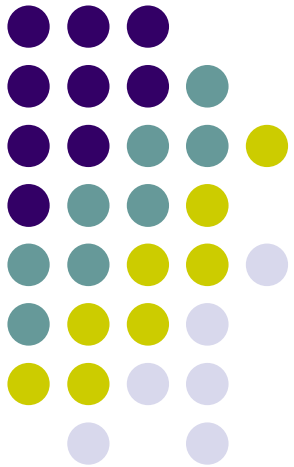
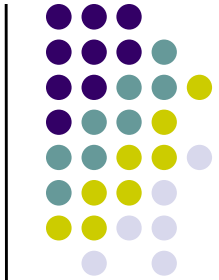
Unsupervised Learning of Human Actions Categories Using Spatial-Temporal Words



Juan Carlos Niebles, Hongcheng Wang and Li Fei-Fei, ***Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words***

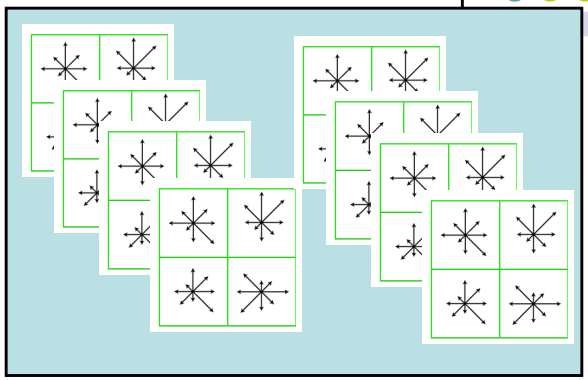
Outline



- Introduction
- Explaining the Model
- Results
- Discussion

Standard Approach
(adopted from text IR)

Feature extraction and representation (e.g., SIFT)



Quantization + histogram

"Bag of visual words"

Classification (e.g., SVMs)

- sheep? ✗
- bus? ✓
- cat? ✗
- bicycle? ✓
- car? ✓
- cow? ✗
- dog? ✗
- horse? ✗
- mbike? ✓
- person? ✓

SVM
SVM
SVM
SVM
SVM
SVM
SVM
SVM
SVM
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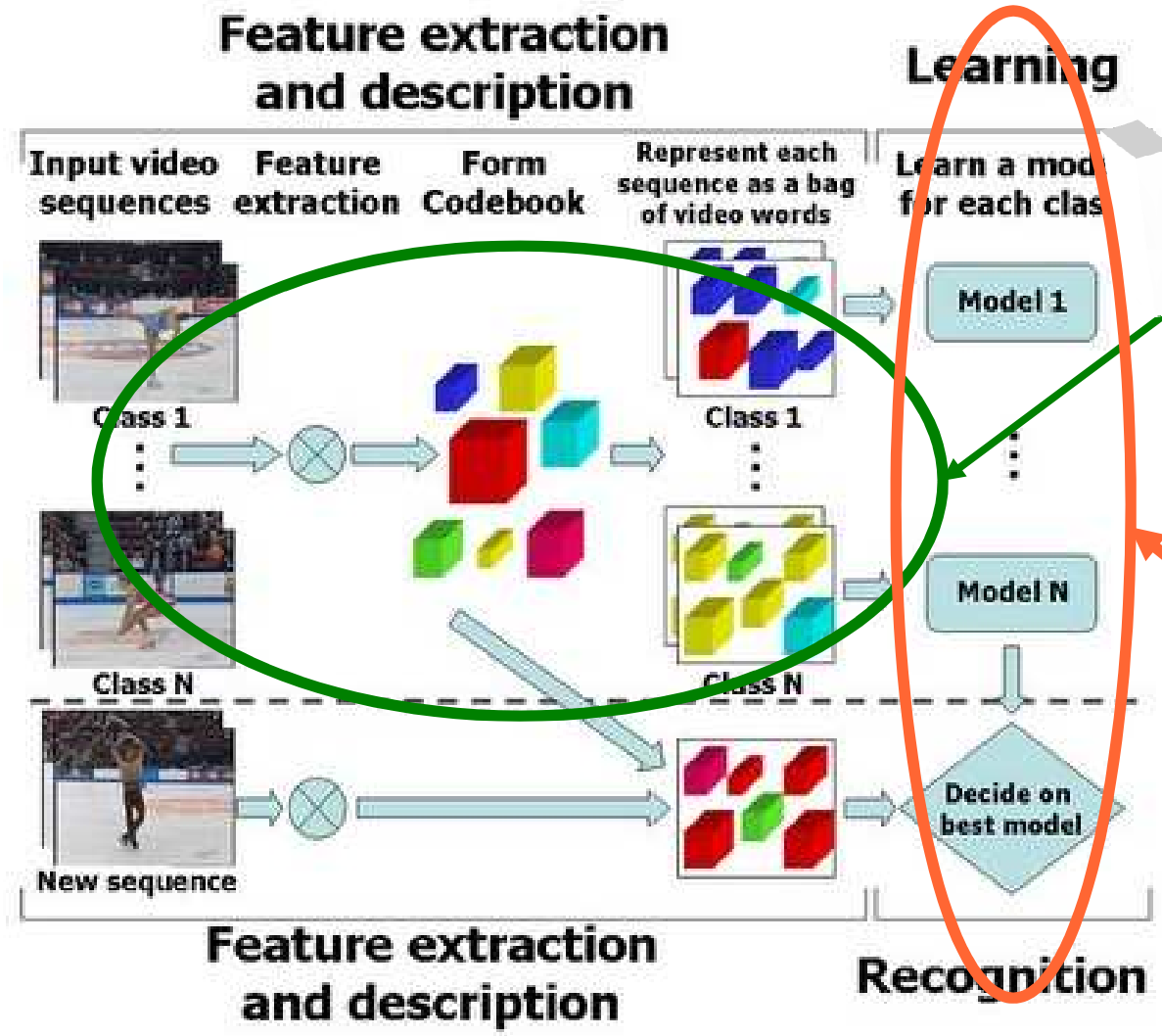
SVM

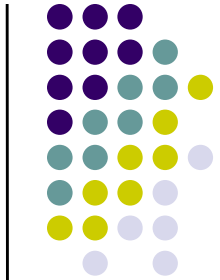
[Fei-Fei *et al.*, 2005];
[Sivic *et al.*, 2005];
and many others

In our case:



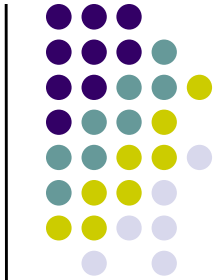
Probabilistic Graphical Models:
pLSA / LDA

Extending the Analogy



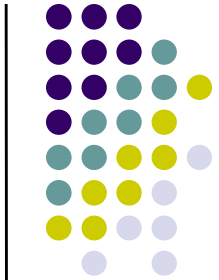
	Text	Images	Videos
Building Blocks	Words	2D visual words	3D spatio-temporal words
Input	Documents	Images	Image Sequences
Latent Topics	Politics, Sports	Cars, Elephants	Walking, Clapping

Goal



- Input: a collection of unlabeled videos
- Automatically learn classes of actions
- Apply learned model to categorize and localize actions in new video sequences

