kernel, 2.5 ped ind detector

## Conclusions

- generally used methods covered

$$\lim_{R \rightarrow 0^+} p(\mathbf{x}, R) = \lim_{R \rightarrow 0^+} \sum_{\alpha=1}^N p_{\alpha}(\mathbf{x}, R) = \sum_{\alpha=1}^N \delta_{\mathbf{x}, \mathbf{x}_{\alpha}}$$

- range based kernels converge to standard definition
- parameter based convergence of one method to the other
- important features identified
- useful even for discrete systems

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- generally used methods covered

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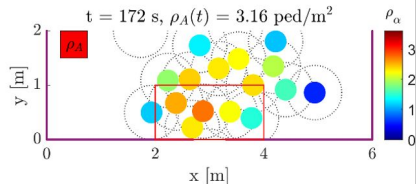
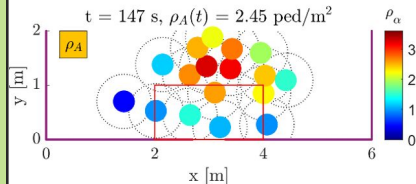
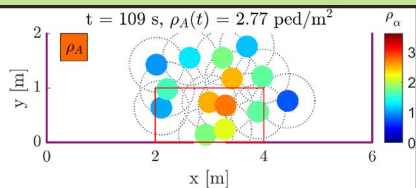
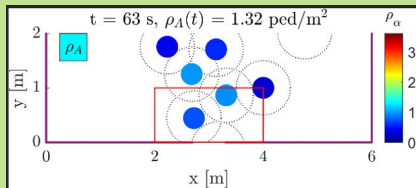
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**Thank you for your  
attention!**

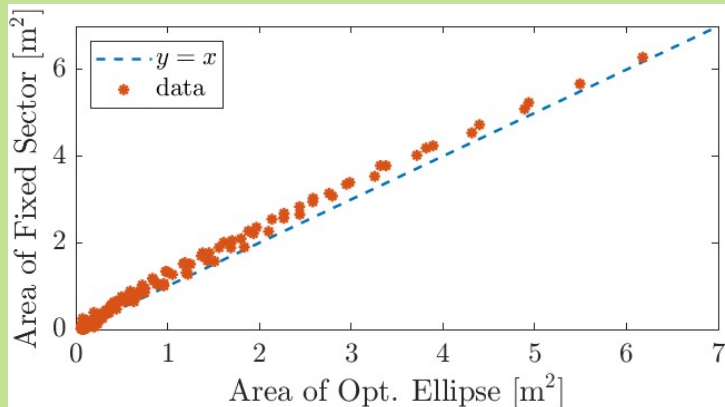


**G | A**  
**M | S**

Katedra matematiky FJFI ČVUT v Praze



## Area of an ellipse vs area of circular sector



## Width of an ellipse vs width of circular sector

