4th International Workshop on Shape Perception in Human and Computer Vision

Shape of Human Activities

Sinisa Todorovic joint work with William Brendel



Activity Recognition





Activities with:

- Rich temporal structure
- Shared subactivities

Goal: Recognition and Segmentation

long jump



high jump

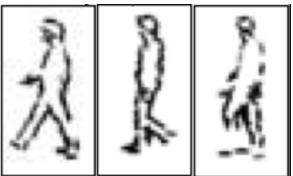


- Recognize activities
- Identify the start and end frames
- Explain recognition: space-time structure
- Segment people and objects

Prior Work – Video Representation

- Space-time points
 - Laptev & Schmid 08, Niebles & Fei-Fei 08,...
- Still human postures
 - Soatto 07, Ning & Huang 08,...
- Action Templates
 - Yao & Zhu 09,...
- Point tracks
 - Sukthankar & Hebert 10,...
- Motion segments
 - Gorelick & Irani 08, Pritch & Peleg 08,...







Prior Work – Video Representation

- Space-time points
 - Laptev & Schmid 08, Niebles & Fei-Fei 08,...
- Still human postures
 - Soatto 07, Ning & Huang 08,...
- Action Templates
 - Yao & Zhu 09,...
- Point tracks
 - Sukthankar & Hebert 10,...
- Motion segments
 - Gorelick & Irani 08, Pritch & Peleg 08,...

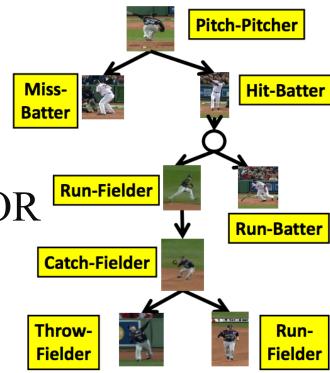
Too local

Do not capture long-term spatiotemporal structure

Prior Work – Activity Representation

- Classifiers, e.g., Bag-of-Words
 - Ke, Herbert ICCV'05
 - Hamid, Essa ICCV07
 - Laptev, Schmid CVPR'08
 - **–** ...

- Graphical models, e.g., AND-OR
 - Ivanov, Bobick PAMI00
 - Xiang, Gong IJCV'06
 - Ryoo, Aggarwal ICCV'09
 - Gupta, Davis CVPR09
 - Liu, Zhu CVPR09
 - **–** ...



Prior Work – Activity Representation

- Classifiers, e.g., Bag-of-Words
 - Ke, Herbert ICCV'05
 - Hamid, Essa ICCV07
 - Laptev, Schmid CVPR'08

- Require many examples
- Narrow goal: classification
- Graphical models, e.g., AND-OR
 - Ivanov, Bobick PAMI00
 - Xiang, Gong IJCV'06
 - Ryoo, Aggarwal ICCV'09
 - Gupta, Davis CVPR09
 - Liu, Zhu CVPR09

- Pre-fixed model structure
- Hard to learn
- Hard to infer

Hypothesis

- Point-based features provide poor cues
- More expressive models are needed

Hypothesis

- Point-based features provide poor cues
- More expressive models are needed



To bridge the semantic gap

- Use mid-level features: Activity shape
 - Less training examples
 - Allow simpler learning and inference

Spatiotemporal Segmentation

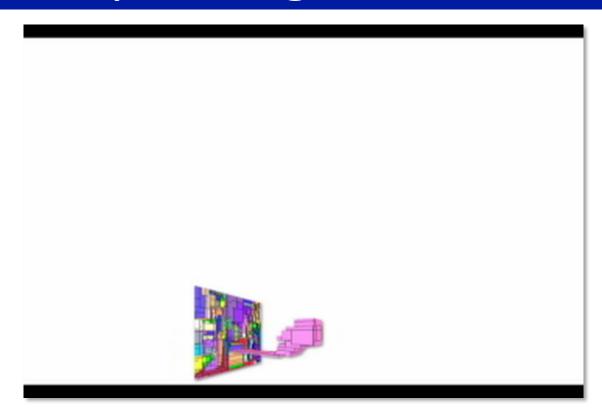


Irani & Peleg 94, Weiss 97, Shi & Malik 98, DeMenthon 02, Cohen 04, Greenspan et al. 02, Ahuja 05, Medioni 05, Todorovic 09, Essa 10,...