Outline



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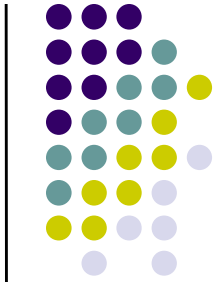
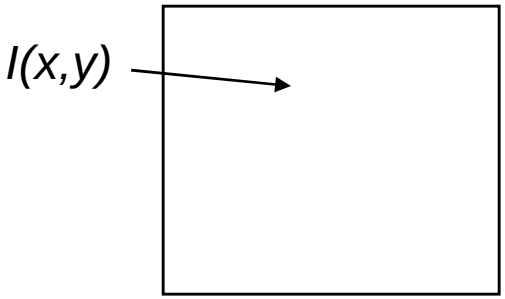
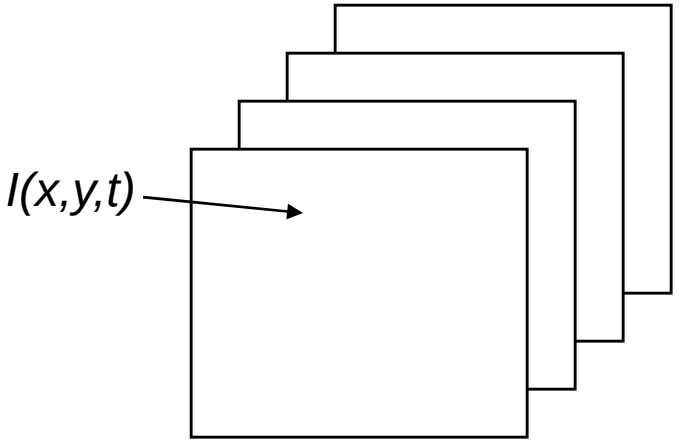
Digression – The Space Time Volume



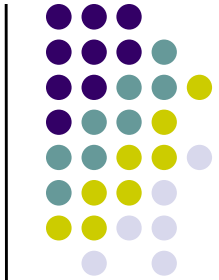
Static image:



Video:

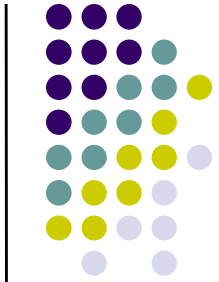


Codebook Generation – Space Time Interest Points



- What are we talking about?
- Space-Time Corners
  - Gradient can be taken over temporal dimension as well
  - Strong response where a spatial corner whose velocity is reversing direction
  - Well suited for recognizing human actions such as walking, clapping, hand waving, etc...
  - Too sparse for more articulated behaviours: facial expressions, rodent behaviour
  - Agnostic to periodic circular motion

Codebook Generation – Space Time Interest Points (2)



- Separable Linear Filter Method

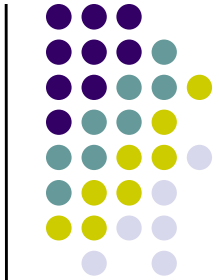
  (as suggested in [3] "*Behaviour Recognition via Sparse Spatio-Temporal Features*", Dollar et al., 2005)

  - Compute response function at different spatio-temporal scales:

$$R = (I * g * h_{ev})^2 + (I * g * h_{od})^2$$

  - ... and choose local maxima

Codebook Generation – Space Time Interest Points (3)



$$R = (I * g * h_{ev})^2 + (I * g * h_{od})^2$$

- Smooth each image with a gaussian kernel:

$$g(x, y; \sigma)$$

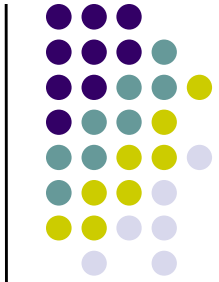
- Apply a quadrature pair of 1D Gabor filters along the temporal dimension:

$$h_{ev}(t; \tau, \omega) = -\cos(2\pi t\omega) e^{-t^2/-\tau^2}$$

$$h_{od}(t; \tau, \omega) = -\sin(2\pi t\omega) e^{-t^2/-\tau^2}$$

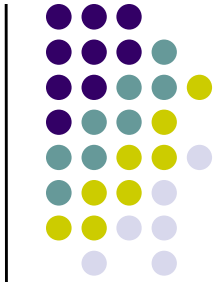
- In all cases, $\omega = 4/\tau$ giving *R* two controlled parameters, responding to the scale of the detector

Codebook Generation – Space Time Interest Points (4)



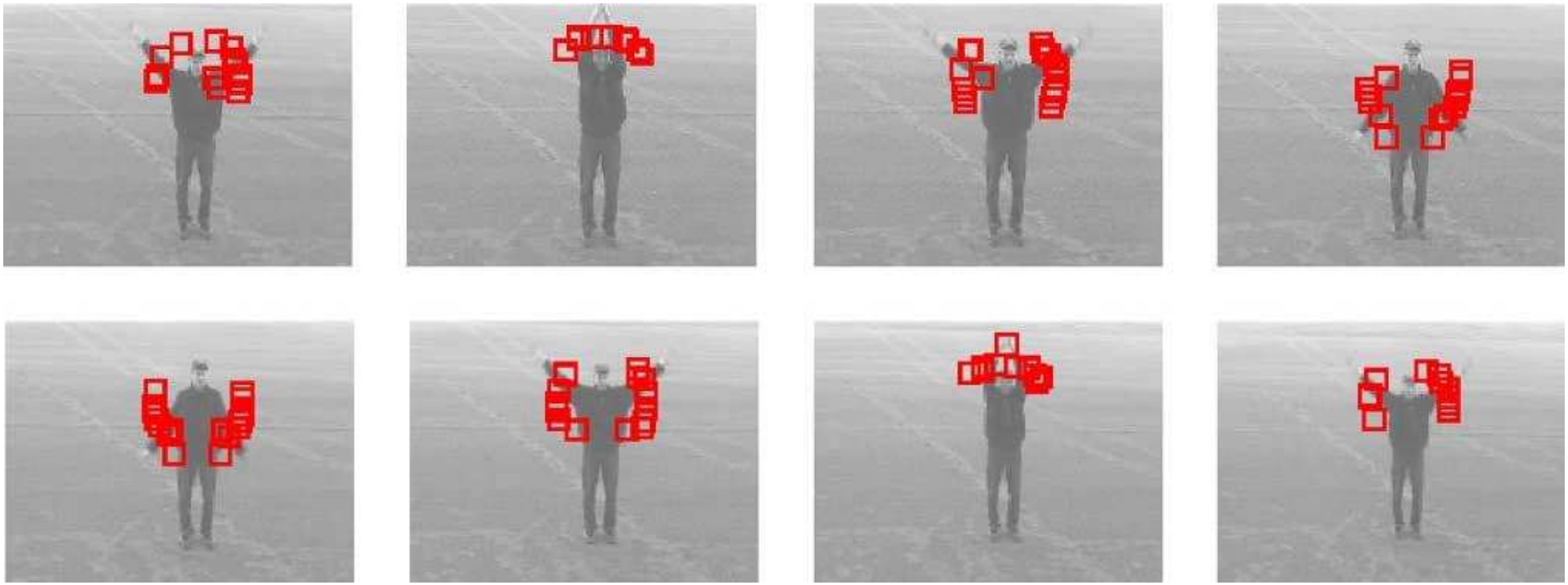
- Separable Linear Filter Interest Point Detector:
  - Assumes stationary camera or a process that can account for camera motion
  - Tuned to fire whenever intensity varitations contain periodic frequency components
  - Responds strongly to other types of motion as well, including spatio-temporal corners
  - In general, any area containing interesting spatial features that undergoes complex motion will trigger a response
  - Pure translational motion will go unnoticed

Codebook Generation – Space Time Interest Points (5)

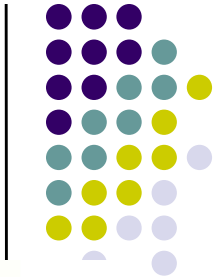


- Separable Linear Filter Interest Point Detector:
  - To handle multiple scales, a set of detectors must be used
  - In this work, only one scale is employed: " *... [we] rely on the codebook to encode the few changes in scale that are observed in the dataset.* "

