Activity Recognition Using Dense Long-Duration Trajectories

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Outline

1. Representation for Activity Analysis
2. Extraction of Dense Trajectories
3. Description of Dense Trajectories
4. Preliminary Evaluations
5. Summary and Discussion

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Activity Analysis – State of the Art

- Almost perfect performance on controlled video (KTH, Weizmann), but very poorly on less controlled (Hollywood – 2, TRECV challenge, general Internet video sequences)
- Learning-based recognition frameworks abound, but not features! [1]

[1] P Turaga, R Chellappa, VS Subrahmanian, O Udrea, "Machine recognition of human activities: A survey". TCSVT, 18(11):1473 – 1488, 2008.

Representation – State of the Art

- We'll focus on representation/features from raw video sequences.
- Most popular features people have been using
  - Laptev's STIP (HOG & HOF, Laptev & Lindeberg 2003)
  - Dollar's dense cuboids (Dollar *et al.* 2005)
  - Volumetric Features (such as Silhouettes, Shapes, *e.g.*, in Veeraraghavan *et al.*)
- And the less popular
  - Long-Duration Trajectories (but was popular in 1990's).

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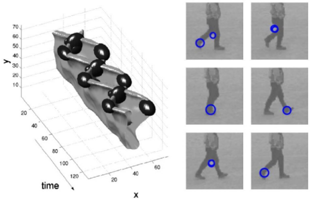
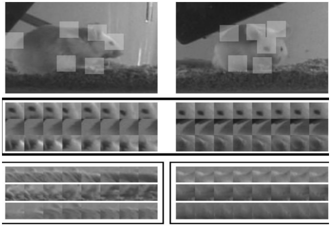
Laptev's (sparse) STIP & Dollar's Dense Cuboids



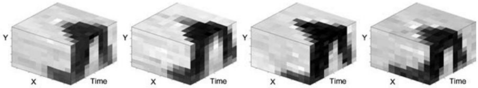
(a) (b)

Sparse Corner Points



Dense Strong-Response Regions

$\Downarrow$



Description (Statistics of optic flows, spatial gradients, pixel values, etc)

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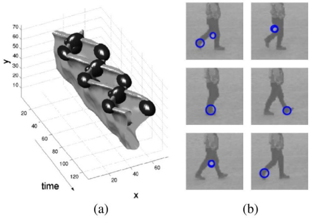

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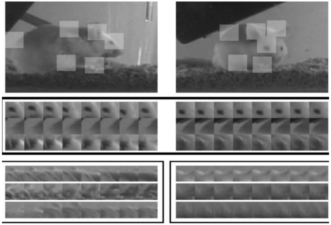

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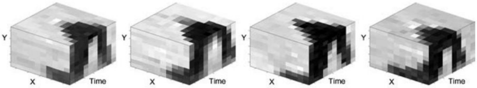

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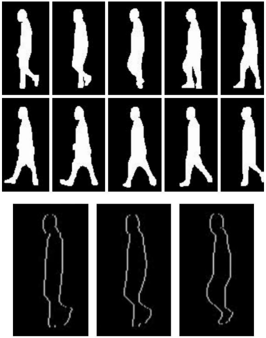
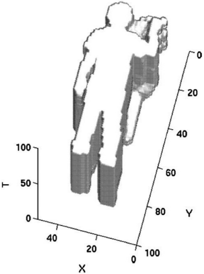
Volumetric Features



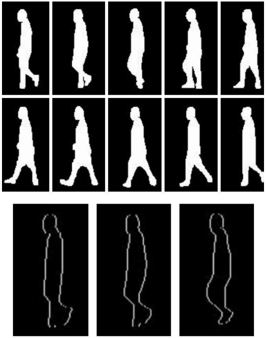
Motion Shapes/Silhouettes

Temporal Template: Motion Energy Image/Motion History Image



Spatio-Temporal Template: motion volumes

Volumetric Features



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Temporal Template:

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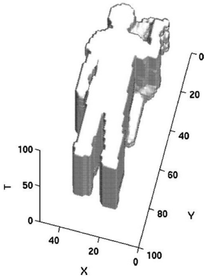

Spatio-Temporal

Template: motion

volumes

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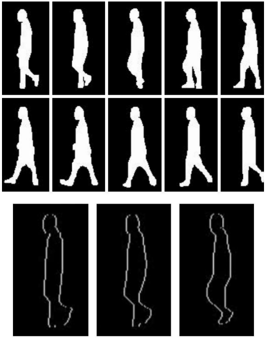

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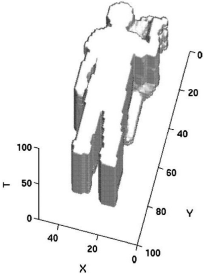

Spatio-Temporal Template: motion volumes

Long-Duration Motion Trajectories as Features

Distinct in video are the motion features, as compared to a single frame. Hence the interest to extract and encode long-duration *Motion Trajectories*.

