

Multiscale Modeling of Pedestrian Dynamics

Individuality vs. Collectivity

Andrea Tosin*

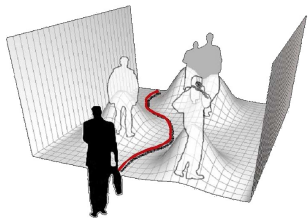
Istituto per le Applicazioni del Calcolo "M. Picone"
Consiglio Nazionale delle Ricerche
Rome, Italy

ICMMA 2014 "Crowd Dynamics"
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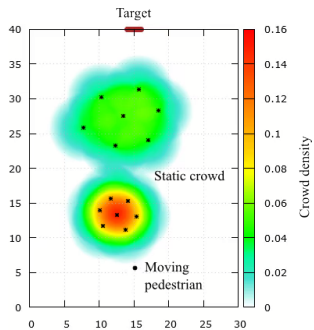
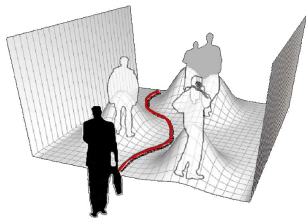


* Joint with: L. Bruno, A. Colombi, A. Corbetta, E. Cristiani, B. Piccoli, L. Preziosi, F. Priuli, M. Scianna

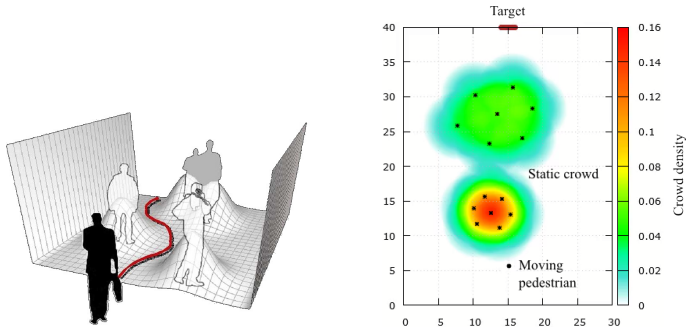
Moving in a Crowd: Human Perception as a Multiscale Process



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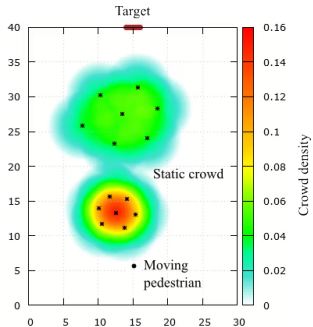
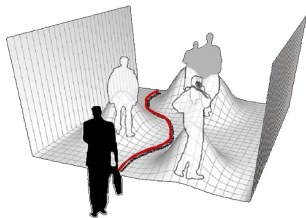


Moving in a Crowd: Human Perception as a Multiscale Process



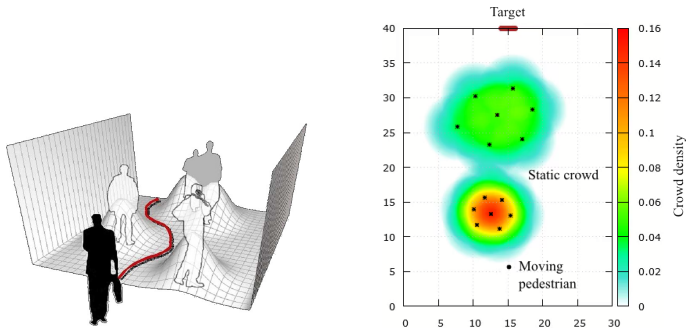
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Moving in a Crowd: Human Perception as a Multiscale Process



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- **Continuous** perception: the moving pedestrian senses the group

Moving in a Crowd: Human Perception as a Multiscale Process



- **Discrete** perception: the moving pedestrian senses the individuals
- **Continuous** perception: the moving pedestrian senses the group
- **Multiscale**: the moving pedestrian tunes his/her perception

Modeling Perception with Measures

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- $\mu : \mathcal{B}(\mathbb{R}^2) \rightarrow \mathbb{R}_+$ distribution of the static crowd

$$\mu = C_\theta \left(\theta \sum_{k=1}^N \delta_{\xi_k} + (1 - \theta) \rho \right)$$

