Measuring Crowd Collectiveness

Bolei Zhou, Xiaoou Tang, and **Xiaogang Wang**

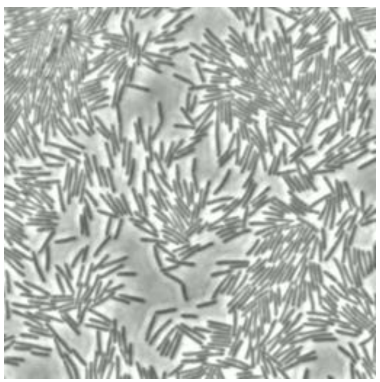
The Chinese University of Hong Kong

Outline

- **Motivation**
- Emergence of Collective Manifold
- Collectiveness Descriptor
- Experiments and Applications
- Conclusion

Collective Crowd Behaviors

- Complex crowd behaviours may result from repeated simple interactions among neighboring individuals without centralized coordination
- Generate complex patterns, quickly process information, engage in collective decision making



Bacteria colony

Fish school

Traffic flow

Human crowd

Human crowd

Human crowd

Scientific Studies on Collective Behaviours

- Empirical studies on various crowd systems: bacterial colonies, locust swarm, fish shoals and bird flocks
  - Criticality of crowd density [Zhang et al. 2010]
  - Phase transition [Vicsek et al. 1995]
  - Self-organization [Couzin and Krause 2003]
- Different models are proposed for simulation and understanding the mechanism of collective behaviours
  - Self-driven propelled particle models [Vicsek'95, Chate'95]
  - Maximum entropy model [Bialek et al. 2011]
  - Differential equations of continuum [Toner and Tu, 1998]
- Complex networks: detecting community with shared collective behaviours [Girvan'02, Palla'07]

Collective Motion Analysis in Vision

- Learn global motion patterns of crowd behaviours
  - Ali CVPR'07, Wang CVPR'07, Lin CVPR'09, Hospedales ICCV'09
  - Mehran ECCV'10, Emonet CVPR'11
- Detect coherent or incoherent motions from crowds
  - Rabound CVPR'06, Chan PAMI'08, Kratz CVPR'09, Rodriguez ICCV'09
  - Mahadevan CVPR'10, Wu CVPR'10, Saligrama CVPR'12, Zhou ECCV'12
- Analyze interactions among individuals in crowds
  - Mehran CVPR'09, Scovanner ICCV'09, Pellegrini ICCV'09
  - Yamaguchi CVPR'11, Kratz ECCV'12
- Detect social groups
  - Lan TPAMI'11, Ge TPAMI'11, Chang ICCV'11

The models and descriptors are scene-specific and cannot be used to compare behaviours of different crowd systems

Challenges to Understand Crowds

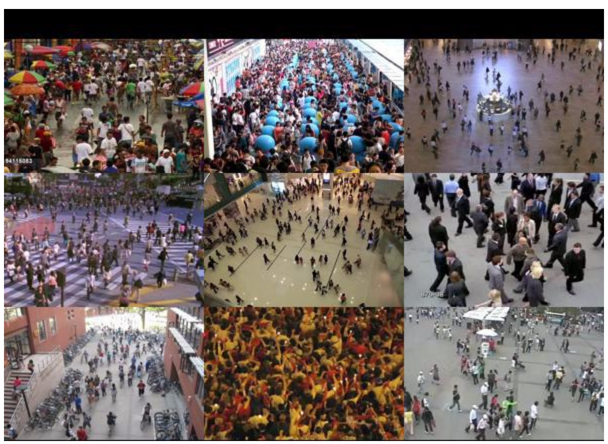
Crowds have different shapes, dynamics, and scales

- How to compare the dynamics of different crowd systems?
- Can different crowd systems be characterized by a set of universal properties and how to quantify them?
  - Yes. There are general principles underlying different types of crowd behaviours [Toner'05, Parrish'99]

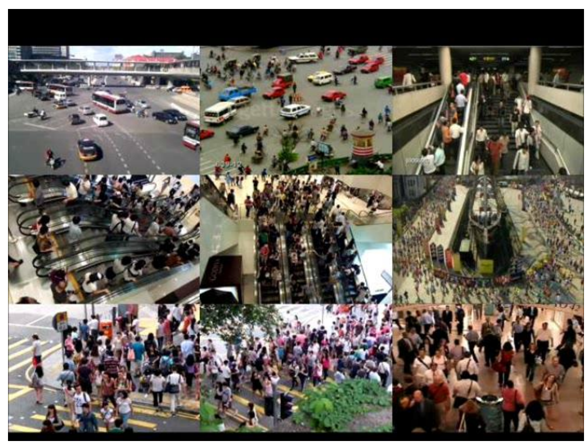
Contributions

- A new descriptor **collectiveness** to measure crowd dynamics and its efficient computation
- Definition of collectiveness: the degree of individuals acting as a union in collective motion
- A new algorithm Collective Merging to detect collective motions

Low Collectiveness



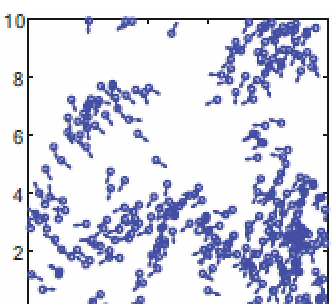
Medium Collectiveness



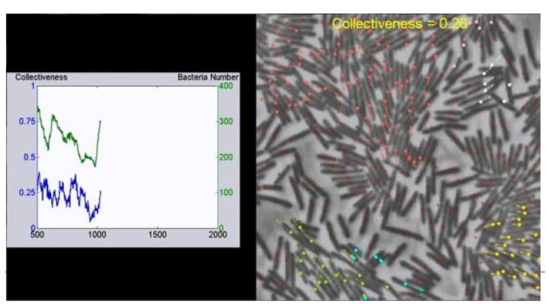
High Collectiveness

Contributions

- Applications on various datasets:
  - Comparing collectiveness of different crowd systems
  - Monitoring crowd dynamics
    - Transition from disordered to ordered states
    - Correlation between collectiveness and crowd density
    - Dynamic evolution of collective motion
  - Detecting collective motions in time-series data
  - Generating collective map of scenes
- Video database of evaluating crowd collectiveness with human perception as benchmark



