SS5-31: Automatic Action Video Dataset Construction from Web using Density-based Cluster Analysis and Outlier Detection

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Introduction

Action Concept → Web videos / *Automatic Approach* → *Relevant Shots*

Action Dataset

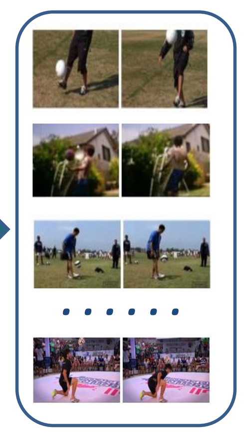
- **Previous work: require additional data (e.g.: tags[3]), ignore concept diversity problem**
- **This work: exploits only visual features of Web videos, copes with concept diversity**

Proposed Approach

soccer juggling **Action concept** → *Video search, download & segmentation* / ***Shot Collection***

→ ***Shot Clustering with OPTICS[1]***

→ ***Shot Ranking by LOF*** / ***Shot Selection***



i. Word preparation

- "verb" (dive), "verb+non-verb" (throw hammer), "non-verb" (vault)

ii. Video search

- "verb" & "verb-ing" (dive & diving)

iii. Video filtering

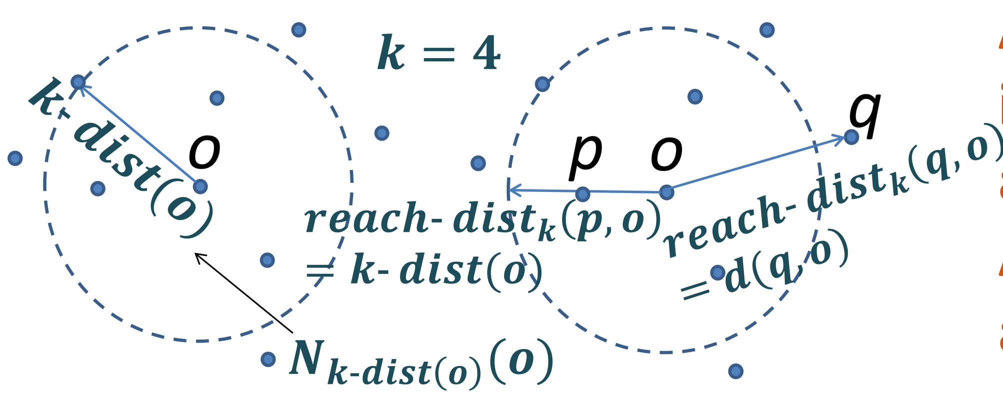
- No videos of "Entertainment"

iv. Video downloading

- Web API (e.g. Youtube API)

v. Shot segmentation

- Color histogram



A low reachability distance indicates an object within a cluster.
A high reach-dist indicates a noise or a jump from one cluster to another.

$$k\text{-}dist(o) = d(o,p): \begin{cases} 1.\ at\ least\ k\ objects\ q:\ d(o,q) \le d(o,p) \\ 2.\ at\ most\ k-1\ objects\ q:\ d(o,q) < d(o,p) \end{cases}$$

$$reach-dist(p,o) = max\big(k\text{-}dist(o), d(p,o)\big)$$

As visual features, we extract motion features using ConvNet models trained on UCF-101 dataset (split 1) with multi-frame stacking optical flows[4].

LOF (Local Outlier Factor) [5]

$$LOF_{MinPts}(p) = \frac{\sum_{o\in N_{MinPts-dist(p)}(p)} \frac{MinPts-dist(p)}{MinPts-dist(o)}}{\left|N_{MinPts-dist(p)}(p)\right|}$$

Small $MinPts - dist$ corresponds to a region with high density.
Shots with low LOF are considered as relevant shots and ranked to the top.

Shots are selected from all clusters to guarantee diversity of selection results.

