Calibration Of Pedestrian Sizes In Decision-Based Modelling

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Katedra matematiky FJFI ČVUT v Praze

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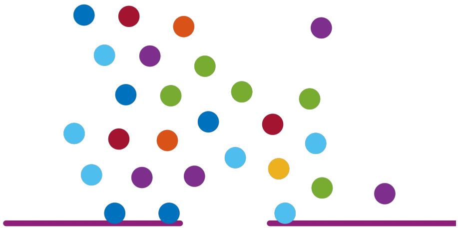
- Experimental Data
- Calibration Episode

Decision-based Model and Pedestrian Sizes - Definition

- Pedestrian reduces their initial size until the physical size is fulfilled
- Their sizes are reduced only to themselves - they see each other still at the initial size
- **Initial size** $s > 0$
- **Physical size** $\tau_s > 0$
- Social size $s_\alpha(t) > 0$ of the pedestrian $\Rightarrow$ social compression
- $0 < \tau_s \leq s_\alpha(t) \leq s$
- Not allowed to expand again



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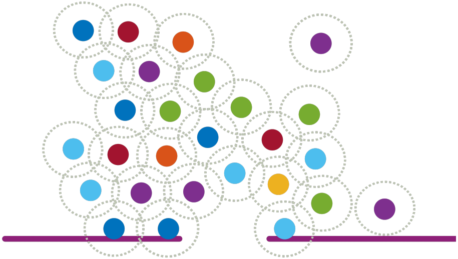

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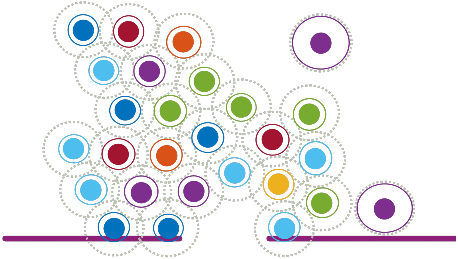
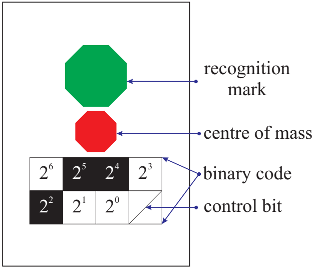


Calibration Concept

- Consists of separate calibration episodes
- Every of them covers one type of pedestrian behaviour captured by (one or several) model parameters
- Calibration quantities
- Episode test is needed

Experimental Data

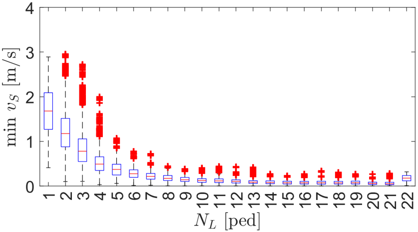


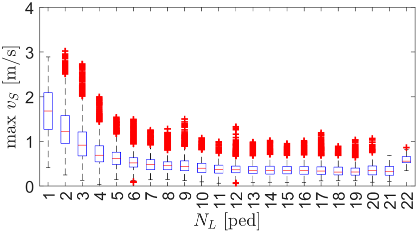
- Study hall of our faculty
- Artificial room with one exit
- Three entrances
- Three cameras
- Recognition caps
- 10 runs

Calibration Episode - Calibration Quantities

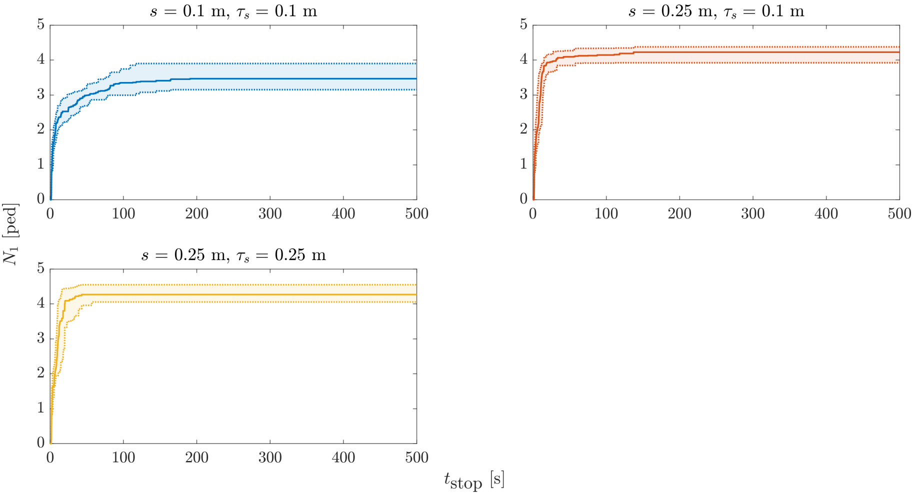
- Need to capture two different modes: free flow and congestion
- Small rectangular detector S = at the exit area
- Large rectangular detector L = whole room
- Conditions in S with the help of conditions in L
- Smooth number of pedestrians (kernel estimate): $N_{S,L} \in \mathrm{R}^+$

$$N_1 := \max_{t \in \mathrm{R}^+} \{N_S(t) | N_L(t) \leq 8\}, \qquad N_2 := \max_{t \in \mathrm{R}^+} \{N_S(t) | N_L(t) > 18\}$$





