Leveraging Textural Features for Recognizing Actions in Low Quality Videos

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Visual human actions

- Human actions: major visual events in movies, news, ...
- Low quality videos: low frame resolution, low frame rate, compression artifacts, motion blurring

- We recognize human actions from low quality videos
- Leverage textures with shape and motion features to improve action recognition form low quality videos.

Motivation

- Recognizing human actions from video is of central importance due to its large real-world application domain:
  - surveillance, human computer application, video indexing etc.
- Many methods have been proposed in recent years but majority are focused on high quality videos that offer fine details and strong signal fidelity.
  - not suitable for real-time and lightweight applications
- Current methods are not designed for processing low quality videos.

Summary of Approach

- Detect space-time patches by feature detector and describe using shape and motion descriptor.
- Calculate textural features from entire space-time volume.
- Combine shape, motion and textural features to improve performance.

Summary of Contribution

- Propose textural features to alleviate the limitation of shape and motion features.
- Use BSIF-TOP as a textural feature descriptor for action recognition in low quality videos.
- Evaluate various textural features on low quality videos.

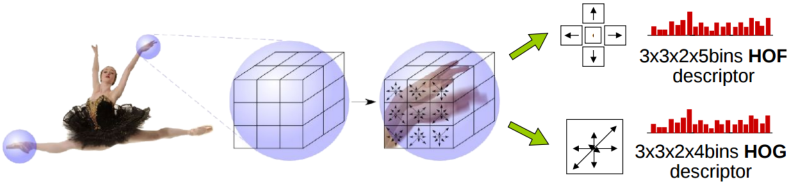
Related Work

- Shape and motion features
  - Space-Time Interest Points [Laptev et al'05]
  - Dense Trajectories [Wang et al.'11]
- Textural features
  - LBP-TOP [Kellokompu et al'09]
  - Extended LBP-TOP [Mattvi and Shao'09]
- Similar approaches
  - Joint Feature Utilization [Rahman et al'15, See and Rahman'15]

Outline

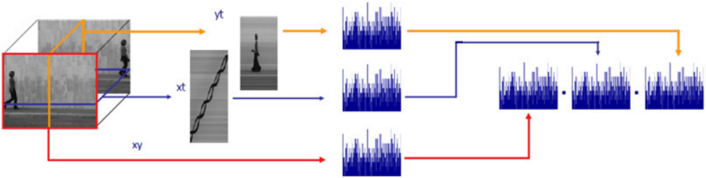
Shape and Motion Feature Representation

- Spatio-temporal interest points are detected by Harris3D detector [Laptev'05].
- Description of 3D patch around IPs using HOG and HOF [Laptev'08].
  - HOG - histogram of oriented gradients (encodes shape)
  - HOF - histogram of optical flow (encodes motion)



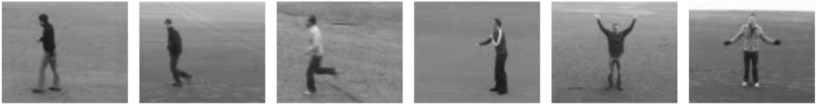
Textural Feature Representation

- Three types of textural features are calculated form entire space-time volume:
  - LBP - Local Binary Pattern [Zhao et al.'08].
  - LPQ - Local Phase Quantization [Zhao et al.'08].
  - BSIF - Binarized Statistical Image Features [Kannala and Rahtu'12].
- To obtain dynamic textures we apply three orthogonal plane (TOP) technique [Zhao et al.'08].
  - Features are calculated from XY, XT and YT plane of space-time volume (XYT).



Dataset : KTH Action [Schüldt et al'04]

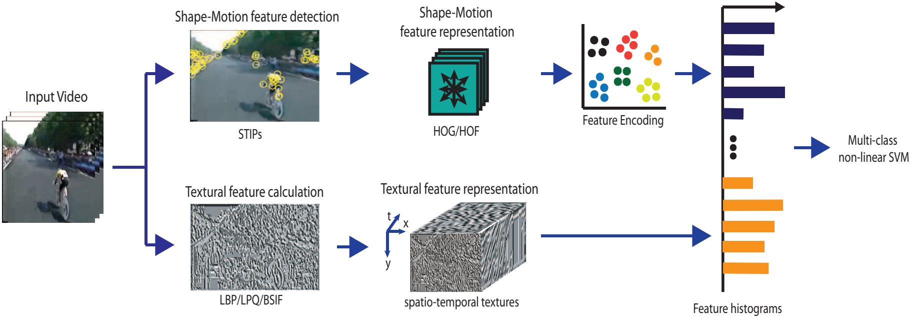
- Total 599 videos captured in a controlled environment.
- 6 action classes performed by 25 actors in 4 different scenarios.
- Sampling rate: 25 fps, Resolution: 160×120 pixels.
- Evaluation protocol: original experimental setup by authors.
- Six downsampled versions were cerated (3 spatial (SD_α) and 3 temporal (SD_β))
  - We limit $\alpha, \beta = \{2, 3, 4\}$, where α, β denotes spatial and temporal downsampling to half, one third and one fourth of the original resolution or frame rate respectively.



