Medial Features for Superpixel Segmentation

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Summary

We present a novel algorithm that segments an image into superpixels employing a new kind of shape centered feature which serve as seed point for image segmentation, and which are derived from Gradient Vector Flow fields (GVF) [1]. The features are located at image locations with salient symmetry, denoted by singularities in the vector field. We compare our algorithm to state-of-the-art superpixel algorithms and demonstrate a performance increase on the standard Berkeley Segmentation Dataset.

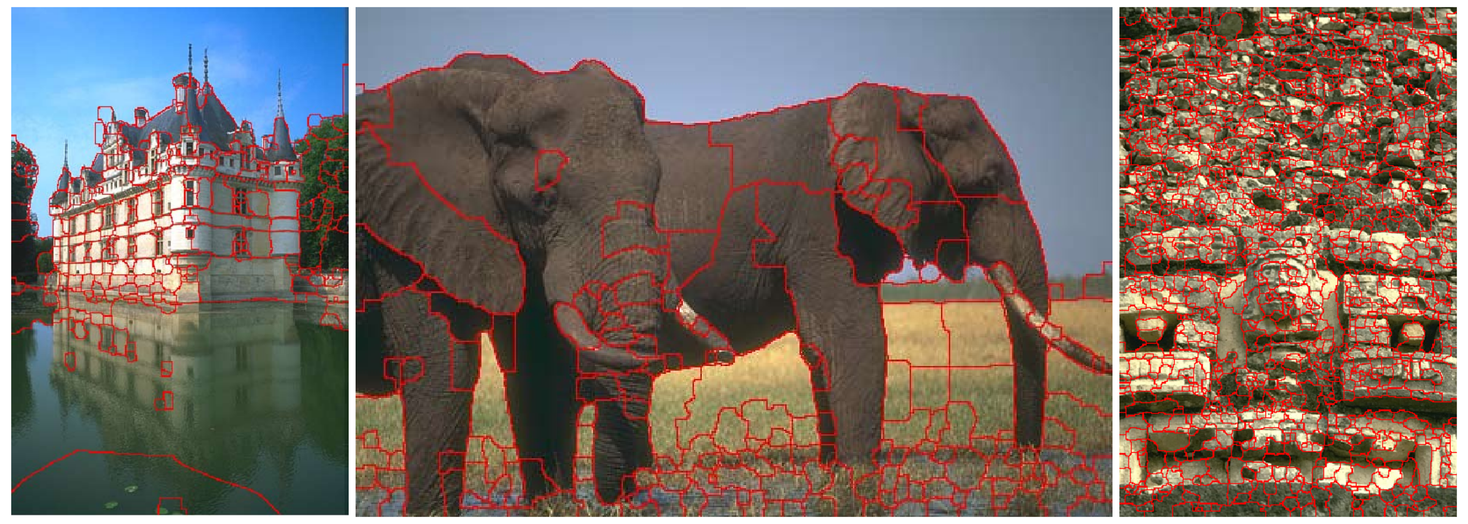


Image oversegmentation is a common technique to overcome the problem of managing the high number of pixels and the reasoning among them. Specifically, a superpixel is denoted as a local and coherent cluster that contains a statistically homogeneous region.

