Visual Crowd Surveillance Through a Hydrodynamics Lens

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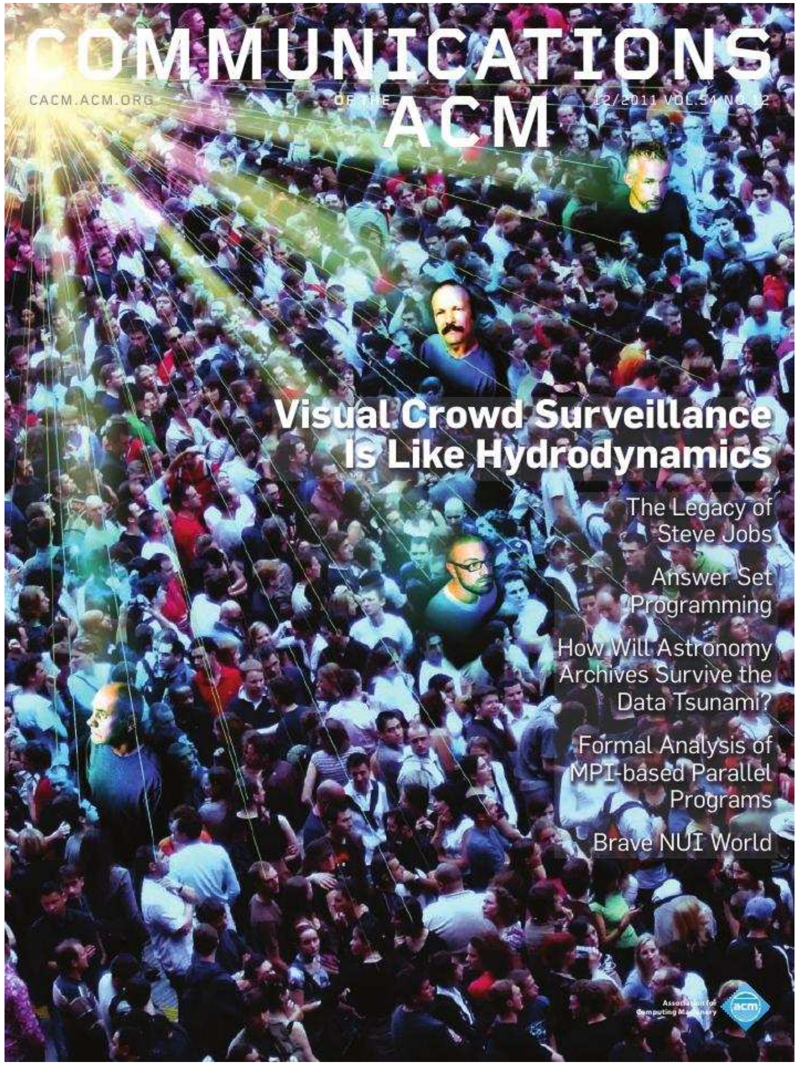


B.E. Moore, S. Ali, R. Mehran, and M. Shah, Visual Crowd Surveillance through a Hydrodynamics Lens, *Communications of the ACM*, 54(12):64-73, December 2011.

Traffic Flow, Crowd Flow, Fluid Flow

Contents

- Macroscopic Scale: Segmentation of Motion
- Mesoscopic Scale: Abnormal Behavior Detection
- Microscopic Scale: Tracking Individuals
- Further Explorations

Mathematical Tools

- Lagrangian approach to fluid dynamics
- Lyapunov exponents, dynamic modeling

BLOOD	SWEAT	TEARS

Flow Segmentation

Lyapunov Exponents for Flow Segmentation

- Track movement of pixels as particle trajectories.
- Compute the distance between neighboring particles at the end of a trajectory.
- Particles that stay close together are part of the same coherent flow pattern.
- Particles that diverge belong to separate coherent flow patterns.
- Tool: Finite Time Lyapunov Exponent (FTLE)

Flow Segmentation
Example Video Sequence

Flow Segmentation
Particle Advection

- Every pixel has a position (x, y).
- Optical flow provides the velocities (u, v) at each pixel.

$$\frac{dx}{dt} = u(x, y, t), \qquad \frac{dy}{dt} = v(x, y, t)$$

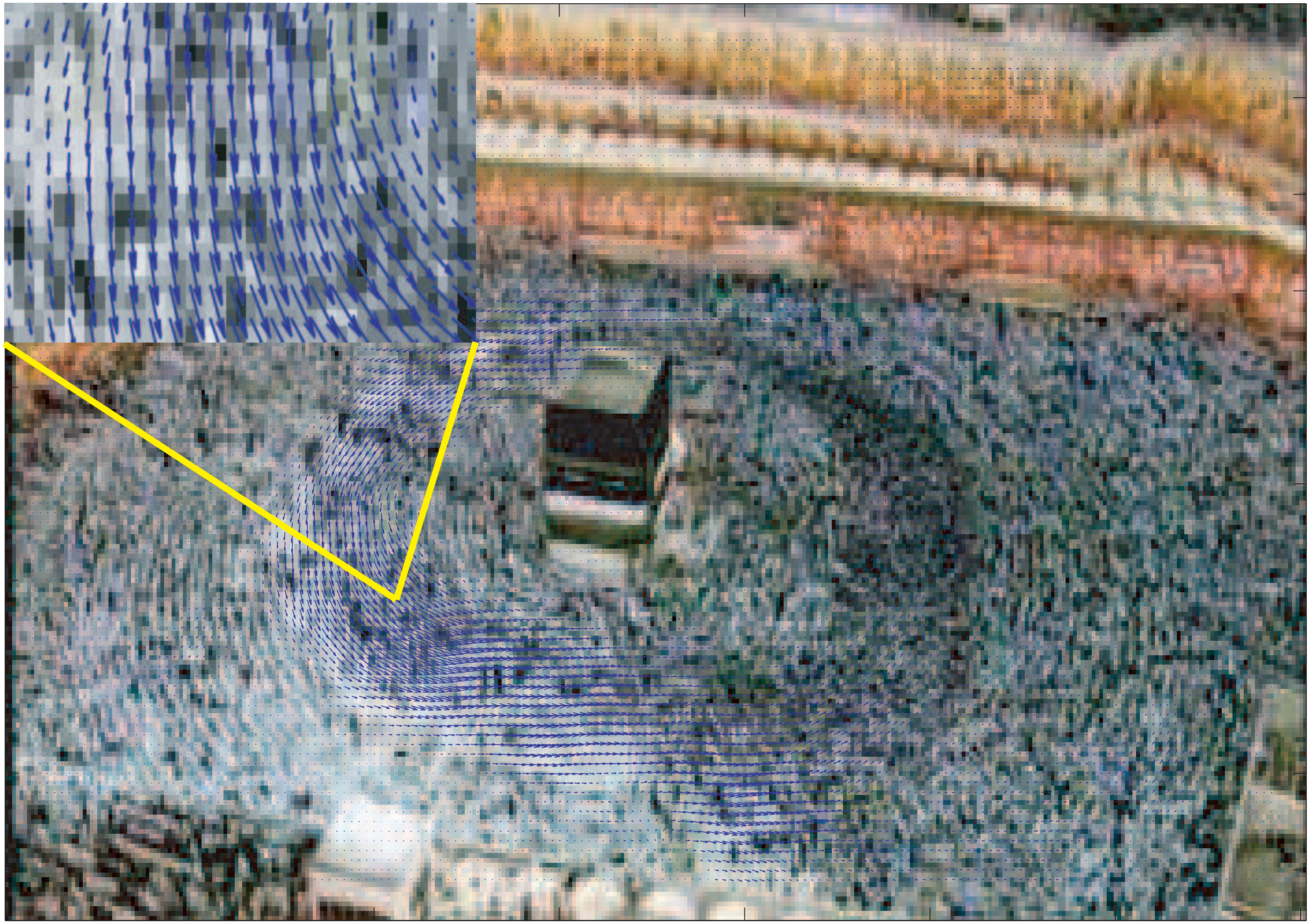
- Initial Condition: Overlay scene with a grid of particles
- Particles transported to new coordinates by time-stepping.