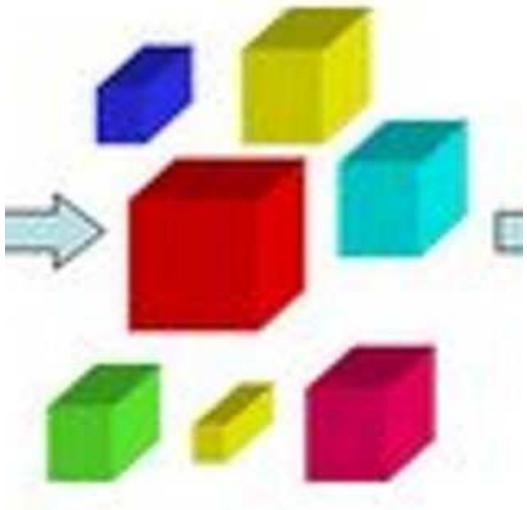
Codebook Generation – Space Time Interest Points



Codebook Generation – Space Time Descriptors



- The Cuboids:
  - Side length of six times the scale at which they were detected
- Descriptor:
  - Transform
  - Create feature vector
  - Reduce dimensionality (PCA)



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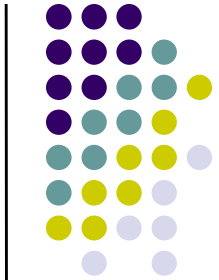
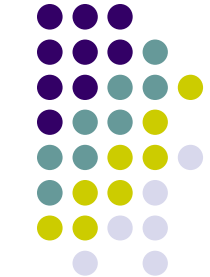
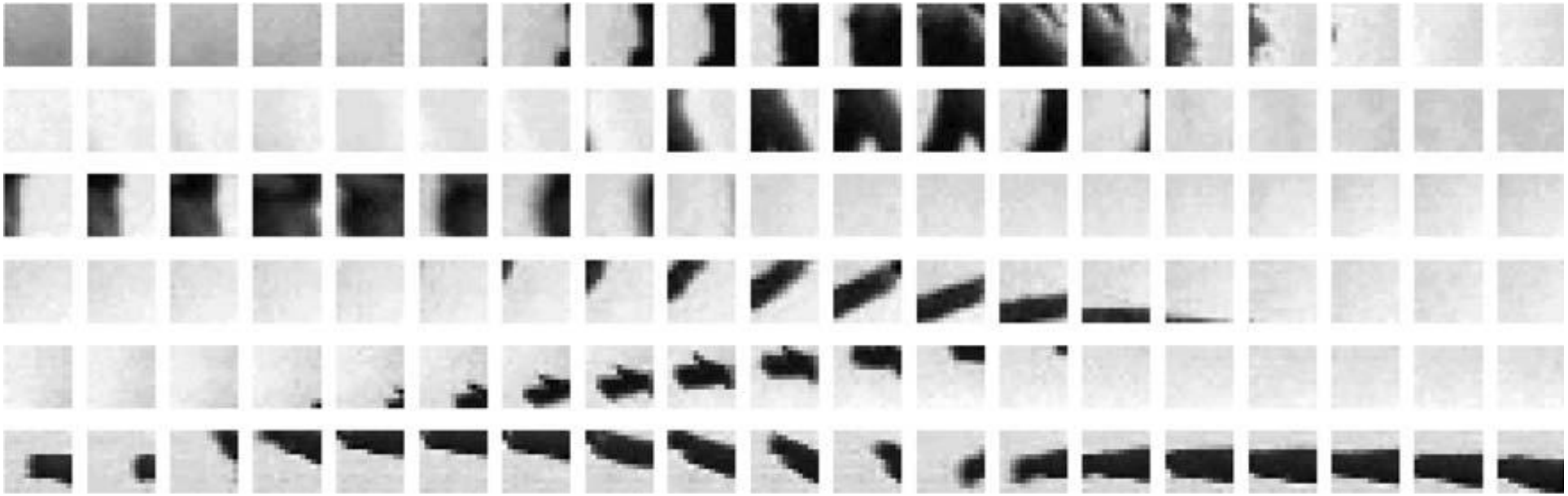


- The Descriptor:
  - Transform using one of three methods:
    - Normalized pixel values, Brightness Gradient, Windowed Optical Flow
  - Create feature vector, using one of three methods:
    - Vectorize, Histogram, Local Histograms (SIFT-style)
  - Nine combinations compared in [2]
    - Brightness gradient and local histograms performed best, and used in our paper.

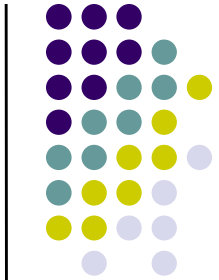
Codebook Generation – That's It



- Once we have a set of descriptors extracted from the training videos, we create a codebook of size *k* using the *k*-means algorithm.



Outline



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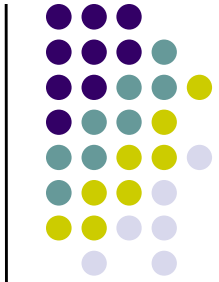
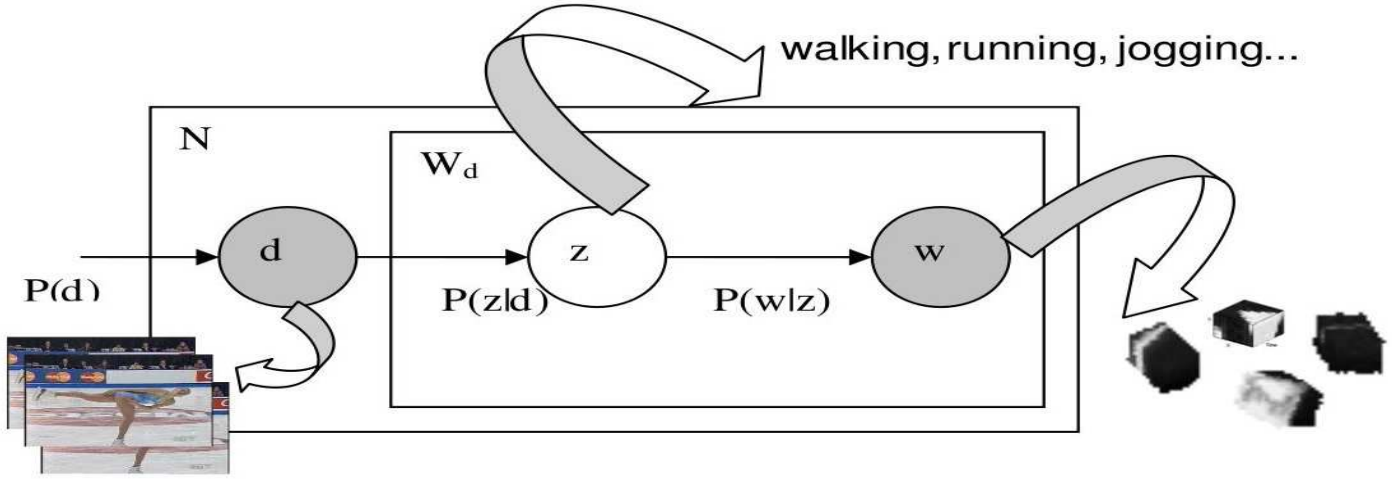
Learning the Action Models: pLSA



- *N (j = 1 , .. ,N)* video sequences containing video words from vocabulary of size *M(i = 1, .. M)*
- Summarized as co-occurence matrix ***N***, where $n(w_i, d_j)$ - number of occurences of w_i in video d_j
- Assuming latent topics, the joint distribution is:

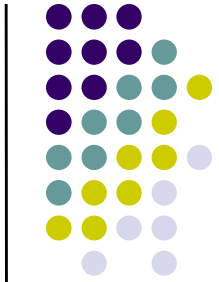
$$P[w_i, d_j, z_k]$$

Learning the Action Models: pLSA



- Basic probability: $P(d_j, w_i) = P(d_j) P(w_i | d_j)$
- Sum out latent topics: $P(w_i | d_j) = \sum_{k=1}^{K} P(z_k | d_j) P(w_i | z_k)$