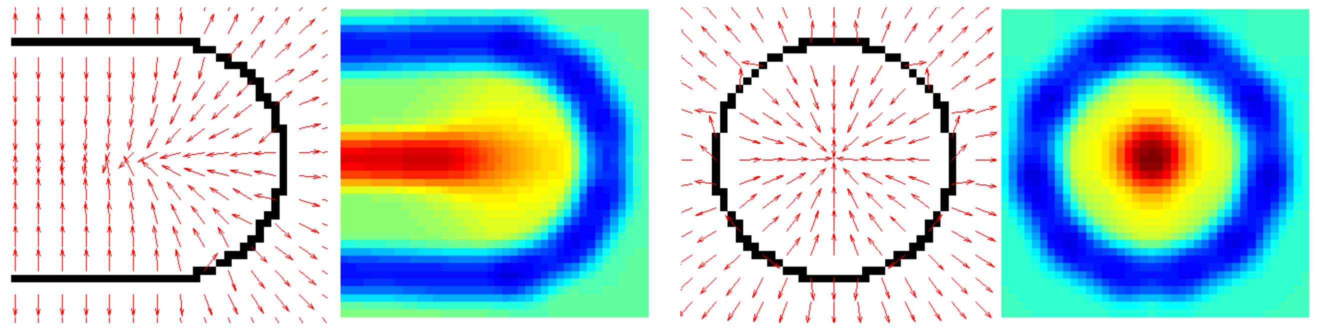
Medial Features

We use a novel medial feature transform [6] based on GVF fields. The GVF is the result of a simulated diffusion process minimizing the following functional:

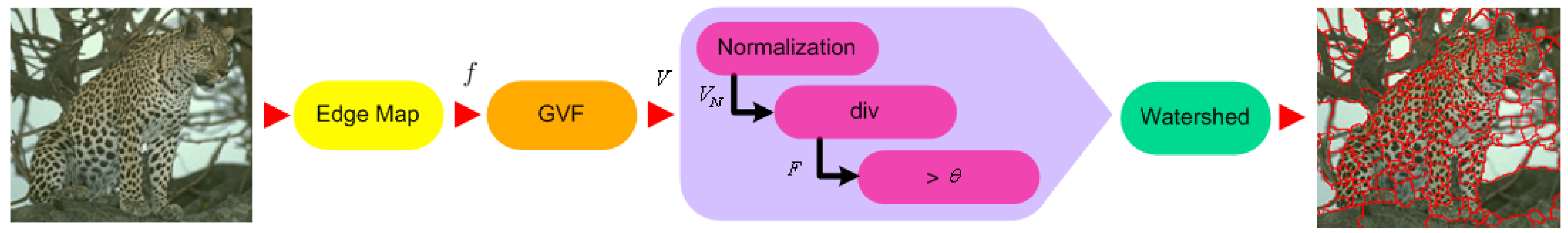
$$\mathcal{E} = \int\int \underbrace{g\left(|\nabla f|\right)|V - \nabla f|^2}_{\text{data term}} + \underbrace{h\left(|\nabla f|\right)\nabla^2 V}_{\text{smoothing term}}\, dxdy$$

We compute the flux flow of the normalized GVF field using a ring integral. The resulting medial feature map is stable against noise and clutter thanks to the GVF framework and offers a compact way to describe shape in clutter.

$$div\, V_N = \mathcal{F}\left(V_N\left(p\right)\right) = \frac{\oint \langle V_N, \mathcal{N}\rangle\, ds}{Area}$$



