Leibniz Universität Hannover

Temporally Consistent Superpixels

ICCV 2013 Paper

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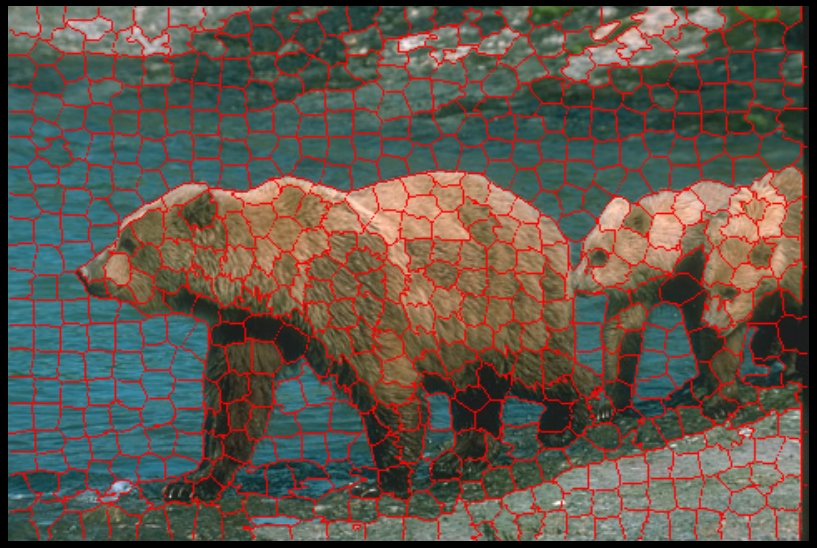
technicolor

Introduction

Original

Boundary image



Label map

Average map

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SLIC Superpixels

- Introduced by Achanta et al. [1]
- Pixels are viewed as data points in a 5D feature space [labxy]
- Superpixels form clusters in this 5D feature space and are represented by cluster centers
- Cluster analysis by minimizing the energy term [2]

$$E_{total}(\Delta) = \sum_{n \in \mathcal{N}} (1-\alpha) E_{color}(n, \delta_n) + \alpha E_{spatial}(n, \delta_n)$$

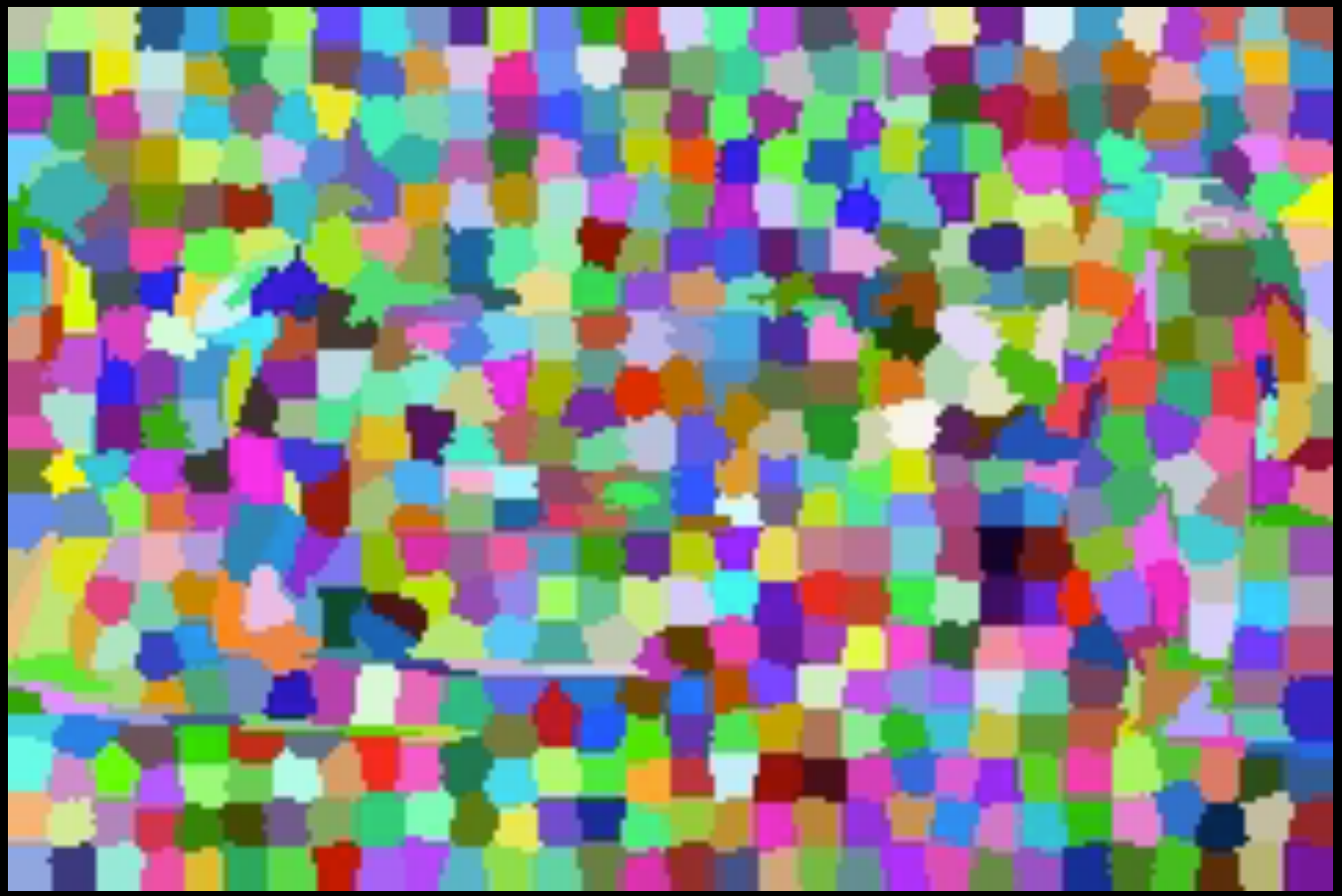
- Energies E_{color} and $E_{spatial}$ are proportional to Euclidean distances
- Optimization by employing an Expectation-Maximization-scheme

