Action Recognition in Low Quality Videos by Jointly Using Shape, Motion and Texture Features

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Motivation

- Local space-time features have become popular for action recognition in videos.
- Current methods focus on *high quality videos* which are not suitable for real-time video processing applications.
- Current methods handles various complex video problems (such as *camera motion*) but problem of *video quality* is still relatively unexplored [Oh et al'11].

Goal of this work

- Investigate and analyze the performance of action recognition under two low quality conditions:
  - Spatial downsampling
  - Temporal downsampling
- Joint utilization of shape, motion and texture features for robust recognition of actions from *downsampled* videos.
- Investigate ‘good’ feature combinations for action recognition in low quality video.

Related Works

- Shape and motion features
  - Space-time interest points [Laptev'05]
  - Dense Trajectories [Wang et al.'11]
- Textural features
  - Local Binary Pattern on three orthogonal planes [Kellkompu et al.'08]
  - Extended Local binary pattern on three orthogonal planes [Mattivi and Shao'09]

Outline

- Spatio-temporal video features
- Action recognition framework
- Video downsampling
- Experiments

Spatio-temporal video features

Action recognition framework

Video downsampling

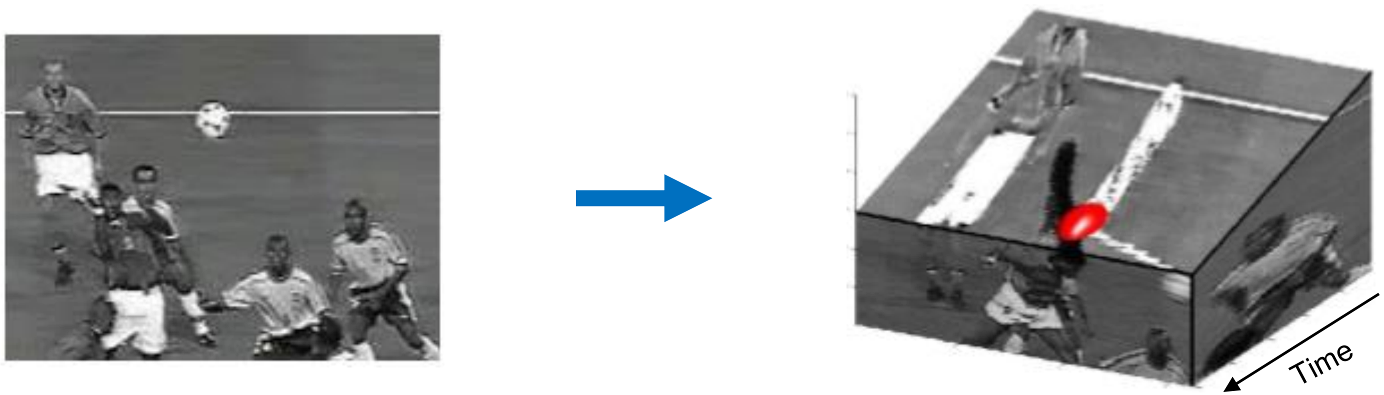
Experiments

Spatio-temporal video features

- Shape and Motion Features *(structures and its change with time)*
  - Feature detector – Harris3D
  - Feature descriptor – HOG and HOF
- Textural Features *(change of statistical regularity with time)*
  - Feature detector and descriptor – LBP-TOP

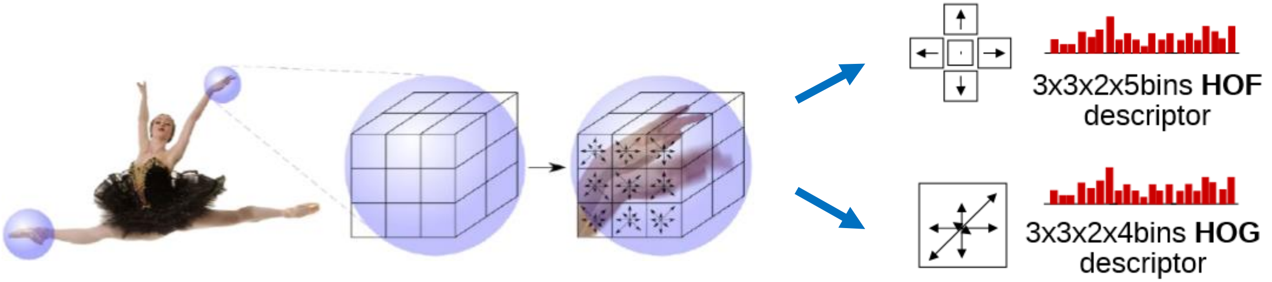
Harris3D detector [Laptev'05]

- Space-time corner detector
- Capable of detecting any spatial and temporal interest point
- Dense scale sampling (no explicit scale selection)



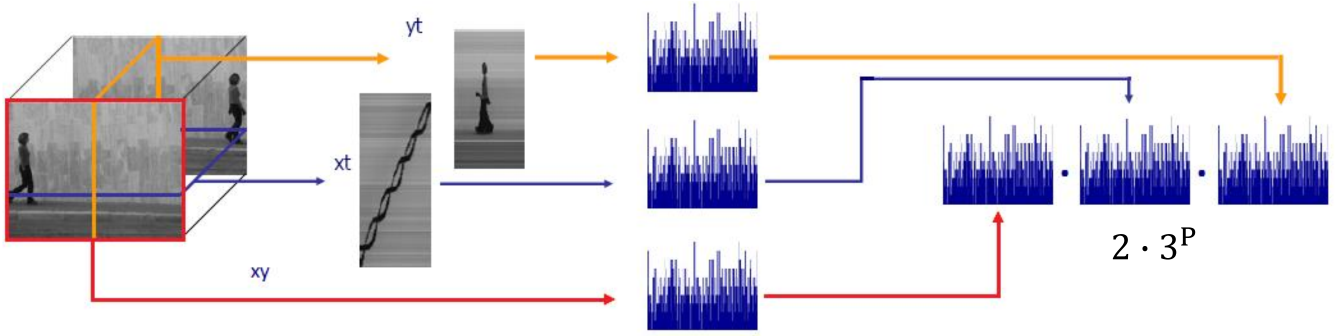
HOG/HOF descriptor [Laptev'08]

- Based on gradient and optical flow information
  - HOG – Histogram of oriented gradients
  - HOF – Histogram of Optical Flow
- Detected 3D patch (xyt) is divided into grid of cells
- Each cell is described with HOG and HOF.