$$x(t+1) = x(t) + u(x(t), y(t), t), \quad y(t+1) = y(t) + v(x(t), y(t), t)$$

Performing computations over a time interval ($\approx$ 60 frames) gives particle trajectories describing the motion in the scene.

Flow Segmentation

Computed Particle Trajectories for Video Sequence



Flow Segmentation
Computing the FTLE

The jth pair of nearest neighbors diverge at a rate L.

$$d_j(t_i) \approx k_j e^{Lt_i} \quad \Longleftrightarrow \quad \ln d_j(t_i) \approx \ln k_j + Lt_i$$

- $t_i = i$, sampling time and frame number are synonymous
- k_j is the initial separation
- $d_j(t_i)$ denotes the distance between the jth pair of nearest neighbors after i discrete time steps.

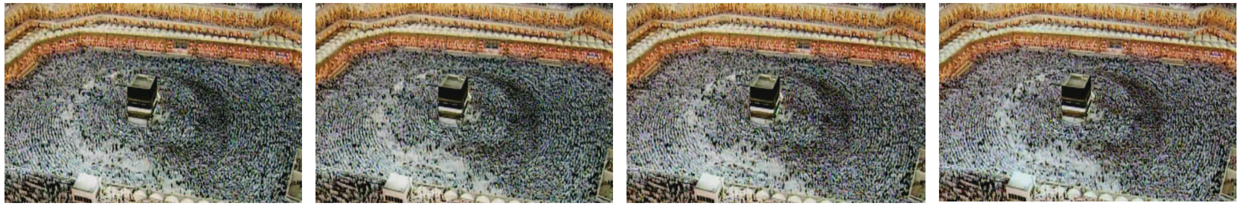
This is a set of approximately parallel lines with slope L. The largest FTLE is approximated by fitting the average line

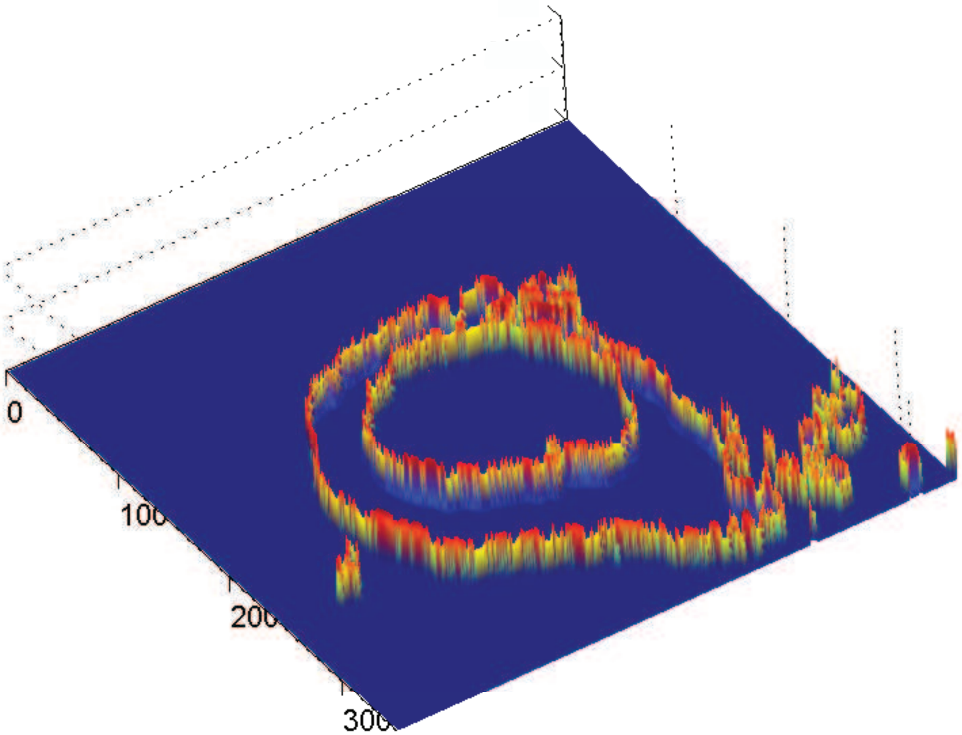
$$a(t_i) = \langle \ln d_j(t_i) \rangle,$$

$\langle \cdot \rangle$ denotes the average over j, crucial for small/noisy data sets.