Calibration Episode - Simulation Time



Calibration Episode - Simulation Time

- Maximum (needed) experimental time t_{stop}
- Our stationary value $N_i^S := N_i(t = 500)$
- Relative error

$$t_{\text{stop}}^{(i)} := \min \left\{ t \in \mathrm{R}^+ : \frac{\left| N_i(t) - N_i^S \right|}{N_i^S} \leq \varepsilon \right\}$$

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-	s [m]	τ_s [m]	$t_{\text{stop}}^{(1)}$ [s]	$t_{\text{stop}}^{(2)}$ [s]
PS1	0.10	0.10	82.20	-
PS2	0.25	0.10	31.85	136.40
PS3	0.25	0.25	32.70	36.50

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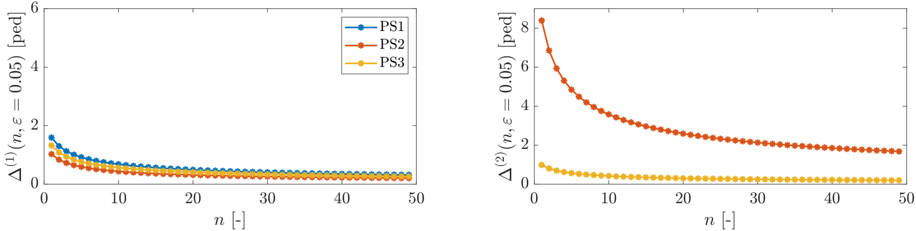
- Final value of t_{stop} can be defined as

$$t_{\text{stop}} := \left\lceil \max_{i \in \{1,2\}} \max_{j \in \{1,2,3\}} t_{\text{stop}}^{(i)}(j) \cdot \frac{1}{100} \right\rceil \cdot 100$$

- $t_{\text{stop}} = 200$ s

Chebyshev's inequality

$$\mathbb{P}\left[|\overline{\xi} - \mu| < \Delta(n, \varepsilon)\right] \geq 1 - \varepsilon, \text{ where } \Delta(n, \varepsilon) = \frac{\sqrt{\mathrm{Var}(\xi)}}{\sqrt{n\varepsilon}}$$



Calibration Episode - Number of Iterations

Chebyshev's inequality

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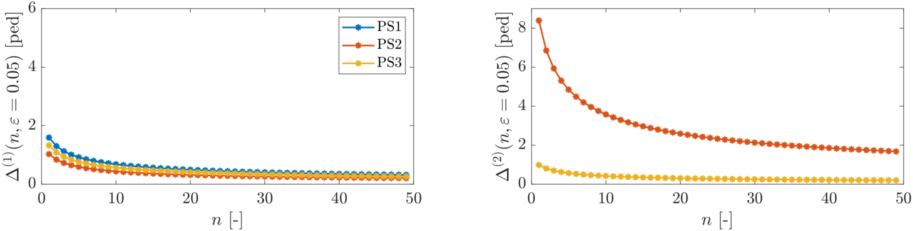
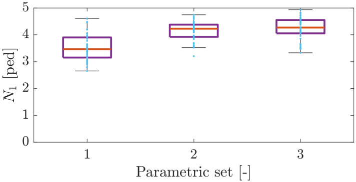
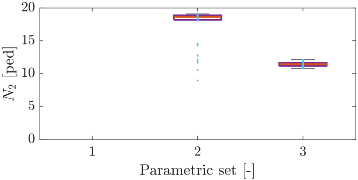


-	$\Delta^{(1)}(n,\varepsilon)$					$\Delta^{(2)}(n,\varepsilon)$				
n [-]	10	20	30	40	50	10	20	30	40	50
PS1	0.71	0.50	0.41	0.36	0.32	-	-	-	-	-
PS2	0.46	0.33	0.27	0.23	0.21	3.75	2.65	2.17	1.88	1.68
PS3	0.59	0.42	0.34	0.30	0.27	0.44	0.31	0.26	0.22	0.20

Calibration Episode - Test of Episode - Change?





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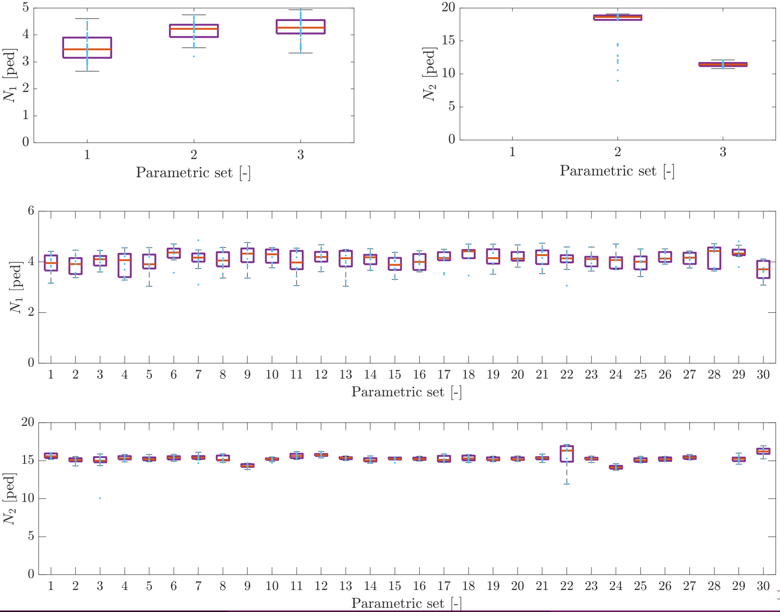

