

# Image Segmentation Enhancements and Optimizations: A Stochastic Approach

Final Presentation, November 2019  
Seminar Project (CSE-435)  
MANIT, Bhopal (India) - 462003

# Outline

- About Project
- About Team
- Proposed Work
- Abstract Description
- Advantages of the technique
- Results
- References

# About Project

- So called “seminar” project; not actually seminar!
- No innovation expected, but appreciated any.
- Elements of research required – Paper presentation later.
- Hands-on theoretical and practical contributions
- *Deliverables*: Report, Presentation, Code, Paper, etc.
- Preparation of a paper based on project; project paper
- No. of credits: 1

# About Team

- Team members:

- Jishan Shaikh (161112013) CSE-1
- Ankit Chouhan (161112051) CSE-1
- Sudhanshu Ranjan (161112046) CSE-1

- Supervisor:

- Dr. Jyoti Bharti (Dept of CSE, MANIT Bhopal)
- Dr. Vasudeva Dehalvar (Dept of CSE, MANIT Bhopal)

# Proposed Work

- Theoretical works
  - Study of previously created image segmentation techniques
  - Development of new technique for enhancement with optimization
- Practical works
  - Implementation of the technique using Python 3.8
    - Created 2 intensity filter matrices (8x8) of stochastic nature
    - Using otsu, li, and local techniques from skimage
    - Advanced techniques such as linear iterative model, snake based contour segmentation, and Felzenswalb segmentation

# Abstract Description (1 of 2)

This project proposes a novel technique for image segmentation providing customized parameters. Predefined customized parameters makes the technique usable for supervised segmentation, but the results of unsupervised segmentation can be used as an input to the method to get combined results. Image segmentation is very important in visual detection and visual recognition such as facial recognition, object detection, etc. It is quite adaptive to all the supervised segmentation techniques, and also flexible to the unsupervised techniques. Major features of the technique includes easy customization, neutrality towards nature of the segmentation technique, open-source nature, and uniformity of segmentation procedure. The core idea of technique lies in random probabilistic distribution (stochastic model), in which we created 2 matrices of size  $8 \times 8$ ; one for highly bright image and one for a highly dim image. Matrices were constructed on the basis of random nature of image and we can also use other matrices also (customization). Those initial matrices were then weighted to an score of 10 and -10 (Plus for brightness and Minus for dim image) for effective manipulation and operations. The smallest image that can be processed using this technique is  $8 \times 8$ , in that case only one iteration is necessary to calculate the resulting segmented matrix.

# Abstract Description (2 of 2)

If the size of image is greater than  $8 \times 8$ , matrices act as filters and calculate filtered value for each row-column element for the image. Since there are two matrices, we calculate 2 filtered results and then average out them for best results of highly bright image and highly dim image. We've tested some images with supervised techniques such as thresholding technique as well as some of unsupervised techniques such as otsu, li, local, etc. We've also demonstrated the technique on some advanced techniques such as snake based contours and Felzenszwalb; and that gives excellent results from a human perspective. We've also implemented this technique for a clustering technique – linear iterative clustering that also give very promising results.

**Categories:** Computer Vision, Digital Image Processing, Optimization Techniques.

**Index terms:** Image Segmentation, Enhancement, Optimization, Stochastic.

# Advantages of the technique

- New technique = Segmentation + Optimized Enhancements
- Open Source (Created repository at Github)
- Useful for supervised as well as unsupervised segmentation
- Output = High filter output + Low filter output
- Compatible with all traditional segmentation techniques
- Also applicable for clustering technique in images
- Suitable for highly bright as well as highly dimmed images
- Hidden Markov Model + Stochastic Matrices (Random Probability Distribution)
- Developed in Python 3.8 over OpenCV implementation of otsu, li, and local.
- Abstract demonstration of human brain visual senses



# Results (1 of 6)

- Demonstrated on multiple images
  - For otsu method

## Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
>>> markers = np.zeros_like(coins)
```

## Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
>>> markers = np.zeros_like(coins)
```

# Results (2 of 6)

- Demonstrated on multiple images
  - For li method

## Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
>>> markers = np.zeros_like(coins)
```

## Non-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
>>> markers = np.zeros_like(coins)
```