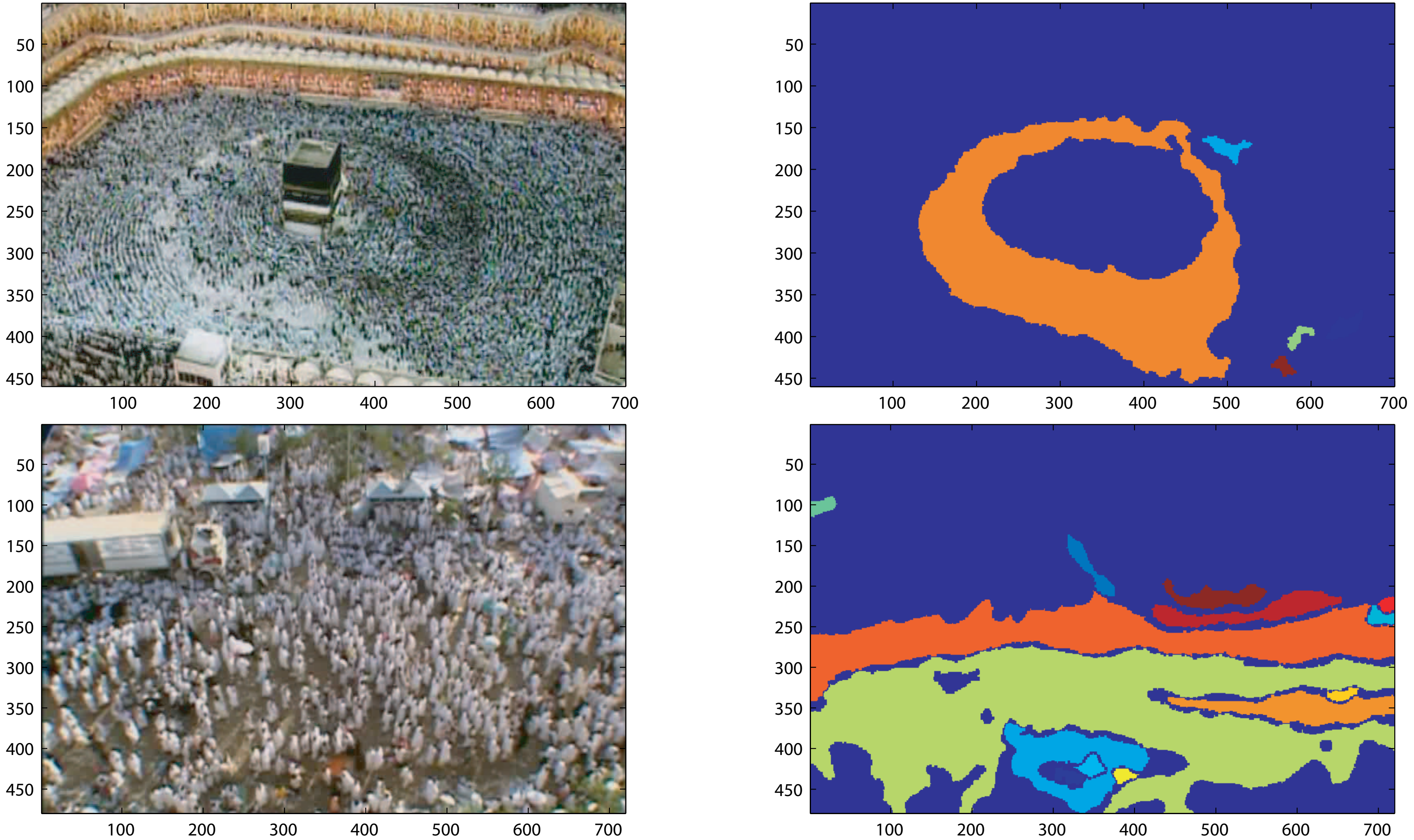
Flow Segmentation

Computed FTLE for a Video Sequence





Flow Segmentation for Video Sequences



Flow Segmentation

Flow Representations

Streamlines are tangent to the velocity vectors at every point in the flow.

Pathlines are trajectories that individual particles in a fluid flow will follow.

Streaklines represent the locations of all particles at a given time that passed through a particular point.

For steady flows the representations are the same.
For unsteady flows each provides a different point of view.

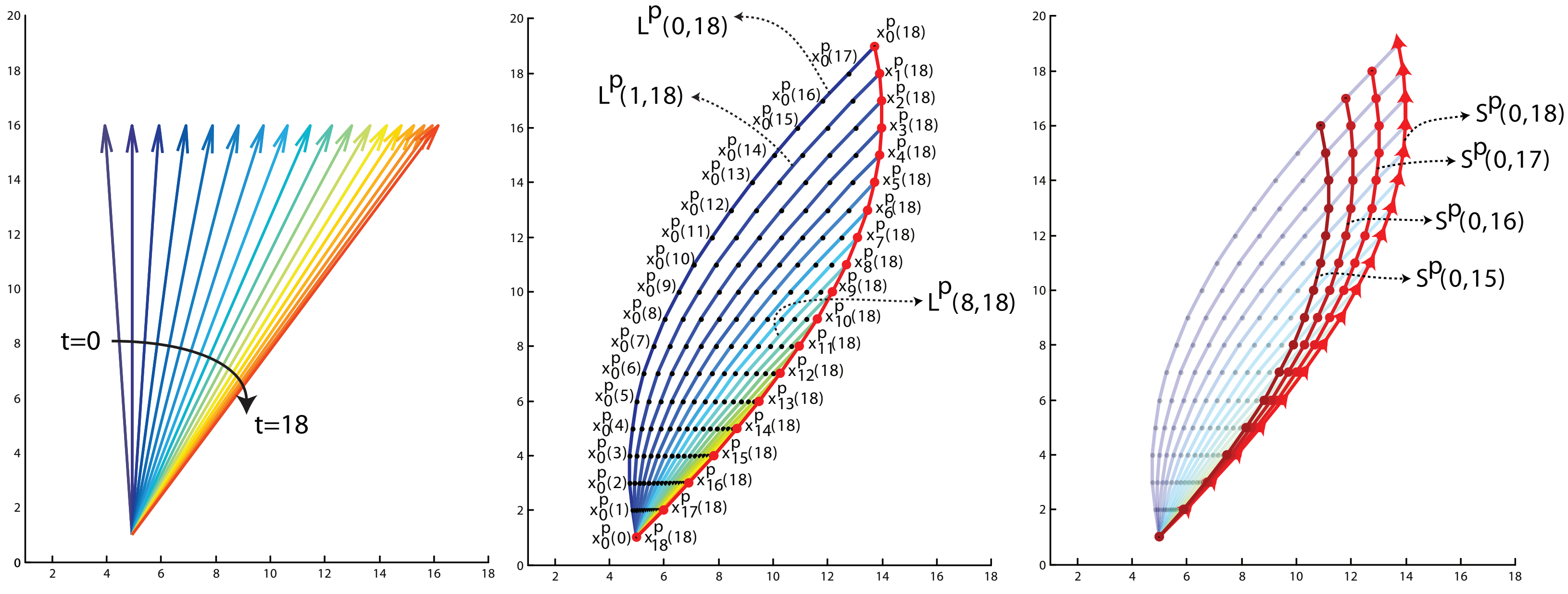
YouTube Videos:

