

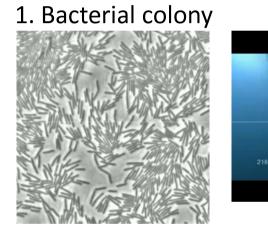
### Understanding Collective Crowd Behaviors: Learning a Mixture Model of Dynamic Pedestrian-Agents

Bolei Zhou, Xiaogang Wang, and Xiaoou Tang Department of Information Engineering Department of Electronic Engineering The Chinese University of Hong Kong



## **Collective Crowd Behaviors**

#### • Examples of Collective Crowd Behaviors:



2. Fish school



3. Human crowd



4. Human crowd



5. Human crowd



6. Traffic flow

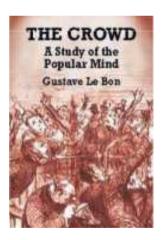


## **Understand Collective Crowd Behaviors**

- Features of Collective Crowd Behavior
  - Vanishing of individual personalities
  - > New characteristics beyond individual behaviors
  - Shared beliefs and common goals



Crowd in Grand Central Station



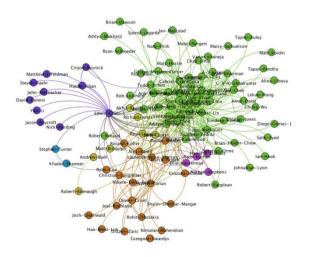
by Le Bon (1841~1931) in "The Crowd: A Study of the Popular Mind"

- Biology and Statistical Physics
  - Exploring the mechanisms that lead to the collective movements
  - Studying the statistical principles and dynamics of the crowd behaviors





- Social Networks and Complex Networks
  - Studying how individuals are connected into collective communities
  - Investigating how information propagates among complex networks





• Computer graphics

Simulating virtual crowds in games and movies









Computer Vision

### $\succ$ Learning and segmenting the motion patterns:

**Flow fields** Ali CVPR'07

#### Hospedales ICCV'09

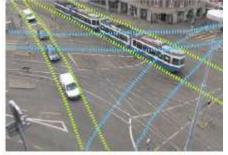


#### Lin CVPR'09, 10





#### Kuettel CVPR'10

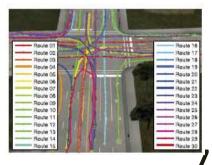


#### Topic models Trajectory clustering

Makris SMC'05

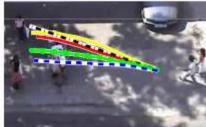


#### Morris PAMI'11



- Computer Vision
- > Analyzing the social interaction between pedestrians:

Social-force model Helbing PRL'95, Nature'00  $m_i \frac{d\mathbf{v}_i}{dt} = m_i \frac{v_i^0(t)\mathbf{e}_i^0(t) - \mathbf{v}_i(t)}{\tau_i} + \sum_{j(\neq i)} \mathbf{f}_{ij} + \sum_{w} \mathbf{f}_{iw}$  Tracking Pellegrini ICCV'09



Abnormality detection

Mehran CVPR'09



Group detectionInteraction analysisGe PAMI'11Scovanner ICCV'09





# Our Work

### To quantitatively analyze crowd behaviors

Framework of Dynamic Pedestrian-Agents

➤Applications:

- ✓ Learning collective behavior patterns
- ✓ Recognizing collective behaviors
- ✓ Detecting abnormal behaviors
- ✓ Predicting future behaviors
- ✓ Estimating scene statistics

### • Challenges:

- Detection and tracking errors
- Different collective patterns mixed







## Contributions of Our Work

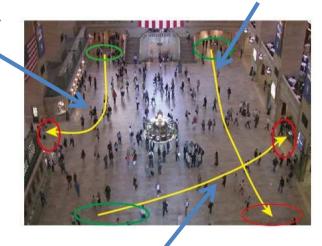
- 1. Agent-based modeling of crowd behavior
- 2. Three factors to analyze crowd behavior
- 3. Learning from highly fragmented trajectories

## 1. Agent-based modeling of crowd behavior

- Simple behavioral rules for multiple agents to generate complex behaviors
- Simulating crowds and classifying collective behaviors
- Integrating with social-force model

Agent 2

Agent 1



Agent 3

Interactive dynamics



Social-force model

Collective dynamics



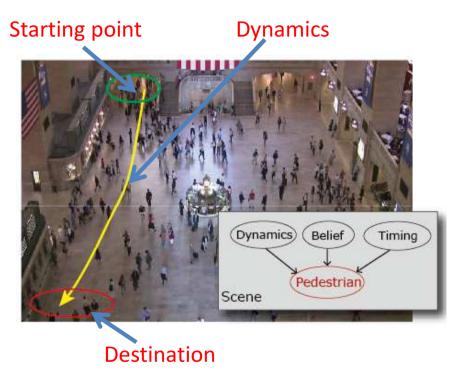
Our model

## 2. Three factors to analyze crowd behavior

Beliefs of Pedestrian
Starting point and destination

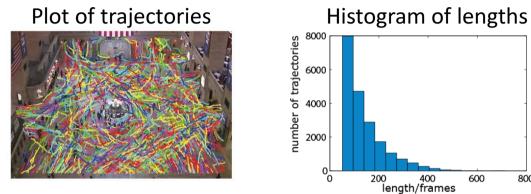
Collective Dynamics
Pedestrian movement patterns

