Hierarchical Histogram Threshold Segmentation – Auto-terminating High-detail Oversegmentation

Supplementary Material

1. More Visual Results

1.1. Hierarchical Fine-tuning

Fig. 2 shows HHTS segmentation results for four BSDS500 images [2] at different segmentation levels. Due to the iterative split of inhomogeneous segments, homogeneous areas can be maintained while areas with many details will be segmented into smaller superpixels. This allows for capturing tiny and thin image components, even at a relatively low superpixel count. Further iterations (*cf*. higher superpixel count) will extract more subtle object outlines and separate less distinguishable image components. Fig. 1 shows the final HHTS segmentation results after auto-termination while preserving a minimum segment size of 64 pixels.

1.2. Segmentation Results

Fig. 3 shows some more visual results for BSDS500 images that were segmented by HHTS. Many different shapes and types of objects can be detected due to the algorithm's focus on boundary adherence. This approach can adjust to difficult scenes by taking into account more irregular shaped and less compact superpixels.

1.3. Visual Comparison

A visual comparison of HHTS and oversegmentation methods implemented in Stutz's *et al*. superpixel benchmark [7] can be found in Fig. 4 and Fig. 5. HHTS achieves to capture more image details than the compared approaches at the same superpixel resolution.

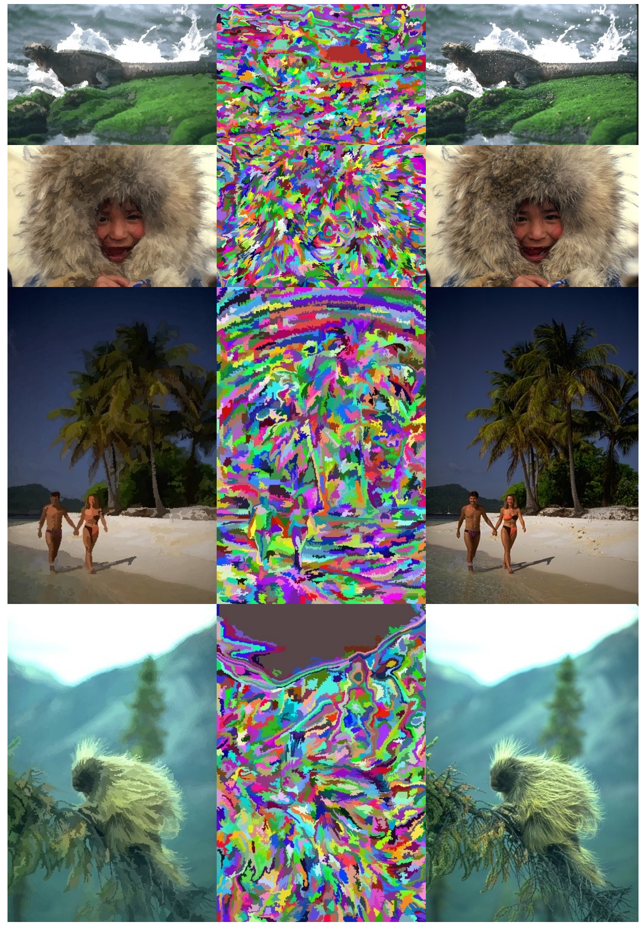

Figure 1. Final HHTS segmentation results (auto-termination at $925 - 996$ superpixel) and the original image as reference.

References

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[8] Jian Yao, Marko Boben, Sanja Fidler, and Raquel Urtasun. Real-time coarse-to-fine topologically preserving segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, 2015. 4, 5