Experiments and Results

Experiment 1: Dataset Construction

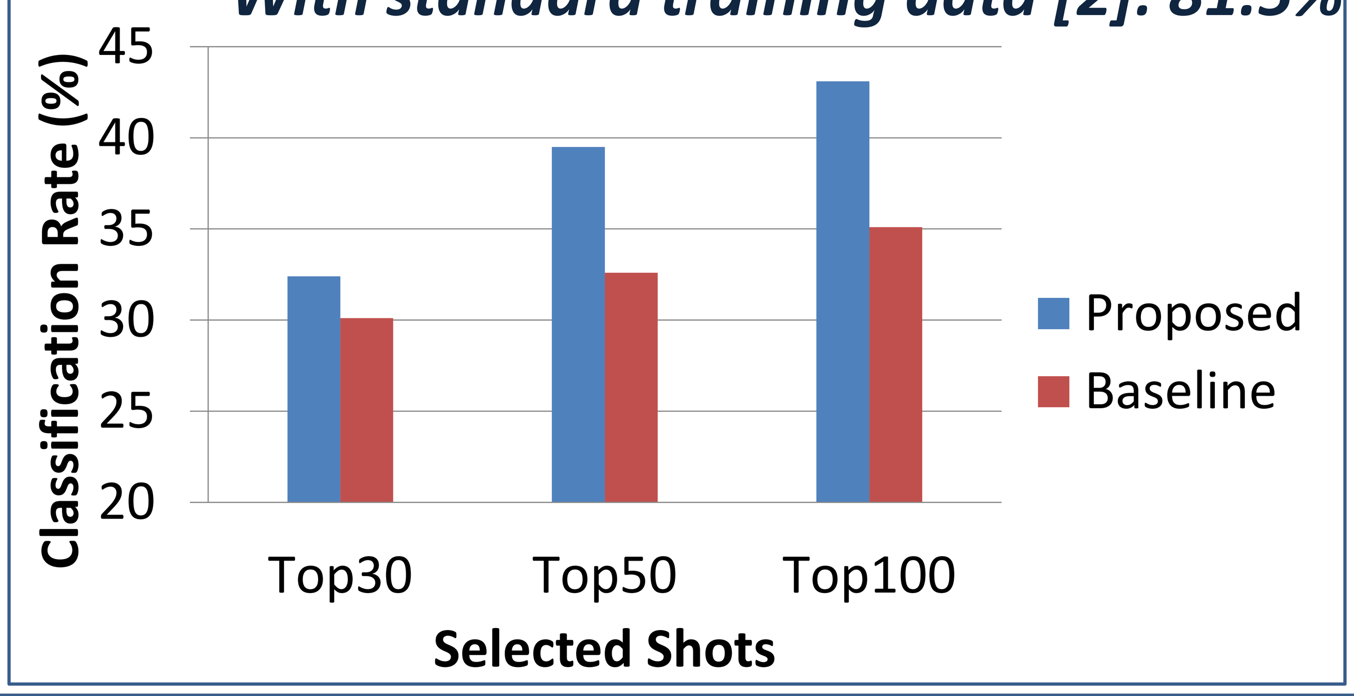
- Data: Web videos (YouTube)
- Actions: 11 actions in UCF11[2]
- Precision rate = percentage of relevant shots among top 100 shots [3]
- Baseline[3]: VisualRank based method

Action	Proposed	Baseline	Action	Proposed	Baseline
basketball	59	**67**	swing	**36**	22
biking	30	**35**	tennis_swing	**38**	37
diving	**25**	19	trampoline_jumping	42	**44**
golf_swing	**59**	52	volleyball_spiking	36	**45**
horse_riding	**49**	48	walking	**25**	11
soccer_juggling	**76**	72	Average	**43.2**	41.1

Experiment 2: Action Classification

- Dataset: UCF11[2]
- Precision = average of 25-fold validation
- Training data: standard data[2] & shots automatically obtained in Experiment 1