- density $\rho : \mathbb{R}^2 \rightarrow [0, +\infty)$ s.t. $\int_{\mathbb{R}^2} \rho(x) dx = N$
- $\theta = \theta(X_t, y) \in [0, 1]$ level of perception
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- $S_R(X_t) \subset \mathbb{R}^2$ sensory region of the moving pedestrian [▶ Figure](#)
- $K : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ interaction kernel (collision avoidance) [▶ Figure](#)

The Path-Perception Relationship

Assumptions:

- $\theta = \theta(X_t)$, i.e., the level of perception depends on the position of the moving pedestrian (“Lagrangian” perception);
- $\theta : \mathbb{R}^2 \rightarrow [0, 1]$ Lipschitz continuous;
- smooth desired velocity, i.e., v_d is Lipschitz continuous in \mathbb{R}^2 ;
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Denote $\epsilon := \sum_{k=1}^N \delta_{\xi_k}$ for brevity. Then:

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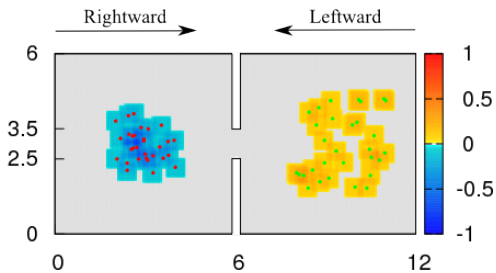
Theorem (Stability of the trajectories)

Let θ^1, θ^2 be two perception functions which generate the trajectories $t \mapsto X_t^1$, $t \mapsto X_t^2$, respectively. Fix any final time $0 < T < +\infty$. There exists a constant $C_T > 0$ such that

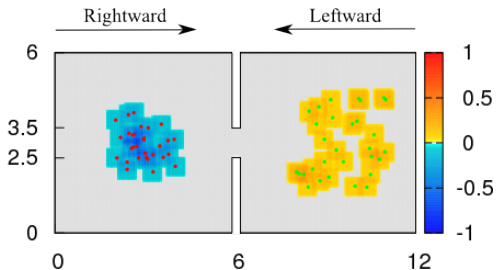
$$\|X_t^2 - X_t^1\| \leq C_T t \cdot e^{C_T \ell(\theta^1, \theta^2) W_1(\rho, \epsilon) t} W_1(\rho, \epsilon) \|\theta^2 - \theta^1\|_\infty \quad \forall t \in [0, T],$$

where $\ell(\theta^1, \theta^2) := \min\{\text{Lip}(\theta^1), \text{Lip}(\theta^2)\}$.

Multiscale Modeling of the Whole Crowd Dynamics

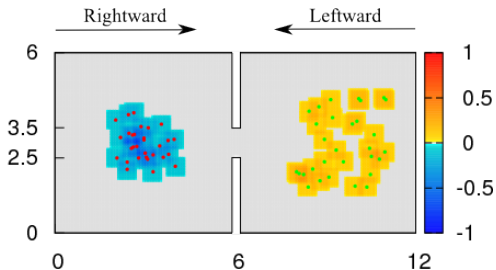


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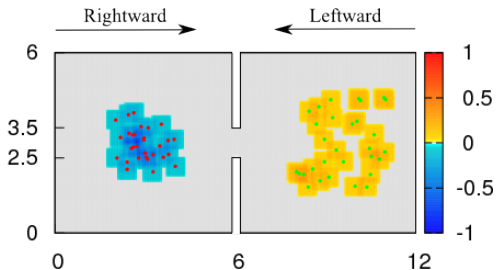
- **Discrete perception:** formation of parallel lanes

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- **Continuous** perception: clogging of the bottleneck

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- **Discrete** perception: formation of parallel lanes
- **Continuous** perception: clogging of the bottleneck
- **Multiscale** perception: alternate passage (traffic light effect)

Modeling by Transport of Measures

- $X_t(x) \in \mathbb{R}^2$ position at time t of the individual who was initially in $x \in \mathbb{R}^2$

$$\dot{X}_t = v[\mu_t](X_t) := v_d(X_t) + \frac{1}{a + \mu_t(S_R(X_t))} \int_{S_R(X_t)} K(y - X_t) d\mu_t(y)$$

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- μ_t as a **material quantity**: μ_0 is transported to μ_t by $(t, x) \mapsto X_t(x)$

$$\mu_t = X_t \# \mu_0 \Leftrightarrow \mu_t(E) = \mu_0(X_t^{-1}(E)) \Leftrightarrow \int_{\mathbb{R}^2} \varphi d\mu_t = \int_{\mathbb{R}^2} (\varphi \circ X_t) d\mu_0$$