SDP



Bacterial colony

Collective motion detection

Collective map

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- **Emergence of Collective Manifold**
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Emergence of Collective Manifold

Observation in different crowds:

- spatially coherent structures emerge in collective motions

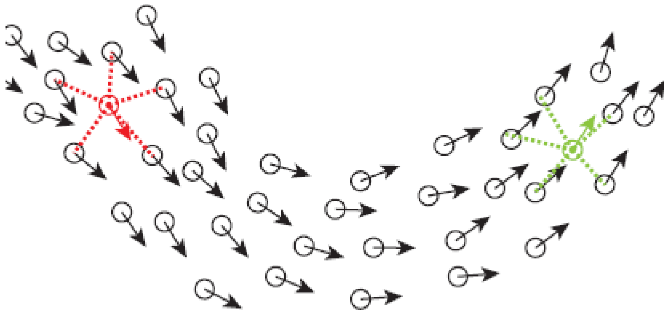
Emergence of Collective Manifold

Structural Properties of Collective Manifolds:

- Behavior consistency in neighborhood
- Information transmission between non-neighbors

Origins of Collective Manifolds:

- Local alignment
- Limited sensing ability of individuals

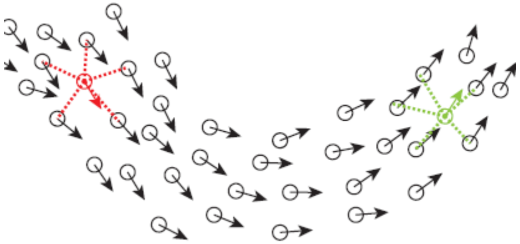


Emergence of Collective Manifold

- Failure of existing measurement for crowd dynamics due to structural properties of the collective manifold.

Average velocity of all the individuals

$$v = \left\| \frac{1}{N} \sum_{i=1}^{N} \frac{v_i}{\|v_i\|} \right\|$$



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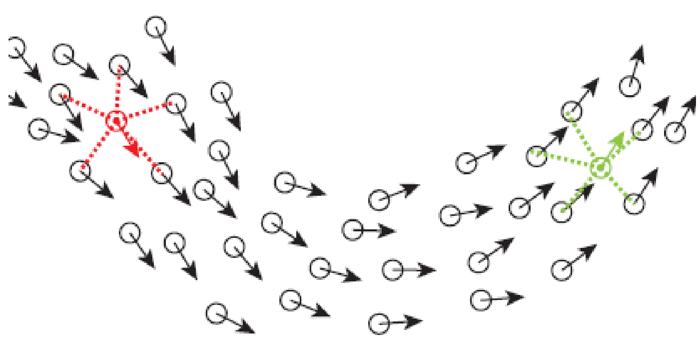
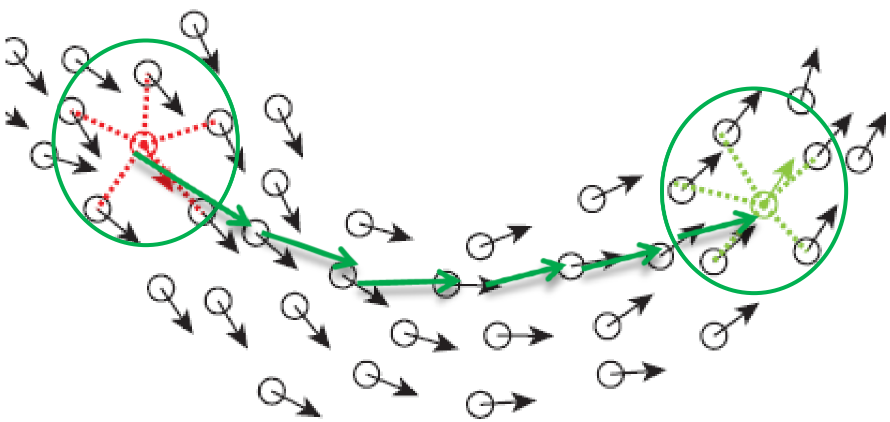
Formulation of Collectiveness Descriptor

- Our new collectiveness descriptor is based on the structural properties of collective manifold
- Collectiveness: the degree of individuals acting as a union in collective motion
  1. Individual collectiveness: the behavior consistency between one individual and all the other individuals
  2. Crowd collectiveness: the behavior consistency among the whole crowd of individuals



Formulation of Collectiveness Descriptor

- Steps of measuring collectiveness
  I. Behavior consistency in neighborhood
  II. Behavior consistency via paths on collective manifolds
  III. Measuring individual collectiveness
  IV. Measuring crowd collectiveness



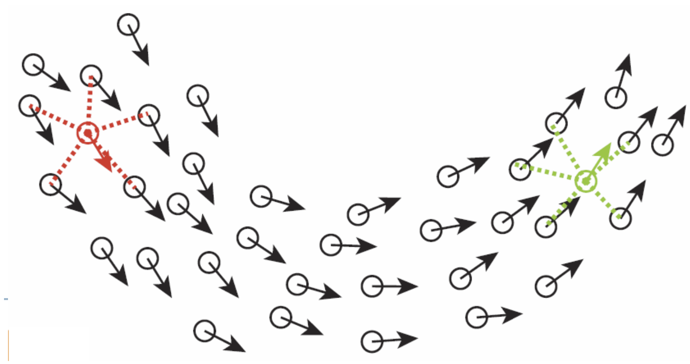
Behavior consistency of individuals in neighborhood

$$w_t(i,j) = \max(C_t(i,j), 0),\ j \in \mathcal{N}(i)$$

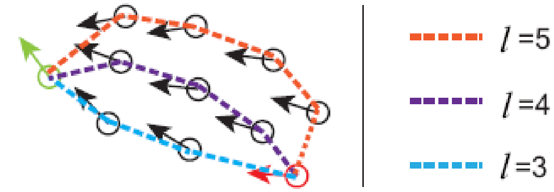
$C_t(i,j)$ is the velocity correlation at t

$\mathcal{N}$ is defined as K-nearest-neighbor

- A graph is built from the crowd set C and its weighted adjacency matrix is **W**
- K determines the topological range of neighborhood. Estimation of behavior consistency becomes inaccurate when out of this range.