[1] Achanta, Shaji, Smith, Lucchi, Fua, and Susstrunk. SLIC superpixels compared to state-of-the-art superpixel methods. TPAMI, 34(11):2274–2282, 2012

[2] Schick, Fischer, and Stiefelhagen. Measuring and evaluating the compactness of superpixels. In ICPR, 930–934, 2012

Introduction

First Challenge: Temporal Consistency



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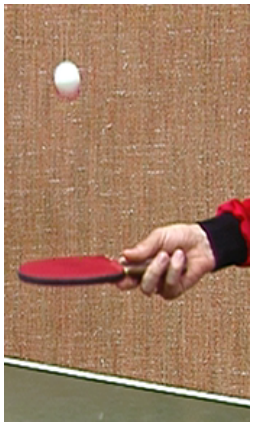
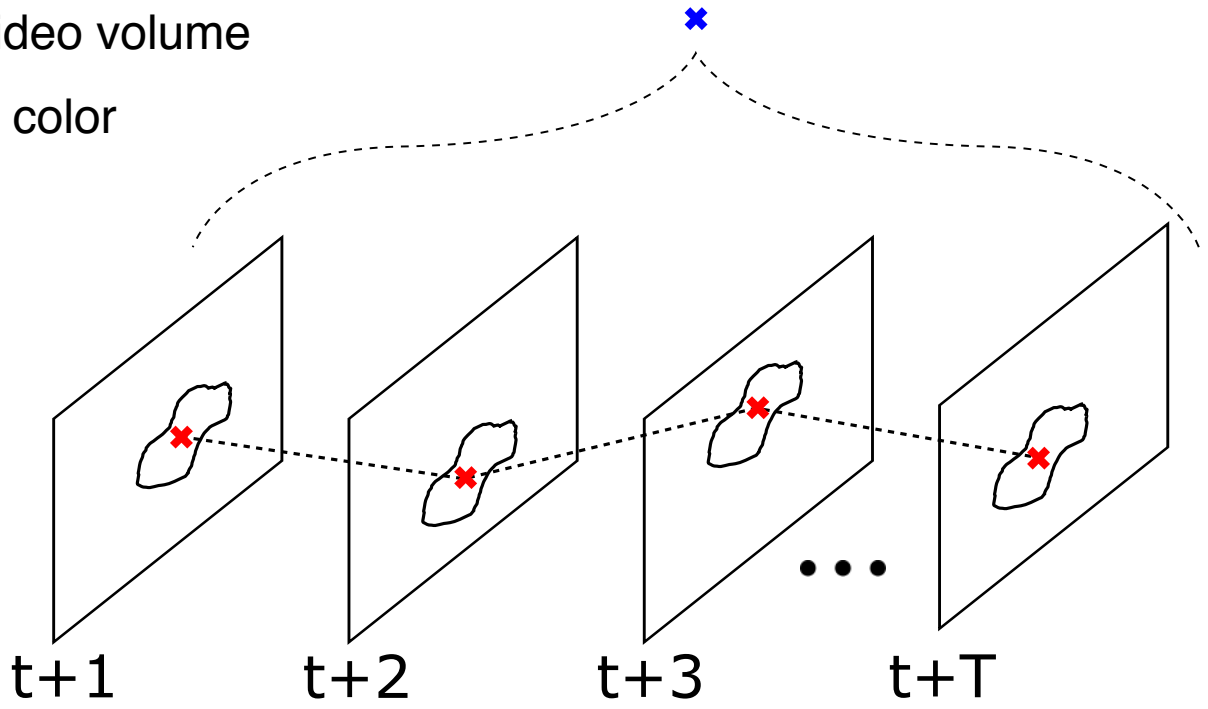
Basic Idea