Calibration Episode - Perform of Episode

- **Hypothesis testing**
  - For each parametric set $j \in \mathrm{N}$: $H_0 : \boldsymbol{\mu}_j = \boldsymbol{\mu}_E$ vs. $H_1 : \boldsymbol{\mu}_j \neq \boldsymbol{\mu}_E$,
  - Multivariate James' test

$$T := (\boldsymbol{\mu}_j - \boldsymbol{\mu}_E)' \left(\frac{1}{n_1} \boldsymbol{S}_j + \frac{1}{n_2} \boldsymbol{S}_E \right)^{-1} (\boldsymbol{\mu}_j - \boldsymbol{\mu}_E),$$

    where $\boldsymbol{S}_j, \boldsymbol{S}_E$ are estimates of covariance matrices
  - Approximately distributed as $T \sim \chi^2_2$ when H_0 is true
  - Assumption: normally distributed data
  - Fixed significance level $\alpha = 0.05$
  - Optimum set = p-value greater than α

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  - Fixed significance level $\alpha = 0.05$
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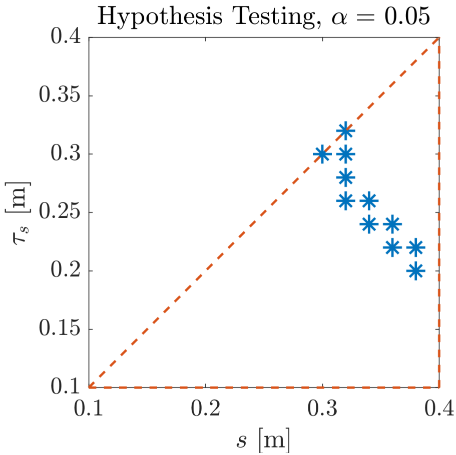
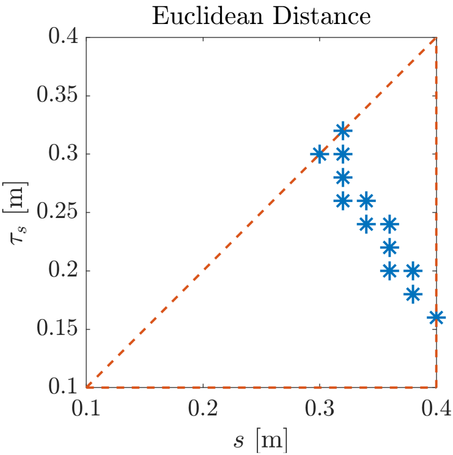
- **Minimization of Euclidean distance**
  - Finding a minimum of an objective (error) function
  - For each parametric set $j \in \mathrm{N}$:

$$\text{error}(j) = \sqrt{(\overline{N}_{1,j} - N_1^E)^2 + (\overline{N}_{2,j} - N_2^E)^2}$$

  - Weakness: does not work with variance
  - Optimum set = top 10 % with the smallest deviations

Calibration Episode - Results





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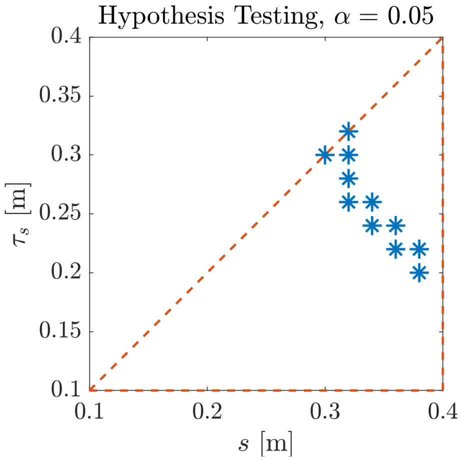

j [-]	s [m]	τ_s [m]	p-value [-]
87	0.34	0.26	0.62
75	0.32	0.26	0.53
86	0.34	0.24	0.44
99	0.36	0.24	0.33
111	0.38	0.20	0.30
76	0.32	0.28	0.21
78	0.32	0.32	0.17
98	0.36	0.22	0.15
77	0.32	0.30	0.15
66	0.30	0.30	0.15
112	0.38	0.22	0.10

Conclusions

- Concept of separate calibration episodes
- Design of episode
- Set-up of episode properties
- Statistical approach brings many benefits

Thank you for your attention.