- Lots of previous work on visual tracking, e.g., KLT
- Visual tracking is normally sparse and unreliable

Target: efficient long-duration (moderately) dense motion estimation to improve upon simple tracking, and application in action/activity analysis

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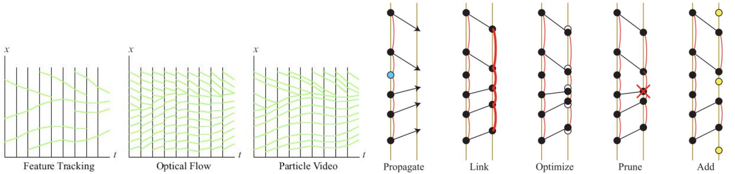
Particle Video



- Particle video algorithm[2] depends upon (expensive) variational optic flow calculations
- Optic flow estimation is less reliable than keypoint tracking.

[2] P Sand and S Teller, "Particle video: Long-range motion estimation using point trajectories". IJCV, 80(1):72 – 91, 2008.

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Initial tracking

$\Downarrow$

Triangulation

$\Downarrow$

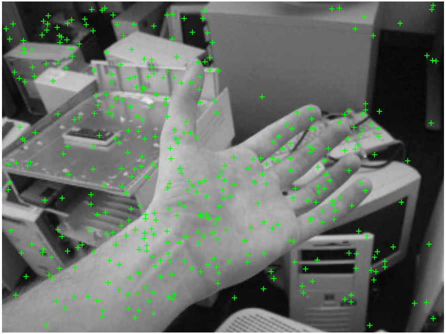
Trajectory Optimization

$\Downarrow$

Tracker Maintenance

Initial Tracking

- SIFT Trackers
  - Blobs and Corners
- KLT Trackers
  - Corners
- Random Trackers
  - Less Structured Regions
  - Connectivity & Density Adaptiveness



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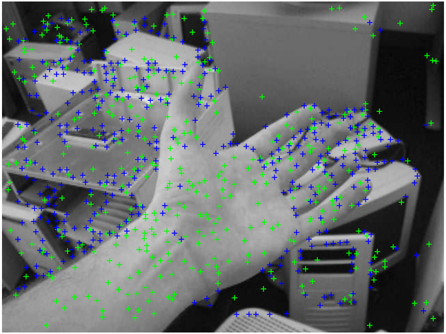

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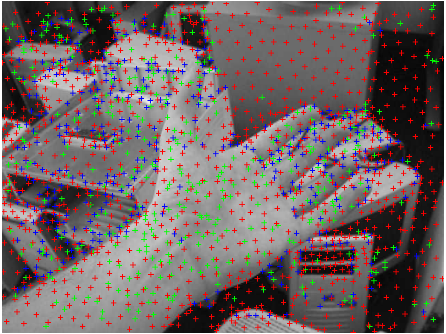

Random Trackers

- Structure-Aware Random Tracker (local gradient variance)
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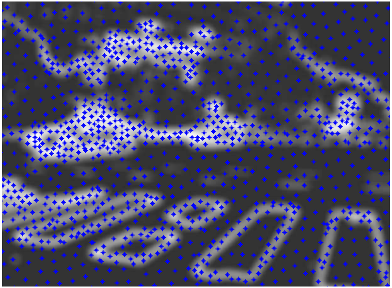
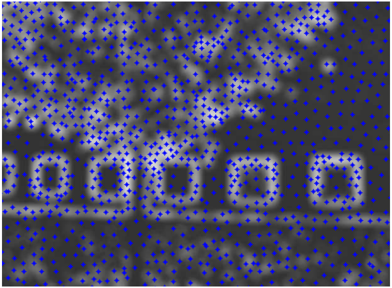
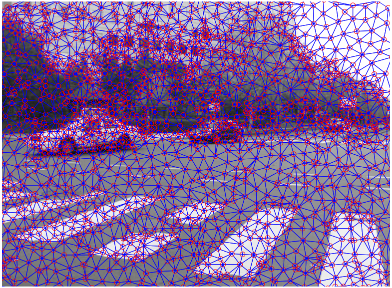
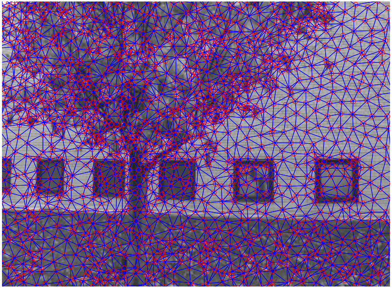