- Extend SLIC to the video volume
- We assume constant color
- But we can't assume constant position

Frame t



Frame t + 1



1 Global Color Center

T Local Spatial Centers

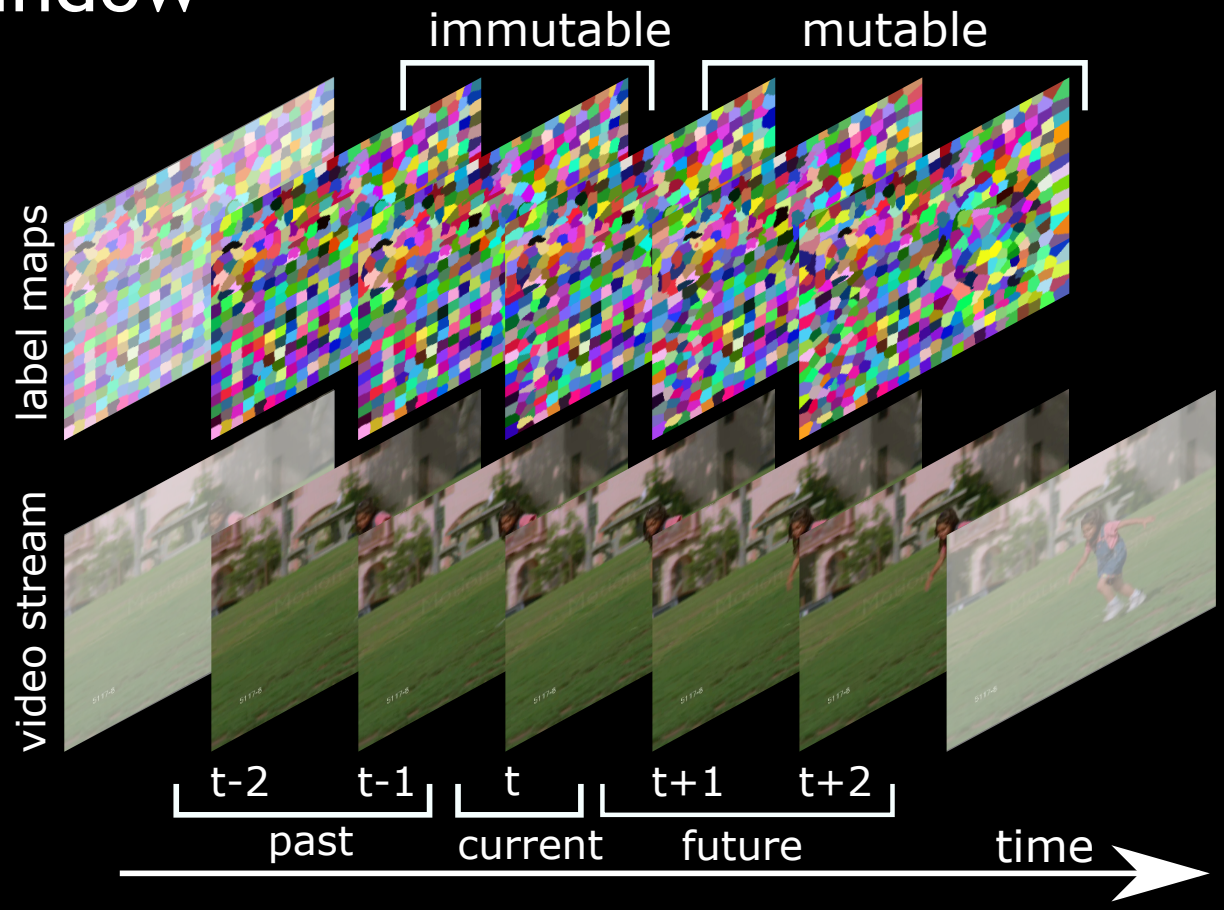
Extended Energy Term

- Minimization over multiple-frames

$$E_{New}(\Delta) = \sum_{\tau \in \mathcal{T}} \sum_{n \in \mathcal{N}(\tau)} (1-\alpha) E_{color}(n, \delta_n) + \alpha E_{spatial}(n, \delta_n, \tau)$$

