

# Data-driven Crowd Analysis in Videos

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WILLOW project

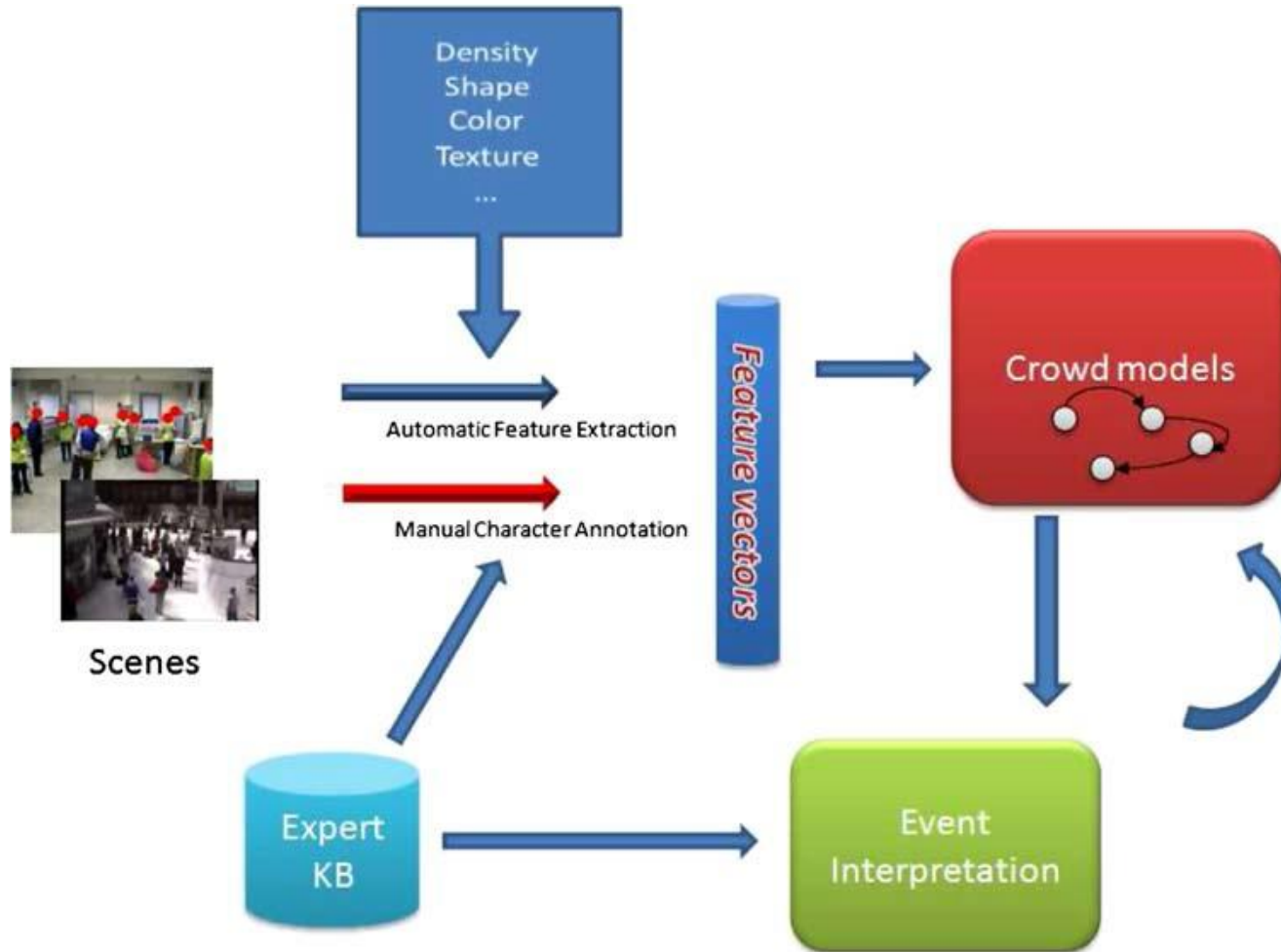
# Crowd Analysis



~~Public surveillance~~  
Crowd management

[Crowd analysis: a survey](#), Zhan, B., Monekosso, D.N., Remagnino, P., Velastin, S.A., Xu, L., Machine Vision and Applications, Vol 19, No 5-6, p. 345-357, DOI: 10.1007/s00138-008-0132-4.