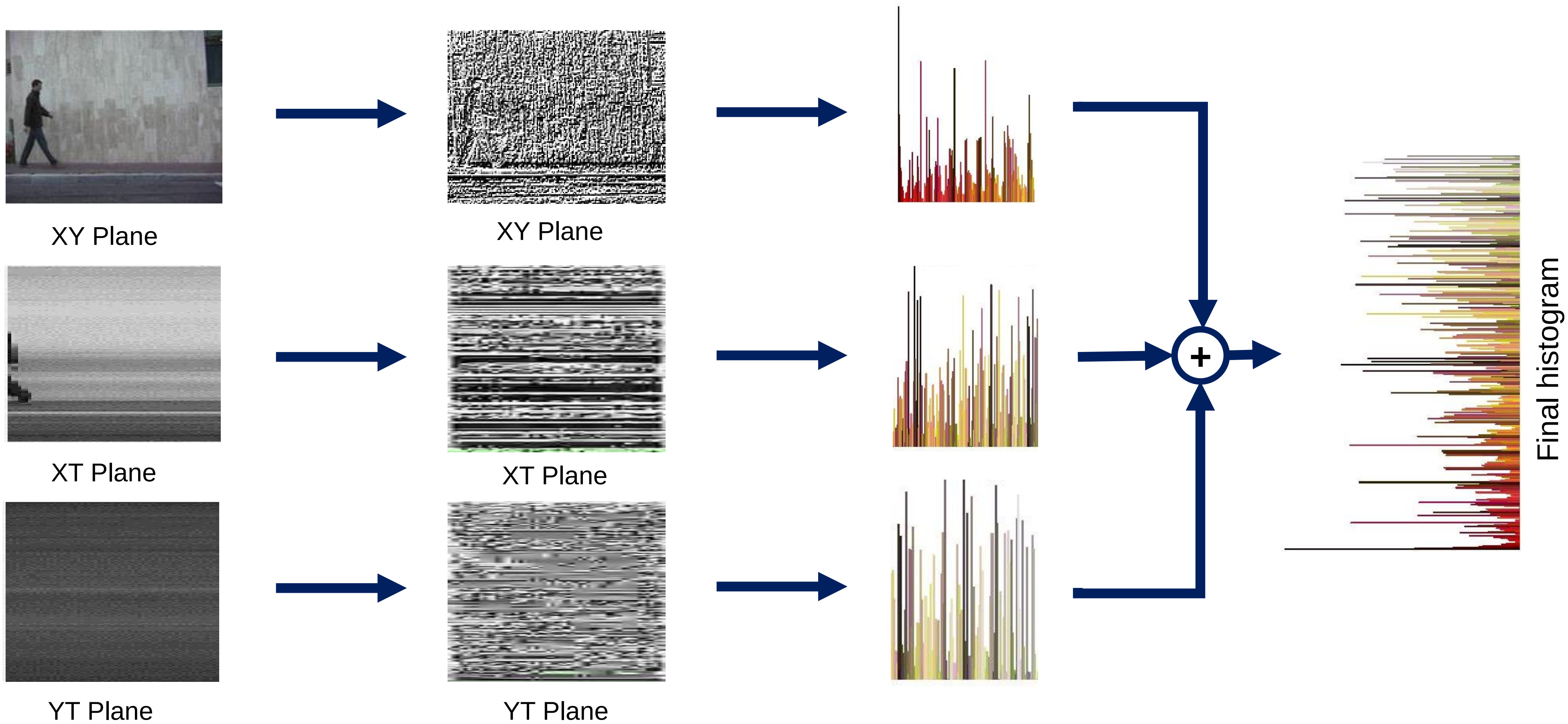
LBP-TOP detector + descriptor [Zhao'07]

- Extension of popular local binary pattern (LBP) operator into three orthogonal planes (TOP)
- Encodes shape and motion on three orthogonal planes (XY, XT and YT)
- Calculate occurrence of different plane histograms to form final histogram ($H = h^{XY} \cdot h^{XT} \cdot h^{YT}$)