Timing of Emerging It determines population in the scene  $\underbrace{\downarrow\downarrow}_{t}$ 

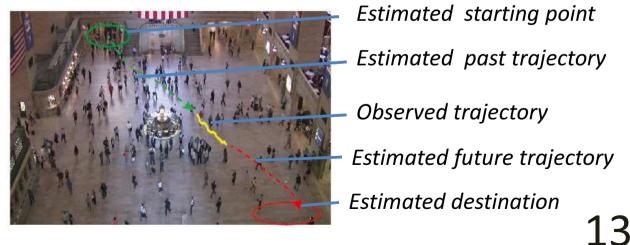


Every pedestrian is driven by one type of agents, and the whole crowd is modeled as a mixture of pedestrian-agents

## 3. Learning from fragmented trajectories



- Estimating missing observations through model inference
- Regularizing the trajectories through estimating its starting point and destination



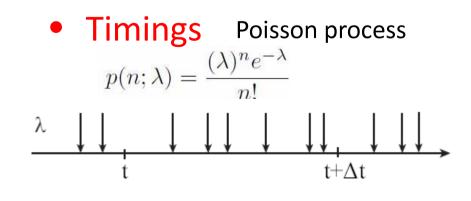
800

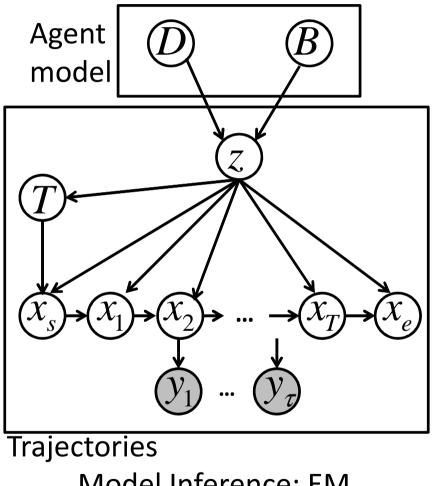
## **Dynamic Pedestrian-Agents**

• Beliefs: 
$$B = (\mu^s, \Phi^s, \mu^e, \Phi^e)$$

 $p(\mathbf{x}_s) = \mathcal{N}(\mathbf{x}_s | \mu^s, \Phi^s),$  $p(\mathbf{x}_e) = \mathcal{N}(\mathbf{x}_e | \mu^e, \Phi^e).$ 

• Dynamics 
$$D = (\mathbf{A}, \Gamma)$$
  
 $\mathbf{x}_t = \mathbf{A}\mathbf{x}_{t-1} + \omega_t, \ p(\mathbf{x}_t | \mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x}_t | \mathbf{A}\mathbf{x}_{t-1}, \Gamma),$   
 $\mathbf{y}_t = \mathbf{C}\mathbf{x}_t + \varepsilon_t. \qquad p(\mathbf{y}_t | \mathbf{x}_t) = \mathcal{N}(\mathbf{y}_t | \mathbf{x}_t, \Sigma),$   
linear dynamic system  
with affine transform





Model Inference: EM  $\Theta^* = \arg \max_{\Theta} \sum_{k=1} \log p(\mathbf{y}^k; \Theta).$ 

## Experiments

- Simulating Crowd
- Segmenting Semantic Regions
- Classifying Collective Behaviors
- Predicting Behaviors of Pedestrians
- Detecting Abnormal Behaviors