L-1011 Airliner Wing Vortice Tests at NASA Langley Research | Streaklines 00000

R. Mehran, B.E. Moore, and M. Shah, A Streakline Representation of Flow in Crowded Scenes, *European Conference on Computer Vision*, 2010.

Flow Segmentation

Streaklines vs Pathlines

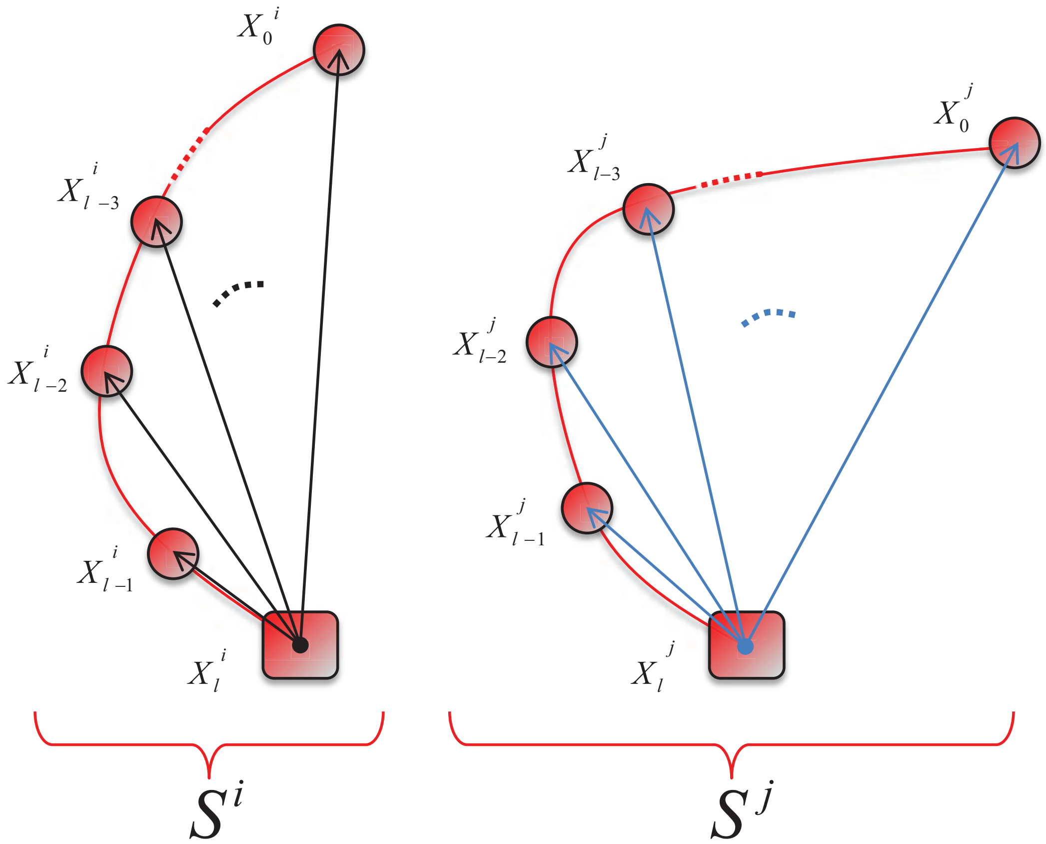


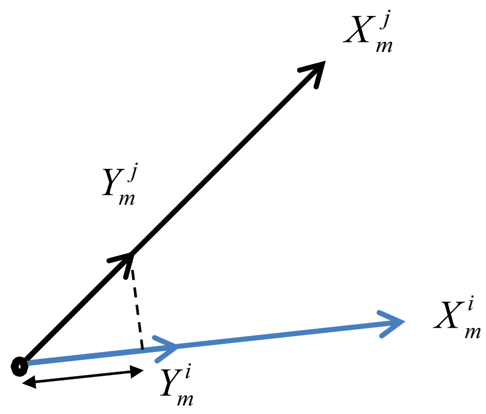
(a) (b) (c)

Let $(x_i^p(t), y_i^p(t))$ be particle position at time t, initialized at point p and frame i for $i, t = 0, 1, 2, \ldots, T$. Repeated initialization at p implies $(x_i^p(i), y_i^p(i)) = (x_0^p(0), y_0^p(0))$. Positions are updated by

$$
\begin{aligned}
x_i^p(t+1) &= x_i^p(t) + u(x_i^p(t), y_i^p(t), t) \\
y_i^p(t+1) &= y_i^p(t) + v(x_i^p(t), y_i^p(t), t)
\end{aligned}
$$