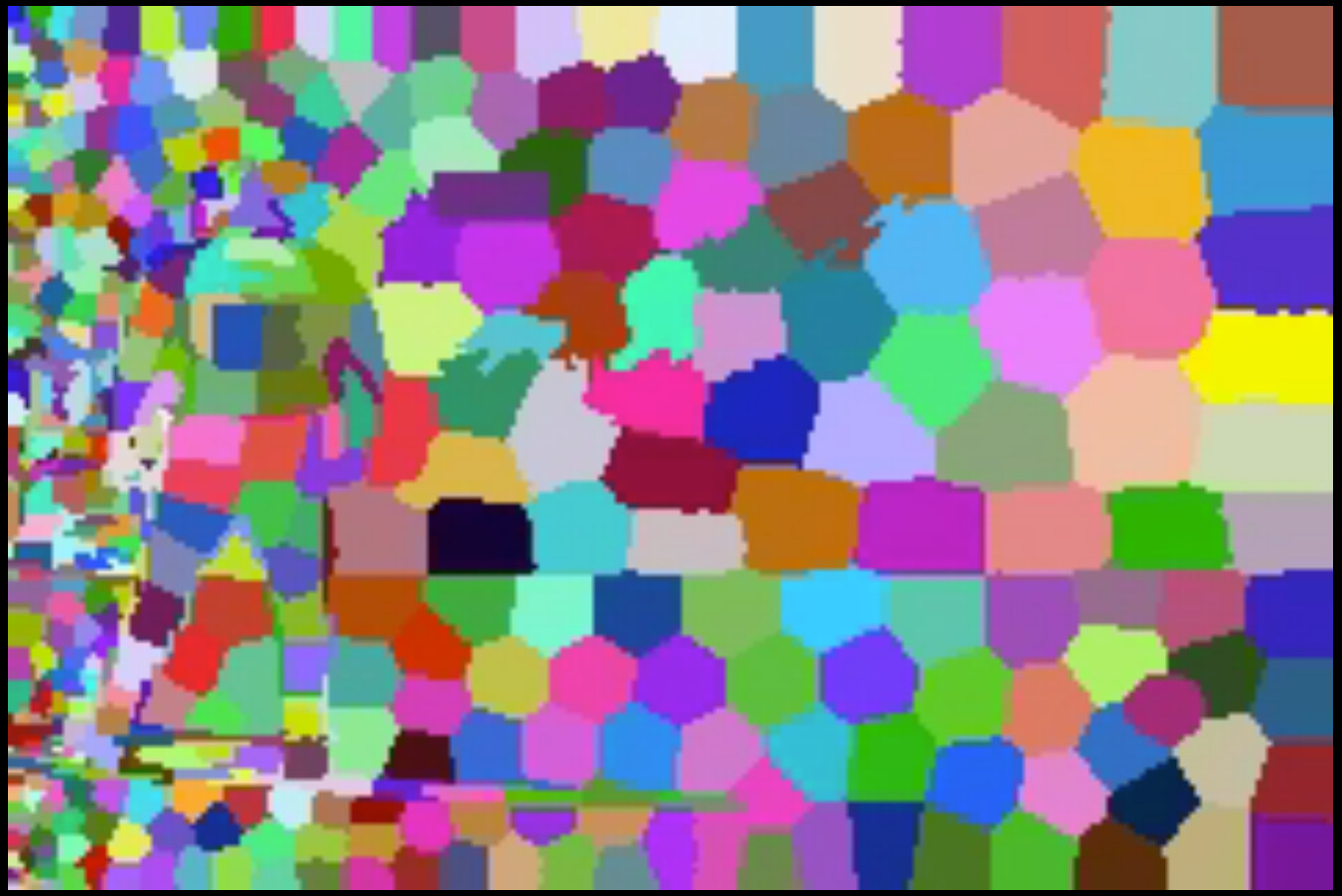
- Energy $E_{spatial}$ now depends on frame τ
- A sliding window is introduces to allow
  - Streaming capabilities
  - Gradual illumination changes