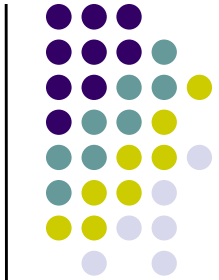
Learning the Action Models: pLSA



- Intuitively, each video is expressed as a convex mixture of *K* action category vectors
- Videos are characterized with a specific mixture of factors with weights $P(z_k|d_j)$
  - => amounts to matrix decomposition, with probability constraints
- MLE of parameters is obtained through EM maximization of:

$$\prod_{i=1}^{M}\prod_{j=1}^{N} P(w_i|d_j)^{n(w_i,d_j)}$$

Outline



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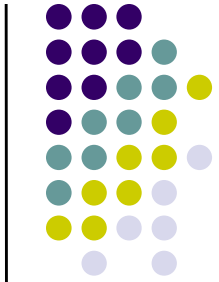
Categorization of New Videos



- Project new video on the simplex projected by the learnt *P(w|z)*, and:

$$\text{Find} \quad P(z_k \mid d_{test}) \text{ such that}$$

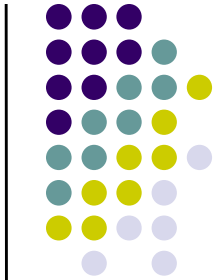
$$KL\left(P(w \mid d_{test}), P(w \mid d_{test})\right)$$

$$\text{where } P(w \mid d_{test}) = \sum_{k=1}^{K} P(z_k \mid d_{test}) P(w \mid z_k)$$

- Solved by EM as well

$$\text{Action Category} = \text{argmax } P(z_k \mid d_{test})$$

Localization in New Videos



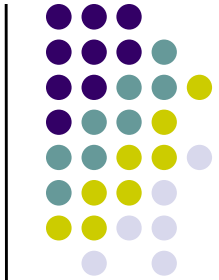
- Already seen this, in Sivic et al. (2005)
- pLSA models posteriors as:

$$P(z_k \mid w_i, d_j) = \frac{P(w_i \mid z_k) P(z_k \mid d_j)}{\sum_{l=1}^{K} P(w_i \mid z_l) P(z_l \mid d_j)}$$

- MAP:

$$\text{Word's Topic} = \operatorname{argmax} P(z_k \mid w_i, d_j)$$

Outline



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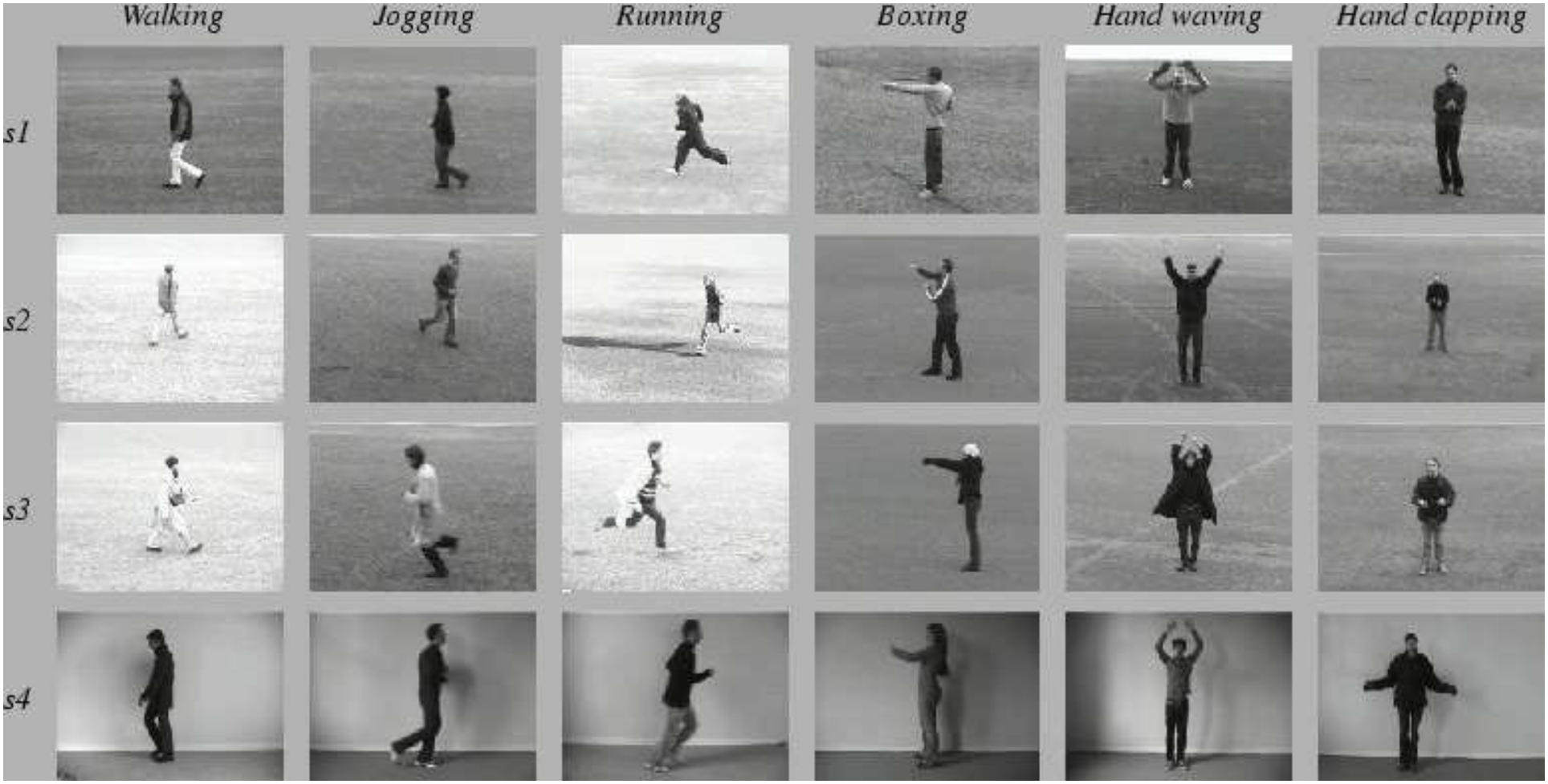
Experiments and Results: KTH database



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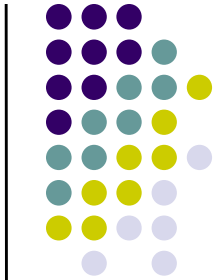

- Codebook built from two videos of each action, from three subjects
- Randomly select ~60,000 cuboids
- Leave-one-out Cross-validation: learn the model from 24 subjects, test on remaining subject