Behavior consistency via paths on collective manifolds



- Path: an important topological structure of graphs
- Behaviour consistency $v_{\gamma l}$ over a path of length l between individuals i and j

$$\gamma_l = \{p_0 \rightarrow p_1 \rightarrow \ldots \rightarrow p_l\}$$

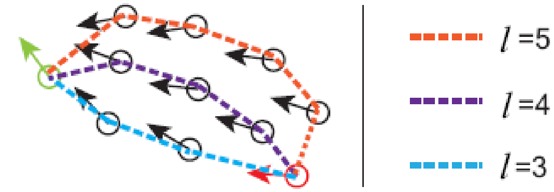
$$\nu_{\gamma_l} = \prod_{k=0}^{l} w_t(p_k, p_{k+1})$$

- Behaviour consistency between i and j over all the paths with length l

$$\nu_l(i,j) = \sum_{\gamma_l \in \mathcal{P}_l} \nu_{\gamma_l}(i,j)$$

Theorem 1. *$\nu_l(i,j)$ is the (i,j) entry of matrix $\mathbf{W}^l$.*

Individual Collectiveness

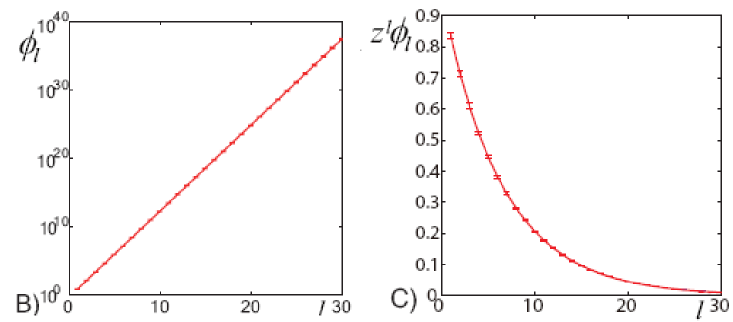


- Individual i's collectiveness at l-path scale:

$$\phi_l(i) = \sum_{j \in \mathcal{C}} \nu_l(i,j) = [\mathbf{W}^l \mathbf{e}]_i. \quad \{\phi_1, \ldots, \phi_l, \ldots, \phi_\infty\}$$

- Integrate individual collectiveness at all the scales with generating function

$$\phi(i) = \sum_{l=1}^{\infty} z^l \phi_l(i) = [\mathbf{Ze}]_i.$$



Theorem 2. $\mathbf{Z} = (\mathbf{I} - z\mathbf{W})^{-1} - \mathbf{I}$. It converges when $0 < z < 1/\rho(\mathbf{W})$. $\rho(\mathbf{W})$ denotes the spectral radius of **W.**

Crowd Collectiveness

$$\Phi = \frac{1}{|\mathcal{C}|}\sum_{i=1}^{|\mathcal{C}|}\phi(i) = \frac{1}{|\mathcal{C}|}\mathbf{e}^{\top}((\mathbf{I} - z\mathbf{W})^{-1} - \mathbf{I})\mathbf{e}$$

- Properties of Collectiveness

Property 1. (Strong Convergence Condition)
$\mathbf{Z}$ *converges* when $z < \frac{1}{K}$

Property 2. (Bounds of Φ) $0 \leq \Phi \leq \frac{zK}{1-zK}$, *if* $z < \frac{1}{K}$.

Property 3. (Upper bound of entries of Z)
$\varpi_{i,j} < \frac{z}{1-zK}$, *for every entry (i,j) of* $\mathbf{Z}$.

Collective Merging

- The algorithm to detect collective motions from moving keypoints

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Algorithm 1 Collective Merging

INPUT: $\{\mathbf{x}_i, \mathbf{v}_i | i \in \mathcal{C}\}_t$.

1:Compute $\mathbf{W}$ from K-NN using Eq. 1.

2:$\mathbf{Z} = (\mathbf{I} - z\mathbf{W})^{-1} - \mathbf{I}$.

3:Set the entry $\mathbf{Z}(i,j)$ to 1 if $\mathbf{Z}(i,j) \geq \kappa$, otherwise to 0.

4:Extract the connected components of the thresholded $\mathbf{Z}$.