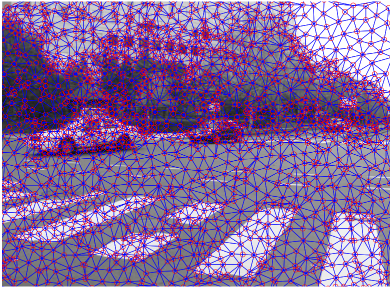
Delaunay Triangulation





Trajectory Optimization

- Goal: to determine and refine the motion vectors $\mathbf{v}$ (from frame t to $t+1$) for each tracker
- The motion vectors for random trackers are initialized with the respective optic flows using the Lucas-Kanade method.



- Quadratic Programming (QP)

$$\min. \sum_{(\mathbf{v}_i,\mathbf{v}_j)\in\mathcal{D}} \omega_{ij}\|\mathbf{v}_i-\mathbf{v}_j\|^2$$

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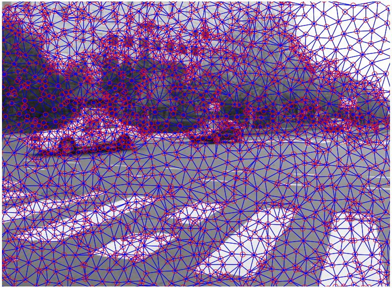

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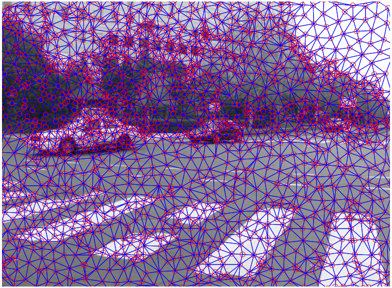

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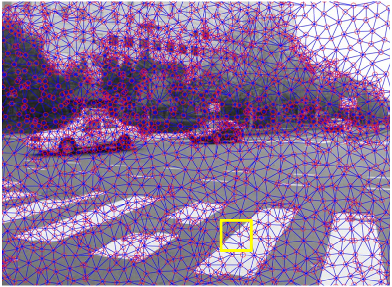

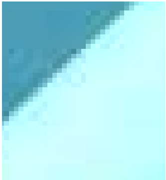

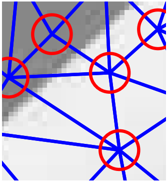

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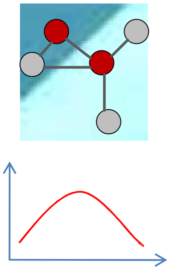

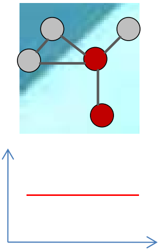

Tracker Addition and Removal

- Tracker Addition
  - Emerging Gaps (e.g., due to occlusions and motions)
  - Lost Trackers (due to appearance changes)
  - Shot Boundaries
- Tracker Removal
  - Mismatches
  - Image Borders
  - Too-Close Trackers
- Straightforward for SIFT and KLT trackers

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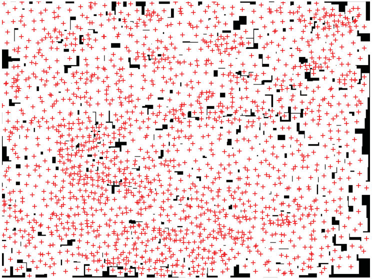
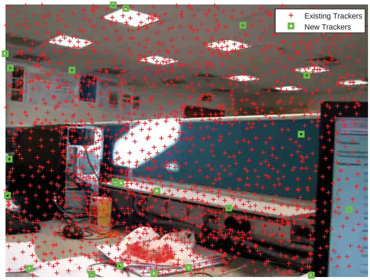
Tracker Addition for Random Trackers