Sliding Window



– New frames are initialized using the optical flow

Further Challenge: Handling of Structural Changes



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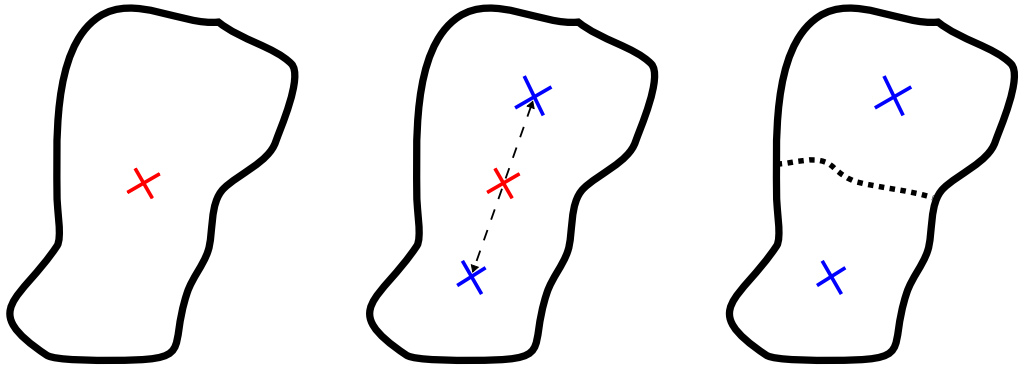
Structural Changes and Spatial Coherency

- Monitor superpixel size inside sliding window
- Extrapolation based on linear growth assumption
- Balanced splitting and termination of superpixels



- Ensuring spatial coherency by a new contour evolution based post-processing step

Benchmarks

- Comparison to
  - SLIC supervoxel approach of Achanta et al. [1]
  - Streaming Hierarchical Video Segmentation of Xu et al. [3]
- Quantitative results on Chen's dataset [4]
  - 3D Undersegmentation Error [5]
  - Mean Temporal Length [5]

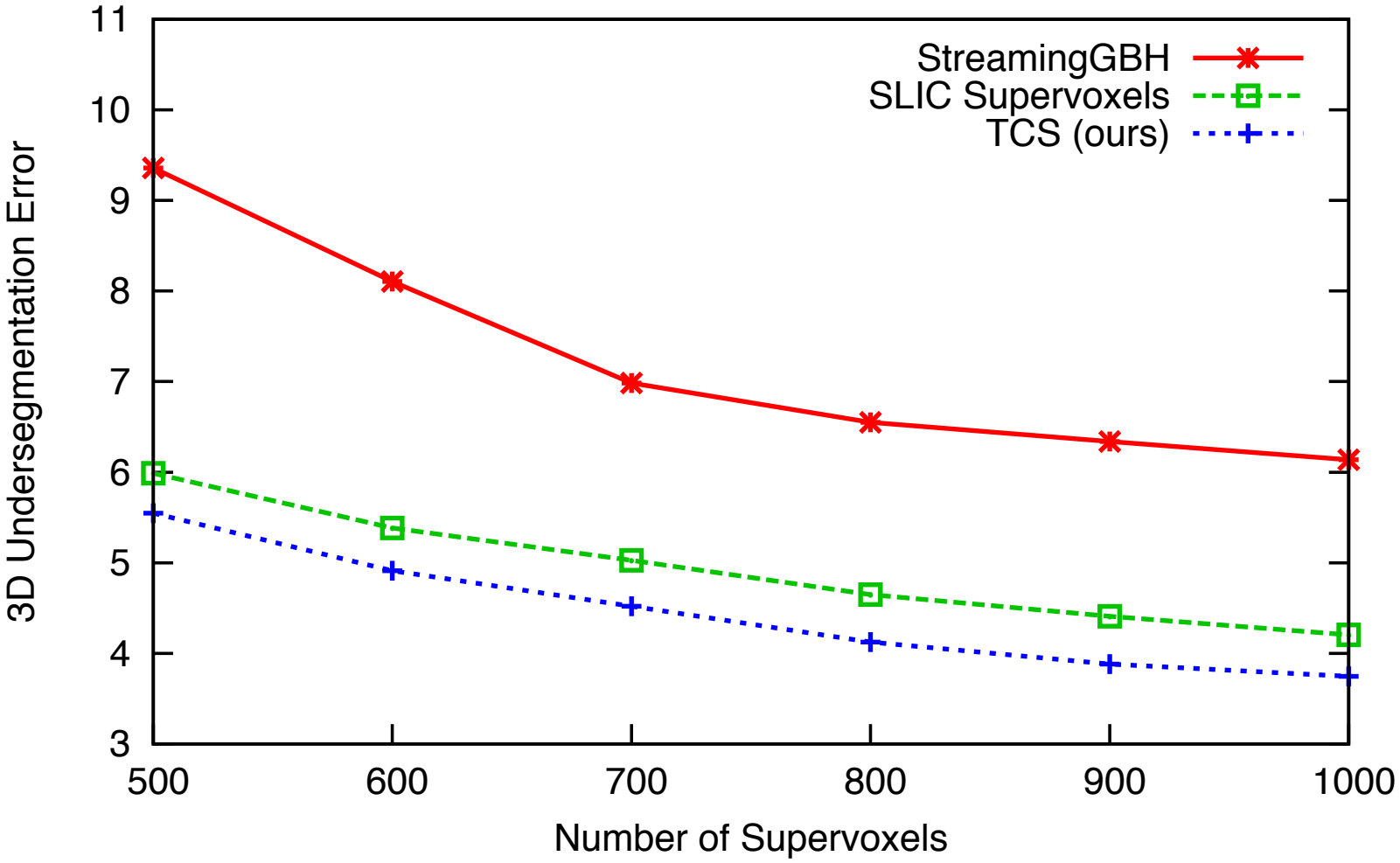
[1] Achanta, Shaji, Smith, Lucchi, Fua, and Susstrunk. SLIC superpixels compared to state-of-the-art superpixel methods. TPAMI, 34(11):2274–2282, 2012