Flow Segmentation
Streakline Comparison



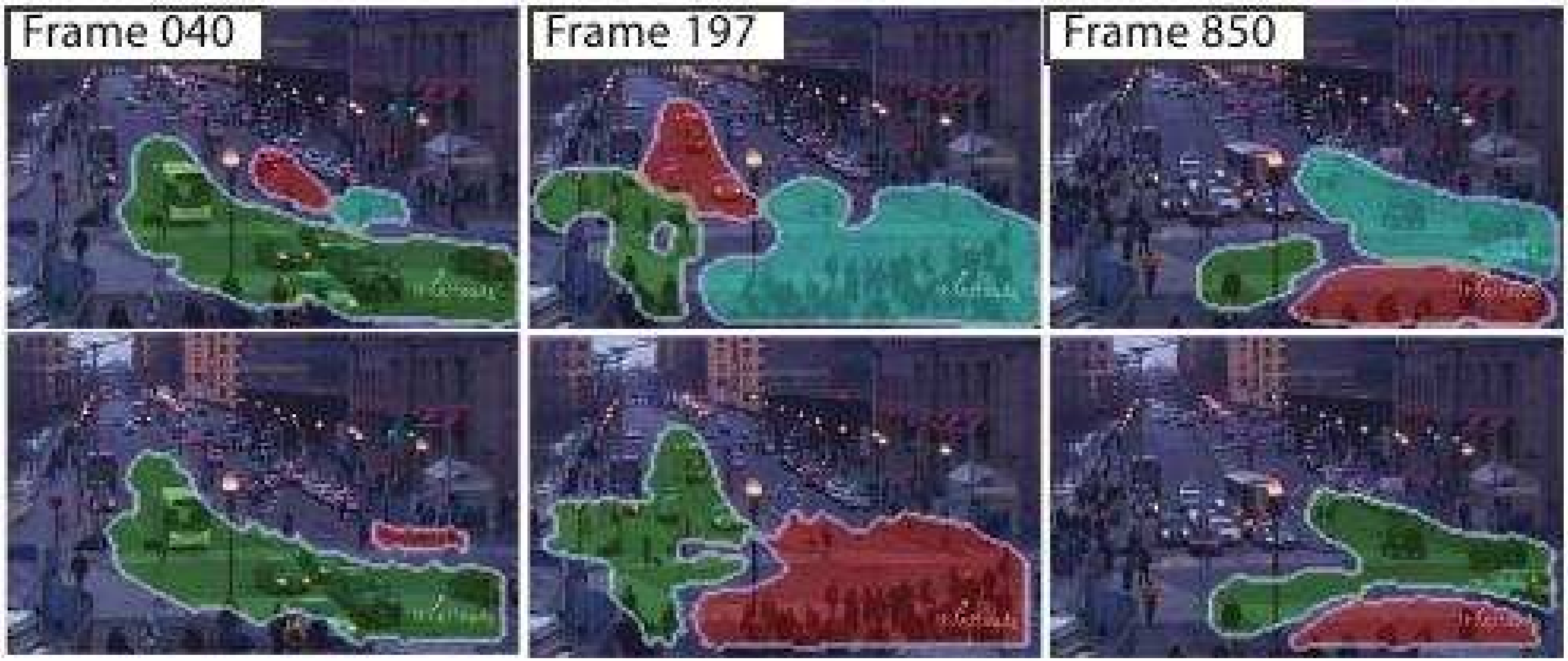


$$prj(X_m^{\ i}, X_m^{\ i}) = \left\langle \bar{Y}_m^{\ i}, \bar{Y}_m^{\ j} \right\rangle$$

$$\bar{Y}_m^{\ i} = \frac{Y_l^i}{\left\| Y_l^i \right\|}, \quad Y_m^{\ i} = X_m^{\ i} - X_l^{\ i}$$

Flow Segmentation

Results



Abnormal Behavior Detection
Social Force Model (Helbing)

Newton's 2nd Law $F = ma$, with $m = 1$.

Change in velocity of pedestrian i is $a = \frac{dv_i}{dt} = F_p + F_{int}$,

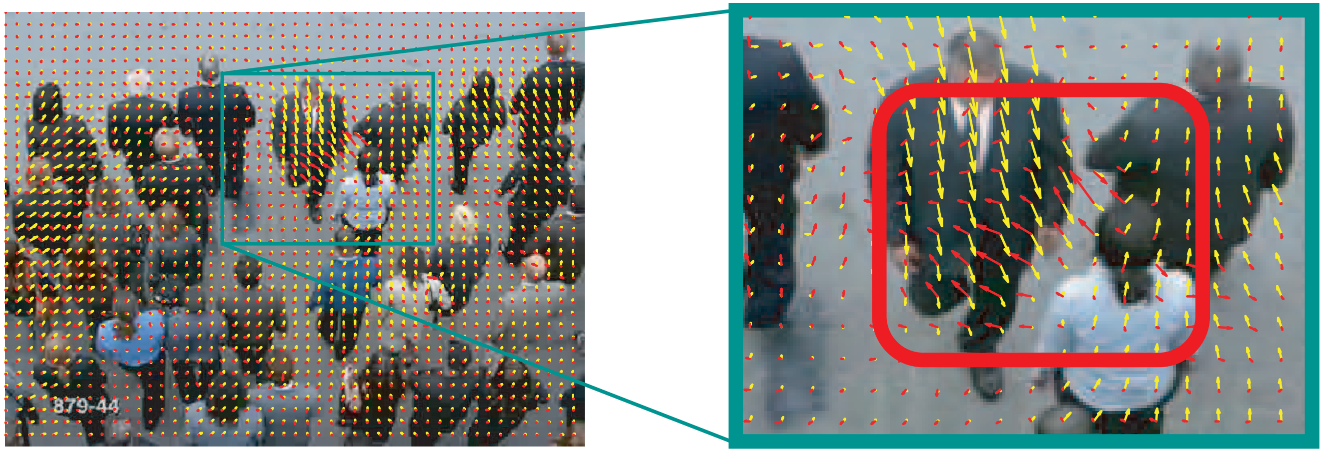
$F_p = \frac{1}{\tau}(v_i^p - v_i)$ is personal desire force
$F_{int} = \frac{dv_i}{dt} - F_p$ is interaction force

Actual velocity v_i of a particle at coordinate (x_i, y_i) is obtained from the spatial-temporal average of optical flow.

Desired velocity v_i^p is a weighted sum of v_i and the optical flow for that particle.