Experiments and Results: KTH database

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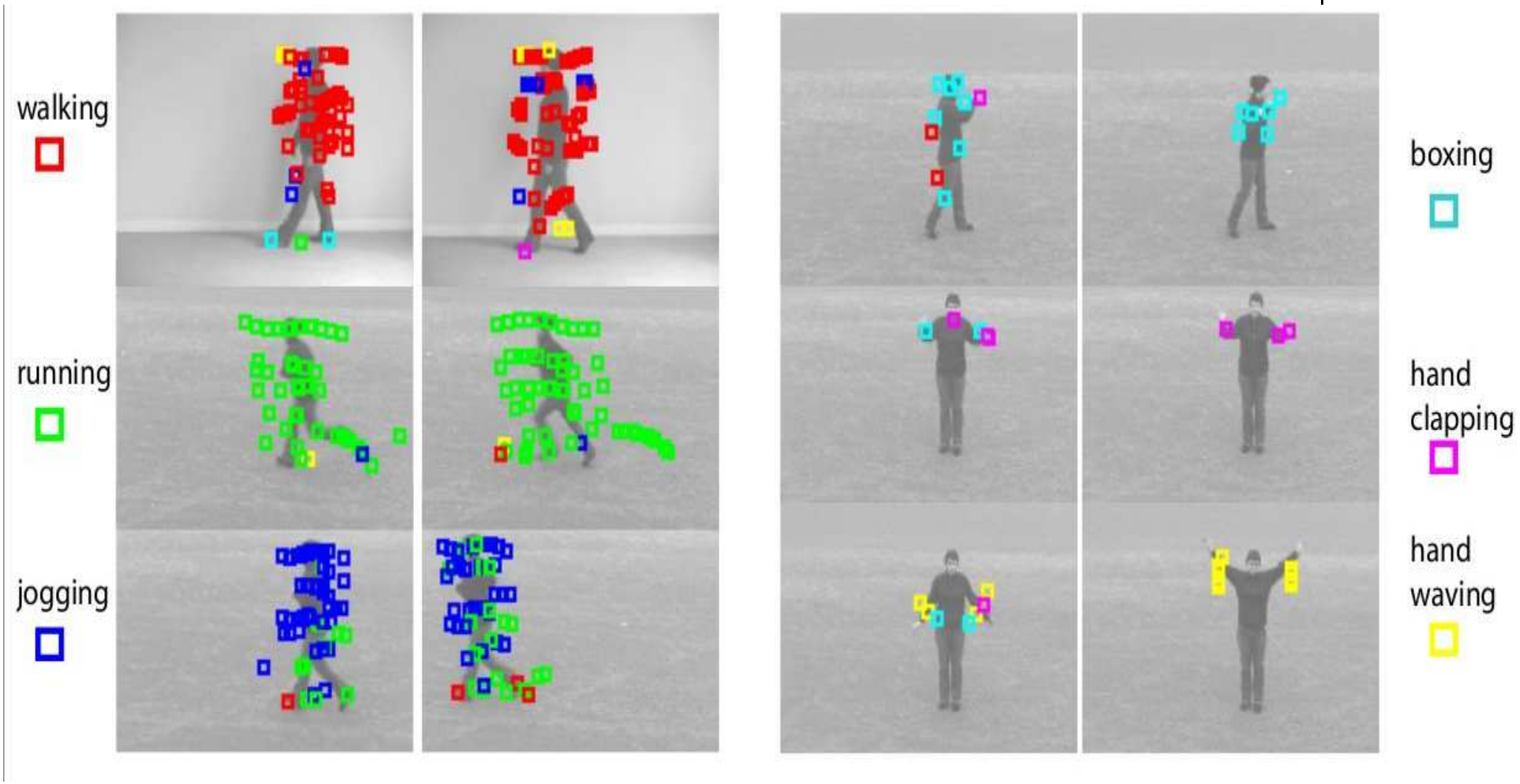

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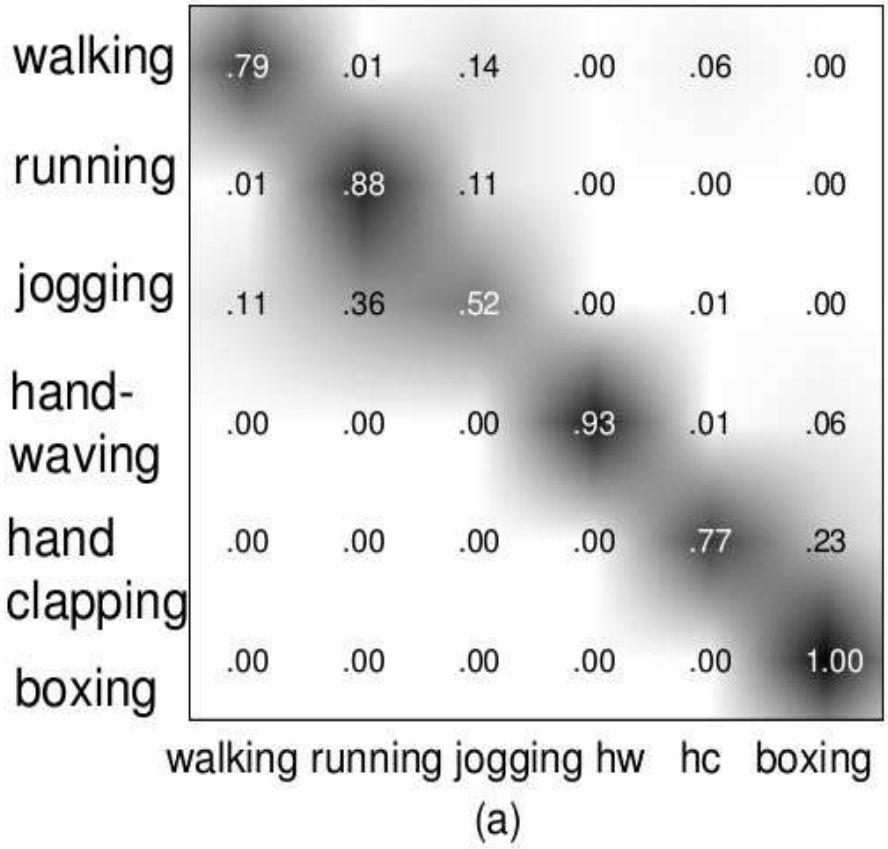
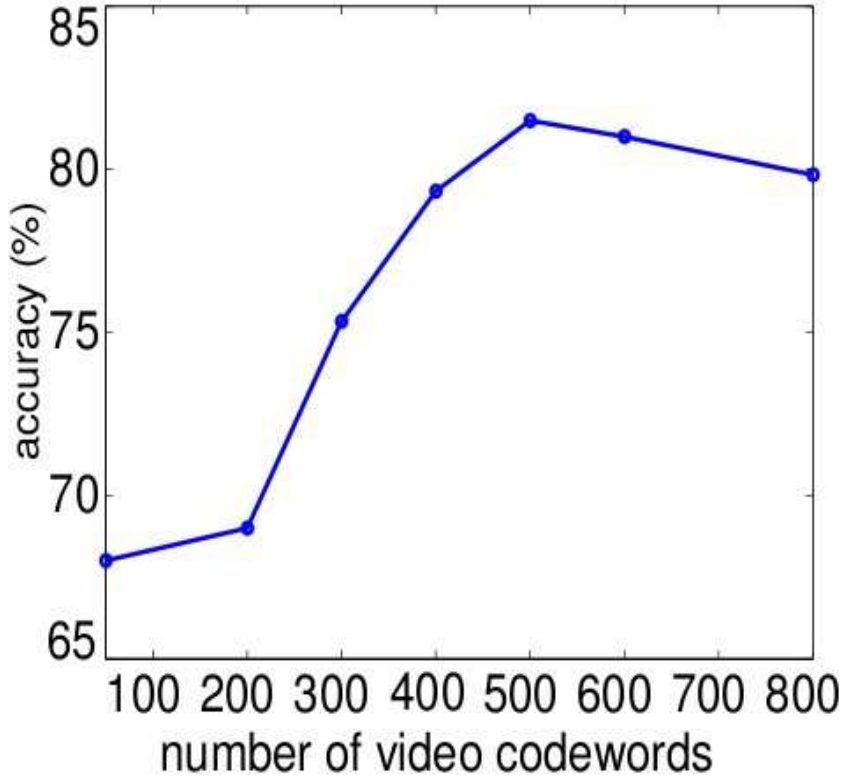
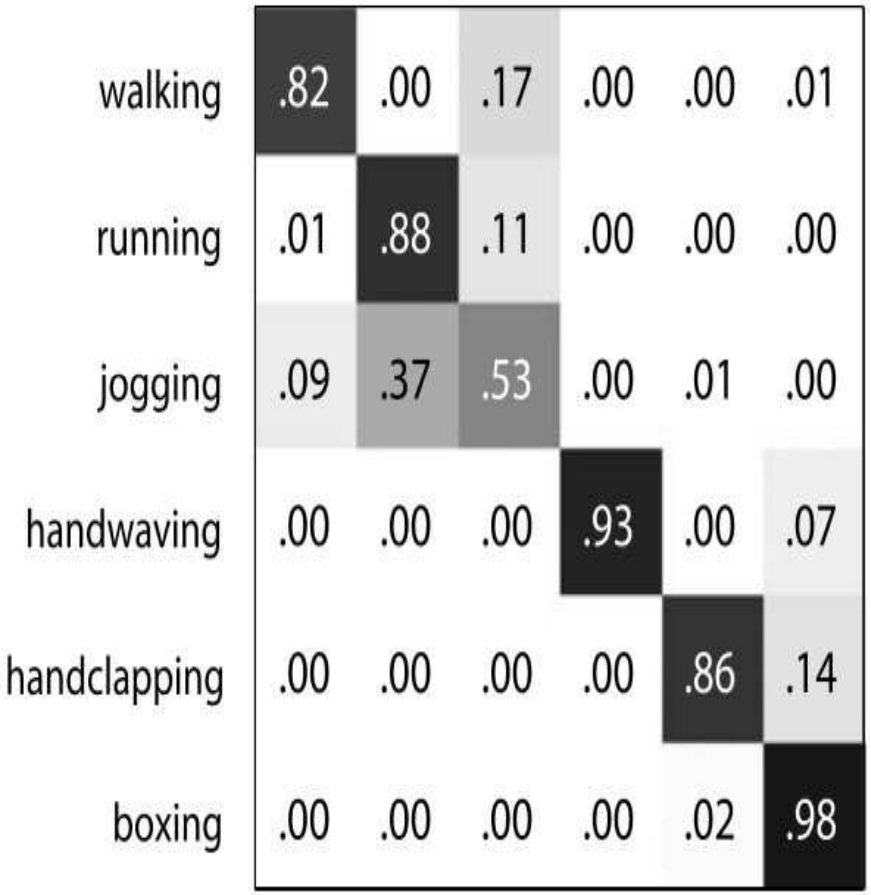


