Exploring Motion Boundary based Sampling and Spatial-Temporal Context Descriptors for Action Recognition

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Introduction

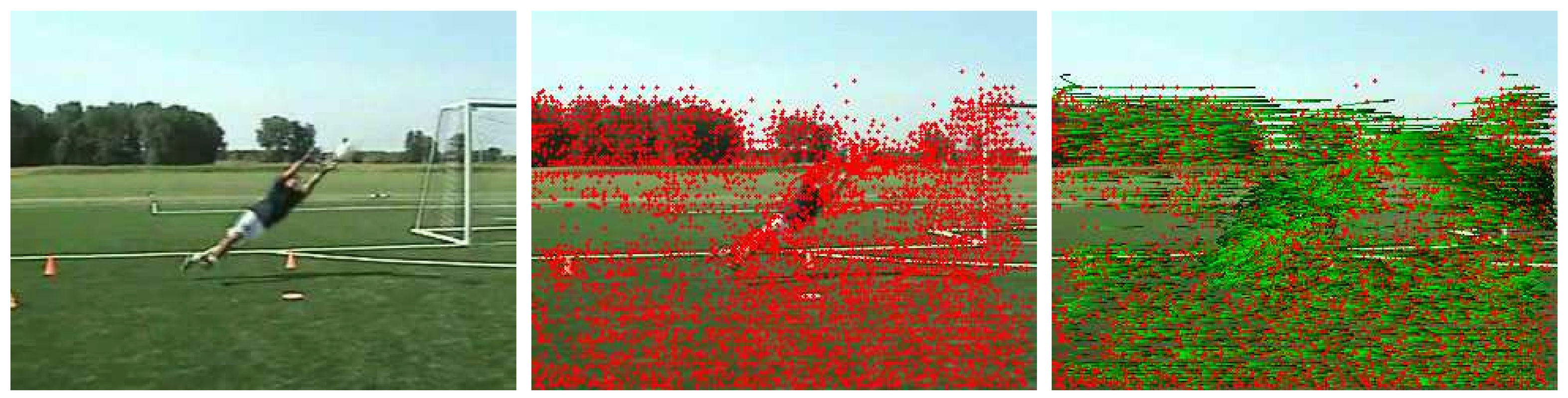
- **Goal**: Design new sampling strategy and descriptors to improve the recent dense trajectory method in storage and performance.
- **Existing works**:
  - **Sampling strategy**: STIP, Cuboid detector, Dense trajectory (DT) etc.
  - **Descriptors**: HOG, HOF, HOG3D, MBH etc.
- **Our idea**:
  - To reduce the number of trajectory yet preserve the power of dense trajectory, we propose a motion boundary based dense sampling strategy, called DT-MB.
  - To enhance the discriminative power of DT, we propose a group of spatial temporal context descriptors, namely spatial co-occurrence HOG (S-CoHOG), S-CoHOF, S-CoMBH, temporal co-occurrence HOG (T-CoHOG), T-CoHOF and T-CoMBH.
- **Properties**:
  - **Faster**: the DT-MB deletes large number of points in sampling step, which sharply reduces the tracking cost for trajectories. It is faster than original DT.
  - **Discriminative**: spatial-temporal motion and appearance context information around pixels can deliver more complex motion and appearance structures.