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- **Reynolds Theorem**

$$\frac{d}{dt} \langle \mu_t, \varphi \rangle = \frac{d}{dt} \int_{\mathbb{R}^2} \varphi d\mu_t = \frac{d}{dt} \int_{\mathbb{R}^2} (\varphi \circ X_t) d\mu_0 = \int_{\mathbb{R}^2} v[\mu_t](x) \cdot \nabla \varphi(x) d\mu_t(x)$$

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- Finally

$$\partial_t \mu_t + \operatorname{div}(\mu_t v[\mu_t]) = 0$$

with μ_0 as initial condition (2)

Sketch of the Theory for the Measure-Valued Equation

Assumptions:

- constant $\theta \in [0, 1]$;
- smooth desired velocity, i.e., v_d is Lipschitz continuous in \mathbb{R}^2 ;
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Theorem (Well-posedness)

Fix a final time $0 < T < +\infty$. There exists a unique weak solution $\mu \in C([0, T]; \mathcal{M}_1^N(\mathbb{R}^2))$ to the Cauchy problem (2), which also satisfies

$$W_1(\mu_t^1, \mu_t^2) \leq CW_1(\mu_0^1, \mu_0^2) \quad \forall t \in (0, T].$$

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Theorem (Multiscale representation)

- If μ_0 is atomic then so is μ_t for all $t \in (0, T]$.
- If μ_0 is absolutely continuous and $\text{Lip}(v)Te^{\text{Lip}(v)T} < 1$ then also μ_t is absolutely continuous for all $t \in (0, T]$.

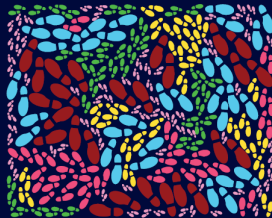
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MS&A

Modeling, Simulation & Applications



 Springer

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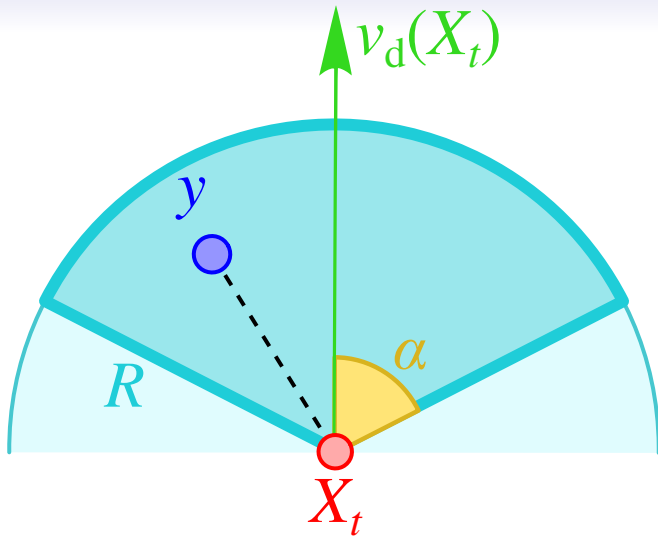


Figure: Sensory region of the moving pedestrian [← Back](#)

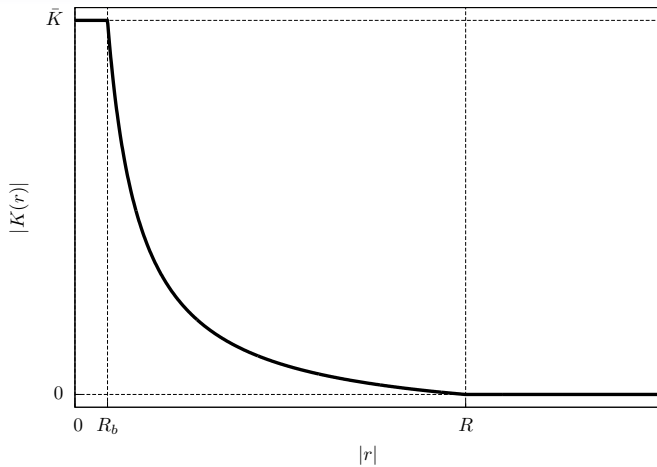


Figure: Modulus of the interaction kernel [◀ Back](#)