Geodesic Distance Histogram Feature for Video Segmentation

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Introduction

-Similarity distances are essential to clustering algorithms, computed from multiple feature types

-Video Segmentation algorithms often rely on **appearance-based, motion-based,** and **shape-based** features.

The similarity distance is computed using only local superpixel features, extracted from within each superpixel.

In this paper, in additional to local features, we use geodesic distance histogram features. They:

- compactly encode **global** similarity relations
- can be used to associate superpixels both **within** and **across** frames
- are **fast** to compute.

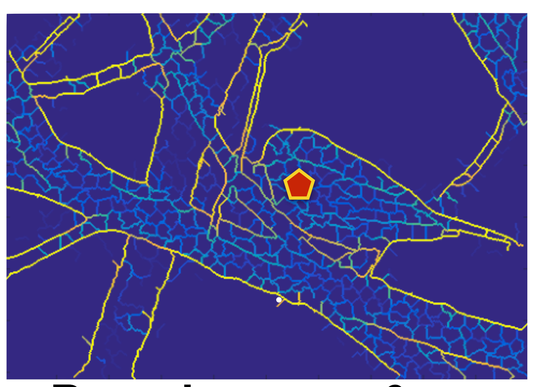
These features can be used for matching, tracking as well.

Geodesic Distance Histogram Feature

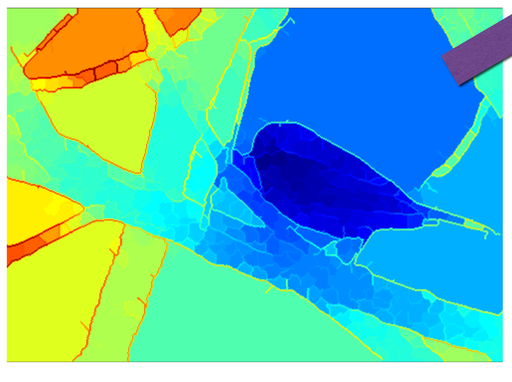
Given **a boundary probability map** [6] and **a superpixel segmentation** of an image, a graph ***G*** is defined as:

- Each node is a superpixel.
- Each edge connects adjacent superpixels.
- The edge weight is the likelihood of an object boundary between two adjacent superpixels, computed from the boundary probability map

Geodesic Distance between two superpixels: The shortest path between two superpixels in ***G***



Boundary map & a superpixel-of-interest



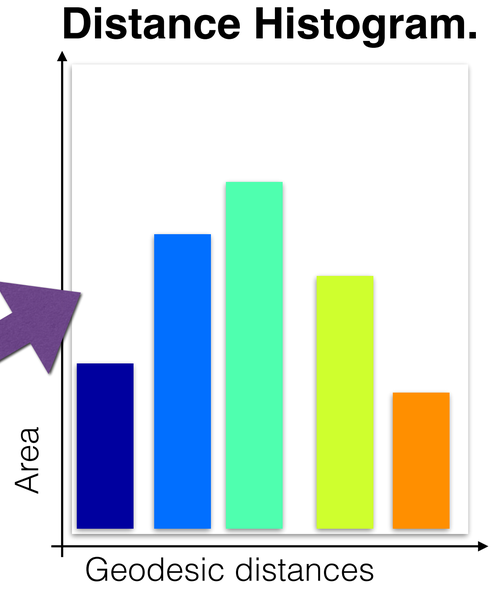
Geodesic distances from the superpixel-of-interest to other superpixels

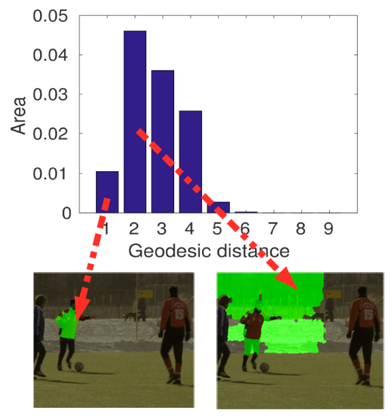
small geodesic distance

large geodesic distance

Geodesic Distance **Histogram** of **a superpixel**: the distribution of the geodesic distances from the superpixel to all other superpixels.

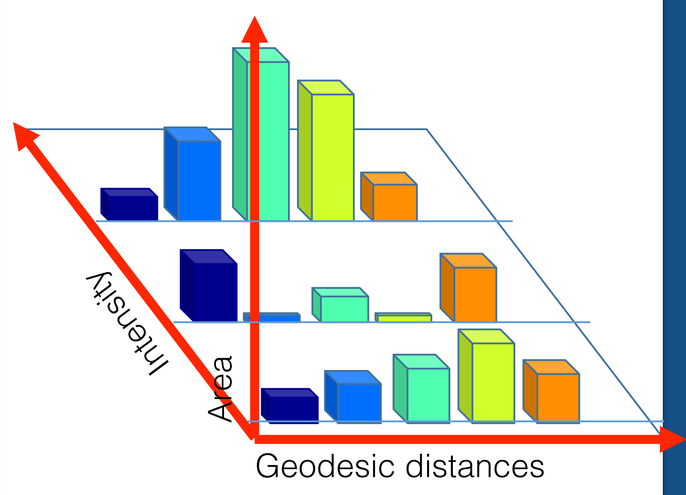
1D Geodesic Distance Histogram.