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- Motivation
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- Collectiveness Descriptor
- **Applications and Experiments**
  - Evaluation on Self-Driven Particles
  - Comparing with Human Perception
  - Detecting Collective Motions in Videos
  - Analyzing Collective Motions in Bacteria
  - Generating Collective Map of Scenes
- Conclusion

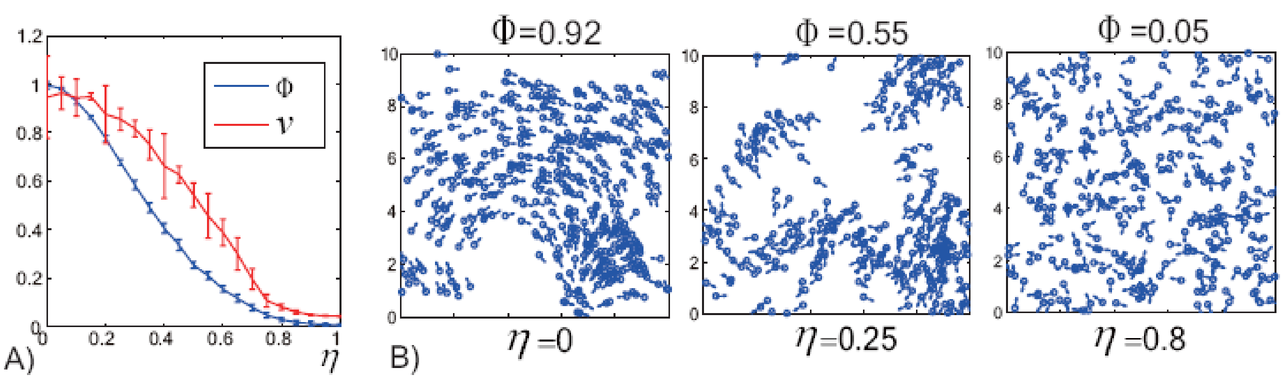
Evaluation on Self-Driven Particles (SDP)

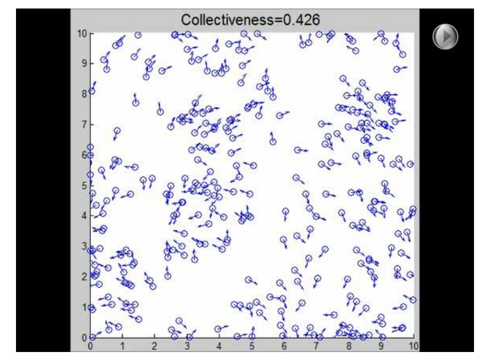
- SDP is a simulation model for collective motion of crowd.

$$\theta_i(t+1) = \langle \theta_j(t) \rangle_{j \in \mathcal{N}(i)} + \Delta\theta$$

$[-\eta\pi, \eta\pi]$

- Results of Φ and ν under different noise level η.



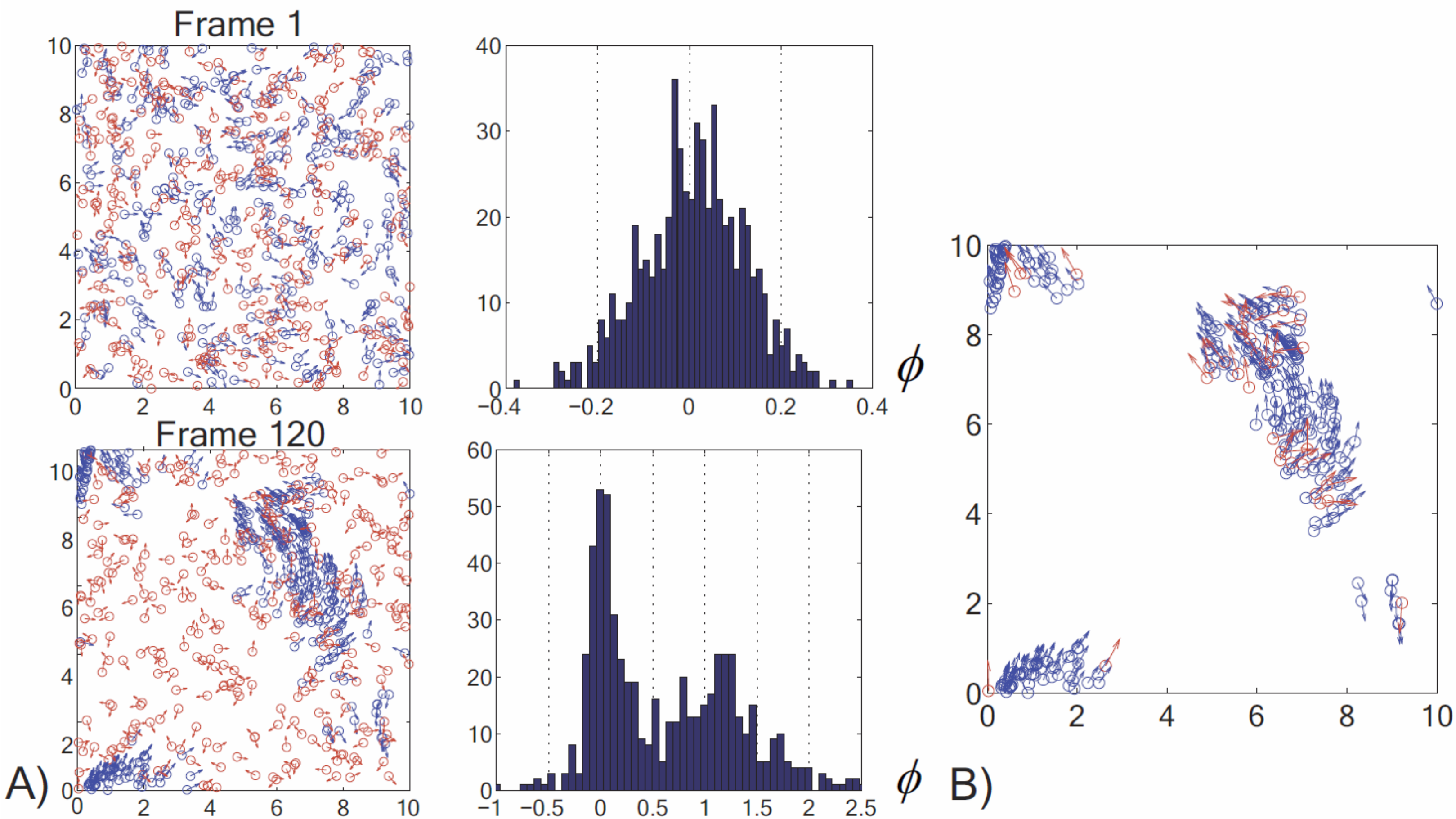


Φ: our collectiveness descriptor

v: average velocity used in existing scientific studies

Evaluation on Self-Driven Particles

- Mixing SDP with outliers (random walk noise)