$\mathrm{LBP-TOP}_{P_{XY}P_{XT}P_{YT}R_XR_YR_T}$

LBP-TOP in action



Spatio-temporal video features

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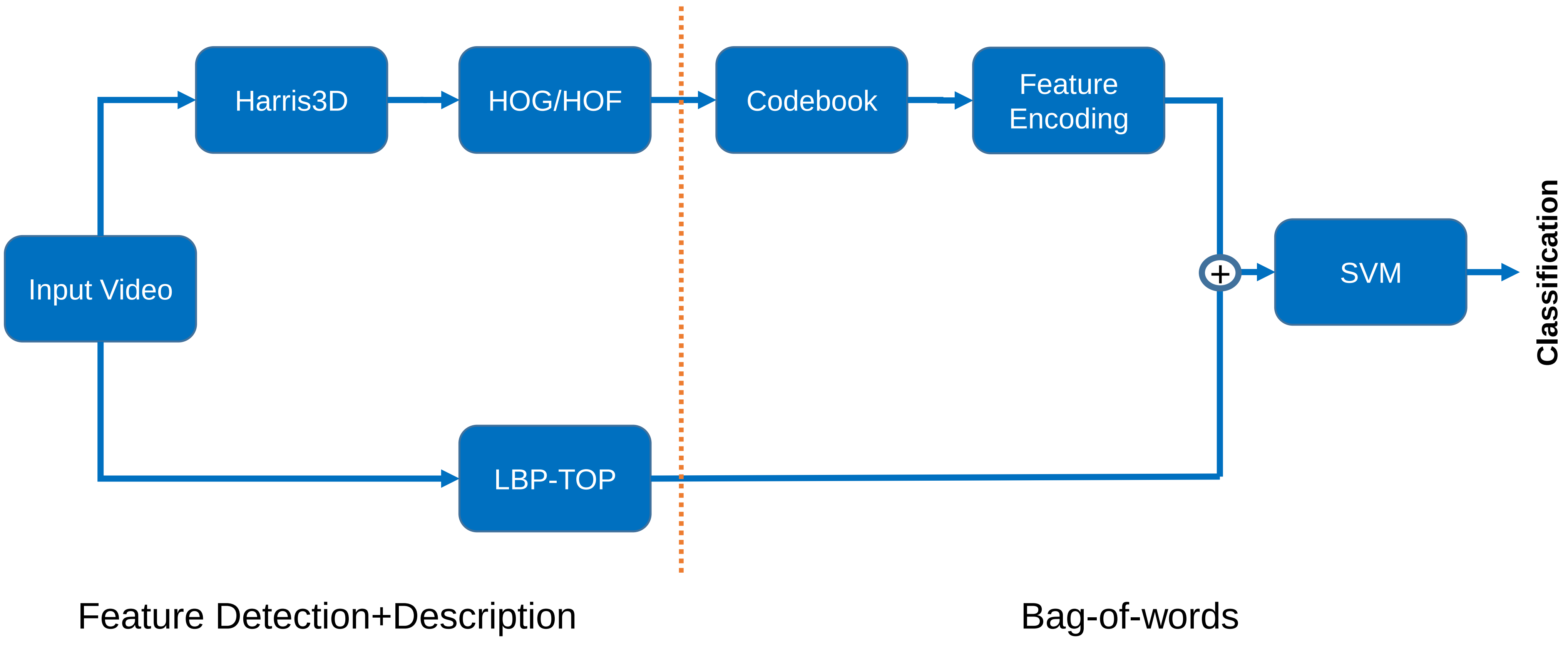
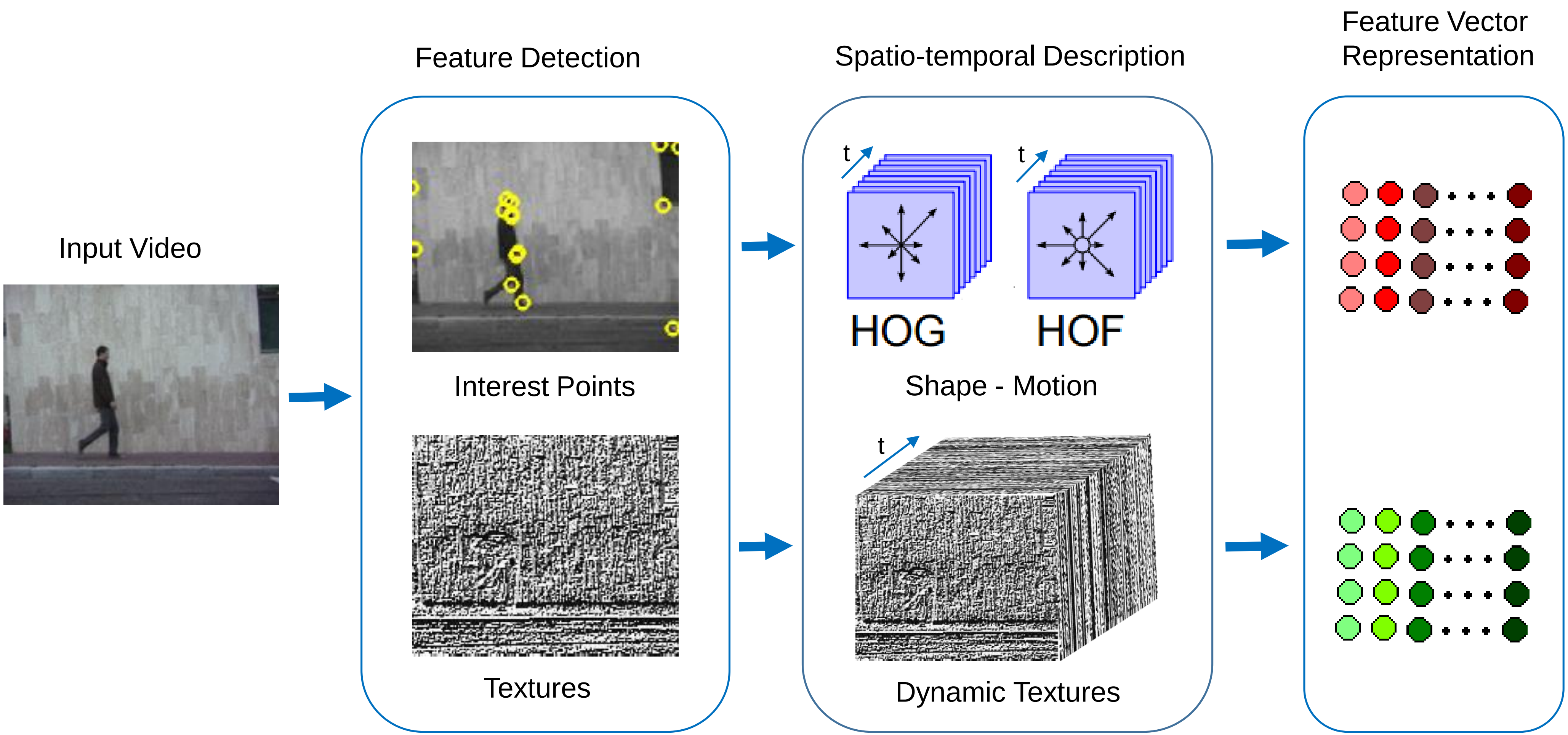
Experiments

