

# BP-net: deep learning-based superpixel segmentation for RGB-D image

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Superpixel



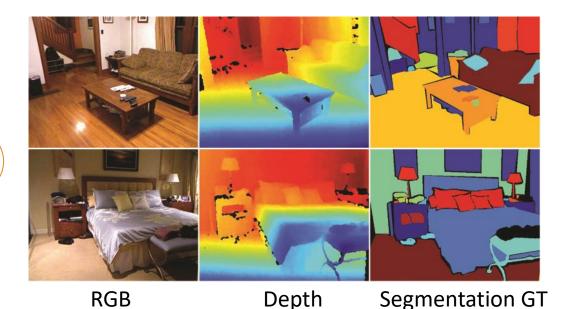
Pre-processing in vision applications

- Reducing the size of inputs
- Providing a meaningful image representation



- Boundary adherence
- Homogeneity within superpixel
- Regular shape

Microsoft Kinect, Intel RealSense, etc.



Call for superpixel algorithm for RGB-D image

Previous works

Superpixel Segmentation for RGB-D Image

- ① Depth-adaptive superpixels
- 2 Voxel cloud connectivity segmentation
- 3 Superpixel segmentation based on weighted geodesic driven metric
- 4 Fast marker-controlled watershed superpixel

1) Hand-crafted feature

3) Unsatisfied seeds initialization

2) No constraint of regularity





Superpixel Segmentation using Deep Neural Network

- ① Sampling superpixel network
- ② Superpixel embedding network

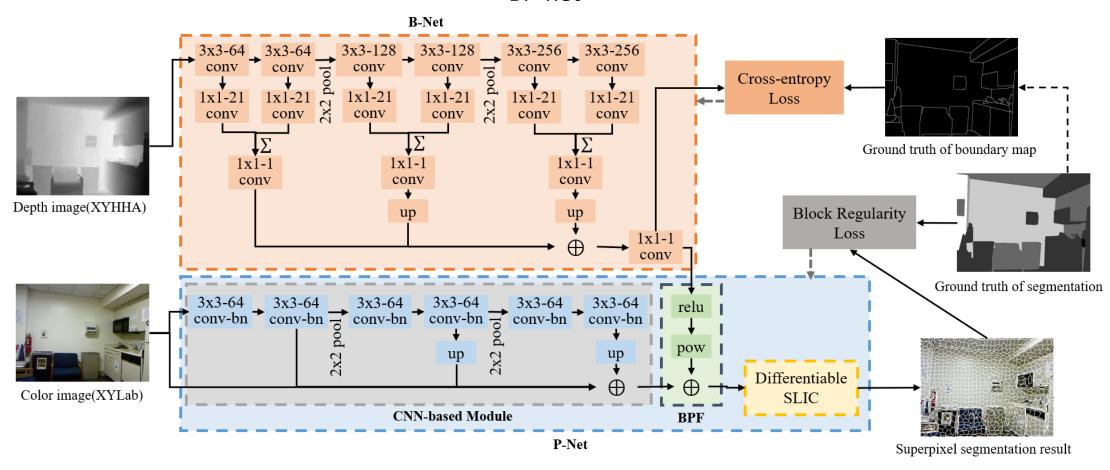


Cannot handle the depth information properly



## Algorithm-Network architecture

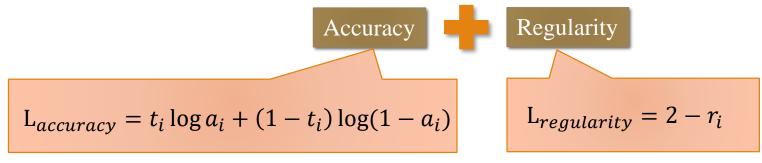
### BP-net





## Algorithm-Loss function

Block regularity loss



## $r_i$ is the **regularity score**

$$SRC(S) = \left(\frac{|S|}{|CH|}\right) * \left(\sqrt{\frac{\min(\sigma_x, \sigma_y)}{\max(\sigma_x, \sigma_y)}}\right) * (|P(CH)|/|P(S)|)$$

$$L_{BRL} = -\sum_{p_i \in I} (\underbrace{(2 - r_i)}_{regularity \ term} * \underbrace{(t_i \log a_i + (1 - t_i) \log(1 - a_i))}_{accuracy \ term})$$



## Algorithm-Seeds initialization

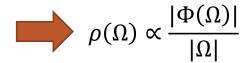
Adaptive seeds initialization

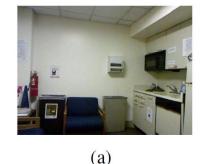
The density of seeds  $\rho(\Omega)$ is associated with region texture richness

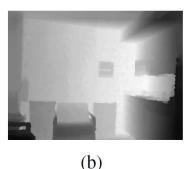


 $\Phi$ : maps pixels to 2-manifold  $\mathcal M$ embedded in 4-dimensional combined spatial and color space









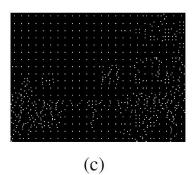


Fig. 2. Seeds initialization for an example image generated by the ASI. (a) The RGB image. (b) The depth image. (c) The result generated by the ASI with 800 seeds.