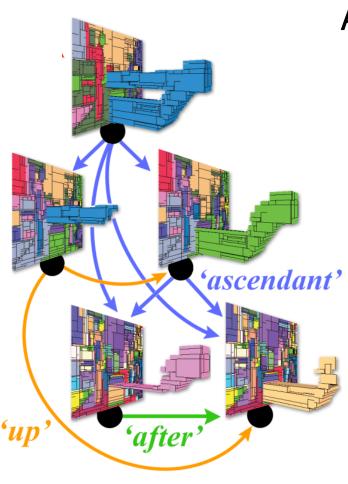
Activity Shape



- Objects occupy space-time tubes
- Because they
 - are cohesive in space
 - -have locally smooth trajectories in time

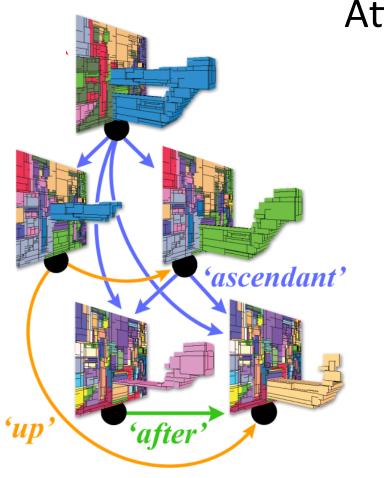


- As the right scale is unknown...
- The graph captures spatiotemporal structure



Attributes of nodes and edges:

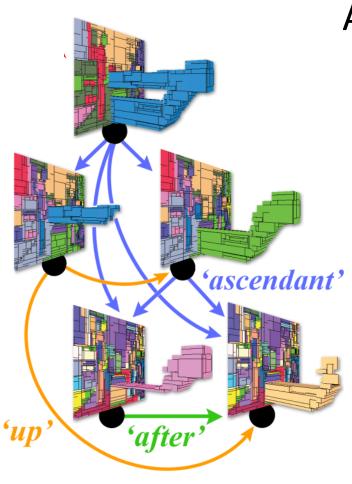
- -Intrinsic properties: F
 - Motion
 - Object shape



Attributes of nodes and edges:

- -Intrinsic properties: F
 - Motion
 - Object shape
- -Adjacency matrices: A
 - Allen temporal relations
 - Spatial relations
 - Compositional relations

$$G = (V, E) = \{(A_1, F_1), ..., (A_L, F_L)\}$$



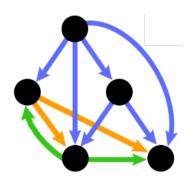
Attributes of nodes and edges:

- -Intrinsic properties: F
 - Motion
 - Object shape
- -Adjacency matrices: A
 - Allen temporal relations
 - Spatial relations
 - Compositional relations

Our Approach

training videos activity model In a new video: Recognize Segment • Explain ;B_Bend;B_Throw Walk

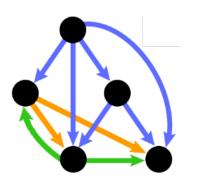
Activity-Shape Model



Video = Graph instance

sampled from the model

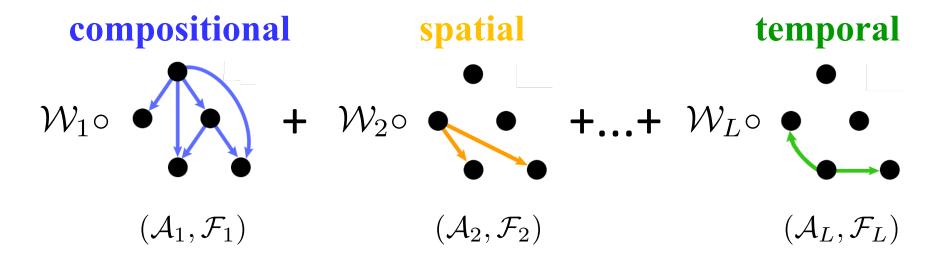
Activity-Shape Model



Video = Graph instance

sampled from the model

Model = Probabilistic Graph Mixture



Generative Process

video:
$$G = \{(A_1, F_1), ..., (A_L, F_L)\}$$

adjacency matrix

node descriptor

$$A_i = P\mathcal{A}_i P^{\mathrm{T}} + \eta_i \qquad F_i = P\mathcal{F}_i + \xi_i$$