Dense Trajectory on Motion Boundary

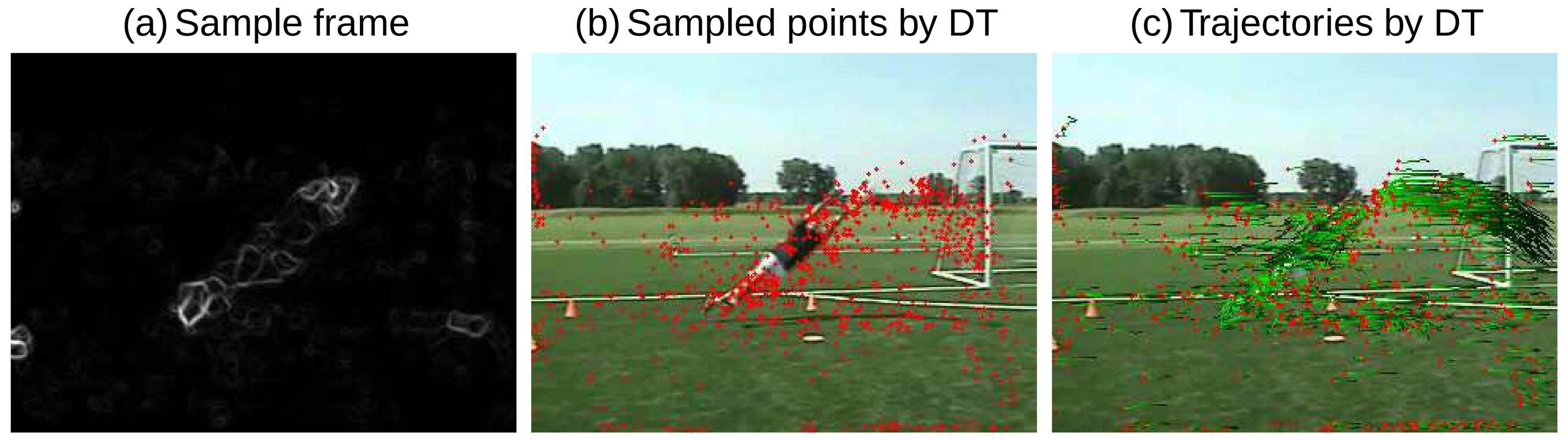
Motion Boundary: the maximum of gradient magnitudes between the horizontal and the vertical components of optical flow.

- **Implementation**:

1. **Sampling**: sample points in current frame on a grid by a step size w at S spatial scales. Two kinds of points will be removed: (1) the minimal eigenvalue of the covariance matrix of derivatives is less than a given threshold $T1$. (2) in the background of the binary mask estimated from motion boundary.
2. **Tracking and Filtering**: the same with Wang's [1].



(a) Sample frame (b) Sampled points by DT (c) Trajectories by DT



(d) Motion boundary image (e) Sampled points by DT-MB (f) Trajectories by DT-MB

Figure 1: Comparison of original DT and our Dense Trajectories on Motion Boundary.

Spatial-Temporal Context Descriptors

- **Spatial Context Descriptors**:

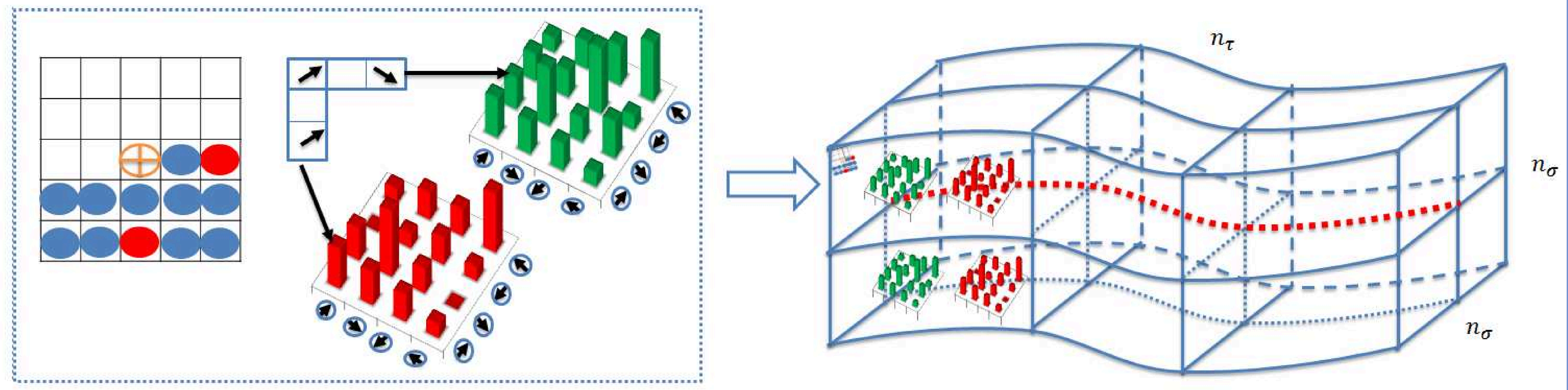
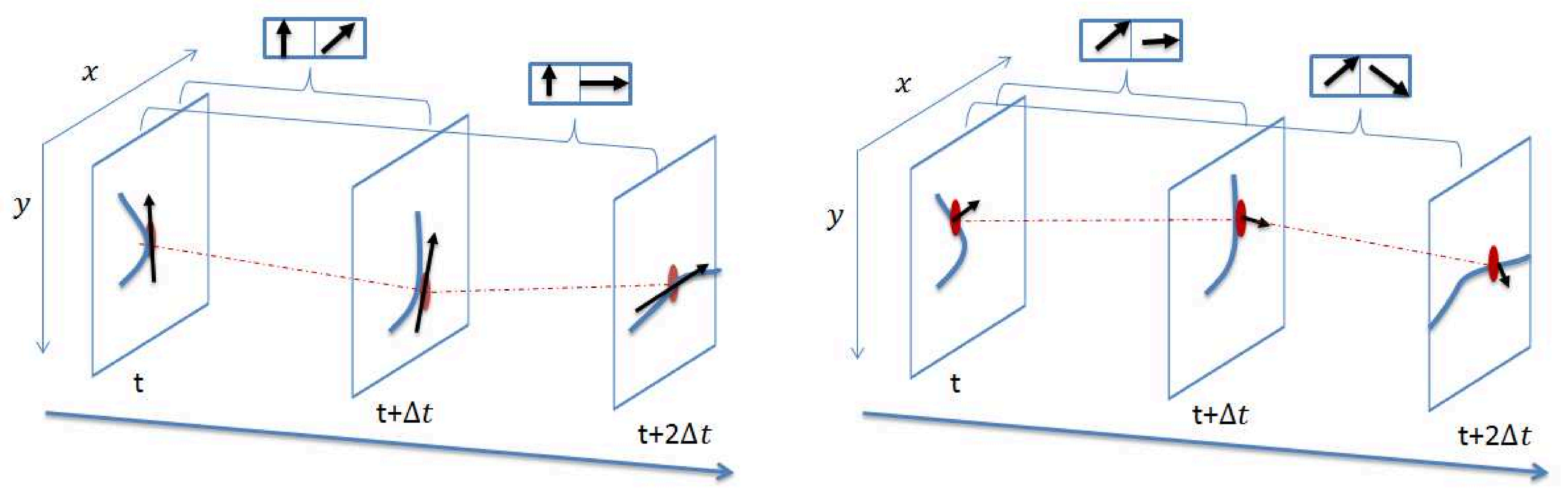


Figure 2: An example of spatial co-occurrence feature with grid of size $n_\sigma \times n_\sigma \times n_\tau$.

- **Co-occurrence matrix for offset (x,y) in a $m \times n$ patch:**

$$C_{x,y}(p,q) = \sum_{i=1}^{m}\sum_{j=1}^{n}\begin{cases}\frac{G(i,j)+G(i+x,j+y)}{2}, & \text{if } O(i,j)=p \text{ and } O(i+x,j+y)=q;\\ 0, & \text{otherwise.}\end{cases} \quad (1)$$

- **Temporal Context Descriptors**:



(a) T-CoHOG and T-CoMBH (b) T-CoHOF

Figure 3: Temporal co-occurrence descriptors. (a): pairs of gradient orientations in T-CoHOG or T-CoMBH. (b): pairs of optical flow orientations in T-CoHOF.

- **Representation**:
  - **Descriptor dimension**: $n_{bin} \times n_{bin} \times n_{offset} \times n_\sigma \times n_\sigma \times n_\tau$ for each type of S-Co ($n_{offset} = 2$) and T-Co ($n_{offset} = 1$) feature.
  - **Bag-of-features**: we use standard BoF pipeline to represent an action video.
  - **Classification**: LibSVM and one vs. all multi-channels RBF χ^2 kernel for multi-class classification.