Comparing with Human Perception

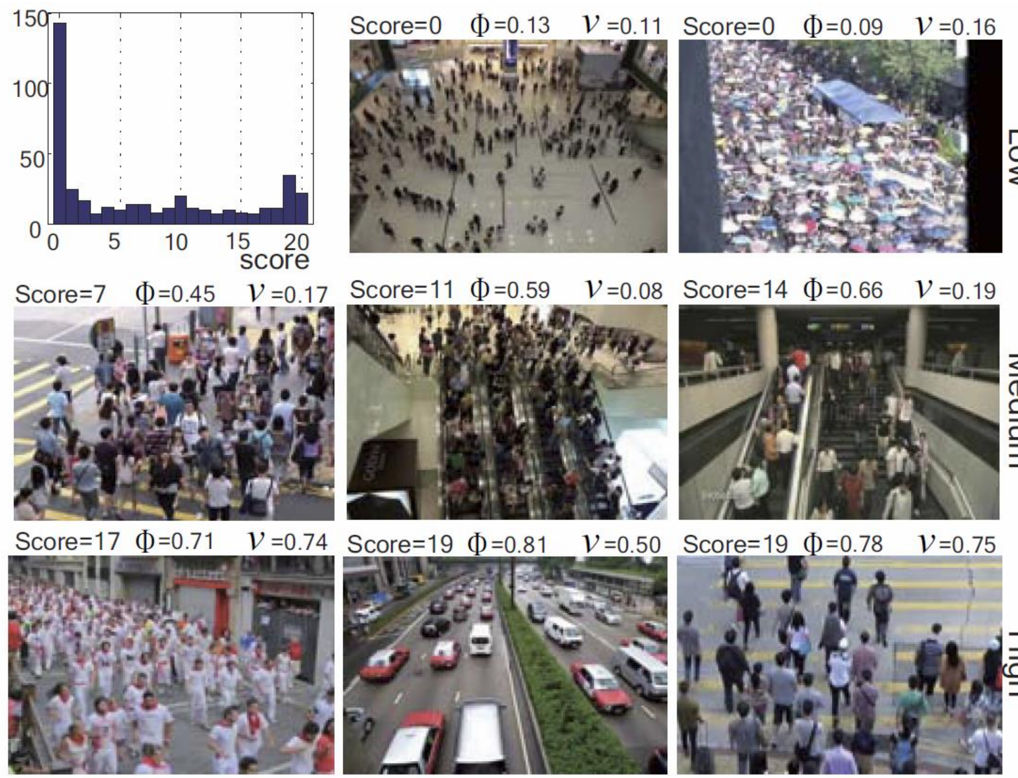
Collective Motion Database: a new video dataset

- 413 video clips from 62 crowded scenes, 10 labelers.
- Label each video into three categories:

High Collectiveness: 2

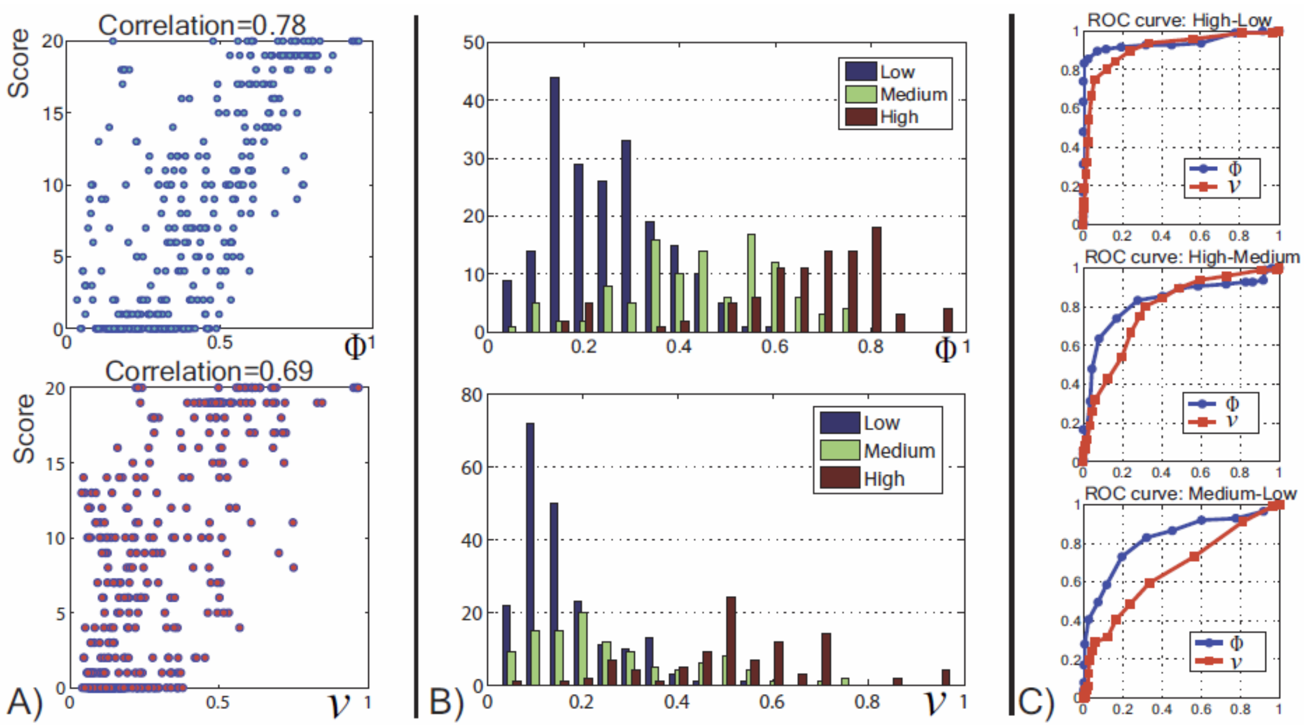
Medium Collectiveness: 1

Low Collectiveness: 0



Comparing with Human Perception

- Our collectiveness descriptor is more consistent to human perception for collective motion than the average velocity.



