Towards robust scene analysis: A versatile mid-level feature framework

David Engel {david.engel@tuebingen.mpg.de} and Cristóbal Curio
Max Planck Institute for Biological Cybernetics
Spemannstr. 38, 72076 Tübingen, Germany

Max-Planck-Institut für biologische Kybernetik

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Summary

We present a novel set of shape-centered interest points. The interest points are formed at locations of high local symmetry. Our symmetry detection is based on Gradient Vector Flow (GVF) [1] fields which provide a high level of stability against noise. The shape centered interest points allow for a robust scale and orientation estimation. We have shown their usefulness for image encoding and superpixel segmentation and demonstrat that they carry information that is to a certain degree complementary to corner based interest points.

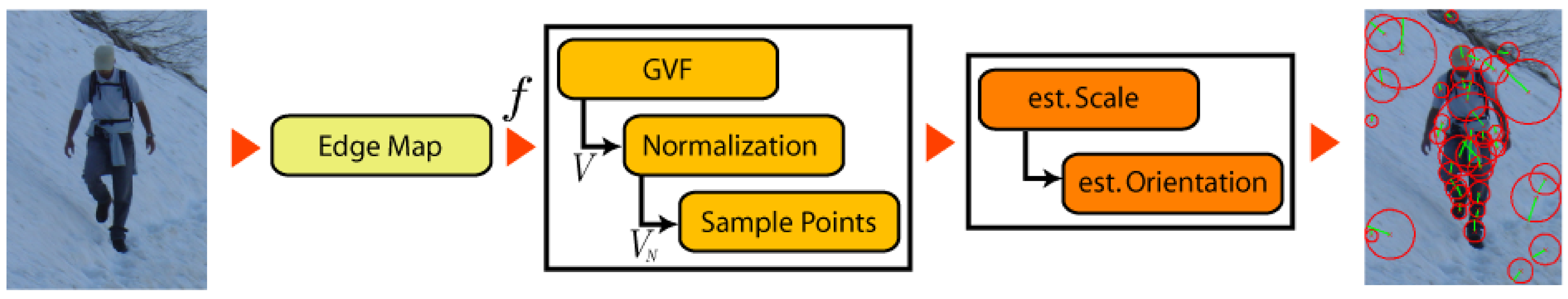

Figure 1: Feature extraction pipeline including scale and orientation estimation [3]

Medial features

We have derived a new set of shape-centered features [2] based on GVF fields [1]. The GVF is the result of optimizing the following functional with respect to the vector field V(x,y):

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

Our proposed shape transform computes the flux flow of the normalized flow field using a ring integral on the normalized solution to the functional at each image locations rendering locations of high symmetry.

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

The resulting medial features form at singularities of the GVF field and owe their stability against noise to the above optimization and are not affected by 'background clutter'.

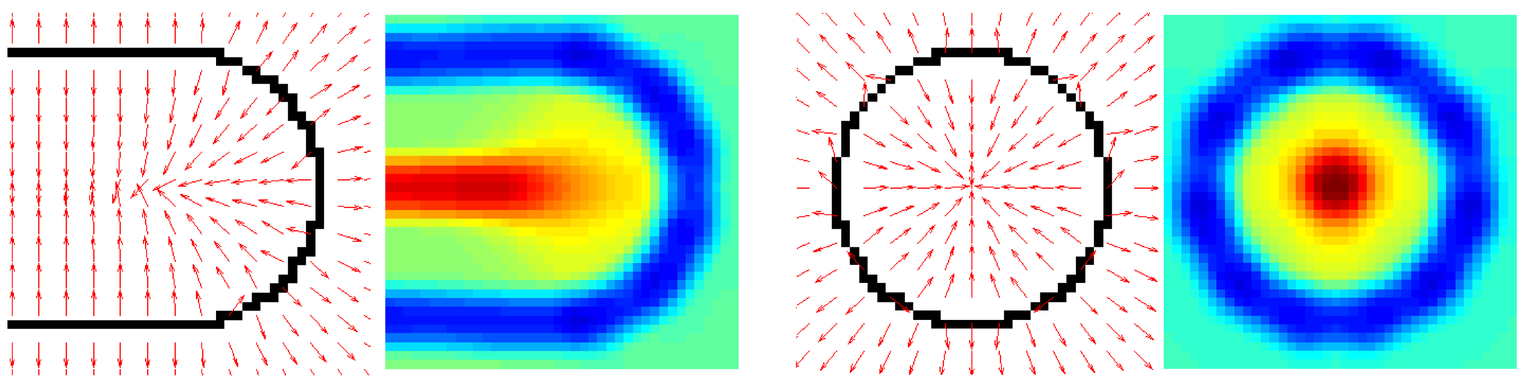

Figure 2: GVF fields and flux flow for typical shape elements [2]

Scale and orientation

At local flux flow extrema we do a scale search with a growing disc. We define a stop criterion by integrating shape boundaries while taking the GVF orientation into account. We find the major orientation at the local scale by taking the direction of the first principal component of the thresholded flux flow field. This robust rotation and scale estimation procedure provides features which are invariant to scaling