[3] Xu, Xiong, and Corso. Streaming hierarchical video segmentation. In ECCV, pages 626–639, 2012

[4] Chen and Corso. Propagating multi-class pixel labels throughout video frames. In WNYIPW, pages 14–17, 2010

[5] Calculated using LIBSVX http://www.cse.buffalo.edu/~jcorso/r/supervoxels/

3D Undersegmentation Error



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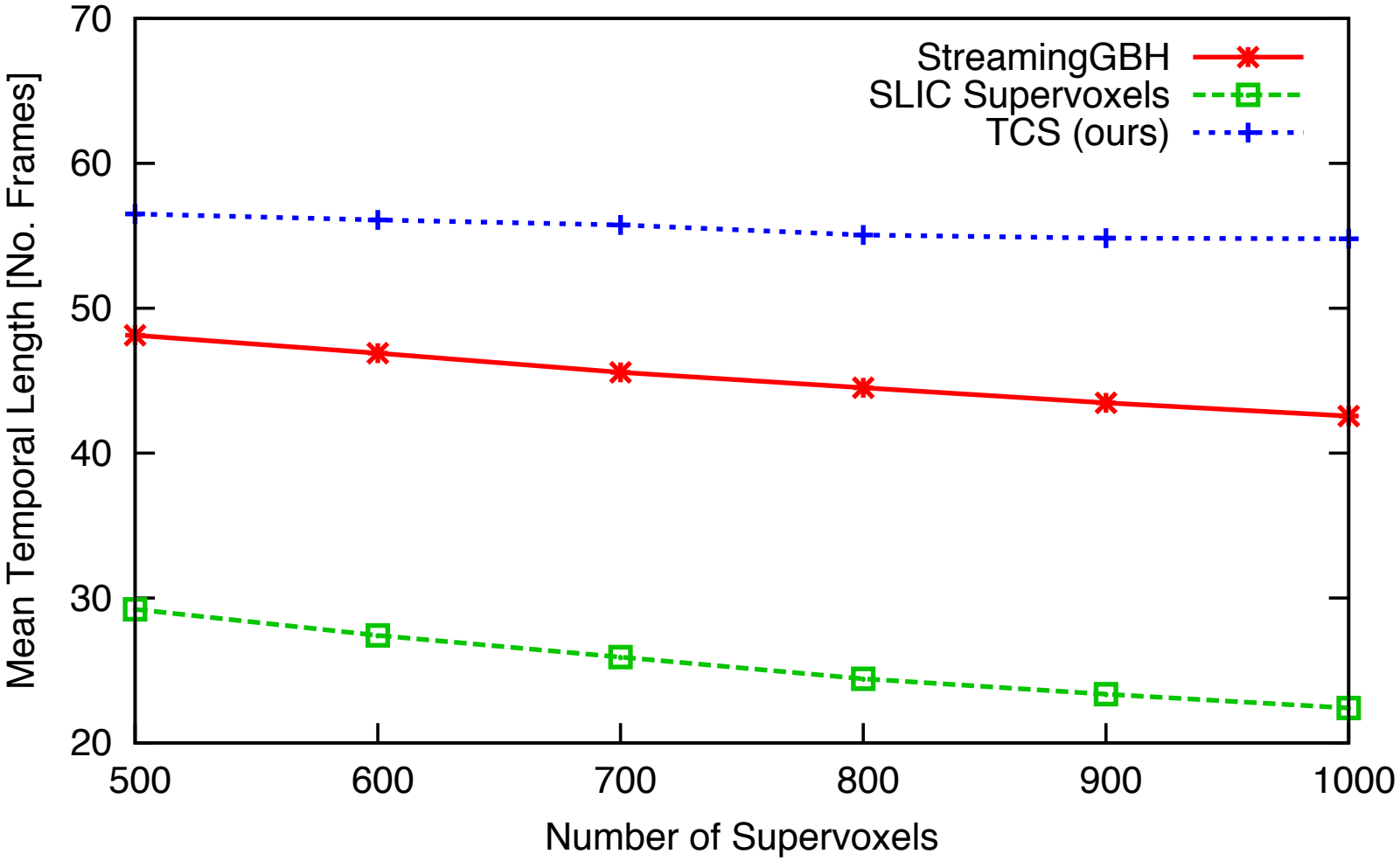
Mean Temporal Length