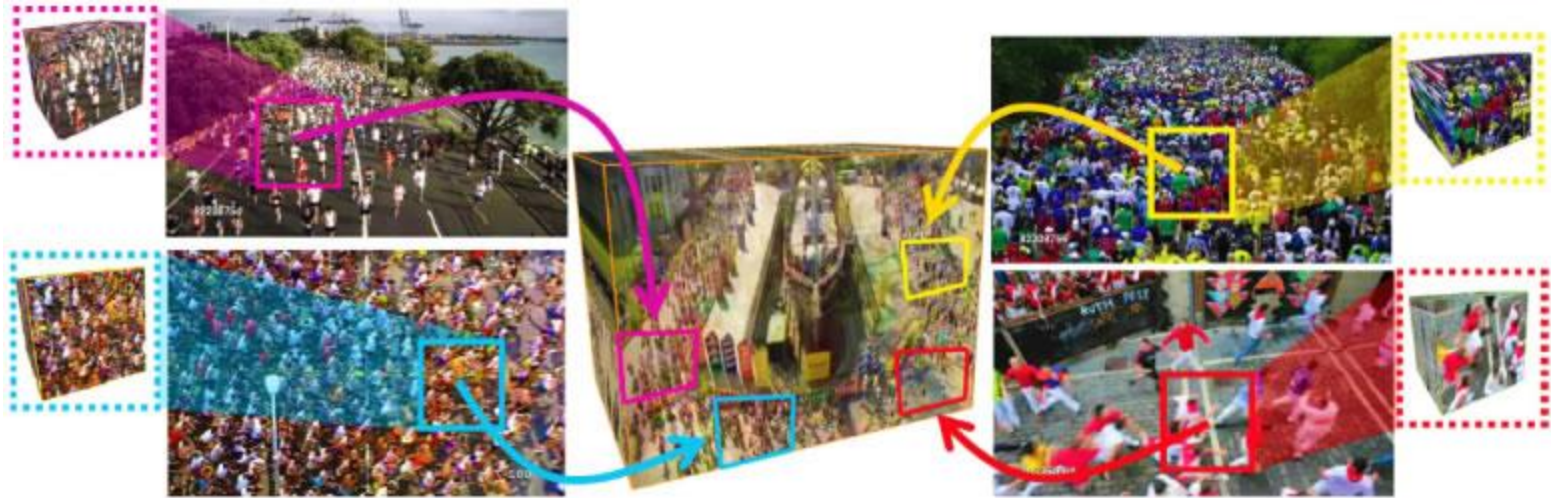
# Crowd Analysis



[Crowd analysis: a survey](#), Zhan, B., Monekosso, D.N., Remagnino, P., Velastin, S.A., Xu, L., Machine Vision and Applications, Vol 19, No 5-6, p. 345-357, DOI: 10.1007/s00138-008-0132-4.

# Data-driven Crowd Analysis

- Any given video can be thought as being a mixture of previously observed videos.



# Learning Motion Patterns

database



# Global Matching

similar scenes



test video



find similar scenes for similar scenes  
query for similar scenes  
find similar cells