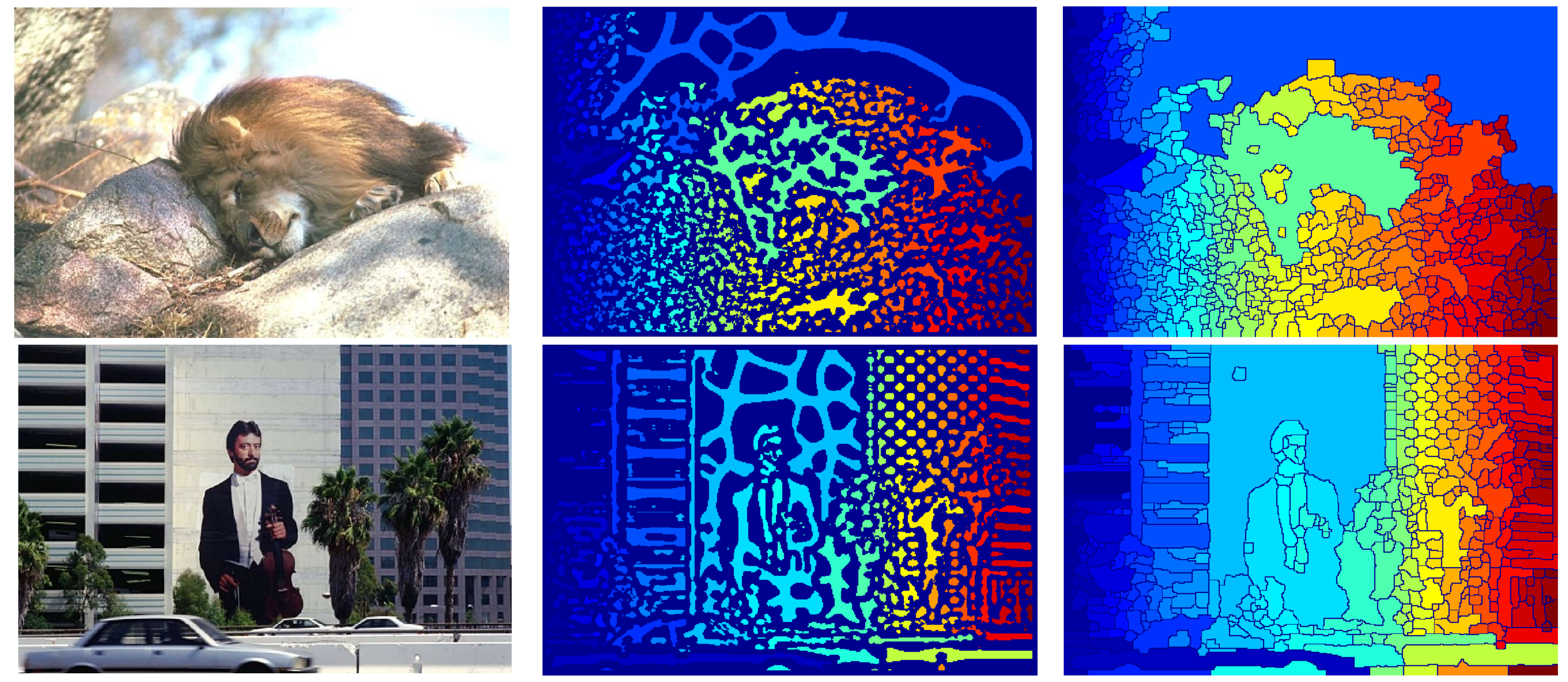
GVF fields and flux flow at characteristic structures



Medial Feature Oversegmentation Pipeline

Superpixel Segmentation Pipeline

The pipeline extracts superpixels starting from an edge map. We compute the normalized GVF and obtain the Medial Feature Map by computing the flux flow at each pixel in the image resulting in a flux flow map. Thresholding the flux yields the seeds for the final watershed segmentation. The watershed is performed employing the flux flow as a height map.



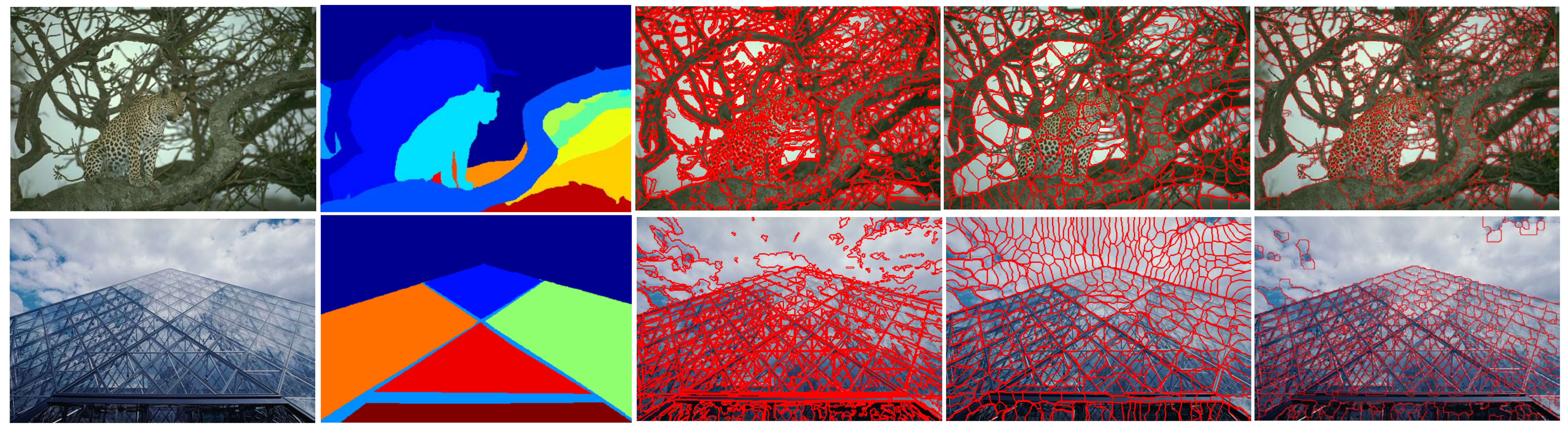
Images, seeds (F > Theta, clustered) and superpixel