Fighting the Flow

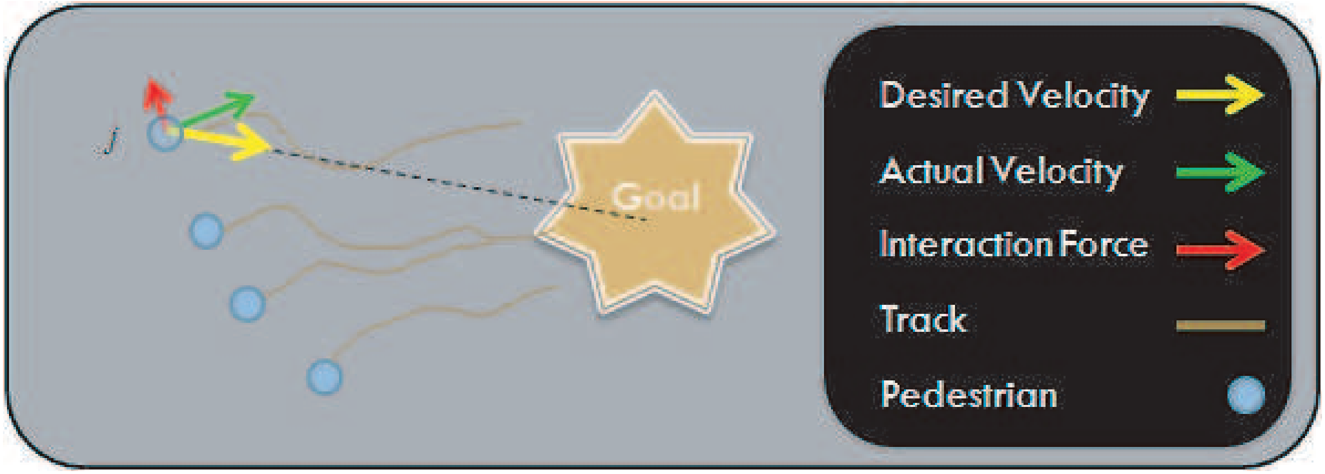
Abnormal Behavior Detection
Problem and Solution

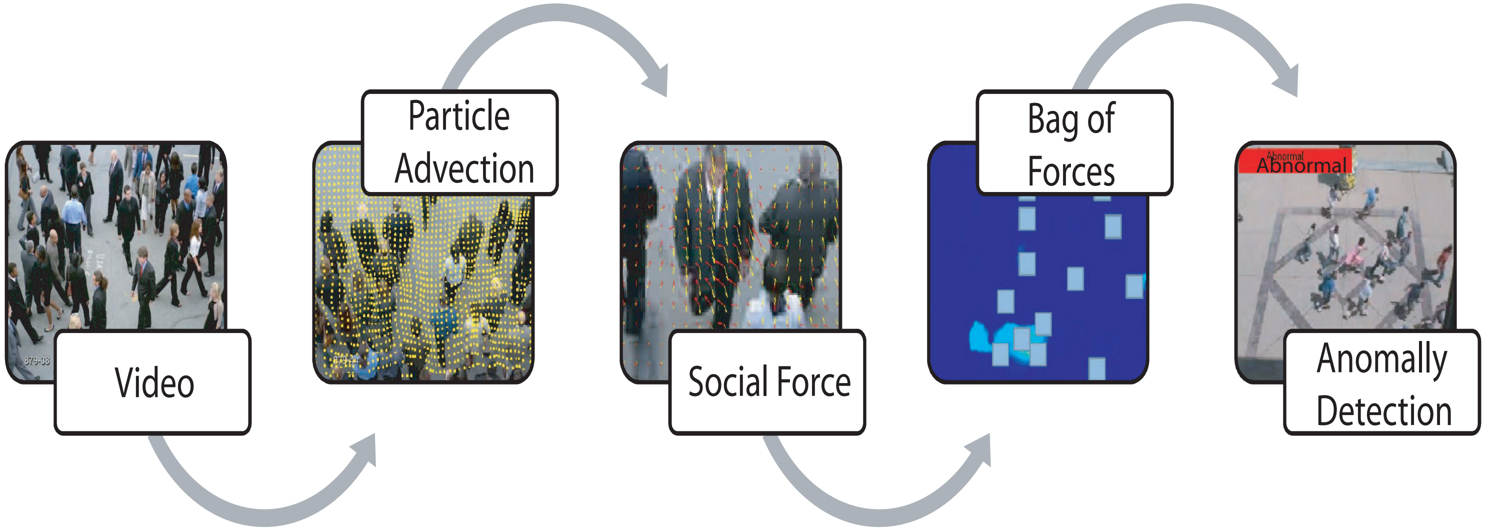


(a)

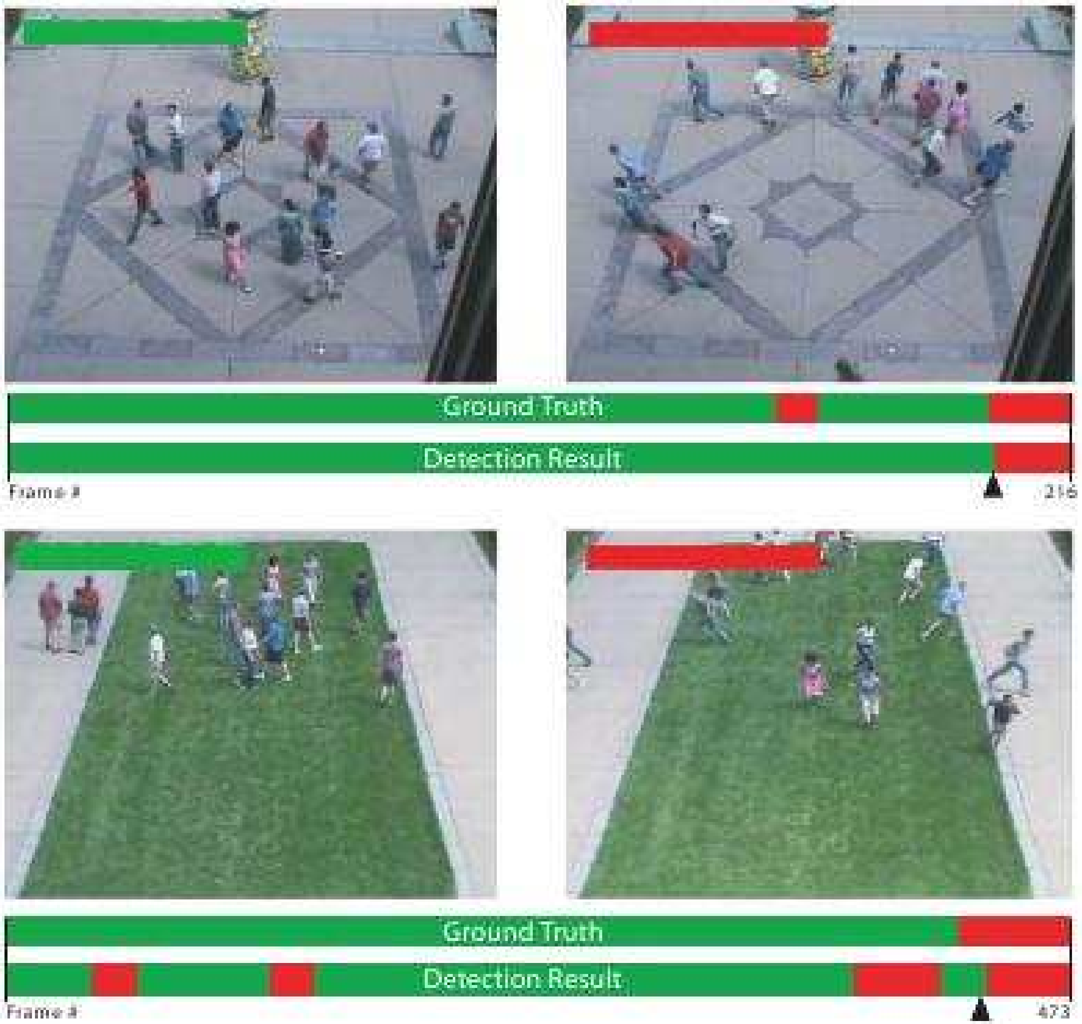
(b)