References

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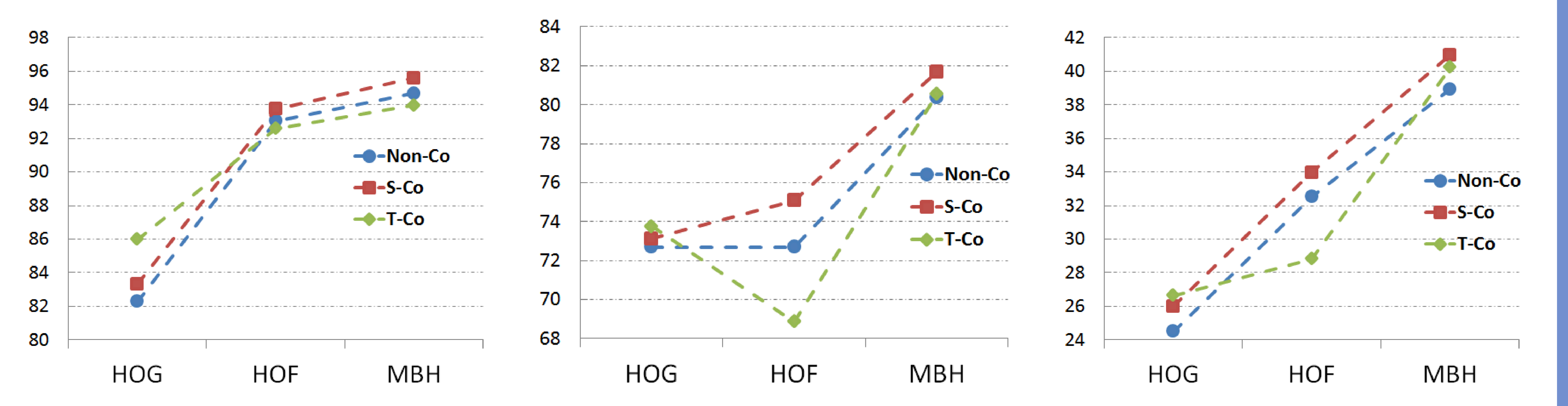
Experiment Results

- **Settings**: We conduct experiments on three datasets: KTH, UCF-Youtube, HMDB51.
- **DT-MB vs. DT**:

Table 1: Comparison of DT and DT-MB with all the raw DT descriptors.

Datasets		$T_{track}(ms)$	Trajectories/clip	fps	Accuracy (%)
HMDB51	DT	46.33	16,133	3.43	46.60
	DT-MB	**12.82**	4,512	4.63	46.03
YouTube	DT	39.01	37,542	4.71	84.25
	DT-MB	**6.60**	10,878	5.85	85.10
KTH	DT	11.72	2,185	12.85	94.81
	DT-MB	**4.00**	1,178	16.05	94.79

- **Spatio-temporal Context Descriptors**:



(a) KTH (b) YouTube (c) HMDB51

- **Descriptor combination**:

Table 2: Different combinations of descriptors using standard BOF.

Combination	KTH	YouTube	HMDB51
Trajectory+HOG+HOF+MBH	93.63	84.25	45.90
HOG+HOF+MBH	93.98	83.48	45.88
Trajectory+S-Co + T-Co	94.79	85.70	48.98
S-Co + T-Co	94.21	85.33	48.89
All combined	94.10	86.30	49.22
Best combined	95.60	86.56	49.22

- **Comparison**:

Table 3: Compare our results to the state-of-the-art results.

KTH		YouTube		HMDB51	
Laptev *et al.*[2]	91.8	Liu *et al.*[3]	71.2	Kuehne *et al.*[4]	23
Le *et al.*[5]	93.9	Le *et al.*[5]	75.8	Sadanand *et al.*[6]	26.9
Ji *et al.*[7]	90.2	B. *et al.*[8]	76.5	Orit *et al.*[9]	29.2
Wang *et al.*[1]	95	Wang *et al.*[1]	84.1	Wang *et al.*[1]	46.6
Our Method	**95.6**	Our Method	**86.56**	Our Method	**49.22**

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