Evaluation framework



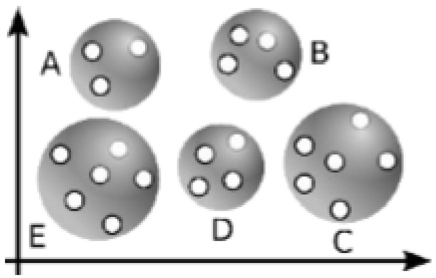
Detection + description of features

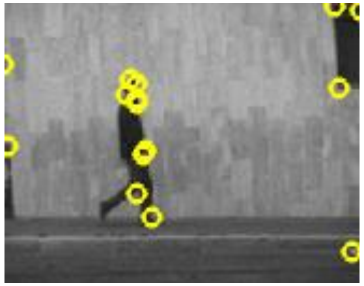


Bag-of-words representation

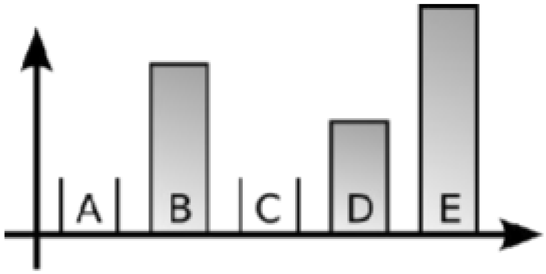
Bag of space-time features + SVM with χ^2 kernel [Vedaldi'08]

Training feature vectors are clustered with k-means





Each feature vector is assigned to its closest cluster center (visual word)



An entire video sequence is represented as occurrence histogram of visual words

Classification with multi-class non-linear SVM and χ^2 kernel

Spatio-temporal video features

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Video downsampling

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Video Downsampling

- Spatial downsampling (SD) decrease the spatial resolution.
- Temporal downsampling (TD) reduces temporal sampling rate.

SD Factor	Description
SD_1	Original Res.
SD_2	$^1/_2$ Res. of Original
SD_3	$^1/_3$ Res. of Original
SD_4	$^1/_4$ Res. of Original

TD Factor	Description
TD_1	Original F.R.
TD_2	$^1/_2$ F.R. of Original
TD_3	$^1/_3$ F.R. of Original
TD_4	$^1/_4$ F.R. of Original

Fig: Spatially downsampled videos. (a) SD_1 (b) SD_2 (c) SD_3 (d) SD_4 .

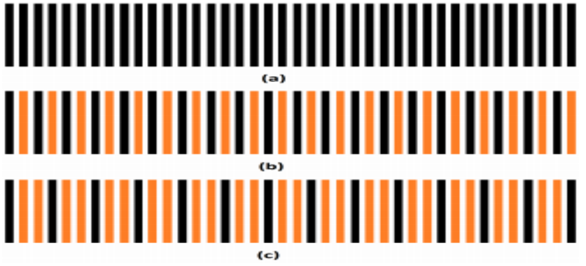
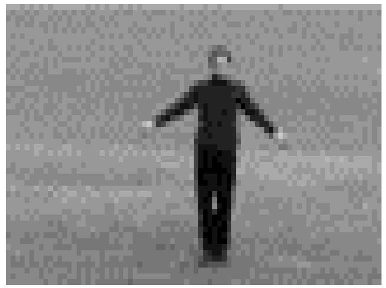


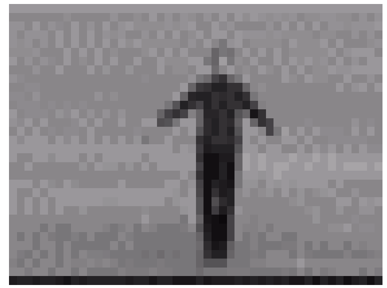
Fig: Temporal Downsampling; (a) Original video (b) TD_2 (c) TD_3

Preview of downsampled videos

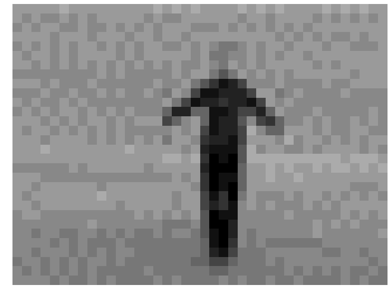
Original Video



SD_2



SD_3



SD_4

TD_2

TD_3

TD_4

Spatio-temporal video features

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Experiments

Datasets

- Two popular publicly available dataset
  - KTH action [Schuldt et al.’04]
  - Weizmann [Blank et al.’05]
- Both captured in a controlled environment with homogeneous background.

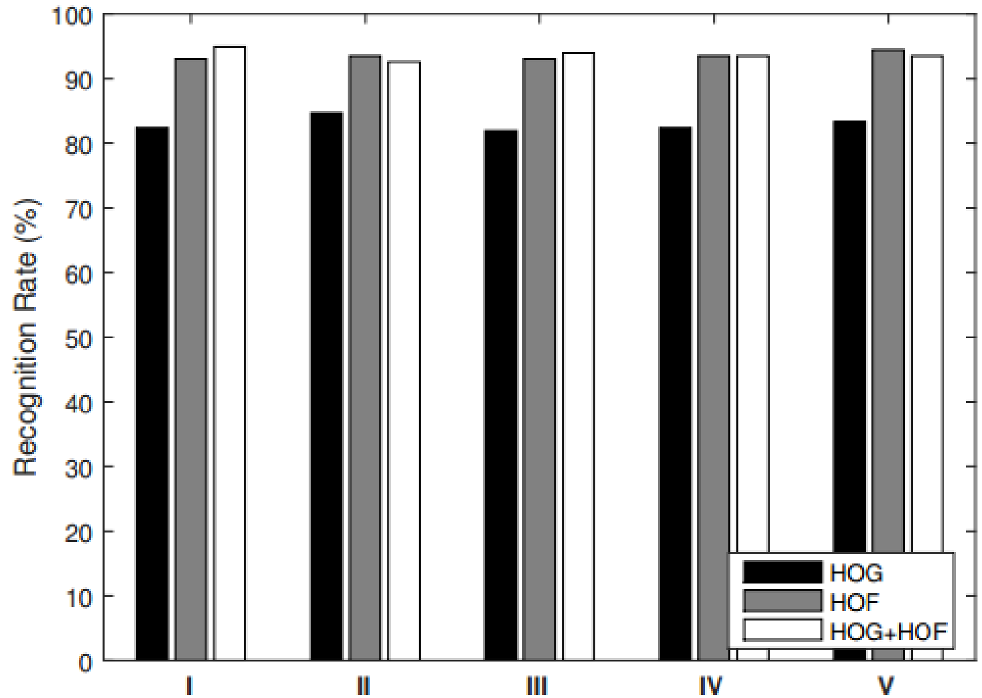
Feature combination used

- Five different feature combinations
  - Combination **I** : (HOG + HOF) - linear kernel
  - Combination **II** : (HOG + HOF) - χ^2 kernel
  - Combination **III** : (HOG + HOF + LBP-TOP) - linear kernel
  - Combination **IV** : (HOG + HOF) + LBP-TOP - χ^2 kernel
  - Combination **V** : (HOG + HOF + LBP-TOP) - χ^2 kernel