Abnormal Behavior Detection Algortihm





Abnormal Behavior Detection Results



3 assumptions about the movement of an individual imply

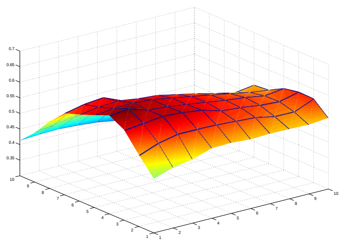
<u>3 Floor Fields</u>

boundary the person avoids permanent fixtures, such as trash cans or walls

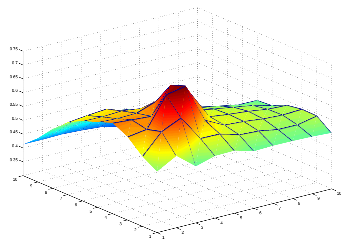
static the person has a goal (place to get to and clear direction on how to get there) and in the absence of obstacles, the person will go directly there

dynamic the person can only move toward the goal as the flow of the crowd around him/her allows it

Marathon



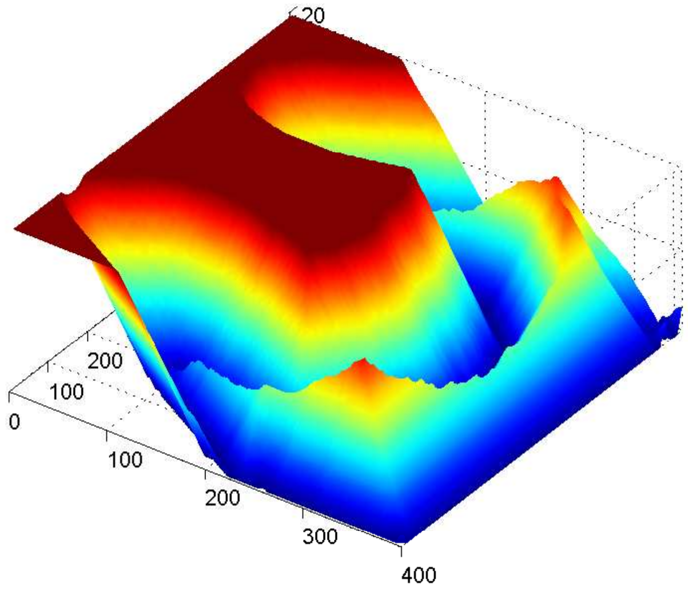
Appearance Similarity Only



Appearance w/ Floor Fields

Boundary Floor Field

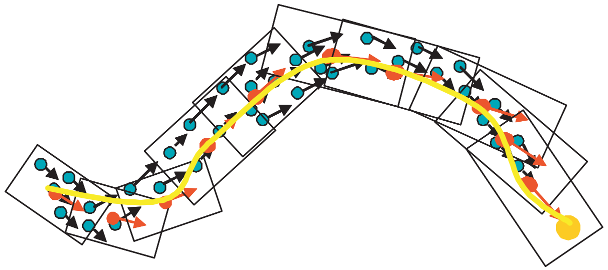
Flow segmentation, using the largest finite time Lyapunov exponent, produces the Boundary Floor Field.



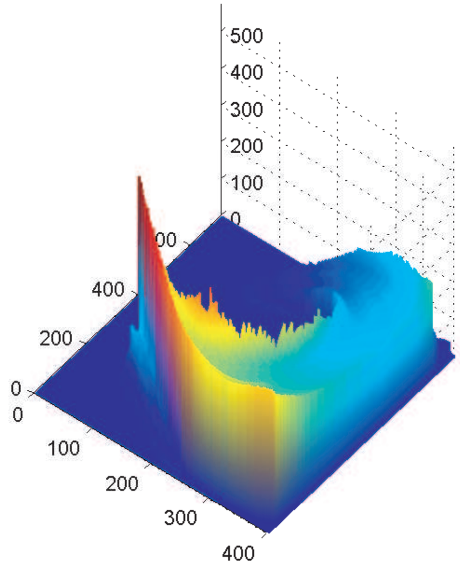
Static Floor Field

$$
\begin{aligned}
x_i(t+1) &= x_i(t) + u(x_i(t), y_i(t), t) \\
y_i(t+1) &= y_i(t) + v(x_i(t), y_i(t), t)
\end{aligned}
$$

Particle advection gives the goals of the crowd.