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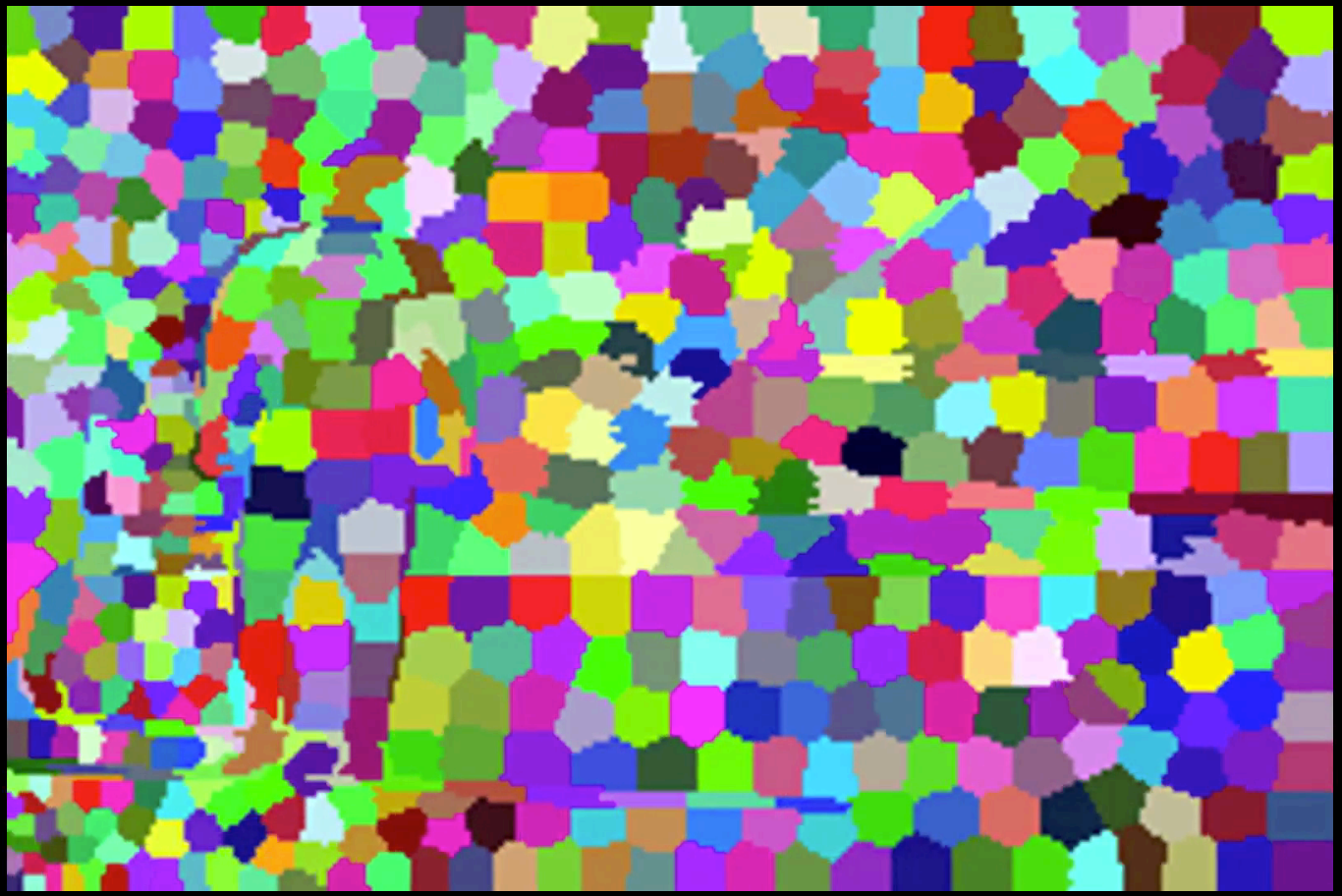
Qualitative Results



