Coupling Video Segmentation and Action Recognition

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Outline

• Action Recognition: an essential task
• Problem Definition
• Motion segmentation using trajectories
• Our proposed methods
• Datasets and results
• Conclusion
Action Recognition – an essential task

- Motivation -> Huge amount of videos

- Applications:
  - Content-based search
  - Summarization
  - Intelligent fast forwarding
  - Abnormality detection in surveillance videos
  - Scientific researches e.g. relation between number of smoking scenes in the movies and human addiction
  - A key for human and robot interaction

Upload rate in YouTube: 1 hour of video per second
Our Question

Whether video segmentation can be exploited for improved action recognition?

Effect of ideal segmentation on classification accuracy

83.5% accuracy improvement

(YouTube dataset)

88.5%
Trajectories

- State-of-the-art video segmentation algorithms use trajectories as their building blocks.

- Densely sampled patches that are tracked over several frames, following the underlying motion of the object or scene.
Trajectories
Motion Segmentation

- Motion segmentation reduces to cluster coherent, spatially close trajectories.
- Building a fully connected graph
  - Each node corresponds to a trajectory.
  - Weight of the edge between node i and node j depends on spatial distance and shape of i and j trajectories.
- normalized-cut /spectral clustering on the graph
  - Assign labels to each node corresponding to each object
- Motion segmentation is a fully bottom-up foreground/background segmentation
An example of Bottom-up segmentation
Recognition Pipeline

Segmentation Algorithm

first video

Segmentation Algorithm

nth video

BoW description

Hf

Hb

Background

Foreground

Learning
Our proposed methods

• We propose several methods that integrate segmentation and recognition:

• Segmentation
  o Split action-related foreground and action-unrelated background in a top-down fashion.

• Co-segmentation
  o Multiple videos of the same action should have consistent segmentation; so we segment a video leveraging segmentation of other videos.

• Iterative learning
  o An iterative learning scheme that alternates between segmentation and recognition.

• Kernels
  o Mapping the original feature space with a non-linear kernel.
Segmentation – Top Down

- initial over-segmentation of the video in \textit{trajectory-groups}
- Positive (action-related) trajectory-groups: those that have more than 25% overlap with ground-truth bounding box
- Learning the similarities that \textit{trajectory-groups} share across the DATASET, \textit{independent} of the action label. We call it \textit{actionness operator}. 
Examples of top-down segmentation
Segmentation – Top Down

Segmentation Algorithm
\[ \Omega(x_i, h_i, \Theta) \]

first video

nth video

foreground
background

BoW description
BoW description

actionness

Hf
Hb

model

Learning activity models
Segmentation – Top Down

\[ \Omega(h, x = 1, \Theta) \propto e^{-\Theta^T h} \]

- Cost function
- Actionness model
- Binary labeling: \( x_i \in \{0,1\}^K \)
- Actionness score

Cost is inversely proportional to score of actionness
Co-segmentation
Co-segmentation

\[ \Omega(h_t, x_t) - \alpha_1 S(h_t, h_y, x_t, x_y) \]

Algorithm

*first video*

*ith class*

*nth video*

*ith class*

actionness

foreground

BoW description

Hf

background

BoW description

Hb

foreground

BoW description

Hf

background

BoW description

Hb

Learning

model

KU LEUVEN
Co-segmentation

\[ E(\{x^j\}_{j \in c}; \Theta) = \sum_{h^i \in G_v} \Omega(h^i, x^i, \Theta) - \lambda \sum_{(h^i, h^i') \in G_e} \text{Sim}(h^i, h^i') x^i x^{i'} \]

- **Unary term: actionness**

- **Co-segmentation cost function**

- **Reward for similar foreground groups**

- Sub-modular \(\Rightarrow\) exact solution using graph-cut
Iterative Learning

- The two previous methods, solve the segmentation and use its output during action classification but in this approach, we alternate between segmentation and recognition.
- Latent-SVM based approach (discriminate classes as much as possible ➔ the goal is not better segmentation but better classification). Latent variables are 1-0 labels of each trajectory-group.
- 2 major restrictions of L-SVM
  - sensitive to initialization
  - works with linear models (will be discussed in next slides)
- This method can be also used in conjunction with the segmentation methods introduced in previous sections
Iterative Learning

Co-segmentation Algorithm

\[ \Omega(h, x_i) - \alpha_2 \sum(h_i, y_i, x_i) + \alpha_2 \psi(h, x_i) \]

first video

nth video

foreground

background

BoW description

Hf

Hb

model

Algorithm
Iterative Learning

\[ E(\{x^j\}_{j \in c}; \Theta) = \sum_{h^i \in G_v} \Omega(h^i, x^i, \Theta^{actionness}) - \lambda \sum_{(h^i, h^{i'}) \in G_e} Sim(h^i, h^{i'}) x^i x^{i'} + \lambda_2 \sum_{h^i \in G_v} \phi(h^i, x^i, \Theta^{glob}) \]

discriminative model

cost of discriminative labeling
Kernels

- So far, we have used linear models for classification. While the iterative learning is a powerful tool, it is limited to linear model.

- Alternative is to map the features into a kernel.

- Excluding the iterative learning, all the other proposed methods can be used together with a kernel:

\[
K(H_i, H_j) = H_i^T H_j \quad \text{linear}
\]

\[
K(H_i, H_j) = \phi(H_i)^T \phi(H_j) = e^{-d \chi^2(H_i, H_j)} \quad \text{non-linear}
\]
Datasets

- **UCF-Sports**
  - 10 categories
  - 150 videos
  - extracted from sport broadcasts.