# Results (3 of 6)

- Demonstrated on multiple images
  - For local method

## Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
>>> markers = np.zeros_like(coins)
```

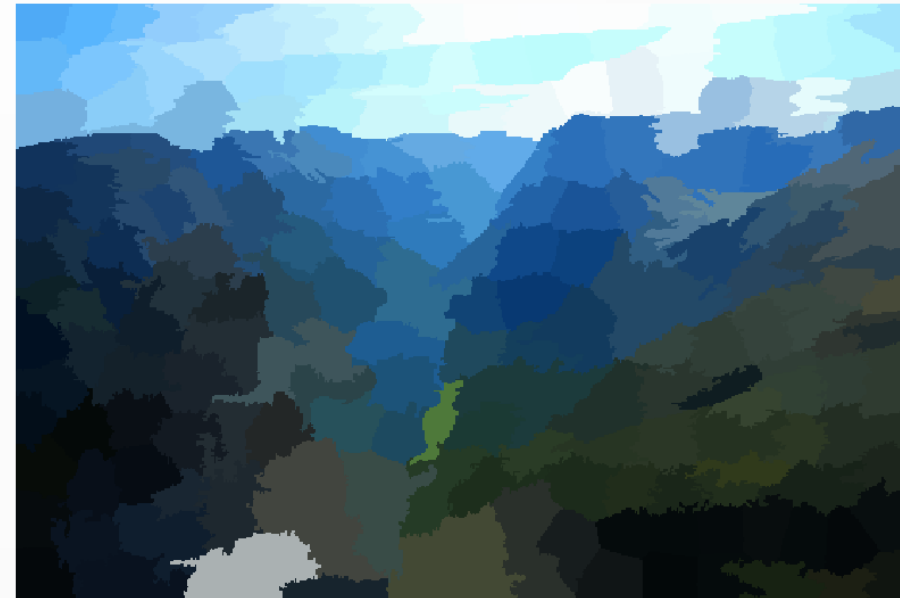
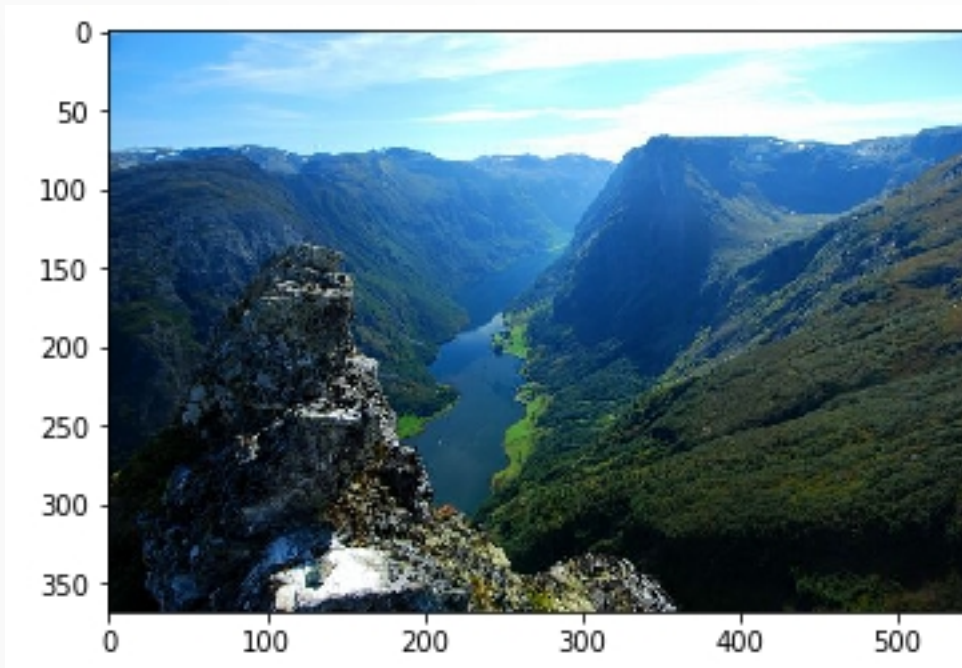
## Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
>>> markers = np.zeros_like(coins)
```

# Results (4 of 6)

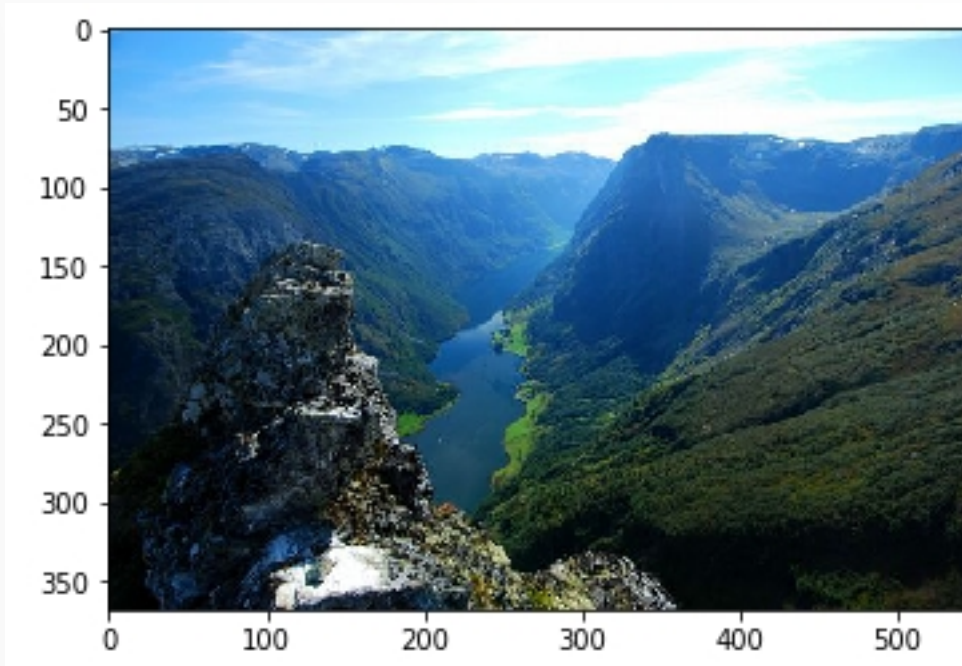
- Demonstrated on multiple images
  - For linear iterative segmentation