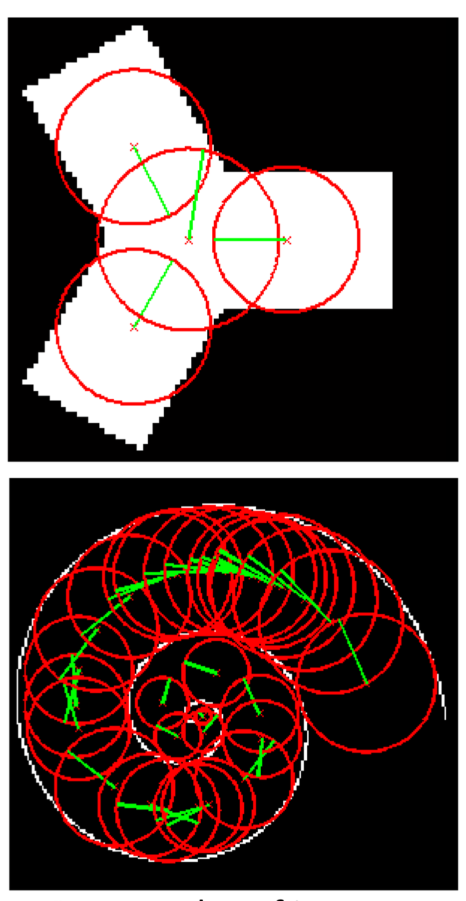

Figure 3: Examples of interest points with local scale and orientation

Robustness against noise and clutter

Our novel shape-centered interest points (SCIPs) are formed by shape boundaries and, therefore, are not affected by the background clutter. Since our features are obtained by a PDE diffusion approach they are robust against noise.

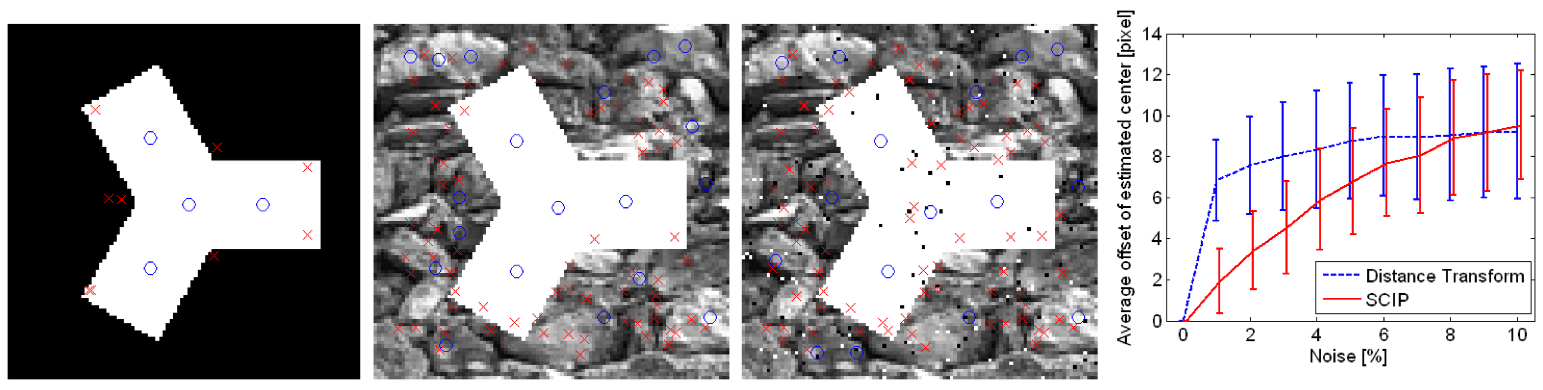

Figure 4: Shape-centered (blue) and corner (red) interest point repeatability in noise and clutter

Superpixel segmentation

Our novel shape transform also offers the opportunity to initialize a segmentation process [3]. We use the thresholded flux flow field to generate well-structured seeds for a watershed method. We employ the noise-suppressed and edge-enhanced flux flow field as a height map for the watershed method.

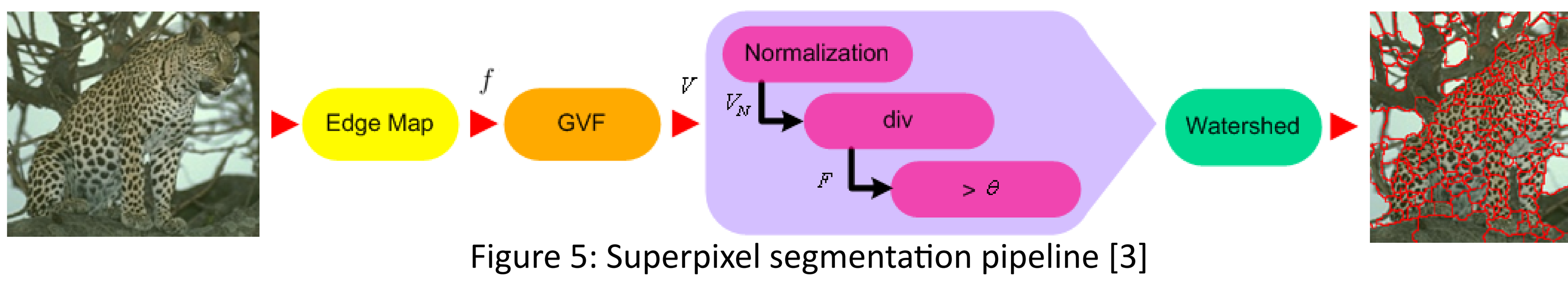

Figure 5: Superpixel segmentation pipeline [3]