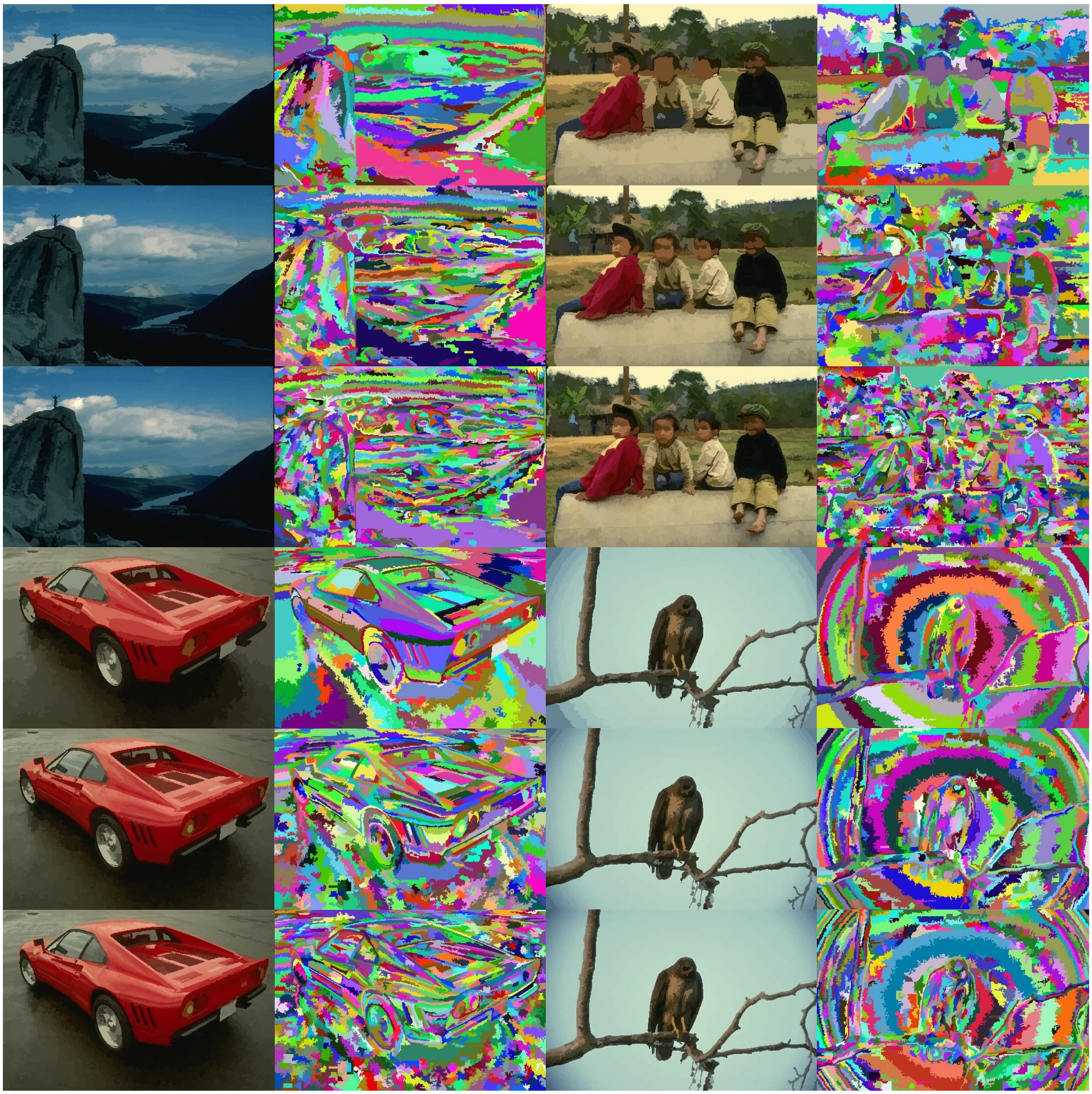
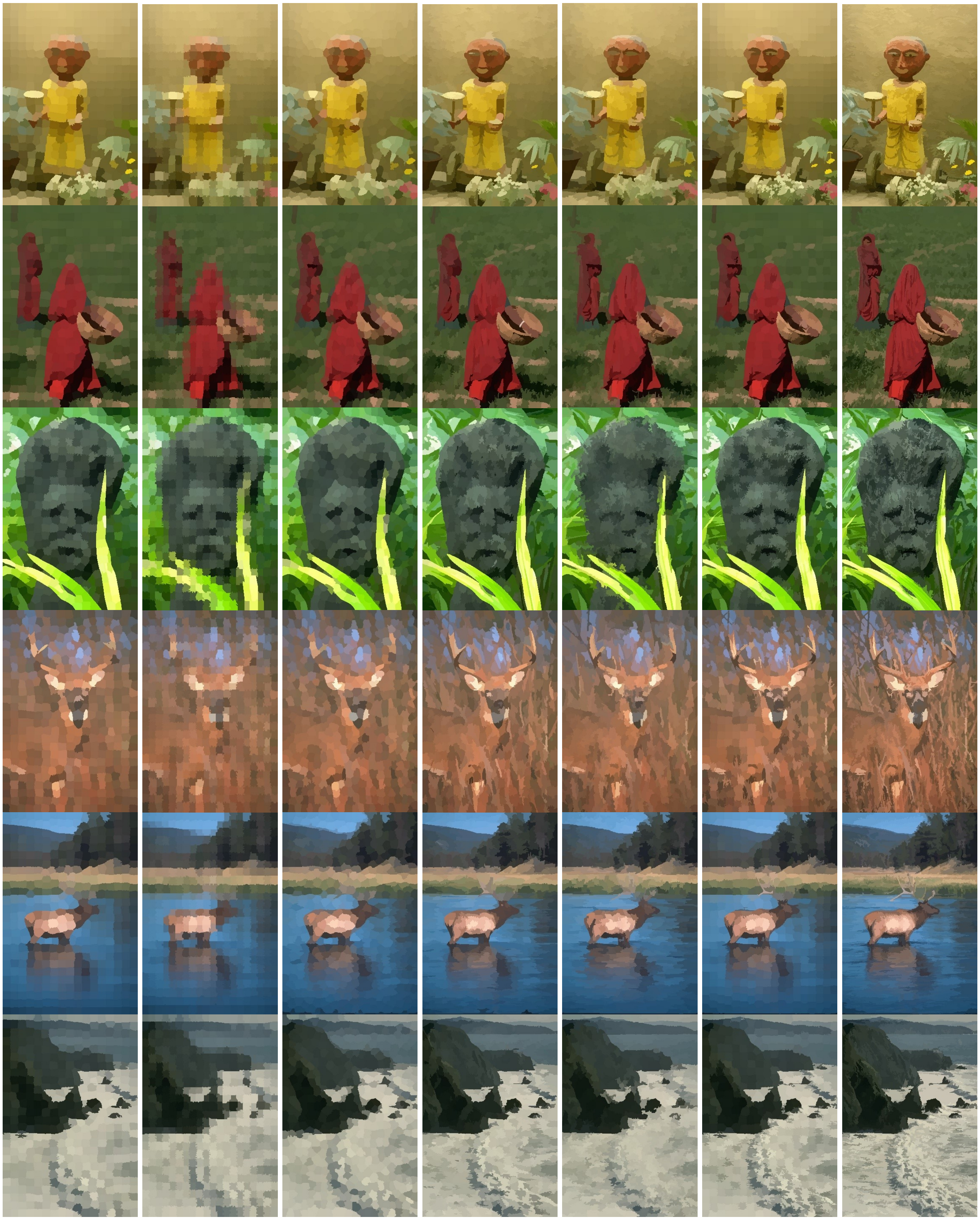


Figure 2. HHTS segmentation results at 250, 500, and 1000 superpixels, adapting to local details while maintaining homogeneous areas.

Figure 3. HHTS segmentation results at 500 superpixels.



(a) SLIC [1] (b) SEEDS [4] (c) CRS [6] (d) ERGC [3] (e) ERS [5] (f) ETPS [8] (g) HHTS

Figure 4. Visual comparison of mean image segments at 500 superpixels for portrait BSDS500 test images [2]

(a) SLIC [1] (b) SEEDS [4] (c) CRS [6] (d) ERGC [3] (e) ERS [5] (f) ETPS [8] (g) HHTS

Figure 5. Visual comparison of mean image segments at 500 superpixels for landscape BSDS500 test images [2]