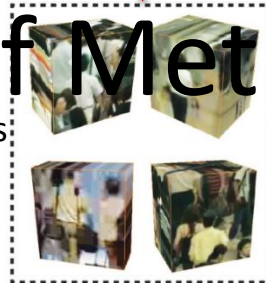
# Local Matching

find similar cells

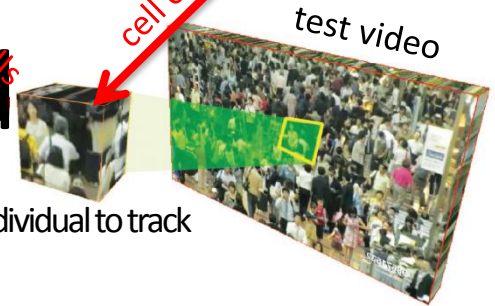
cell of interest

# view of Method

similar cells



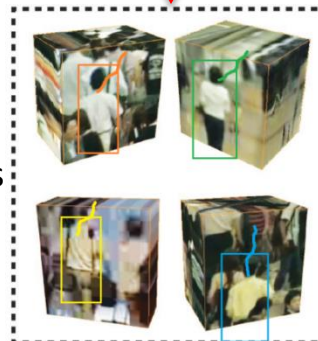
individual to track



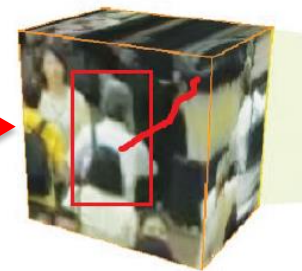
get motion patterns

# Tracking using Motion Patterns

similar cells



predict motion



motion patterns of similar cells

# Learning Motion Patterns

database



# Global Matching

similar scenes

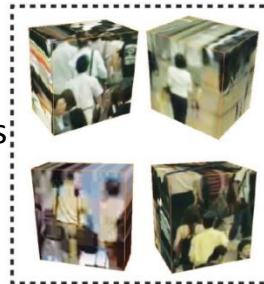


test video

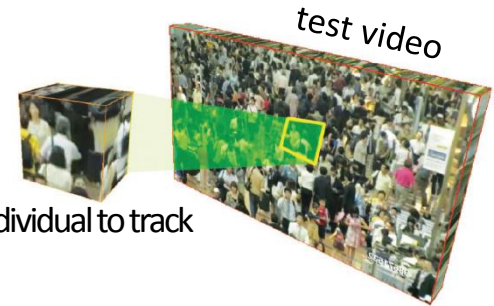


# Local Matching

similar cells

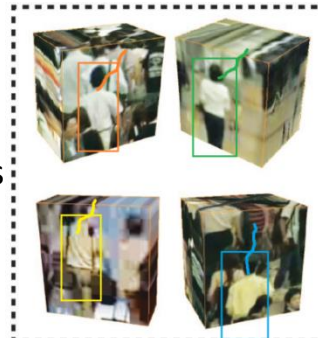


individual to track

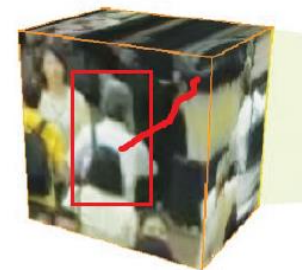


# Tracking using Motion Patterns

similar cells



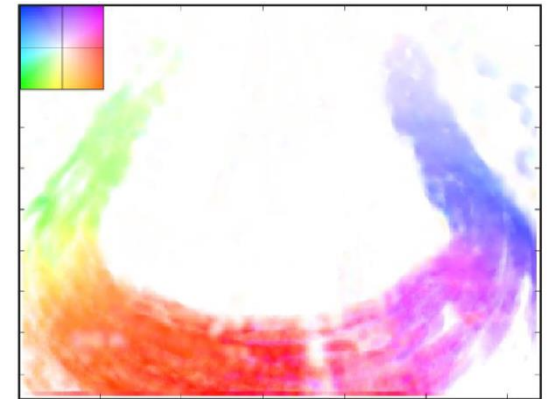
motion patterns of similar cells



# Learning Motion Patterns

## Low-level Representation: Dense Optical Flow

- For each pixel in each frame, calculate average optical flow.
- Combine the optical flow vectors into a global motion field for a temporal window.
  - temporal window  $\omega = 60$  frames
  - spatial window 20 pixel x 20 pixel

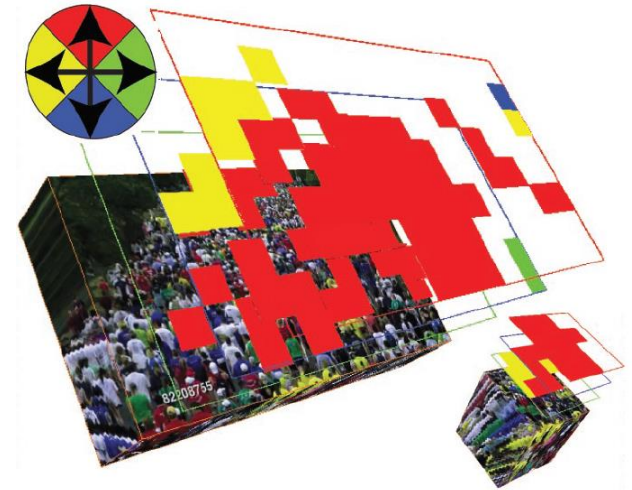


[An iterative image registration technique with an application to stereo vision.](#) B. Lucas and T. Kanade. In IJCAI, volume 3, pages 674–679, 1981.