(a)



(b)

Experiments and Results: KTH database



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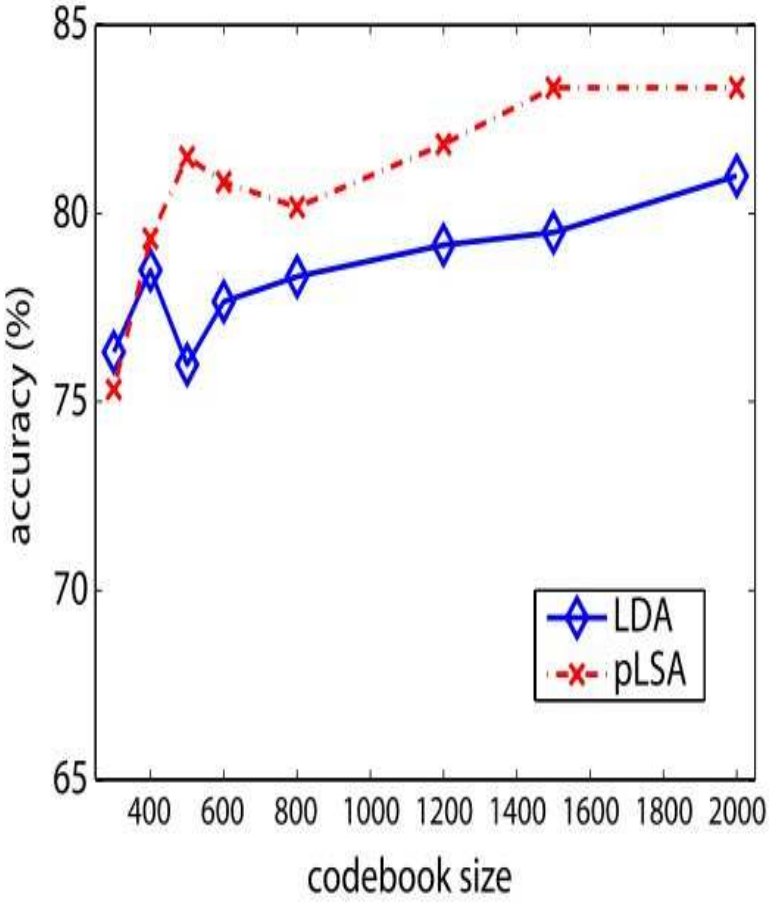
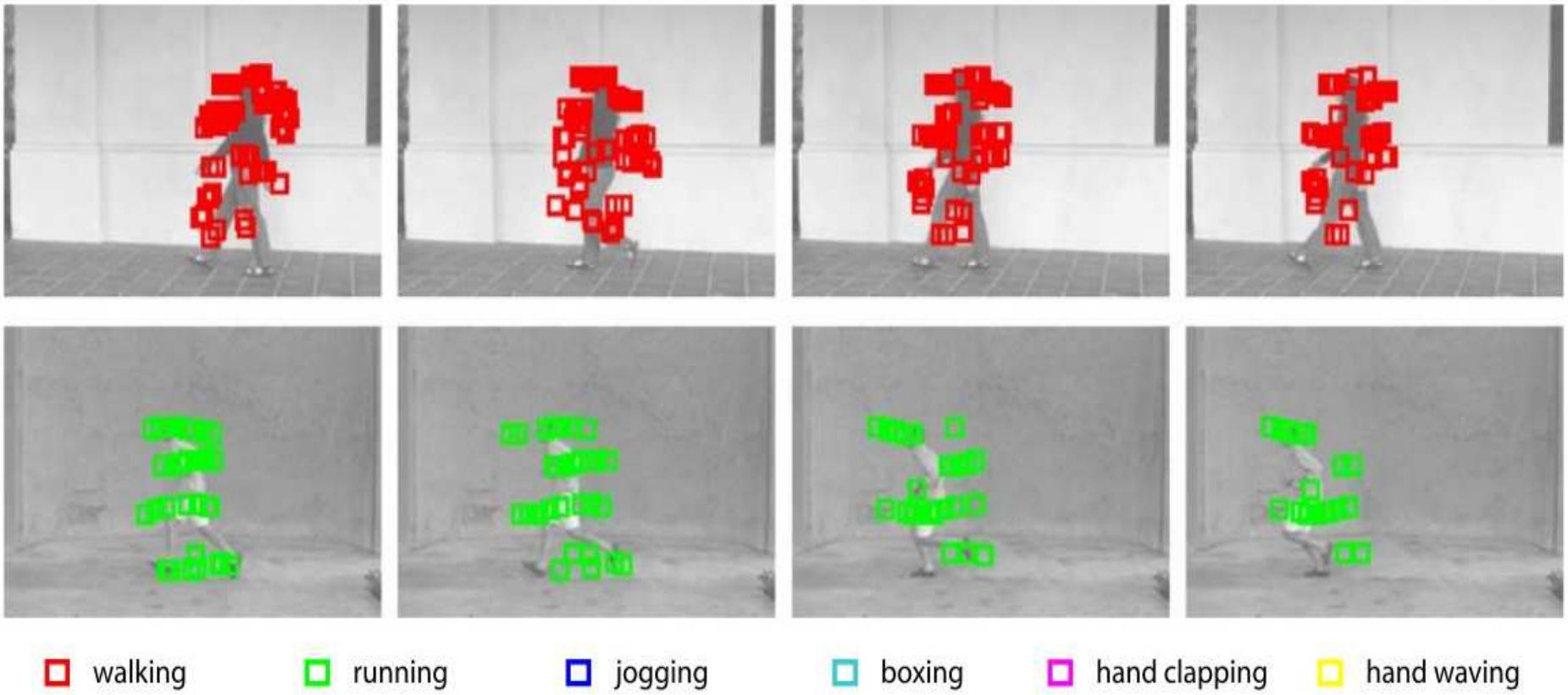