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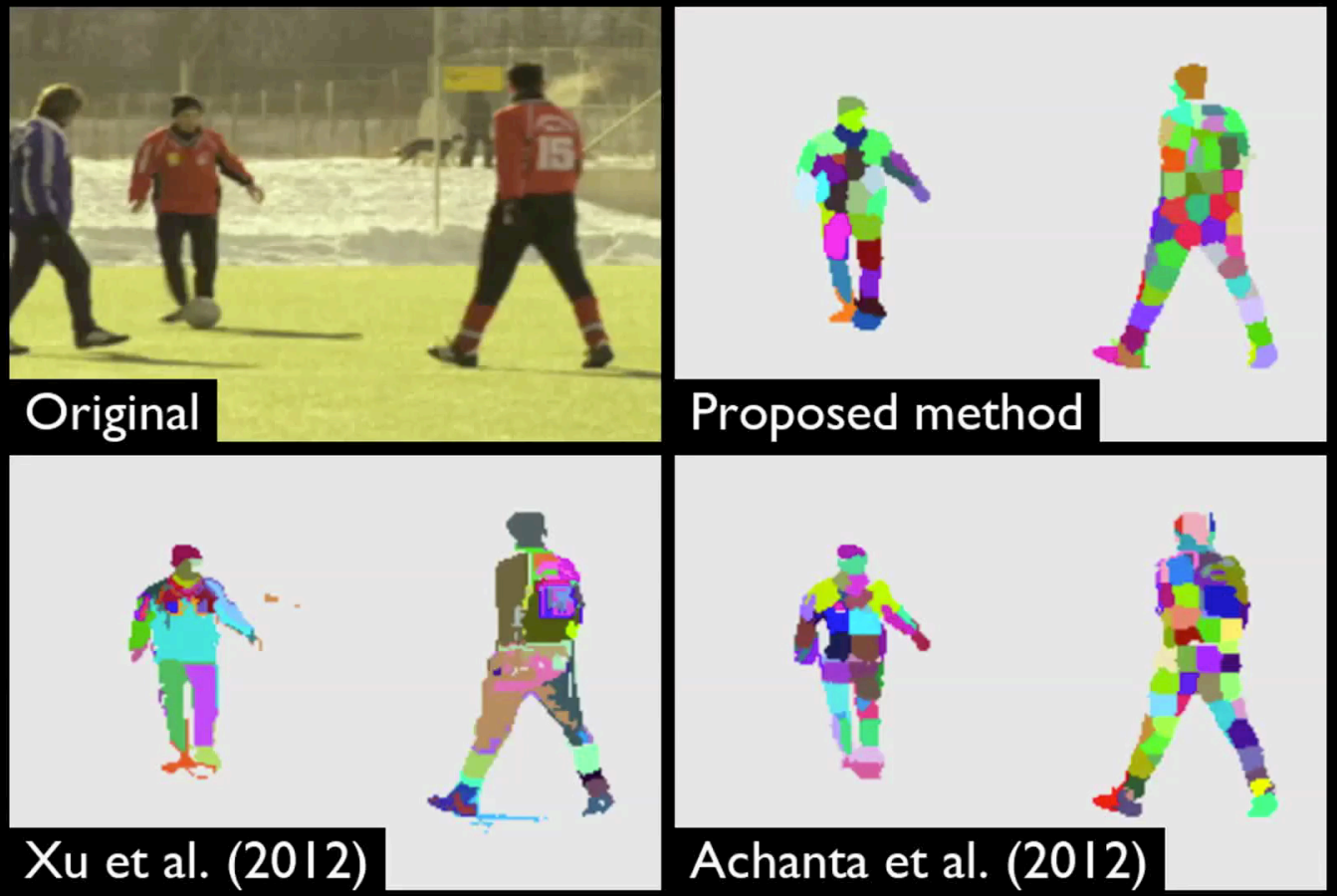
Qualitative Results



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Summary

- Hybrid clustering approach working on the video volume
  - Global color cluster centers
  - Local spatial cluster centers
- Sliding window to enable streaming capabilities
- Handling of structural changes
- Improved 3D undersegmentation error and mean temporal length