Dataset : HMDB51 [Oh et al'11]

- Total 6,766 videos of 51 action classes collected from movies or YouTube.
- Videos are annotated with a rich set of meta-labels including quality information
  - three quality labels were used, i.e. 'good', 'medium' and 'bad'.
- Evaluation protocol: three training-testing split by authors.
- We use the split specified for training, while testing is done using only videos with 'bad' and 'medium' labels; for clarity, we denote them as **HMDB-BQ** and **HMDB-MQ** respectively.

Evaluation Framework



Experimental Results: KTH dataset

- Performance (average accuracy over all class) comparison:

Method	SD_2	SD_3	SD_4	TD_2	TD_3	TD_4
HOG/HOF [6]	83.33	76.39	65.74	86.11	81.94	76.85
HOG+HOF [9]	84.26	80.09	75.46	87.04	80.09	81.48
HOG+HOF + LBP-TOP [10]	87.41	80.74	77.69	87.87	82.50	80.37
HOG+HOF + LPQ-TOP	88.15	81.30	78.52	87.50	81.85	80.00
HOG+HOF + BSIF-TOP	**89.07**	**85.00**	**81.67**	**88.52**	**87.04**	**84.91**

- Best method: **HOG+HOF+BSIF-TOP**
- Spatially downsampled videos are highly benefited by textural features.
- BSIF-TOP outperform other textural features.

Experimental Results: HMDB51 dataset

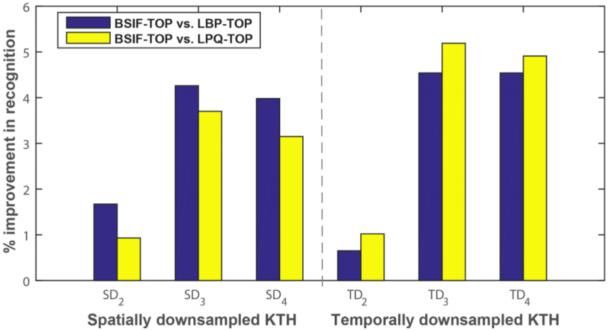
- Performance (average accuracy over all class) comparison:

Method	HMDB-BQ	HMDB-MQ
HOG/HOF [8]	17.18	18.68
C2 [8]	17.54	23.10
HOG+HOF [9]	21.71	23.68
HOG+HOF + LBP-TOP [10]	20.80	24.20
HOG+HOF + LPQ-TOP	23.89	28.36
HOG+HOF + BSIF-TOP	**32.46**	**37.14**

- Best method: **HOG+HOF+BSIF-TOP**
- Texture vastly improve the performance of both ‘Bad’ and ‘Medium’ quality videos.
- BSIF-TOP outperform other textural features.

Experimental Results: BSIF-TOP vs. other textures

- Performance improvement by BSIF-TOP over LBP-TOP and LPQ-TOP when aggregated with HOG+HOF:



- LPQ-TOP is better for spatially downsampled videos.
- LBP-TOP is better for temporally downsampled videos.
- Using BSIF-TOP, HMDB-LQ and HMDB-MQ results improves to almost double of baseline.

Experimental Results: Computational Complexities

- Computational cost (feature detection/calculation + quantization time) of various feature descriptors:

	HOG+HOF	LBP-TOP	LPQ-TOP	BSIF-TOP
Time (in sec.)	13.76	47.57	2.48	5.25

- Runtime reported using a Core i7 3.6 GHz 32GB RAM machine.
- All test run on a sampled video from KTH-SD_2 dataset consist of 656 frames.
- Ranking of descriptors in terms of speed:
  - LPQ-TOP > BSIF-TOP > HOG+HOF > LBP-TOP.

Conclusion

- We leveraged on textural features to improve the recognition of human actions in low quality video clips.
- Considering that most current approaches involved only shape and motion features, the use of textural features is a novel proposition that improves the recognition performance by a good margin.
- BSIF-TOP offers a significant leap of around **16%** and **18%** on the KTH-SD_4 and HMDB-MQ datasets respectively, over their original baselines.
- In future, we intend to extend this work towards a larger variety of human action datasets.
- It is also worth designing textural features that are more discriminative and robust towards complex backgrounds.

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Thank You!

Q & A