(b)

Experiments and Results: Caltech human motion database

- Learn the model using the KTH database, test it on Caltech's



Experiments and Results: Weizmann Institute Human Action Dataset

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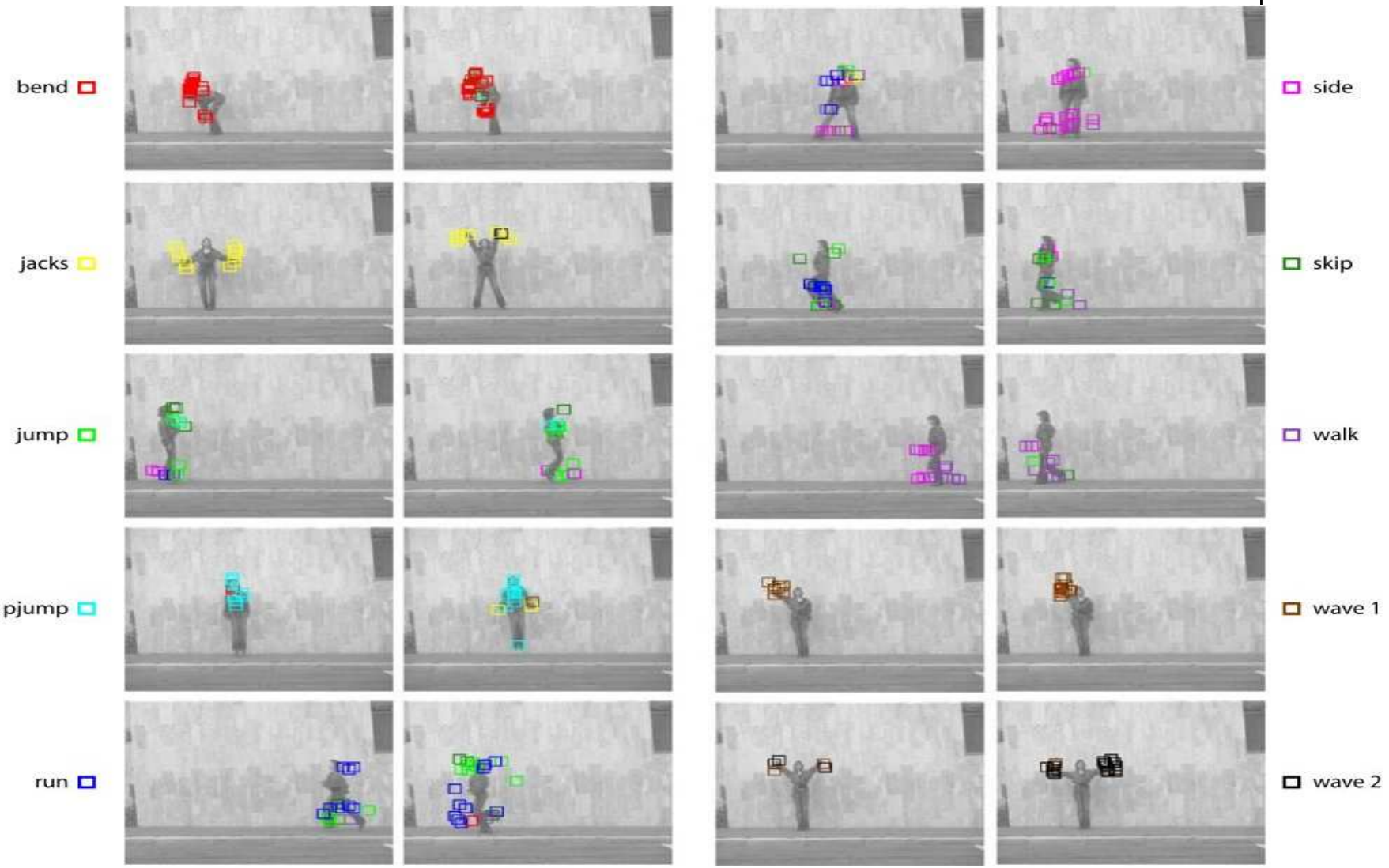
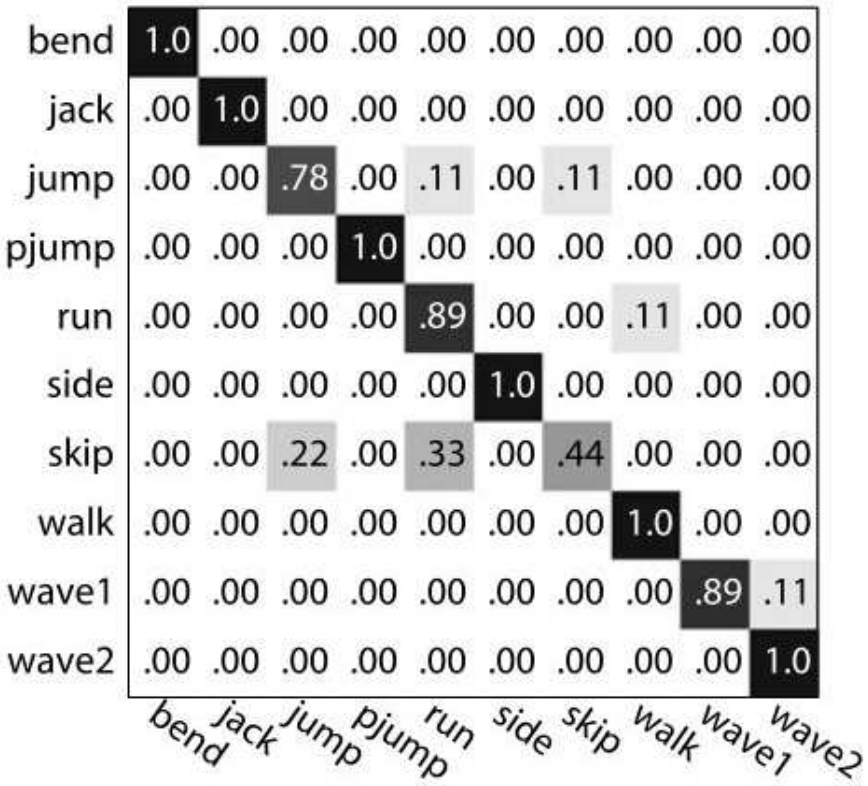
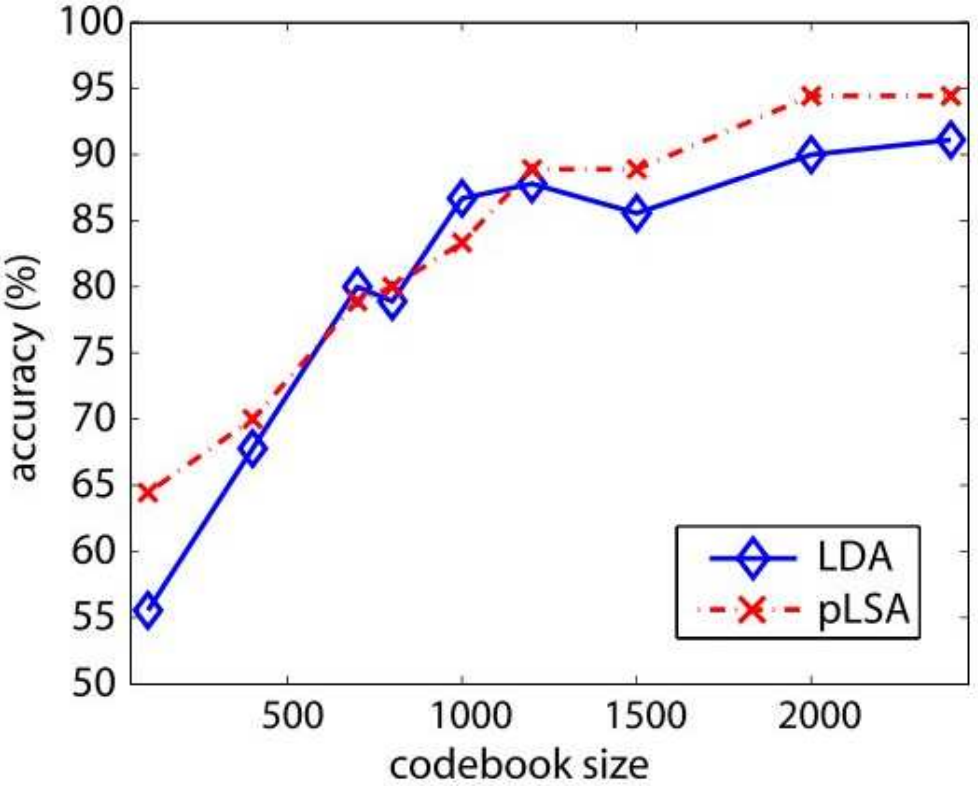