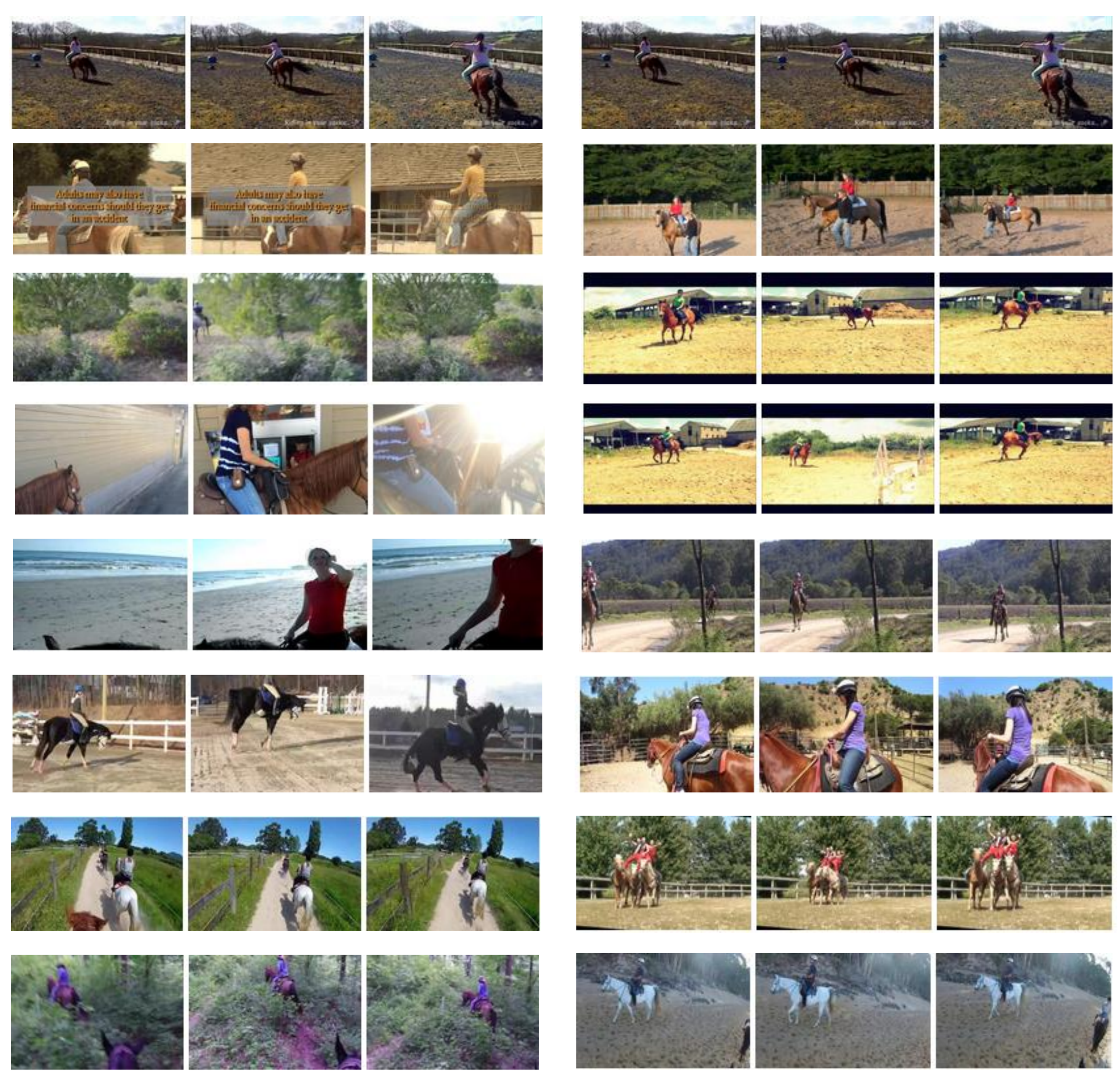
With standard training data [2]: 81.5%



golf_swing

Proposed **Baseline**

horse_riding



Proposed **Baseline**

[1] Mihael et al. *OPTICS: Ordering Points To Identify the Clustering Structure*. ACM SIGMOD International Conference on Management of Data, 1999, pp. 49-60.
[2] Jingen et al. *Recognizing realistic actions from videos*. IEEE Computer Vision and Pattern Recognition, 2009, pp. 1996-2003.
[3] Nga et al. *Automatic Construction of an Action Video Shot Database using Web Videos*. IEEE International Conference on Computer Vision, 2011, pp. 527-534.
[4] Karen et al. *Two-Stream Convolutional Networks for Action Recognition in Videos*. Advances in Neural Information Processing Systems 27, 2014, pp. 568-576.
[5] Chiu et al. *Enhancements on local outlier detection*. IEEE Database Engineering and Applications Symposium, 2003, pp. 298 – 307.