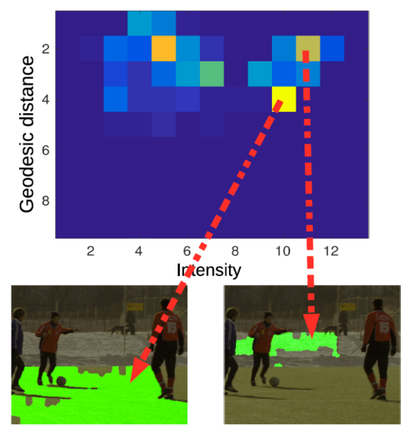




1D Histogram

2D Geodesic Distance - Intensity Histogram.





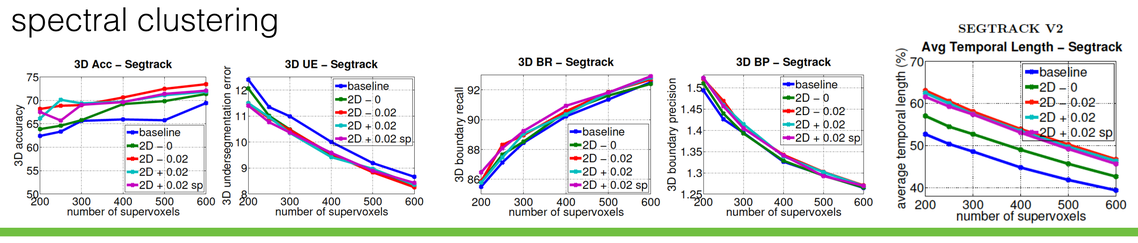
2D Histogram

Spatial distance voting Weight: $weight_y = \frac{|y|}{|f|} \times \exp(-\mu \times L_2(x, y))$

Experiments

We incorporated our features into two existing video segmentation frameworks: spectral clustering [1] and parametric graph partitioning [2] on Segtrack V2 [3] and Chen Xiph.org [4] datasets.

spectral clustering



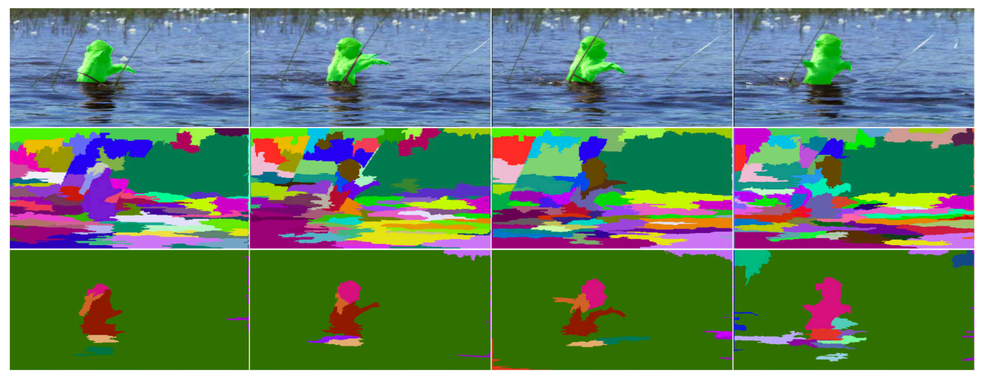
PGP

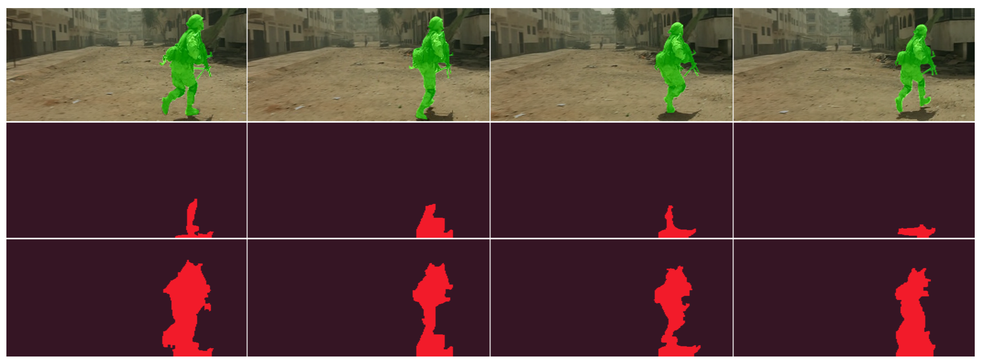
lower is better

Metrics	3D ACC			BR3D			BP3D			UE3D		
Methods	PGP[2]	2D	2Dsp	PGP[2]	2D	2Dsp	PGP[2]	2D	2Dsp	PGP[2]	2D	2Dsp
SegTrack V2	84.16	83.26	**86.86**	84.25	86.45	87.24	2.55	2.23	2.12	10.39	7.4	**6.8**
Chen Xiph.org	77.62	77.25	**80.83**	67.43	67.74	70.47	16.66	17.77	17.4	12.99	19.34	**12.8**

-Better numbers on all 4 benchmarks [5].
-Enhanced temporal consistency.

Qualitative examples





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References

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