# Learning Motion Patterns

## Mid-level Representation: Correlated Topic Model

- CTM captures spatial dependencies of different behaviors in the same scene.
- Video(720x480) $\Rightarrow$  10 sec clips  
 $\Rightarrow$  36x24 cells(20x20)
- Optical flow is quantized into directions  
 $\Rightarrow \{V_0, V_{up}, V_{down}, V_{left}, V_{right}\}$
- Motion word dictionary is constructed
- Behavior is (hidden) topic from which motion words are generated.





# Learning Motion Patterns

database



# Global Matching

similar scenes

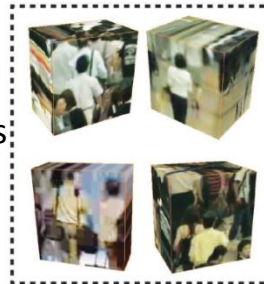


test video

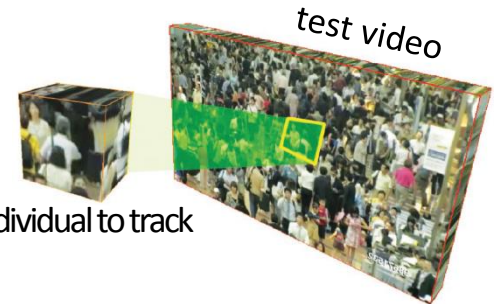


# Local Matching

similar cells

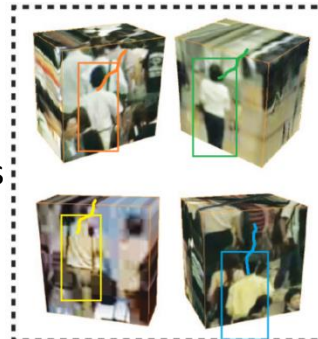


individual to track

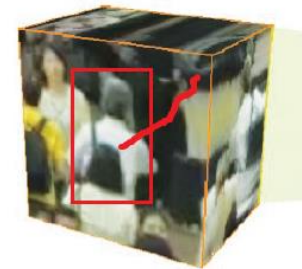


# Tracking using Motion Patterns

similar cells



motion patterns of similar cells



# Global Crowded **Scene** Matching

- Gist scene descriptor is used to retrieve similar scenes from the database.
- Global matching provides semantically similar scenes.

# Learning Motion Patterns

database



# Global Matching

similar scenes

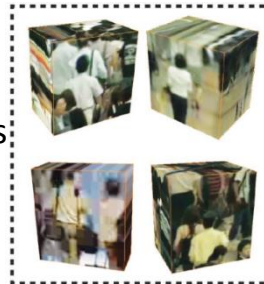


test video

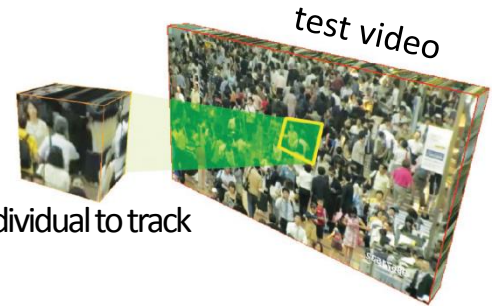


# Local Matching

similar cells

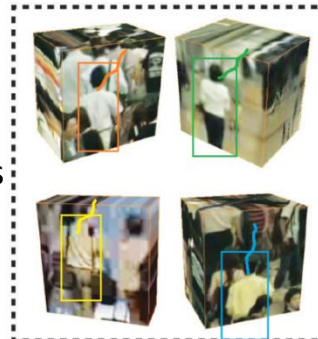


individual to track

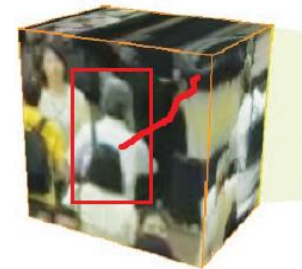


# Tracking using Motion Patterns

similar cells



motion patterns of similar cells



# Local Crowd Patch Matching

- HOG3D is used to retrieve similar patches from the selected scenes.
- HOG3D demonstrates good performance in action recognition.