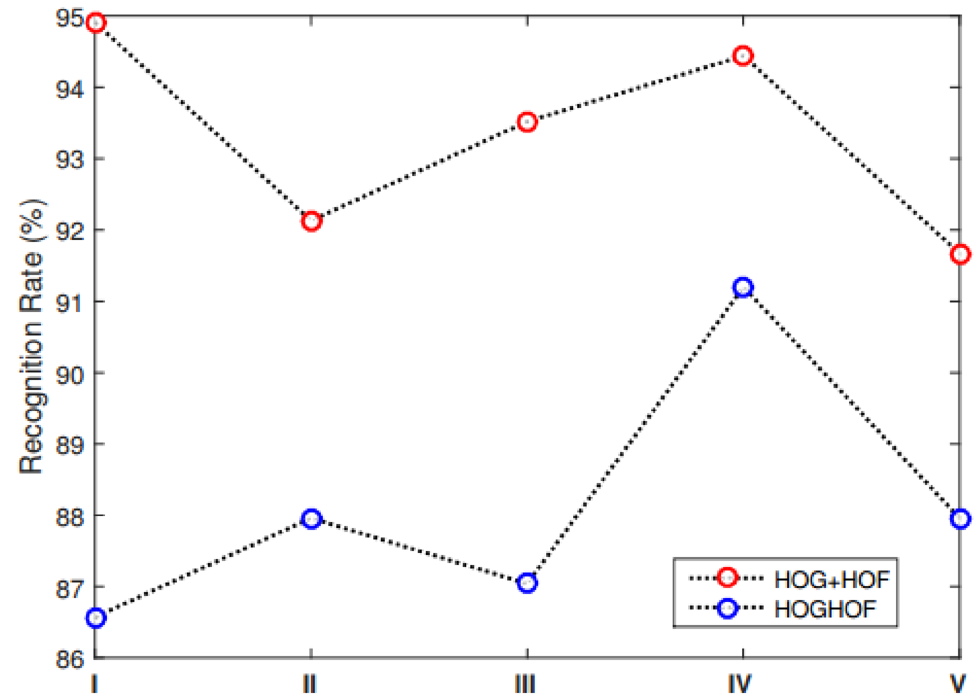
KTH actions [Schuldt et al.'04]

- Total 599 videos divided in 6 action classes
- 25 people performed in 4 different scenarios
- Frame resolution: 160 x 120 pixels
- Frames per second: 25 (average duration 10-15 sec.)
- Followed author specified setup for training-testing splits.
- Performance measure: *average accuracy over all classes*