- **YouTube**
  - 11 categories
  - 1600 videos (quality 240x320)
  - Handheld camera -> camera motion

Challenges: large intra-class variability in view point, speed of action and cluttered background
## Results - YouTube

<table>
<thead>
<tr>
<th>Method</th>
<th>Recognition acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>FG/BG - Using ground-truth bounding box (upper bound)</td>
<td>88.5%</td>
</tr>
<tr>
<td>Baseline BoW (No seg.)</td>
<td>83.5%</td>
</tr>
<tr>
<td>Bottom Up</td>
<td>83.6%</td>
</tr>
<tr>
<td>Top Down (Actionness)</td>
<td>85.0%</td>
</tr>
<tr>
<td>Top Down + Co-segmentation</td>
<td>85.1%</td>
</tr>
</tbody>
</table>
# Results (Iterative) - YouTube

<table>
<thead>
<tr>
<th>Initial Segmentation</th>
<th>Method</th>
<th>Recognition accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Random</strong></td>
<td>Iteration</td>
<td>85.0%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Top Down</td>
<td>85.2%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Co-seg</td>
<td><strong>85.7%</strong></td>
</tr>
<tr>
<td></td>
<td>Iteration + Top Down + Co-seg</td>
<td>85.7%</td>
</tr>
<tr>
<td><strong>Top Down</strong></td>
<td>Iteration</td>
<td>85.2%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Top Down</td>
<td>86.1%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Co-seg</td>
<td>86.2%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Top Down + Co-seg</td>
<td><strong>86.7%</strong></td>
</tr>
<tr>
<td><strong>Ground-Truth</strong></td>
<td>Iteration</td>
<td>85.5%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Top Down</td>
<td>86.4%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Co-seg</td>
<td>86.2%</td>
</tr>
<tr>
<td></td>
<td>Iteration + Top Down + Co-seg</td>
<td><strong>86.7%</strong></td>
</tr>
</tbody>
</table>
## Results (kernel) - YouTube

<table>
<thead>
<tr>
<th>Method</th>
<th>Recognition acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top Down segmentation + kernel-SVM</td>
<td>86.2%</td>
</tr>
<tr>
<td>Top Down + Co-seg + kernel-SVM</td>
<td>86.8%</td>
</tr>
</tbody>
</table>
Results (State-of-the-art) - YouTube

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brendelet al. [1]</td>
<td>77.8%</td>
</tr>
<tr>
<td>Wang et al. [8]</td>
<td>84.2%</td>
</tr>
<tr>
<td>Sapienza et al. [4]</td>
<td>80.0%</td>
</tr>
<tr>
<td>Gaidon et al. [2]</td>
<td><strong>87.9%</strong></td>
</tr>
<tr>
<td>Iterative (1)</td>
<td>86.7%</td>
</tr>
<tr>
<td>Kernel (2)</td>
<td>86.8%</td>
</tr>
<tr>
<td>(1)+(2)</td>
<td><strong>87.4%</strong></td>
</tr>
</tbody>
</table>
**Results (State-of-the-art) – UCFsports**

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lan et al. [5]</td>
<td>73.1%</td>
</tr>
<tr>
<td>Raptis et al. [7]</td>
<td>79.4%</td>
</tr>
<tr>
<td>Shapovalova et al. [3]</td>
<td>75.3%</td>
</tr>
<tr>
<td>Todorovic et al. [6]</td>
<td>86.8%</td>
</tr>
<tr>
<td>Iterative (1)</td>
<td>81.5%</td>
</tr>
<tr>
<td>Kernel (2)</td>
<td>86.1%</td>
</tr>
<tr>
<td>(1)+(2)</td>
<td>86.1%</td>
</tr>
</tbody>
</table>
Qualitative results for segmentation
Conclusion

• A good video segmentation is fundamental to obtain accurate action recognition

• We have proposed and evaluate several ways to integrate segmentation and recognition

• Coupling segmentation and recognition in an iterative learning can always improve the recognition accuracy.

• An alternative way to obtain similar results is to map the features into a non-linear kernel.
References


Thanks For Your Attention! Questions?
Challenges

• **Intra-class variability**
  - In common with objects: varying viewpoints, backgrounds and partial occlusions.
  - Specific for actions: performed by different people, at different speeds and in different ways.

• **Uncertainty in actual extent of action**
  - temporal delineation -> When does the action start/end?
  - spatial delineation -> Does the action include the whole actor or only a part of that? Should objects that are involved be included as well?

• **Number of training data**
  - Cumbersome process of collecting data (accuracy of keyword-based search for 235 terms: 10%)
  - Size of dataset quickly grows
Segmentation – Top Down

\[ H_f = \sum_{k=1}^{K} h_k x_k \quad H_b = \sum_{k=1}^{K} h_k (1 - x_k) \]
Co-segmentation

• Take into account similar motion and appearance characteristics that trajectory-group share with trajectory-groups among other videos of same label.

• Building a graph from all trajectory-groups of all training videos of class c: weight of each node is actionness score of each trajectory-group and weight of edges are similarity between inter-video-connected trajectory-groups.
Setting up experiments and parameters

- **UCF Sports**
  - The dataset is split into 103 training and 47 test samples. This separation reduces the chance of videos in the test set having strong scene correlations with videos in the training set.
  - Performance measuring: mean per-class accuracy

- **YouTube**
  - Dividing the dataset to 25 groups: leave-one-group-out cross validation
  - Performance measuring: average accuracy over all classes

- **Parameters**
  - Trajectories parameters same as their authors
  - Trajectory description: Histogram of Gradients (HOG), Histogram of Flows (HOF) and Motion Boundary Histogram (MBH)
  - Video description: BoW with vocabulary size of 4000
  - $\alpha_1$ and $\alpha_2$ are tuned with cross-validation on training data.