Performance Evaluation

We compared our method to the superpixel algorithms based on pixel similarities [4] and GraphCuts [2]. We use human segmented images from the Berkeley Segmentation Dataset [5] and investigated how well the superpixels created by the algorithms are suited to recreate the human generated segments. Our algorithm outperforms the two state-of-the-art methods. Neither, the number of segments must be fixed [4], nor ragged boundaries are produced as in [2].

$$P = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M_i}\hat{S}_{i,j}}{\sum_{i=1}^{N} M_i S_i}$$

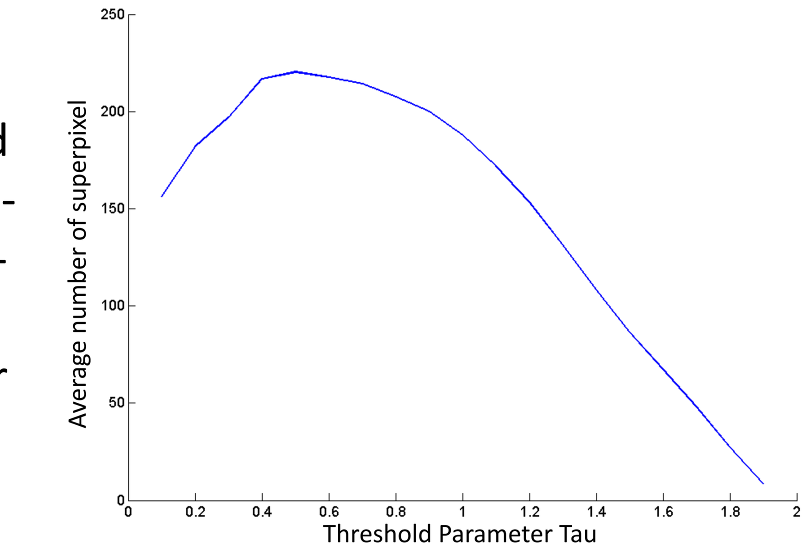
Medial Feature Superpixel	0.88
Ren et al. [10]	0.86
Felzenszwalb et al. [4]	0.83
Watershed on Distance Transform	0.79