KTH original dataset - results



KTH dataset

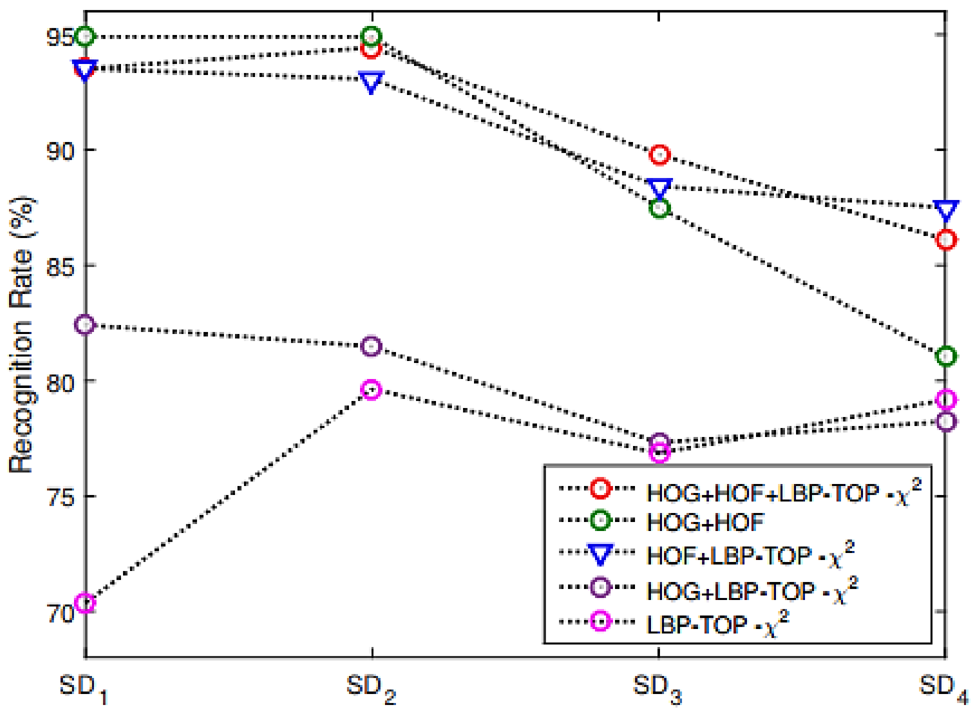


HOGHOF vs. HOG+HOF

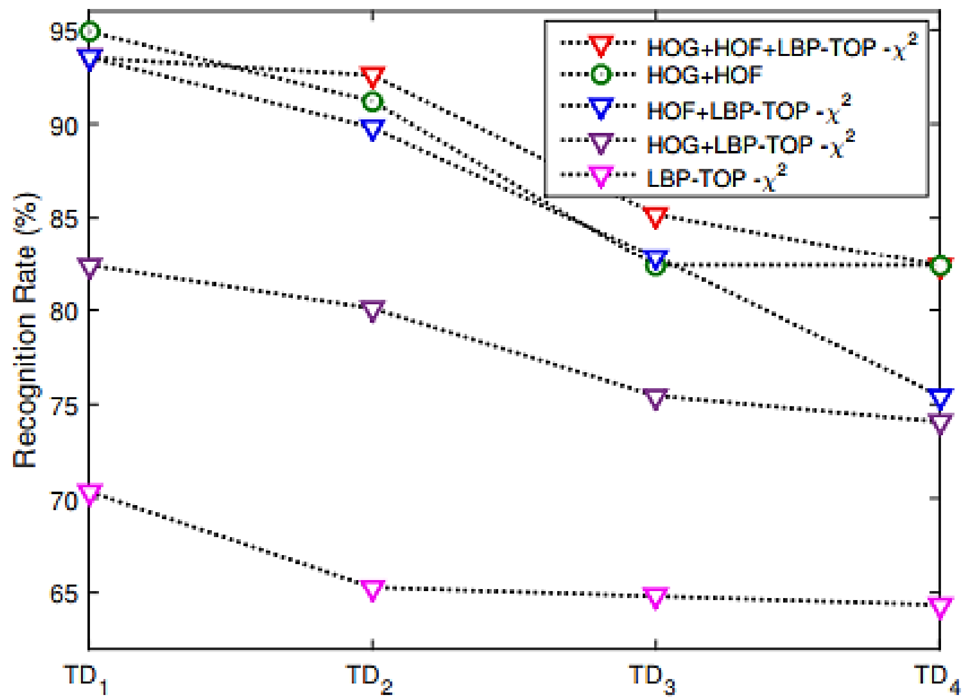
KTH original dataset – results (2)

- Best result for HOG+HOF (94.91%)
- HOG+HOF helps to elevate the overall accuracy by 3–8% ☺
- Kernelization of specific features are able to strengthen results
    - HOF + LBP-TOP : 93.06%
    - HOF + LBP-TOP - χ^2 kernel : 94.44% ☺
- HOF is more effective than HOG but improves when paired with LBP-TOP ☺

KTH downsampled videos – results



Spatial downsampling *(k=2000)*



Temporal downsampling *(k=2000)*

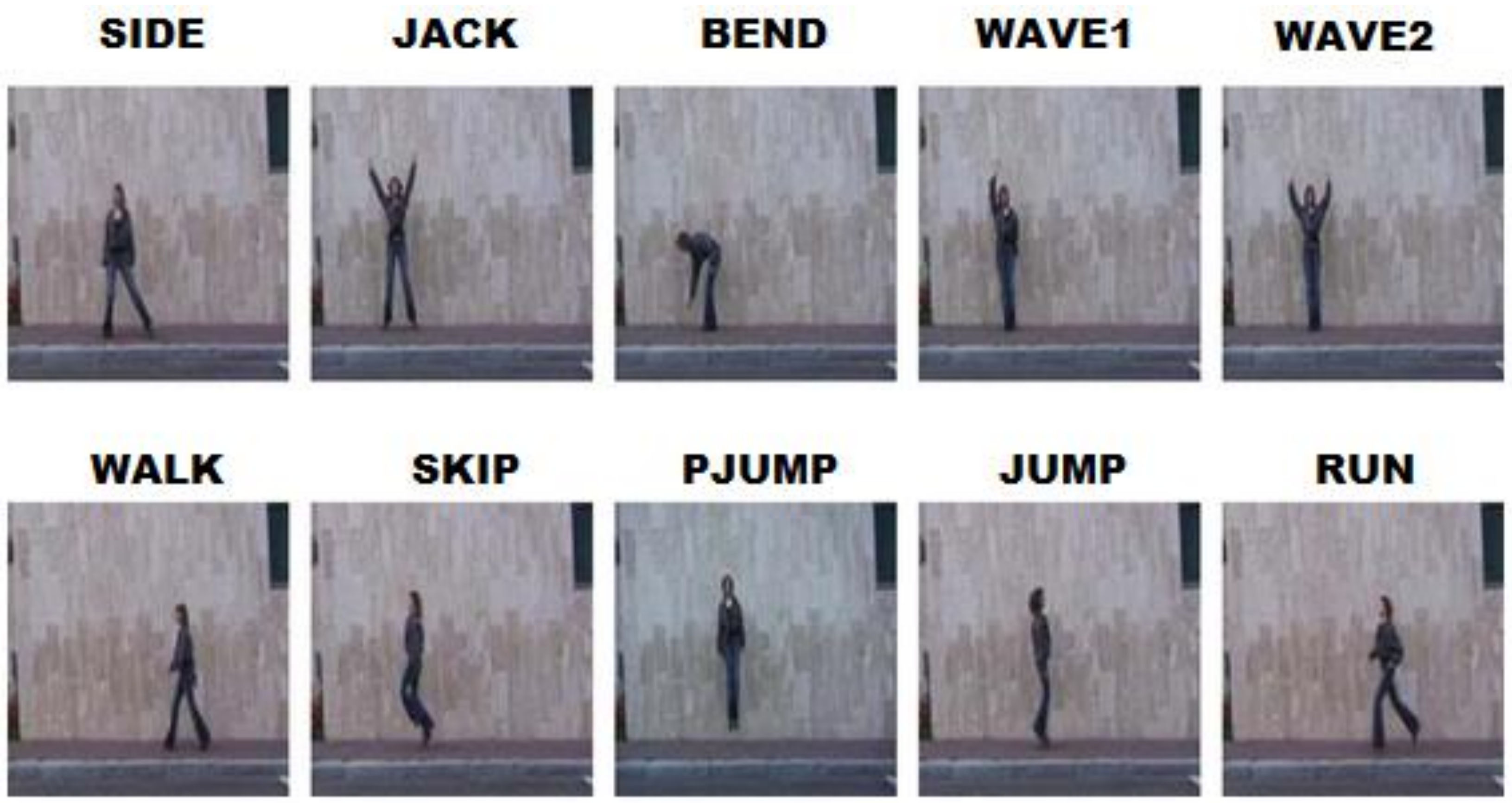
KTH downsampled videos – results (2)