(a)

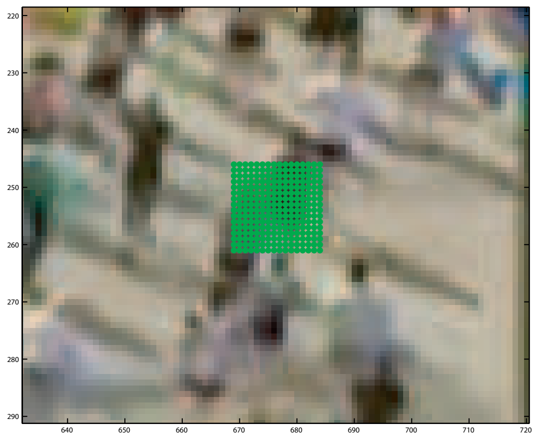


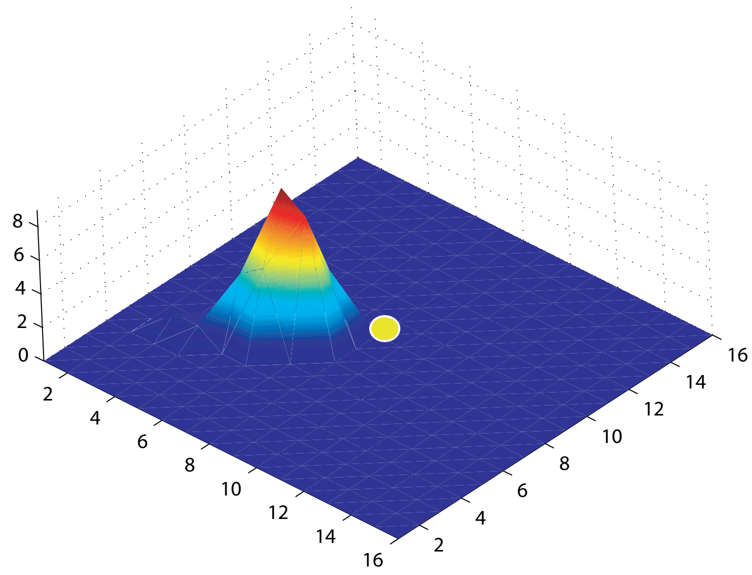
Tracking

Dynamic Floor Field

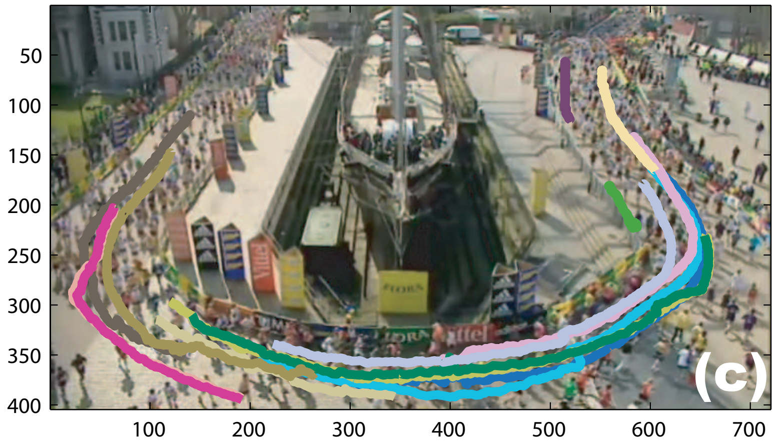
Use particle advection to determine if particles around the tracked individual are moving.

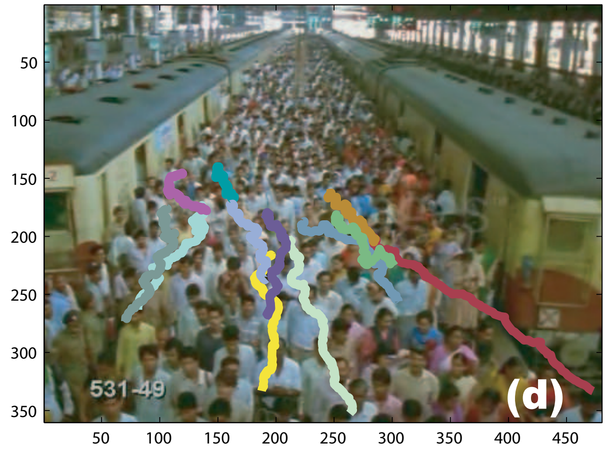
This tells how the surrounding crowd influences the individual's motion.

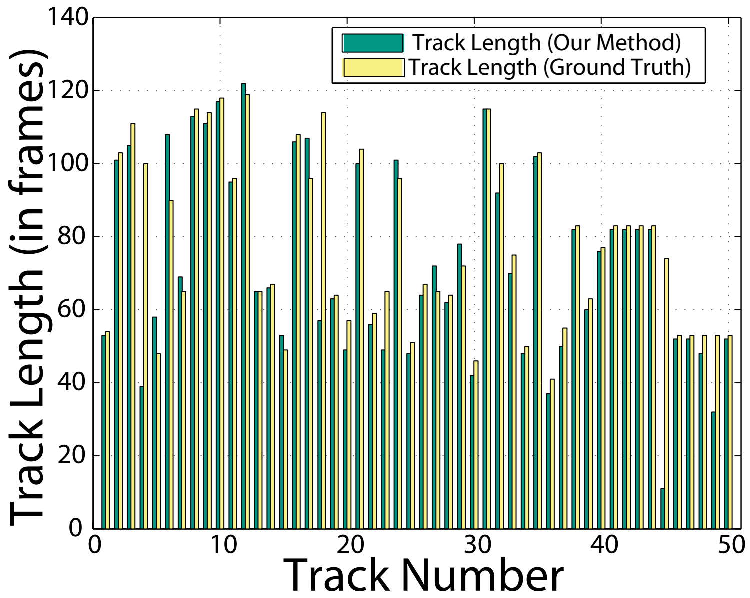




Tracking Results







Further Exploration

- Crowd Behavior Recognition
  B. Solmaz, B.E. Moore, and M. Shah, Identifying Behaviors in Crowded Scenes through Stability Analysis for Dynamical Systems, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, minor revision in review, 2012.
- Potential Functions to Characterize Abnormal Behavior
  R. Mehran, B.E. Moore, and M. Shah, A Streakline Representation of Flow in Crowded Scenes, *European Conference on Computer Vision*, 2010.
- Construction of Chaotic Models of Crowd Behavior
  S. Wu, B.E. Moore, and M. Shah, Chaotic Invariants of Lagrangian Particle Trajectories for Anomaly Detection in Crowded Scenes, *IEEE Conference on Computer Vision and Pattern Recognition*, 2010.