High-Low

	Best Accuracy	Boundary
Φ	0.95	0.42
ν	0.93	0.38

High-Medium

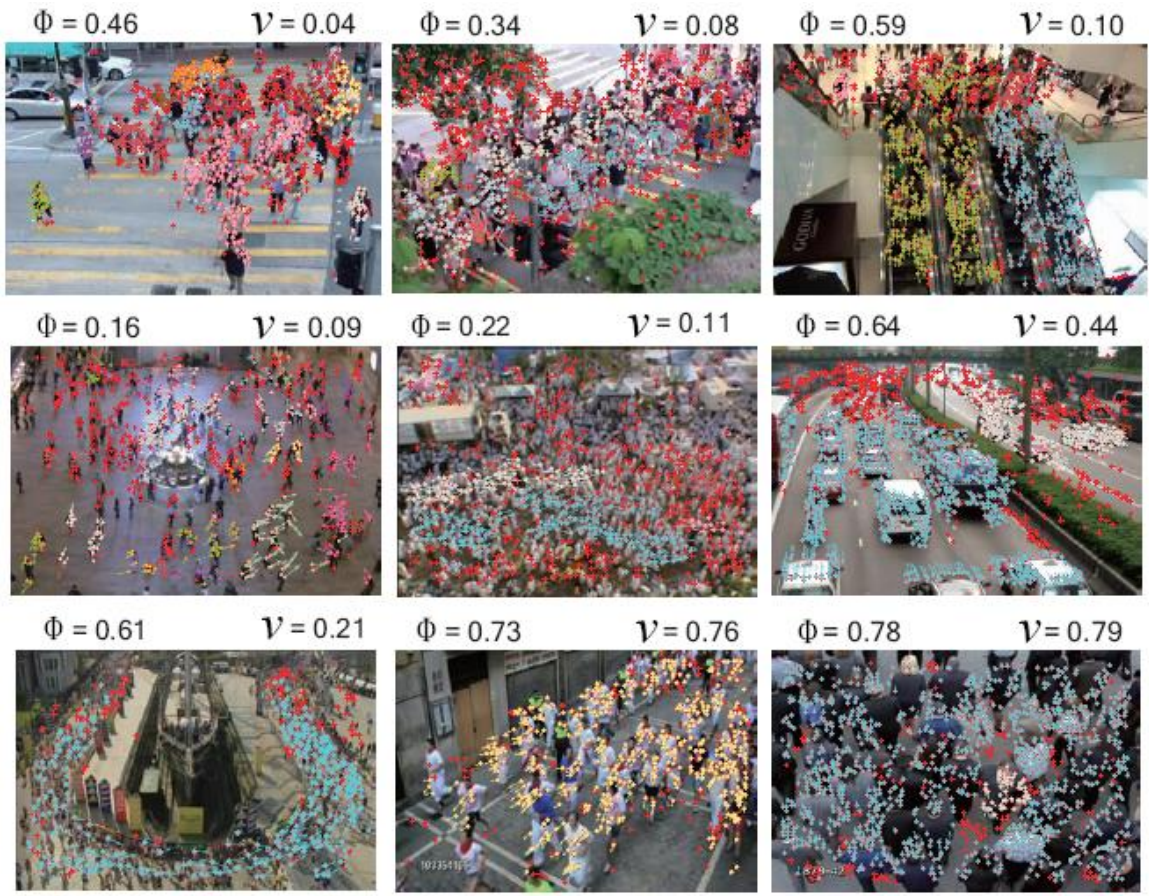
	Best Accuracy	Boundary
Φ	0.84	0.44
ν	0.80	0.36