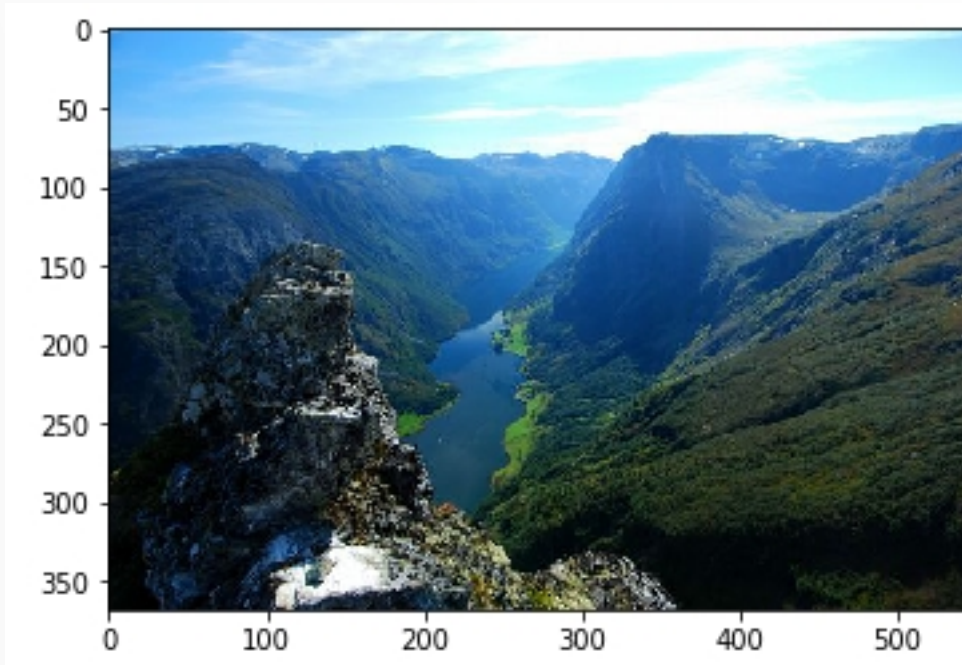
# Results (5 of 6)

- Demonstrated on multiple images
  - For snake based contour segmentation



# Results (6 of 6)

- Demonstrated on multiple images
  - For Felzenswalb segmentation



# References

- [1] Fusion of Image Segmentation Algorithms using Consensus Clustering. Mete Ozay, Fatos T. Yarman Vural, Sanjeev R. Kulkarni, H. Vincent Poor. <https://doi.org/10.1109/ICIP.2013.6738834>. A version of the manuscript was published in ICIP 2013. Journal ref: 20th IEEE International Conference on Image Processing (ICIP), pp. 4049-4053, Melbourne, VIC, 15-18 Sept. 2013
- [2] Combination of Hidden Markov Field and Conjugate Gradient for Brain Image Segmentation. EL-Hachemi Guerrout, Samy Ait-Aoudia, Dominique Michelucci, Ramdane Mahiou.
- [3] An efficient iterative thresholding method for image segmentation. Dong Wang, Haohan Li, Xiaoyu Wei, Xiaoping Wang. <https://doi.org/10.1016/j.jcp.2017.08.020>
- [4] A Replica Inference Approach to Unsupervised Multi-Scale Image Segmentation. Dandan Hu, Peter Ronhovde, Zohar Nussinov. <https://doi.org/10.1103/PhysRevE.85.016101> Journal ref: Phys. Rev. E 85, 016101 (2012).
- [5] Image Segmentation with Multidimensional Refinement Indicators. Hend Ben Ameer, Guy Chavent, Francois Clément, Pierre Weis. Report number: RR-7446, RR-7446. Journal ref: N&deg; RR-7446 (2010).

**For other 70 references, refer report.**

**Thank you :)**