



# “A Review of Different Image Segmentation Techniques”:

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## Abstract

Image segmentation is a abecedarian task in computer vision, aiming to partition an image into meaningful regions for farther analysis and understanding. This paper provides an overview of four common image segmentation ways Thresholding, Edge- grounded segmentation, Region- grounded segmentation, and Clustering, pressing their advantages and disadvantages. Thresholding involves classifying pixels as focus or background grounded on a predefined threshold value. While simple and computationally effective, thresholding may struggle with variations in illumination and bear careful parameter selection. Edge- grounded segmentation ways concentrate on relating edges in an image to delineate object boundaries. Although effective for images with distinct edges, these styles can be sensitive to noise and may not directly capture object boundaries in complex scenes. Region- grounded segmentation styles group pixels into regions grounded on similarity in color, texture, or intensity. Algorithms like watershed segmentation and region growing excel at landing object boundaries and handling complex scenes but can be computationally ferocious and sensitive to initialization. Clustering algorithms, similar as k- means or mean-shift, group analogous pixels together grounded on features like color or texture. These styles are protean and applicable to colorful image types but may bear homemade parameter tuning and struggle

with lapping regions. In conclusion, each image segmentation fashion offers unique benefits and downsides. The selection of

the applicable system Depends on factors similar as the image characteristics, asked delicacy, and computational coffers available. Understanding the strengths and limitations of each fashion is pivotal for effective image segmentation in different operation.

## 1. Introduction

Over the past two decades, image segmentation has emerged as a dynamic field of research, leading to the development of numerous techniques documented in the image processing literature. This proliferation is driven by the diverse problem domains and applications requiring domain-specific or application-specific image data processing and interpretation. Various types of images, including gray scale, color, depth, thermal, sonar, radiographic, MRI, among others, are encountered depending on the specific problem domain or application. Image segmentation, a critical aspect of image processing, involves partitioning a digital image into multiple segments or sets of pixels, where pixels within a segment exhibit similarity according to predefined homogeneity criteria such as color, intensity, or texture. This segmentation process facilitates the localization and identification of objects and boundaries within an image. Practical applications of image segmentation span a wide range, including noise filtering in images, medical diagnostics [tumor detection, tissue volume measurement, computer-guided surgery, etc.], object localization in satellite imagery [roads, forests], biometric recognition



[face, fingerprint], among others. Numerous segmentation methodologies have been proposed in the literature to address these diverse applications. The selection of a segmentation technique and the granularity of segmentation depend on the specific image characteristics and the requirements of the problem at hand.

## 2. LITERATURE REVIEW

### 2.1 Edge based image segmentation

Edge- rested image segmentation ways are abecedarian in computer vision and image processing, furnishing precious perceptivity into object boundaries and shapes. These styles work the discovery of edges, which are abrupt changes in intensity or color, to partition images into meaningful regions [1]. Over the times, multitudinous edge- rested segmentation ways have been developed, each immolation unique advantages and operations. One of the foremost and utmost vastly habituated edge discovery algorithms is the Sobel automobilist, which calculates the grade magnitude of an image to punctuate edges [2]. Canny edge discovery, another popular fashion, employs multiple stages, including Gaussian smoothing, grade-outside repression, and edge shadowing by hysteresis [3]. The Canny edge sensor is celebrated for its capability to directly descry edges while minimizing noise and false cons. In addition to traditional edge discovery styles, advanced ways similar as the Laplacian of Gaussian [LoG] automobilist and the Marr- Hildreth edge sensor have been proposed [4]. The LoG automobilist combines Gaussian smoothing with Laplacian filtering to descry edges at colorful scales, making it robust to noise. The Marr- Hildreth edge sensor, rested on zero- crossings in the alternate outgrowth of the image, can descry edges with sub- pixel delicacy. These ways are particularly useful in operations taking precise edge localization. also, edge- rested segmentation styles have set up wide use in medical image analysis, where directly delineating anatomical structures is vital for opinion and treatment planning. For illustration, in

glamorous resonance imaging [MRI], edge- rested segmentation ways are employed to member organs and Atkins with high perfection [5]. Despite their effectiveness, edge- rested segmentation ways have certain limitations. One common challenge is the perceptivity to noise, which can affect in false findings and inaccurate segmentation. To palliate this issue, preprocessing way similar as image smoothing or denoising are constantly applied before edge discovery [6]. Another limitation is the reliance on grade information, which may not adequately prisoner complex object boundaries or texture variations. Likewise, edge- rested segmentation styles may struggle with images containing low distinction or regions with gradational intensity changes. In similar cases, reciprocal ways, similar as region- rested segmentation or clustering, may be employed to enhance segmentation delicacy. In recent times, deep knowledge approaches have shown pledge in edge- rested segmentation tasks, using convolutional neural networks [CNNs] to learn hierarchical representations of edges and textures [7]. These CNN- rested styles constantly outperform traditional edge sensors, especially in grueling scripts with noisy or low- quality images. still, they generally bear large annotated datasets for training and may be computationally ferocious. In conclusion, edge- rested image segmentation ways play a vital part in computer vision and image processing, offering precious perceptivity into object boundaries and shapes. While traditional edge discovery styles like the Sobel and Canny drivers remain vastly used, advanced ways similar as the LoG automobilist and Marr- Hildreth sensor give enhanced delicacy and versatility. Despite their limitations, edge- rested segmentation styles continue to find operations in colorful fields, from medical imaging to artificial examination. With the ongoing advancements in deep knowledge, the future of edge- rested segmentation holds pledge for farther advancements in delicacy and effectiveness.