## **Experiments: Simulating Crowd**

• Examples of learned dynamic pedestrian-agents



## **Experiments: Simulating Crowd**

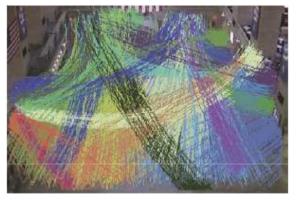
• A Demo Video

Real Crowd and Trajectories

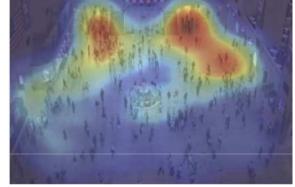
Simulation

## **Experiments: Simulating Crowd**

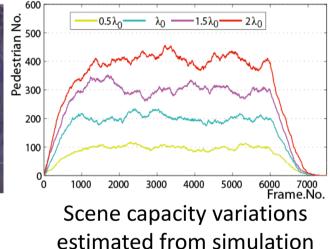
Statistics of the crowd from simulation

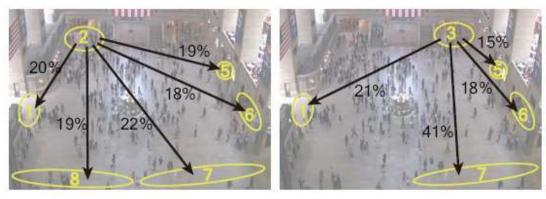


our model



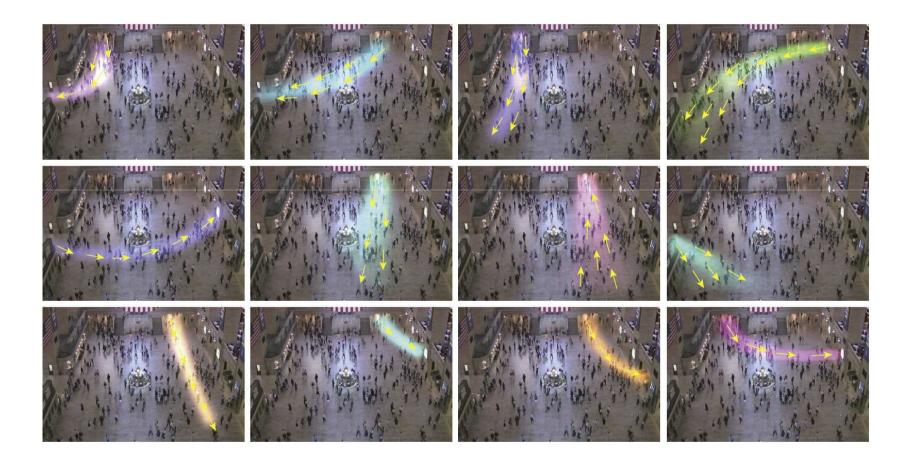
Simulated trajectories from Population density map estimated from simulation





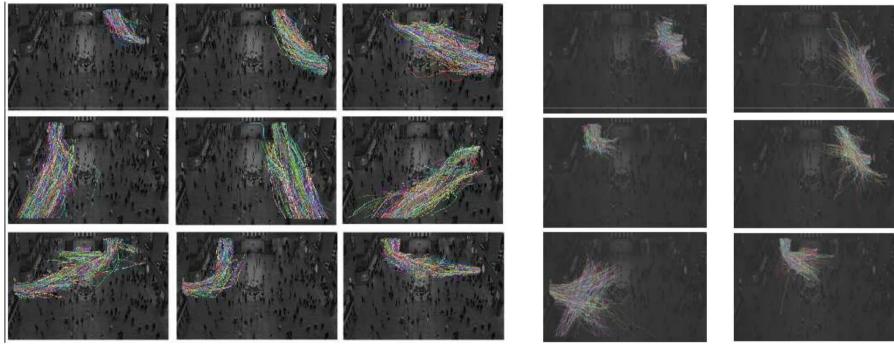
Pedestrian flow transition ratios

### **Experiments: Segmenting Semantic Regions**



## **Experiments: Classifying Behaviors**

• Trajectory clustering

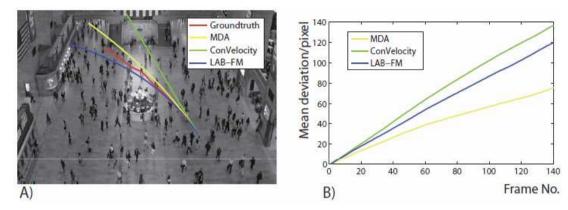


Ours

Spectral clustering (Wang ECCV'06) HDP (Wang CVPR'08)

## **Experiments: Predicting Behaviors**

• Estimating the future path of pedestrians



Detecting abnormal behaviors



Abnormal trajectories



Abnormal: sudden turning



Abnormal: running

## Conclusion

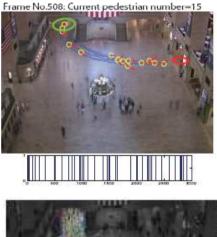
- Agent-based models are used to learn collective crowd behaviors and to simulate crowds.
- *Dynamics, Beliefs, and Timing* are proposed to model pedestrian-agents.
- Learning crowd behaviors from highly fragmented trajectories.
- Various applications to crowd simulation, scene segmentation, collective behavior classification, abnormality detection and behavior prediction.

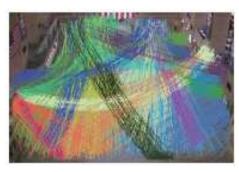
## Questions

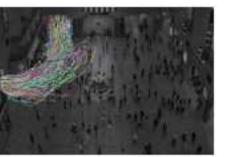


- Enquiry: <u>zhoubolei@gmail.com</u>
- Data (video, trajectories) can be found at my homepage.











Abnormal: sudden turning