## Experiment-Evaluation

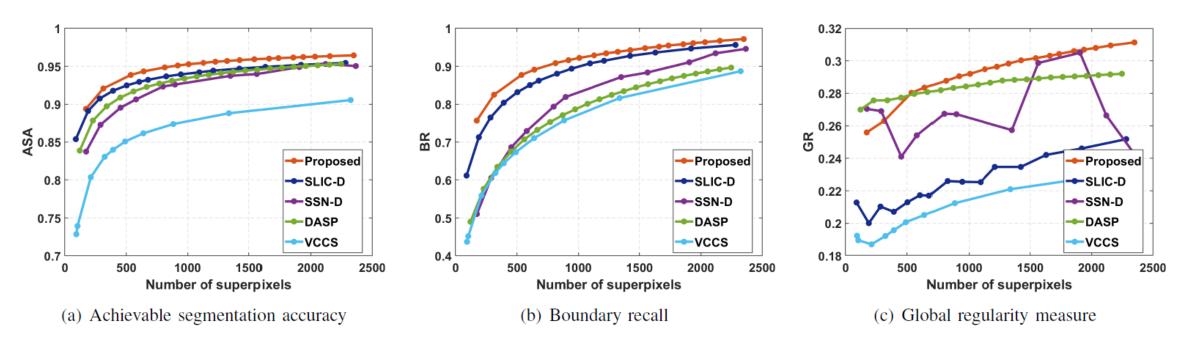


Fig. 3. Evaluation of four representative algorithms and our algorithm on the NYUD2 dataset.



## **Experiment-Ablation study**

TABLE I
OUR ALGORITHM WITH SEVERAL ABLATION STUDIES ON THE NYUD2
DATASET.

	mean ASA	mean BR	mean GR
proposed w/o RT	95.21%	92.65%	21.44%
proposed w/o ASI	92.2%	91.51%	29.23%
proposed	95.09%	92.19%	<b>29.44</b> %



## **Experiment-Sample result**

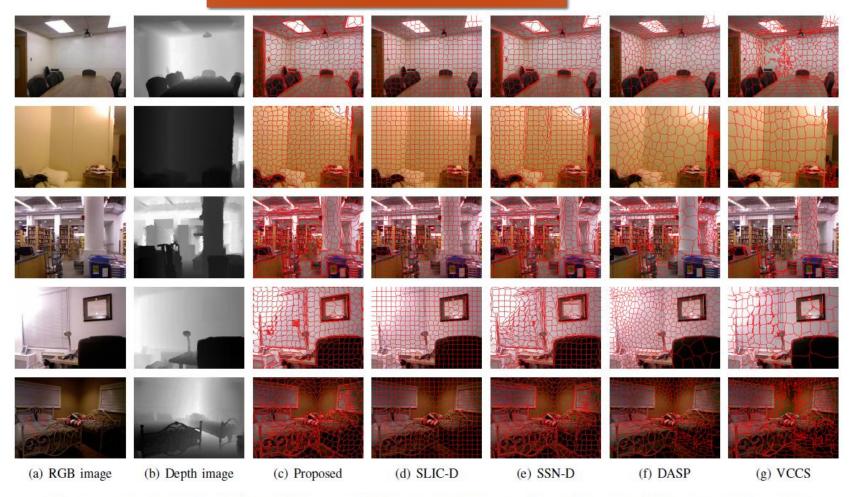


Fig. 4. Sample superpixel segmentation results of our algorithm compared to the several state-of-the-art algorithms on the NYUD2 dataset.



## References

- [1] Zhiqiang Tian, Lizhi Liu, Zhenfeng Zhang, and Baowei Fei, "Superpixel-Based Segmentation for 3D Prostate MR Images," IEEE TRANSACTIONS ON MEDICAL IMAGING, vol. 35, no. 3, pp. 791-801, MAR 2016.
- [2] Waqas Sultani, Soroush Mokhtari, and Hae-Bum Yun, "Automatic Pavement Object Detection Using Superpixel Segmentation Combined With Conditional Random Field," IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, vol. 19, no. 7, pp. 2076–2085, JUL 2018.
- [3] Tao Li, Zheng Liu, Rong Xie, and Lei Ran, "An Improved Superpixel-Level CFAR Detection Method for Ship Targets in High-Resolution SAR Images," IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, vol. 11, no. 1, pp. 184-194, JAN 2018.
- [4] Cheng Shi and Chi-Man Pun, "Superpixel-based 3D deep neural networks for hyperspectral image classification," PATTERN RECOG-NITION, vol. 74, pp. 600-616, FEB 2018.
- [5] Leyuan Fang, Nanjun He, Shutao Li, Pedram Ghamisi, and Jon Atli Benediktsson, "Extinction Profiles Fusion for Hyperspectral Images Classification," IEEE TRANSACTIONS ON GEOSCIENCE AND RE-MOTE SENSING, vol. 56, no. 3, pp. 1803-1815, MAR 2018.
- [6] Rémi Giraud, Vinh Ta, and Nicolas Papadakis, "Robust superpixels using color and contour features along linear path," Computer Vision and Image Understanding, 01 2018.
- [7] Jianbo Shi and Jitendra Malik, "Normalized cuts and image segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, 05 2002.
- [8] M. Liu, O. Tuzel, S. Ramalingam, and R. Chellappa, "Entropy rate superpixel segmentation," in CVPR 2011, June 2011, pp. 2097–2104.
- [9] R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. SÃ<sup>1</sup>/<sub>4</sub>sstrunk, "Slic superpixels compared to state-of-the-art superpixel methods," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 11, pp. 2274–2282, Nov 2012.
- [10] Z. Ban, J. Liu, and L. Cao, "Superpixel segmentation using gaussian mixture model," IEEE Transactions on Image Processing, vol. 27, no. 8, pp. 4105-4117, Aug 2018.