model parameters

$$i = 1, 2, ..., L$$

Activity-Shape Model

adjacency matrix

node descriptor

$$A_i = P\mathcal{A}_i P^{\mathrm{T}} + \eta_i \qquad F_i = P\mathcal{F}_i + \xi_i$$

permutation matrix

noise

$$i = 1, 2, ..., L$$

Learning

GIVEN K training videos $\{G_k : k = 1, ..., K\}$

$$\{G_k : k = 1, ..., K\}$$

$$A_{ki} = P_k \mathcal{A}_i P_k^{\mathrm{T}} + \eta_i \qquad F_{ki} = P_k \mathcal{F}_i + \xi_i$$

permutation matrices

$$i = 1, 2, ..., L$$

Learning

GIVEN K training videos

ESTIMATE

adjacency matrix

node descriptor

$$A_{ki} = P_k A_i P_k^{\mathrm{T}} + \eta_i \qquad F_{ki} = P_k \mathcal{F}_i + \xi_i$$

permutation matrices

$$i = 1, 2, ..., L$$

Learning

GIVEN K training videos

ESTIMATE

adjacency matrix

node descriptor

$$A_{ki} = P_k \mathcal{A}_i P_k^{\mathrm{T}} + \eta_i \qquad F_{ki} = P_k \mathcal{F}_i + \xi_i$$

permutation matrices

noise

$$i = 1, 2, ..., L$$

Learning and Inference

constraint on permutation matrices

$$\forall k, \ P_k P_k^{\rm T} = I, \ P_k \in \{0, 1\}^{m \times n}$$



Learning

= Quadratic Integer Program
Inference

Learning Results



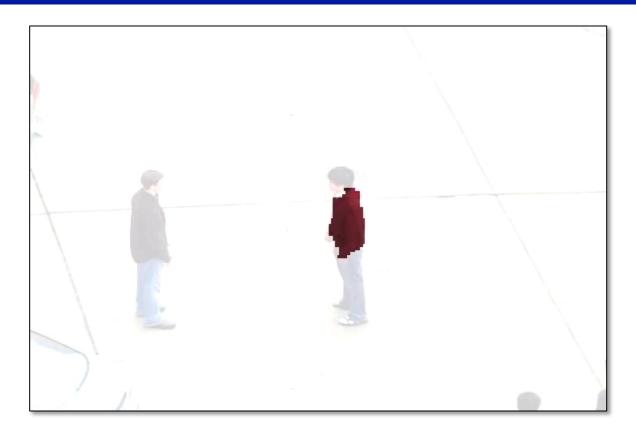
correctly learned activity-characteristic tubes

Learning Results



correctly learned activity-characteristic tubes

Recognition and Segmentation



activity "handshaking" detected and segmented characteristic tube

Recognition and Segmentation



activity "kicking" detected and segmented characteristic tube

Classification on UTexas Dataset



| | | hand shaking | hugging | kicking | pointing | punching | pushing |
|---|-------------------|---------------------|--------------------|--------------------|------------------|------------------|------------------|
| 1 |)ur 17] | 81.7% 75% | 89.6% 87.5% | 68.6% 62.5% | 66.4% 50% | 84.5% 75% | 82.7% 75% |
| L | 1/] | 13% | 07.570 | 02.5% | 30% | 1370 | 1370 |

human interaction activities

Conclusion

- Shape-based video representation enables:
 - Simpler activity models, learning, inference...
 - Richer interpretation: recognition + segmentation

- Difficulties
 - Correspondence between model and data features