Experiments and Results: Weizmann Institute Human Action Dataset

- 10 action categories

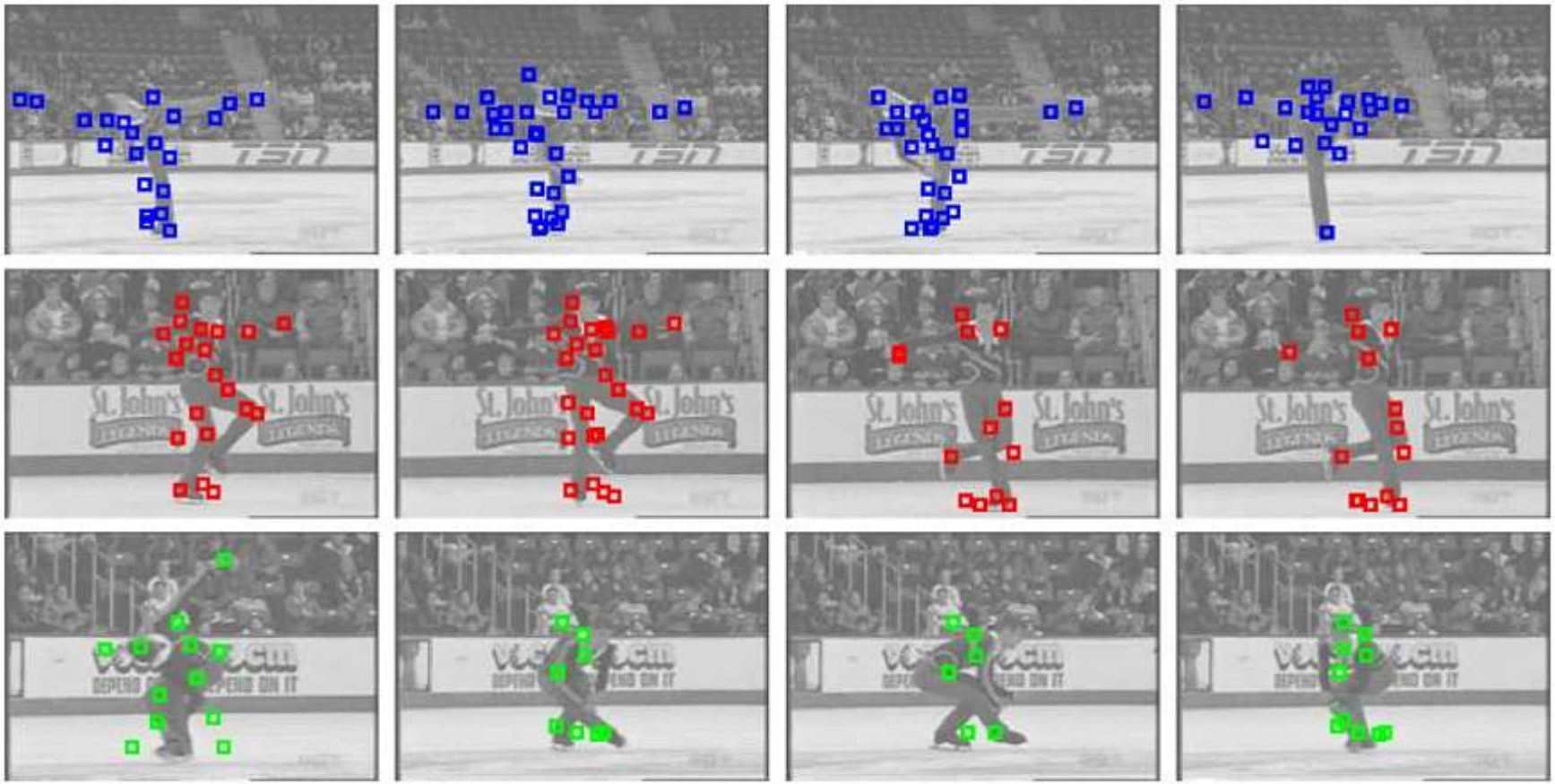


(a)

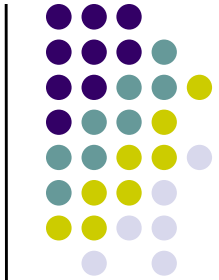


(b)

Experiments and Results: Figure Skating Database from Wang et al. 2006



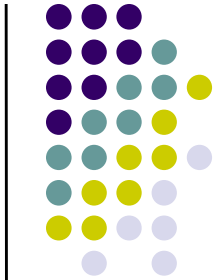
Experiments and Results : Recognition and Localization of Multiple Actions in Long Videos



- Two scenarios:
  - Long sequence, one subject, several actions: sliding temporal window to create subsequences, determine action for each subsequence
  - Multiple simultaneous actions:
    - Identify most prominent actions (must be less than K, number of all learned actions)
    - Use k-means to cluster relevant words spatially
    - Each located word votes for its action, majority wins
    - Actions must be spatially separated!

Experiments and Results : Recognition and Localization of Multiple Actions in Long Videos

Outline



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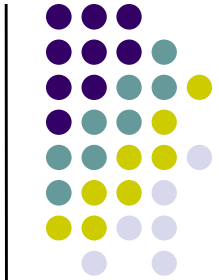
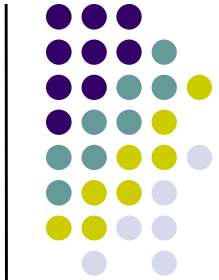
- Explaining the Model – ‘Bag of Video Words’
  - Codebook Generation
  - Learning the Action Models
  - Categorization and Localization
- Results
- Discussion

Recap



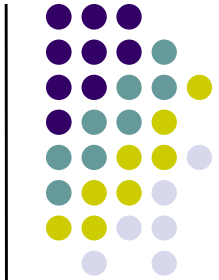
- A ‘bag of video words’ model
- Employs spatio-temporal detectors and descriptors
- pLSA / LDA models for unsupervised learning, recognition and localization

Future Directions



- Larger datasets and more complex videos
- Add discriminative model, to handle confusion between jogging and running
- Incorporate geometrical and temporal models knowledge

References



[1] Juan Carlos Niebles, Hongcheng Wang and Li Fei-Fei, **Unsupervised Learning of Human Action Categories Using Spatial-Temporal Words**, *Accepted for Oral Presentation At British Machine Vision Conference (BMVC)*, Edinburgh, 2006.

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[3] Piotr Dollár, Vincent Rabaud, Garrison Cottrell and Serge Belongie. Behavior Recognition via Sparse Spatio-Temporal Features. VS-PETS 2005, Beijing, China.