Medium-Low

	Best Accuracy	Boundary
Φ	0.79	0.32
ν	0.71	0.38

Detecting Collective Motions in Videos

- Results on videos from Collective Motion Database



Detecting Collective Motions in Videos

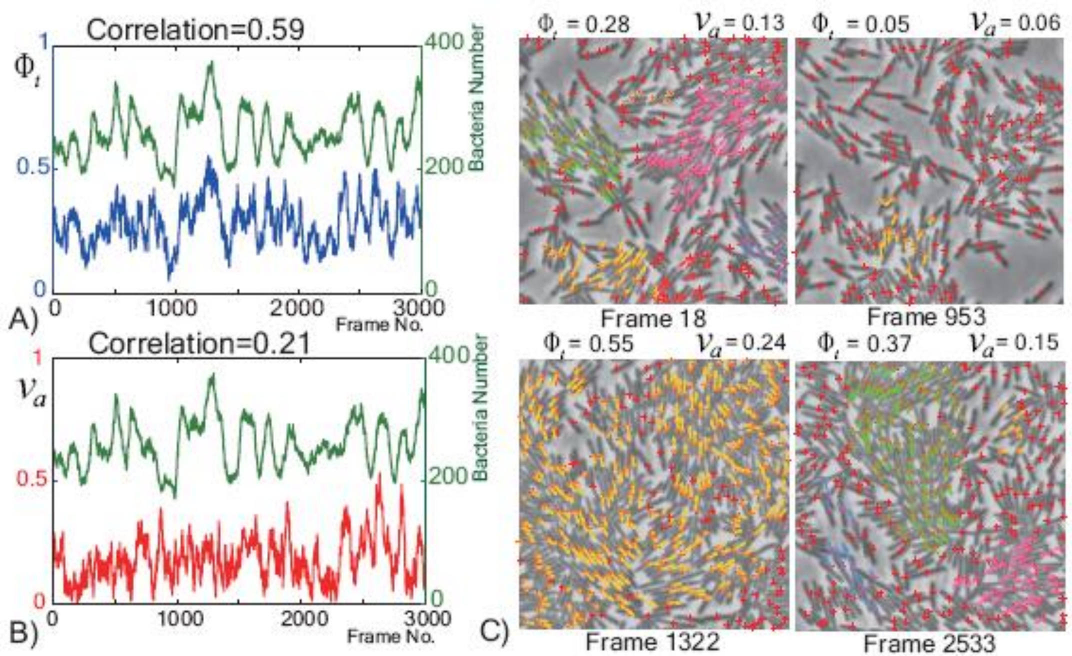
- Demo videos

Detecting Collective Motions in Videos

- Monitoring crowd dynamics in videos

Analyzing Collective Motions in Bacteria

- Measuring collectiveness of bacteria motion.
- Detecting collective motions in bacterial colony

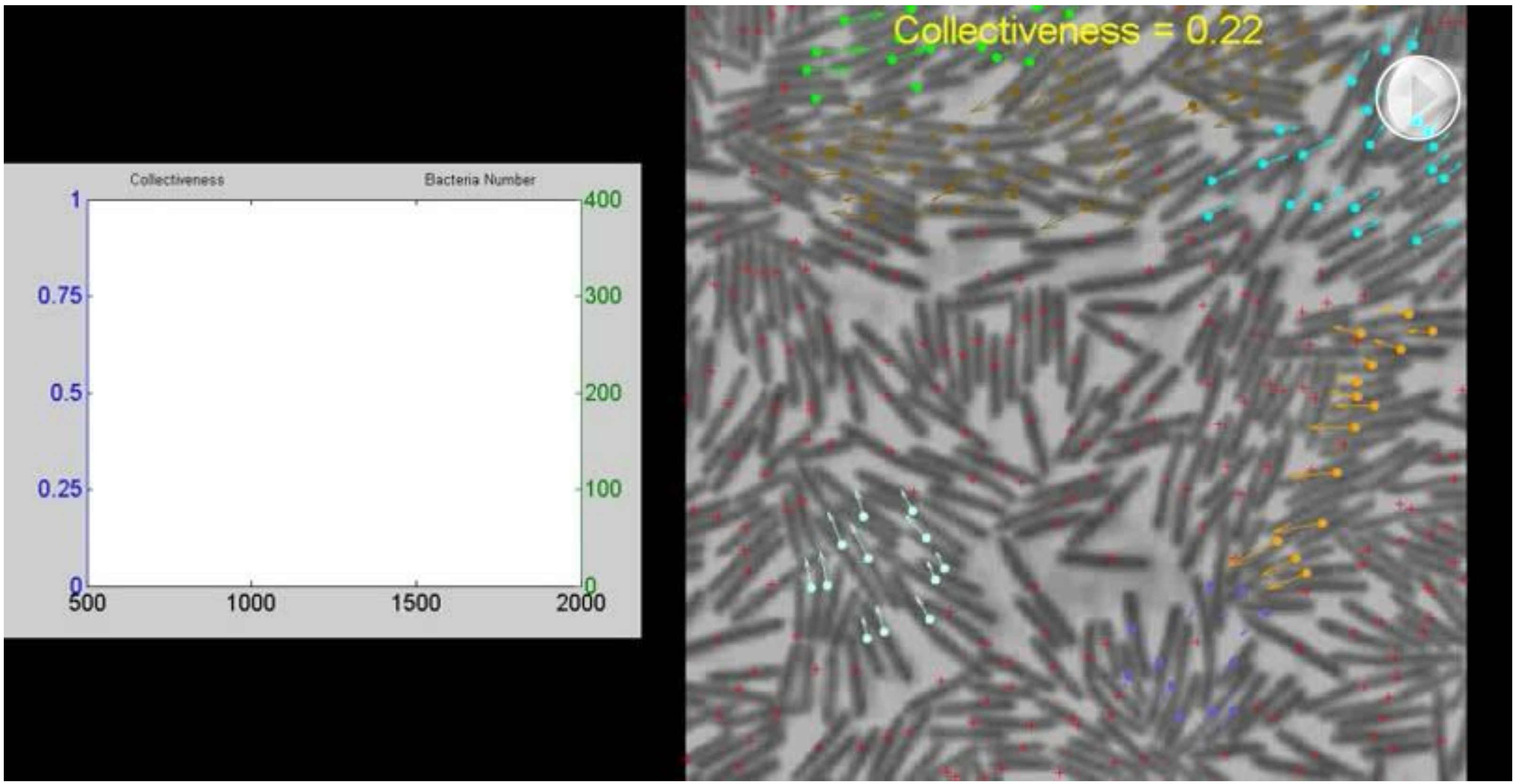


Wild-type Bacillus subtilis colony

H. Zhang, A. Ber, E. Florin, and H. Swinney.
Collective motion and density fluctuations in bacterial colonies. *PNAS, 2010*