- [11] Varun Jampani, Deqing Sun, Ming-Yu Liu, Ming-Hsuan Yang, and Jan Kautz, "Superpixel sampling networks," in Computer Vision -ECCV 2018, Vittorio Ferrari, Martial Hebert, Cristian Sminchisescu, and Yair Weiss, Eds., Cham, 2018, pp. 363-380, Springer International Publishing.
- [12] Wei-Chih Tu, Ming-Yu Liu, Varun Jampani, Deqing Sun, Shao-Yi Chien, Ming-Hsuan Yang, and Jan Kautz, "Learning superpixels with segmentation-aware affinity loss," 06 2018, pp. 568-576.
- [13] D. Weikersdorfer, D. Gossow, and M. Beetz, "Depth-adaptive superpixels," in Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012), Nov 2012, pp. 2087-2090.
- [14] J. Papon, A. Abramov, M. Schoeler, and F. WA¶rgA¶tter, "Voxel cloud connectivity segmentation - supervoxels for point clouds," in 2013 IEEE Conference on Computer Vision and Pattern Recognition, June 2013, pp. 2027-2034.
- [15] Pushmeet Kohli Nathan Silberman, Derek Hoiem and Rob Fergus, "Indoor segmentation and support inference from RGB-D images," in ECCV, 2012.
- [16] Saurabh Gupta, Ross Girshick, Pablo Arbeláez, and Jitendra Malik, "Learning rich features from rgb-d images for object detection and segmentation," in Computer Vision - ECCV 2014, David Fleet, Tomas Pajdla, Bernt Schiele, and Tinne Tuytelaars, Eds., Cham, 2014, pp. 345– 360, Springer International Publishing.
- [17] C. Yang, L. Zhang, H. Lu, X. Ruan, and M. Yang, "Saliency detection via graph-based manifold ranking," in 2013 IEEE Conference on Computer Vision and Pattern Recognition, June 2013, pp. 3166-3173.
- [18] Rémi Giraud, Vinh Ta, and Nicolas Papadakis, "Robust shape regularity criteria for superpixel evaluation," 09 2017, pp. 3455–3459.
- [19] Pedro F. Felzenszwalb and Daniel P. Huttenlocher. "Efficient graphbased image segmentation," International Journal of Computer Vision, vol. 59, no. 2, pp. 167-181, Sep 2004.

- [20] Y. Liu, C. Yu, M. Yu, and Y. He, "Manifold slic: A fast method to compute content-sensitive superpixels," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016, pp. 651-
- [21] Michael Van den Bergh, Xavier Boix, Gemma Roig, and Luc Van Gool, "Seeds: Superpixels extracted via energy-driven sampling," International Journal of Computer Vision, vol. 111, no. 3, pp. 298-314, Feb 2015.
- [22] Rémi Giraud, Vinh-Thong Ta, and Nicolas Papadakis, "Evaluation Framework of Superpixel Methods with a Global Regularity Measure," Journal of Electronic Imaging, July 2017.
- [23] X. Pan, Y. Zhou, F. Li, and C. Zhang, "Superpixels of rgb-d images for indoor scenes based on weighted geodesic driven metric," IEEE Transactions on Visualization and Computer Graphics, vol. 23, no. 10, pp. 2342–2356, 2017.
- [24] L. Jiang, H. Lu, V. D. My, A. Koch, and A. Zell, "Superpixel segmentation based gradient maps on rgb-d dataset," in 2015 IEEE International Conference on Robotics and Biomimetics (ROBIO), 2015, pp. 1359-1364.
- [25] U. Gaur and B. S. Manjunath, "Superpixel embedding network," IEEE Transactions on Image Processing, vol. 29, pp. 3199-3212, 2020.
- [26] Y. Liu, M. Cheng, X. Hu, J. Bian, L. Zhang, X. Bai, and J. Tang, "Richer convolutional features for edge detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 41, no. 8, pp. 1939–1946, 2019.



# Thank you