- Calculate the availability map and density map in F_{i+1}
- Sample candidate random trackers in F_{i+1}
- Select only trackers within the available region





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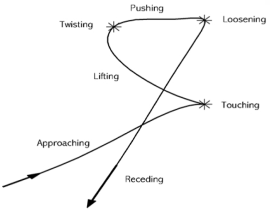
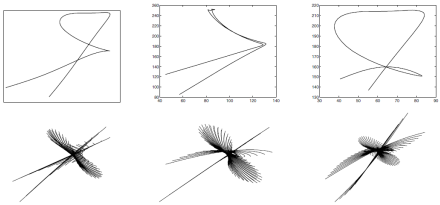
Description of Trajectories: Prior Approaches

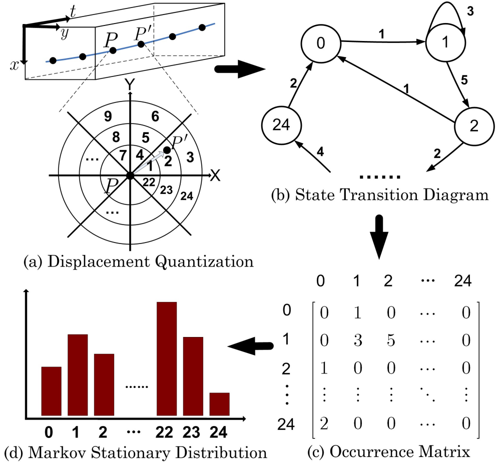


Dynamic Instants



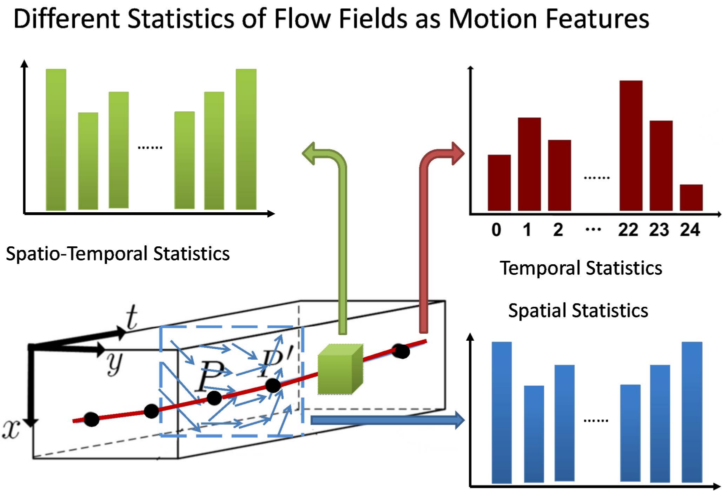
Star Diagrams

Description of Trajectories: Our Prior Approach



Stationary distribution of Quantized Markov Chains

Temporal Quantization and Averaging



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Discrimination on KTH

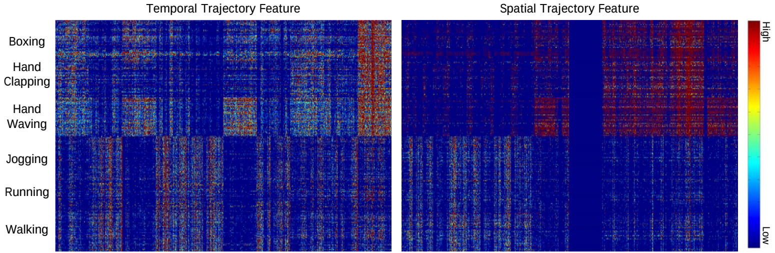

Figure: Visualization of codewords for all KTH video clips. Each row corresponds to a video clip, and those related to the same actions are stacked adjacently.

Performance Figures

- Holistic Bag-of-Features quantization and statistics
- Multiclass SVMs for classification with intersectional kernels
- Feature Combination by simple kernel averaging

Table: Performance of action recognition over all valid training/testing configurations. The first three methods are based on our proposed features. (accuracy±deviation)

Method	Average Accuracy (%)
Spatial Feature	81.3 ± 9.51
Temporal Feature	83.1 ± 7.22
Spatial&Temporal Feature	86.8 ± 10.7
Method by STIP	71.7 ± 16.7

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Summary

- A proposal for extracting dense trajectories
- A simplistic representation
- Experimental validation

Challenges in activity analysis

- Representation
- Information Fusion
- ROI Search
- Large-scale problem solving

Thank you!