Analyzing Collective Motions in Bacteria

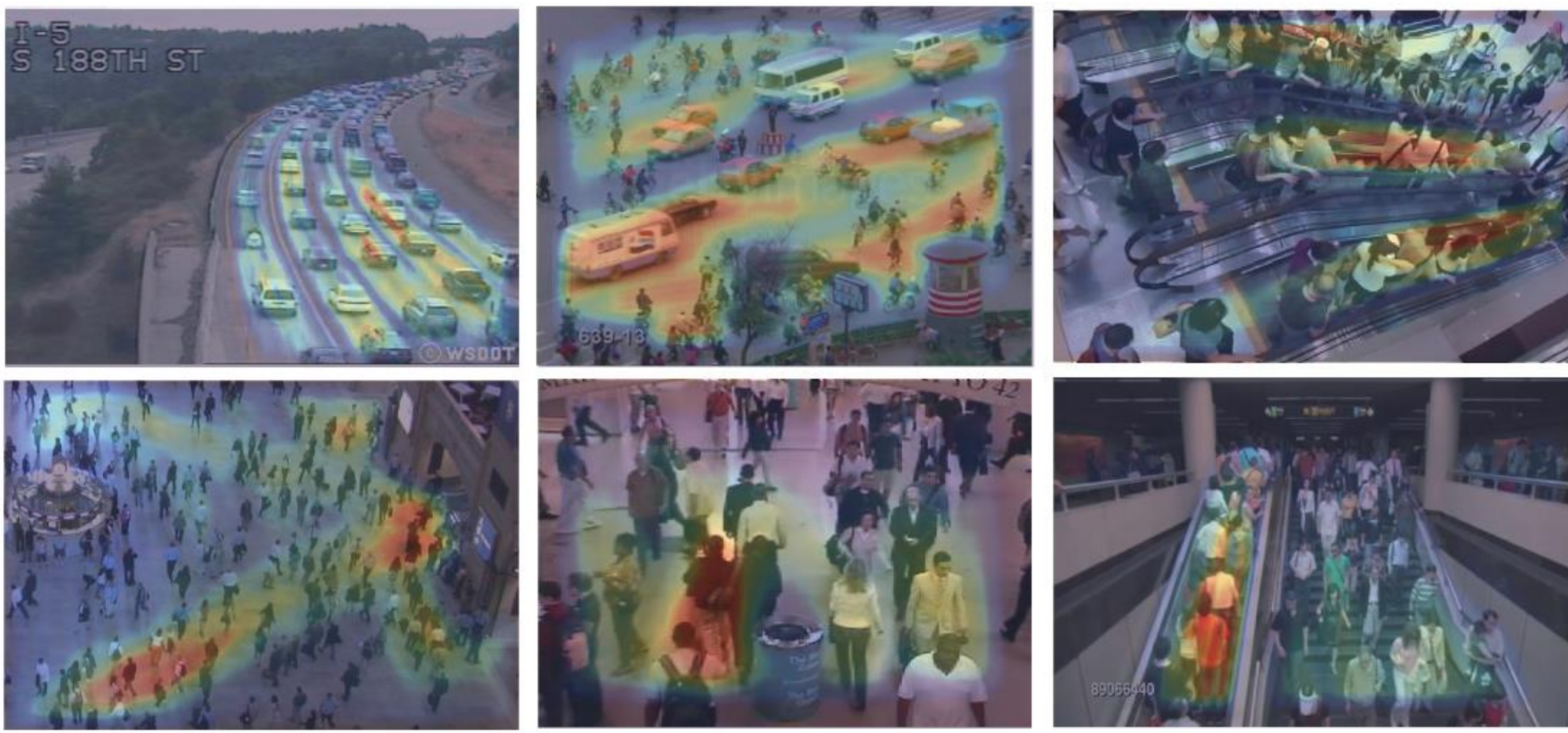
- Measuring collectiveness of bacteria motion
- Detecting collective motions in bacterial colony



H. Zhang, A. Ber, E. Florin, and H. Swinney.
Collective motion and density fluctuations in bacterial colonies. *PNAS, 2010*

Generating Collective Map of Scenes

- Spatial distribution of collectiveness accumulated over an extended period



Conclusion

- A new collectiveness descriptor to characterize crowd dynamics
- A new algorithm Collective Merging to detect collective motions
- Applications:

1. Comparing collectiveness of different crowd systems
2. Monitoring crowd dynamics
3. Detecting collective motions in time-series data
4. Generating collective map of scenes

- Future works
  - Extend to a spectrum vector of characterizing collectiveness at different length scales
  - Enhance the descriptive power by modeling the spatial and temporal variations of collectiveness
  - Cross-scene crowd video retrieval, saliency detection, abnormality detection

Acknowledgement

- Thank Prof. Hepeng Zhang for sharing the bacteria colony data. Thank Deli Zhao and Wei Zhang for valuable discussions.

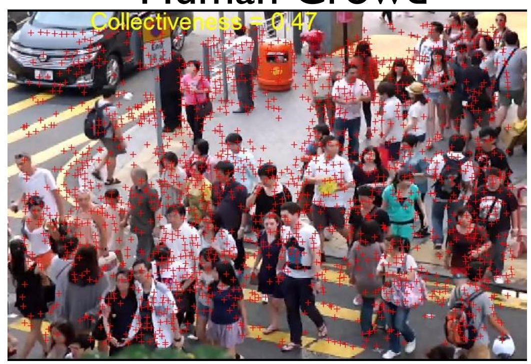
Any questions?

Datasets and code are released. Project page is

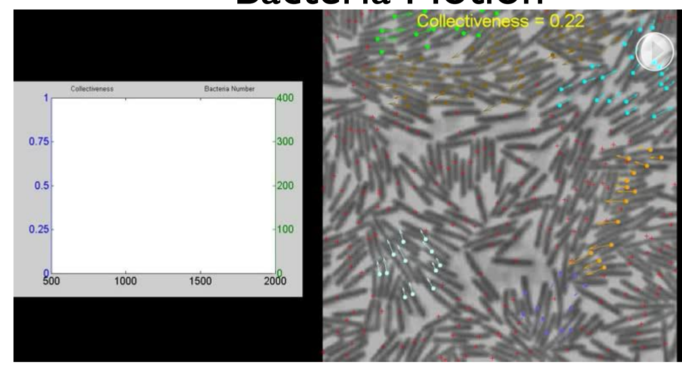
http://mmlab.ie.cuhk.edu.hk/project/collectiveness/

Fish School

Human Crowd



Bacteria Motion



Low Collectiveness

Medium Collectiveness

High Collectiveness