- STIPs and kernalized LBP-TOP appear to dominate the best results within each mode ☺
- LBP-TOP contributes more with the deterioration of spatial or temporal quality (more significant in case of SD_4 & TD_4) ☺
  - Shape information are more important for low temporal resolution ☹
  - Motion information are more important for low spatial resolution ☹
- Note: for STIPs detection in SD modes different *k* parameters are used

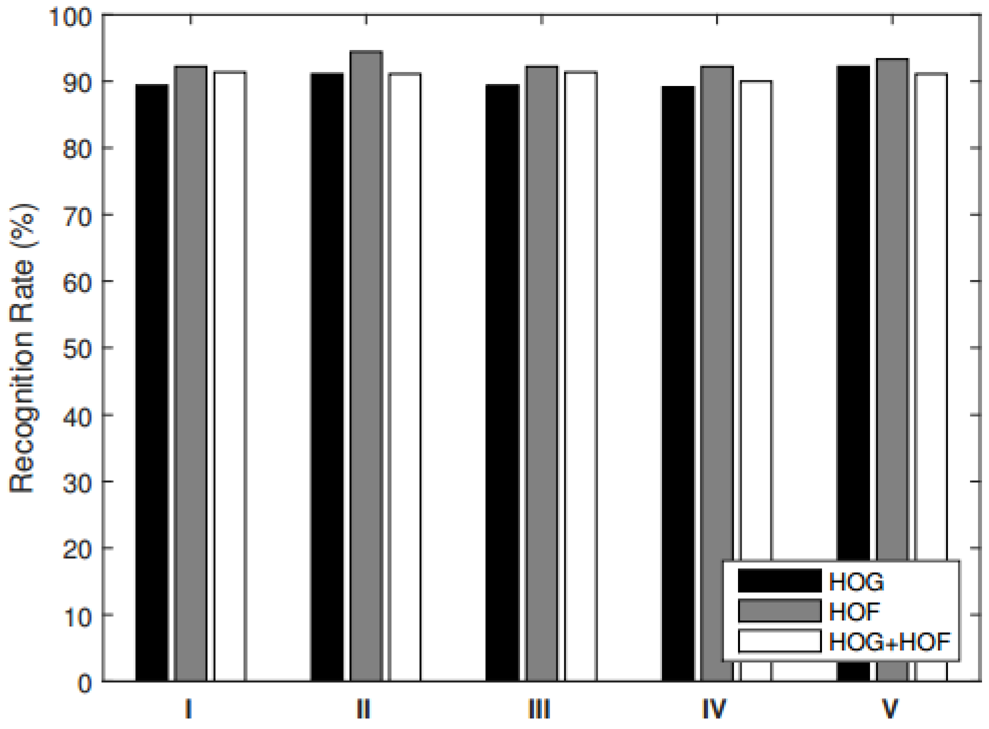
Weizmann [Blank et al'05]

- Total 93 videos divided in 10 action classes
- 9 people performed different actions
- Frame resolution: 180 x 144 pixels
- Frames per second: 50 (average duration 2-3 sec.)
- Performance measure: leave-one-out-cross-validation