# Learning Motion Patterns

database



# Global Matching

similar scenes

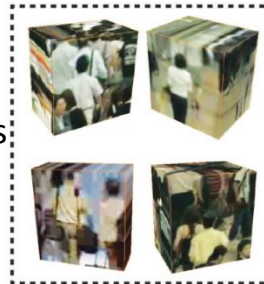


test video

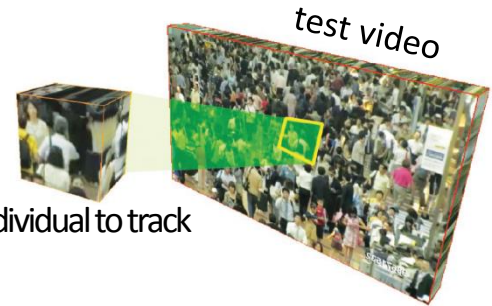


# Local Matching

similar cells

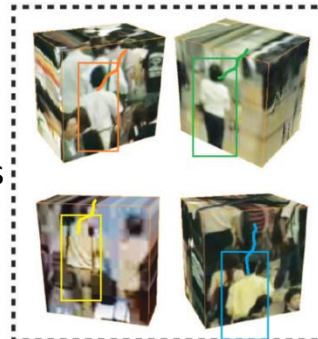


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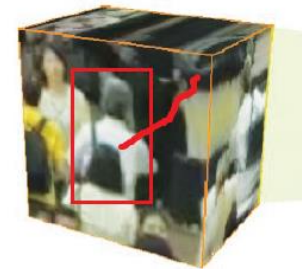


# Tracking using Motion Patterns

similar cells



motion patterns of similar cells



# Tracking using Motion Patterns

Prediction of system

Prediction by Kalman filter

Tracker position for person at location  $O$

Using:

- Optical Flow(low-level)
- CTM(mid-level)

Learnt from:

- Test video
- Database of videos

$$P_O = K + \lambda S$$

# Proposed Tracking Algorithm

- Combines:
  - The linear Kalman Filter on the test video
  - The two-step matching process
    - Gist
    - HOG3D
  - The CTM of the local parts of the selected video

# Experiments

- Data: Downloaded from video web sites using text queries like “crosswalk”, “political rally”, “festival”, “marathon”.
- 2 types of experiment:
  1. Tracking Typical Crowd Behavior
  2. Tracking Rare and Abrupt Events

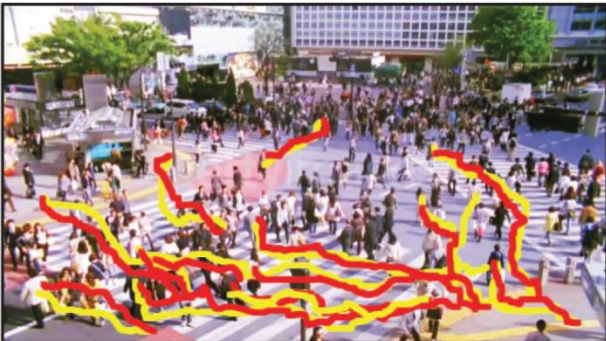


# Experiments



- Test videos are manually annotated to measure the error in pixels.
  - Blue = Typical crowd behavior
  - Red = Rare events

# Experiments



- Error = # of pixels between the positions of tracker and individual in each frame
  - Yellow = ground truth
  - Red = tracking results