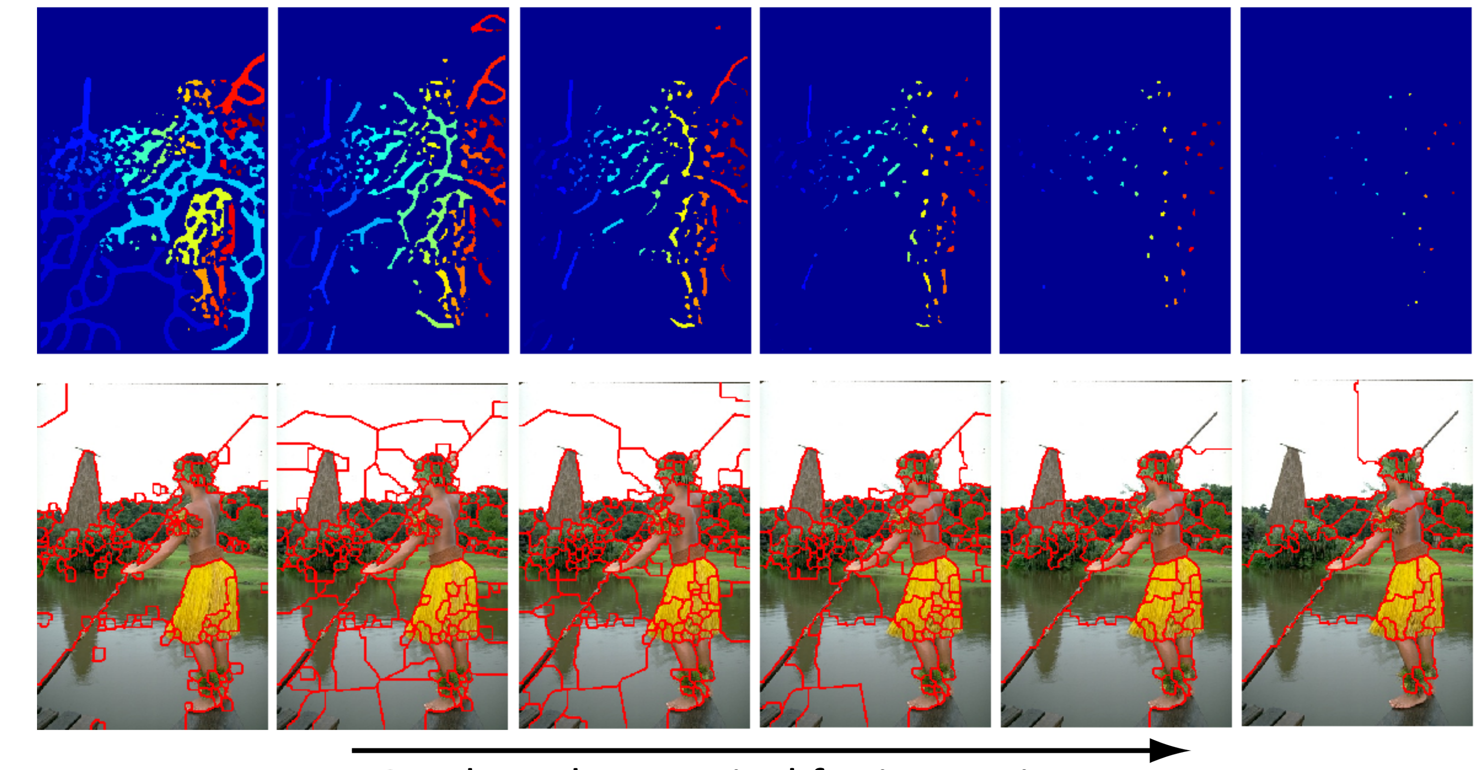


Comparison of superpixel algorithms: Original, human segmentation, segmentations after [2], [4] and our method

Number of Superpixel

The number of superpixels depends on the chosen threshold parameter Tau and the edge operator used for the GVF computation. Average number of created superpixels on Bekeley Database shown in Figure to the right. The absolute number can not be controlled but scales with image content.





Seeds and superpixel for increasing Tau

Outlook

The superpixels obtained by this scheme can be a valuable basis for efficient image encoding of real world images. As they are based on shape centered medial features they can be computed efficiently and thus they can prove useful for a multitude of computer vision problems such as object classification and tracking.

Image reconstruction based on mean color of each superpixel segment

References

[1] C. Xu and J. Prince. Snakes, shapes, and gradient vector flow. IEEE Press 1998
[2] X. Ren and J. Malik. Learning a classification model for segmentation, ICCV 2003
[4] P.Felzenswalb and D. Huttenlocher. Efficient graph-based image segmentation. IJCV 2004
[5] D. Martin, C. Fowlkes, D. Tal, and J. Malik. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. ICCV 2001
[6] D. Engel and C. Curio. Scale-invariant medial features based on gradient vector flow fields. ICPR 2008