The number and structure of the the resultuing superpixels can be controlled by the threshold parameter Θ. We showed that our superpixel algorithm performs closer to human-generated segmentations than state-of-the-art algorithms.

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

Our Algorithm	0.88
Ren et al.	0.86
Felzenszwalb et al.	0.83
Watershed	0.79

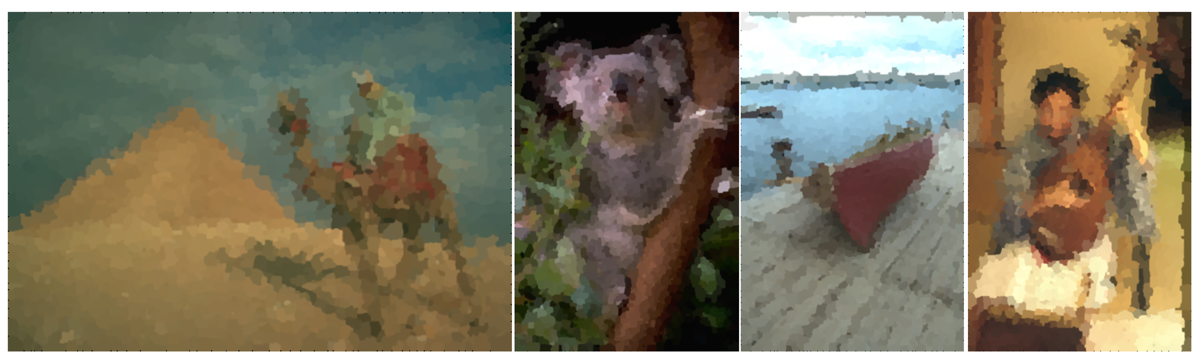

Figure 6: Superpixel Segmentation: Performance measure, results and reconstruction examples [3]

Combination of shape-centered and corner-based interest points

Corner-based and shape-centered interest points encode complementary information. Edge map reconstruction from codebooks of visual words extracted at medial and corner interest points outperforms reconstruction based on just one type of codebook.

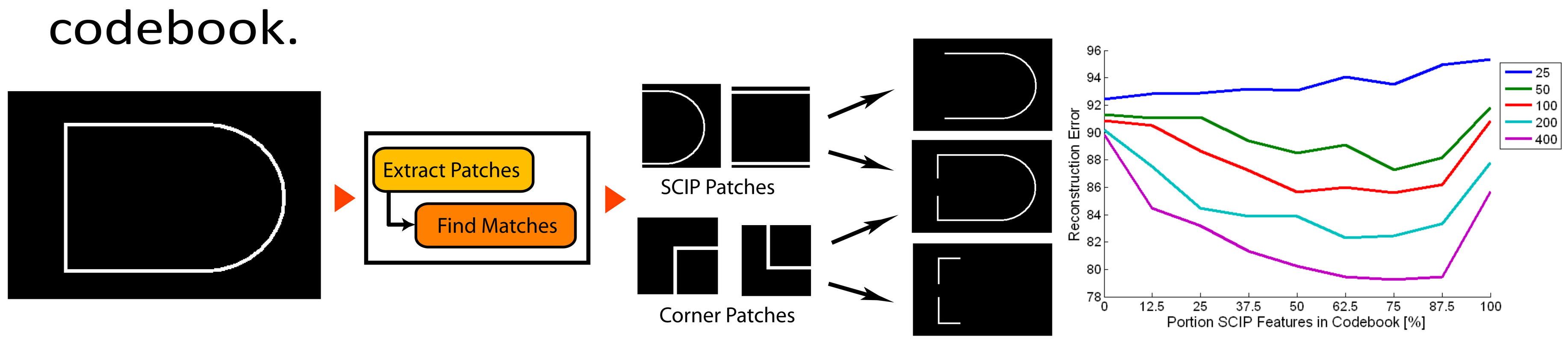

Figure 7: Edge map reconstruction pipeline and performance for different codebook sizes and mixtures [2]

References

[1] C. Xu and J. Prince. Snakes, shapes, and gradient vector flow. IEEE Press 1998
[2] D. Engel and C. Curio. Scale-invariant medial features based on gradient vector flow fields. ICPR 2008
[3] D. Engel, L. Spinello, R. Triebel, R. Siegwart, H. H. Bülthoff, and C. Curio. Medial features for superpixel segmentation. MVA 2009