# 1<sup>st</sup> Experiment

Tracking typical crowd behavior





## Batch-mode tracking

Training and testing video are from the same scene

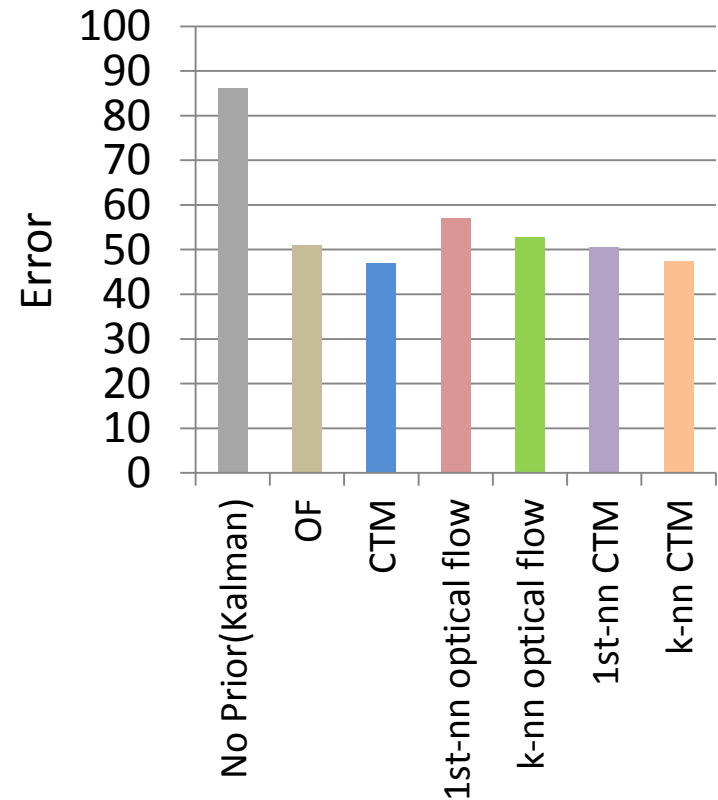


## Proposed data-driven tracking

Motion priors are transferred from the database of crowd videos

# Results for tracking typical crowd behavior

		Error
No prior		86.24
Learned on test video	OF	50.93
	CTM	46.93
Learned on database	1 <sup>st</sup> -nn OF	57.06
	3-nn OF	52.76
	1 <sup>st</sup> -nn CTM	50.59
	3-nn CTM	47.47



Error is measured in pixels.

# 2<sup>nd</sup> Experiment

Tracking rare events





No motion prior



Batch-mode tracking



# Results for tracking rare events

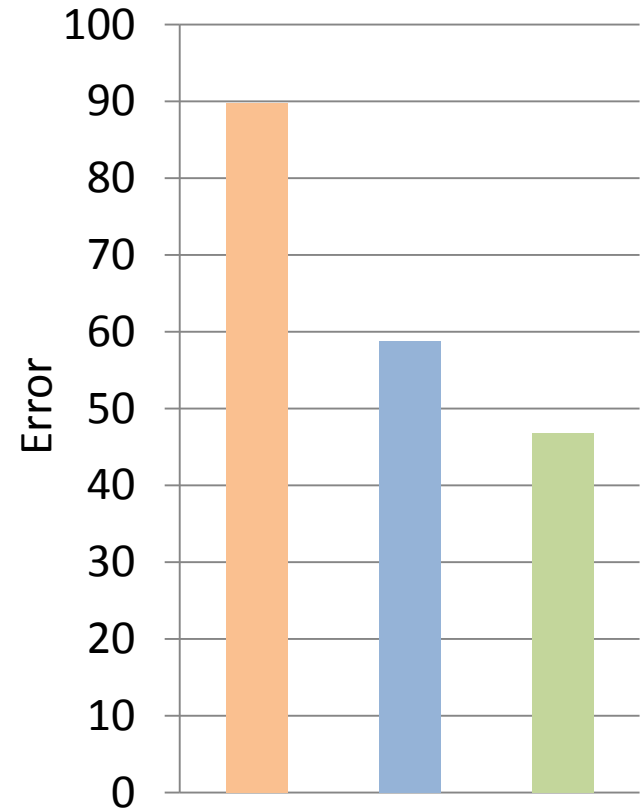


- Red  
Ground Truth
- Yellow  
Batch mode
- Green  
Data-driven

# Results for tracking rare events

		Error
No prior		89.8
Learned on test video	CTM	58.82
Learned on database	k-nn CTM	46.88

k=3



Error is measured in pixels.

# Resources

- Website:

<http://www.di.ens.fr/willow/research/datadriven/index.html>