Weizmann video sample

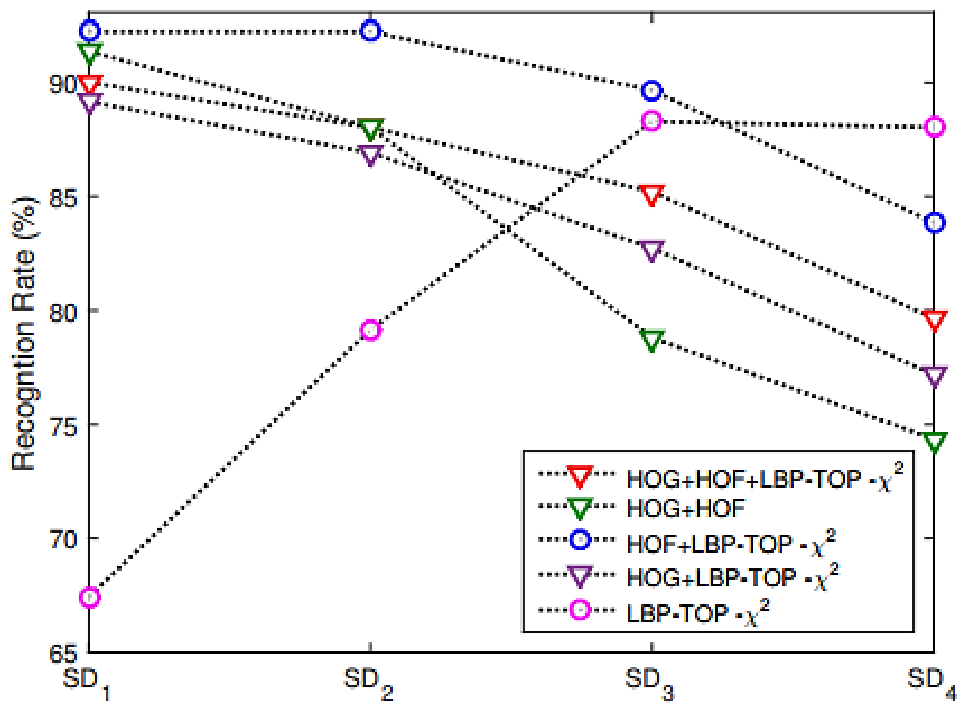


Weizmann original dataset - results

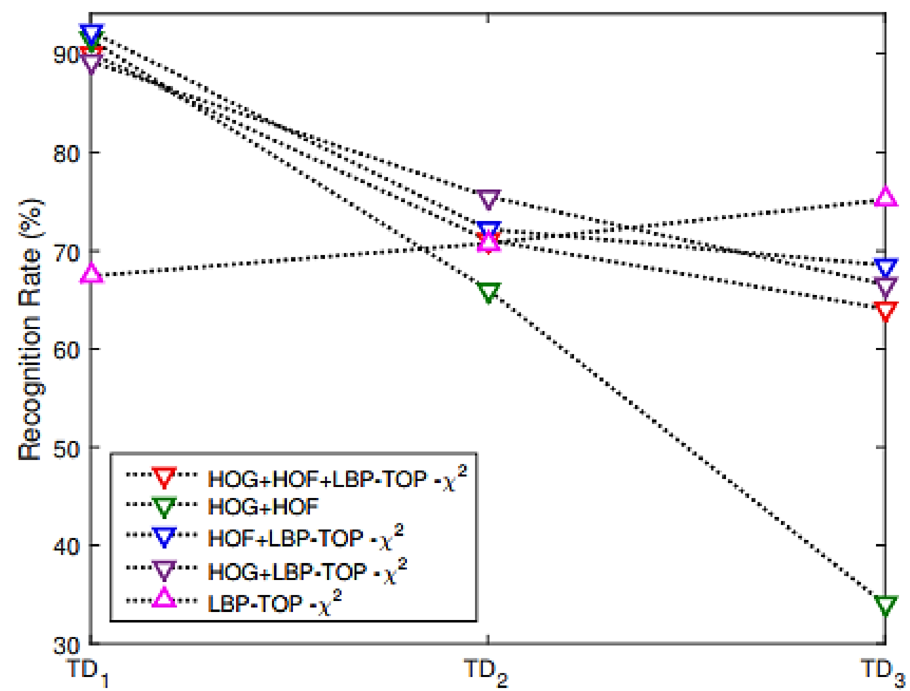


- Best result 94.44% for HOF.
- HOF+LBP-TOP dominate best result within each mode ☺
- Kernelization of LBP-TOP features are able to strengthen results ☺
- Kernelization is less effective for HOF features ☹
- Shape is largely poor on all combinations ☹ but performs better after combining with LBP-TOP ☺

Weizmann downsampled videos – results



Spatial downsampling
$\mathrm{SD}_2, \mathrm{SD}_3$ *(k=2000)* & SD_4 *(k=1500)*

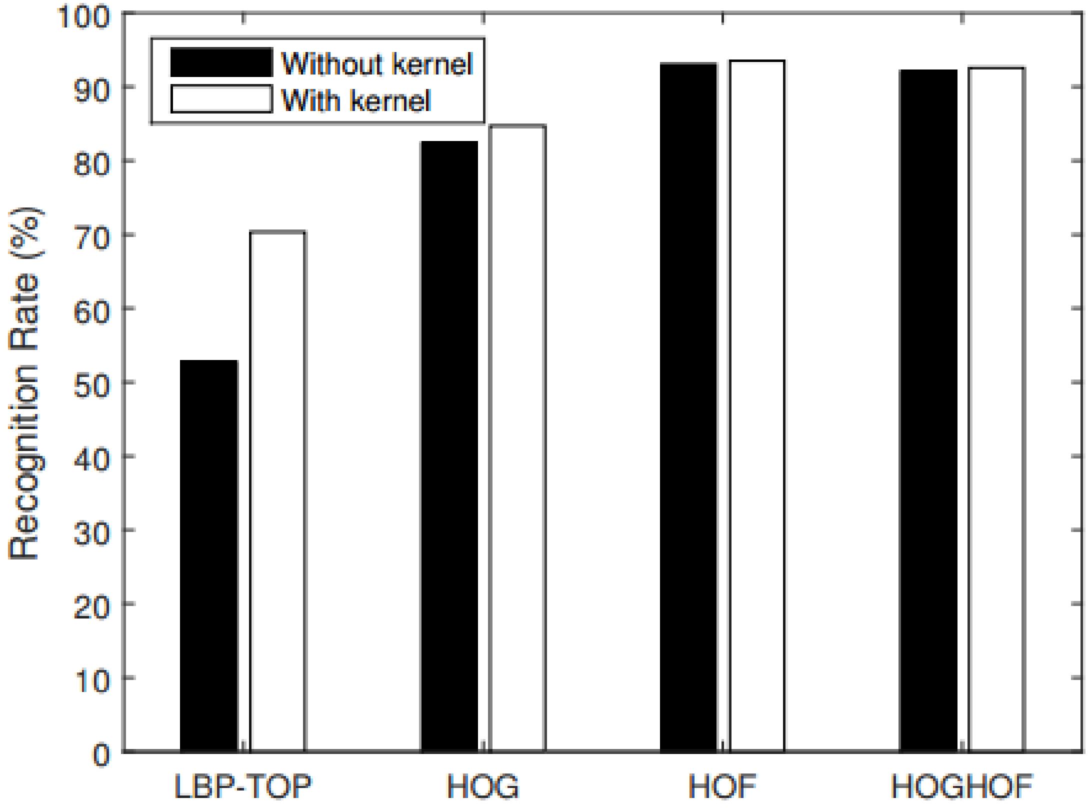


Temporal downsampling
SD_2 *(k=2000)*, SD_3 *(k=400)*

Weizmann downsampled videos – results (2)

- STIPs and kernalized LBP-TOP appear to dominate the best results within each mode ☺
- LBP-TOP contributes significantly more as the resolution quality decreases ☺
- Kernelized LBP-TOP achieves **best accuracy** rate at $\alpha = 4$ and $\beta = 3$ ☺

Effects of kernelization



Recognition accuracy with and without χ^2-kernel, on the original KTH videos.

Conclusion

- This work utilizes a new notion of joint feature utilization for action recognition in low quality videos
- This woks shows how downsampled videos can particularly get benefitted from textural information with shape and motion.
- The combined usage of all three features (HOG+HOF+LBP-TOP) outperforms the other competing methods across a majority of cases.
- Our best method is able to limit the drop in accuracy to around 8-10% when the video resolutions and frame rates deteriorate to a fourth of their original values.

Future Works

- Extend our evaluation to videos from more complex and uncontrolled environments [Laptev et al.'04], [Oh et al.'11]
- Investigate the simultaneous effects of both spatial and temporal downsampling on videos
- Explore other spatio-temporal textural features that might exhibit more robustness towards video quality

Thank You