## 2.2 Region based image segmentation

Region- grounded image segmentation ways are essential in computer vision and image processing, furnishing a important approach to partition images into coherent regions with analogous parcels. These styles aim to group pixels into meaningful regions grounded on criteria similar as color, intensity, texture, or other features. Over the times, multitudinous region-grounded segmentation ways have been developed, each with its own strengths and operations. One of the foremost and most well-known region-grounded segmentation algorithms is the milepost transfigure, which treats the image as a topographic face and simulates flooding to delineate regions( 8). Another popular system is region growing, which starts with seed points and iteratively merges bordering pixels that satisfy certain similarity criteria( 9). Region-grounded segmentation ways are extensively used in colorful fields, including medical image analysis, remote seeing, and scene understanding. In medical imaging, region-grounded segmentation plays a pivotal part in tasks similar as excrescence discovery, organ segmentation, and towel bracket( 5). For illustration, in glamorous resonance imaging( MRI), region-grounded segmentation ways are employed to delineate anatomical structures and identify abnormalities with high delicacy. In remote seeing operations, region-grounded segmentation is used for land cover bracket, object discovery, and change discovery( 11). These ways enable the birth of precious information from satellite imagery for environmental monitoring, civic planning, and husbandry. Region-grounded segmentation styles are also current in scene understanding and image understanding tasks, where the thing is to dissect the content of images and excerpt semantic information( 12). These ways grease tasks similar as object recognition, scene parsing, and image reflection. Despite their effectiveness, region-grounded segmentation ways have certain limitations. One common challenge is the perceptivity to initialization and parameter settings, which can affect segmentation delicacy and robustness( 13). also, these

styles may struggle with images containing complex textures, occlusions, or lapping objects. To address these challenges, experimenters have proposed colorful advancements and extensions to region-grounded segmentation algorithms. For illustration, cold-blooded approaches combining region-grounded and edge-grounded ways have been developed to influence the reciprocal strengths of both styles( 14). also, machine literacy-grounded approaches, similar as deep literacy, have shown pledge in enhancing region-grounded segmentation performance( 15). These styles use convolutional neural networks( CNNs) to learn hierarchical representations of image features and ameliorate segmentation delicacy. In conclusion, region-grounded image segmentation ways play a vital part in computer vision and image processing, enabling the birth of meaningful regions from images for colorful operations. While traditional styles like milepost transfigure and region growing remain extensively used, ongoing exploration sweats concentrate on enhancing their delicacy, effectiveness, and robustness. With the continued advancements in machine literacy and deep literacy, the future of region-grounded segmentation holds pledge for farther advancements in segmentation quality and connection.

## 2.3 Thresholding Technique

Thresholding is the simplest method of image segmentation. It creates greyscale images from binary images. In this technique pixels of image are changed to make it easier for analyzing images. Pixels in an image are categorized according to their intensity values.

There are three types of thresholding ( 1):

### 2.3.1 Global Thresholding:

Global thresholding is a wellliked technique for image segmentation that divides an image into regions or segments based on the pixel intensity values.

The basic idea is to select a threshold that is such that, for a particular pixel intensity, it is categorized, based on its intensity, as either belonging to the background or another group (typically the foreground or object of interest).



Below is a summary of the general steps involved in global thresholding:

**Image Preparation:** Convert the image to grayscale if it is not already in that format. This simplifies the segmentation procedure as you are utilizing a single channel for intensity values.

**Selecting a Threshold:** Choose a threshold value that effectively separates the foreground from the background.

### 2.3.2 Variable thresholding:

In image segmentation, variable thresholding is a technique where the threshold value, represented by  $T$ , may change in various areas of the picture. This means that several threshold values are applied to different regions depending on local features like texture or intensity, rather than applying a single set threshold value for the entire image.

Variable thresholding entails the following steps:

**Image Partitioning:** The image is separated into more manageable areas, called blocks.

**Local Thresholding:** Based on the unique characteristics of each region or block, a threshold value is established. Numerous approaches, including local mean, local median, and adaptive thresholding techniques like Otsu's method, can be used to accomplish this.

**Application of the Threshold:** To binarize or segment the image, the threshold value is applied to each region after it has been established. Foreground pixels are those whose intensities are higher than the threshold; background pixels are those whose intensities are lower than the threshold.

**Post-Processing (Optional):** To further improve the segmented regions, post-processing techniques like noise reduction or morphological operations may be used, depending on the application.

The value of  $T$  (threshold value) in this kind of thresholding can change as the image does. Additionally, this can be of two kinds (15):

- **Local Threshold:** In this case,  $T$ 's value is determined by where  $x$  and  $y$  are located.
- **Adaptive Threshold:**  $x$  and  $y$  determine  $T$ 's value.

### 2.3.3 Multiple Thresholding:

Multiple thresholding works by dividing an image into regions with varied levels of intensity. This allows for the separation of objects or regions of interest with different properties. When multiple portions of the image cannot be sufficiently separated by a single threshold value, or when the objects of interest have distinct intensity ranges, this technique is especially helpful.

The following steps are commonly involved in the multiple thresholding process:

**Choosing Threshold Values:** Ascertain the proper number of thresholds and choose threshold values according to the image's properties and the intended segmentation.

**Thresholding:** Apply the chosen threshold values to the picture to produce a series of binary images, each of which corresponds to a threshold-based segmentation of the image.

**Post-processing:** To improve the segmentation findings and get the final segmented regions, you can optionally carry out extra processing steps like noise reduction, morphological procedures, or region merger.

**Evaluation of Segmentation:** To make sure that the segmentation sufficiently captures the intended regions of interest, evaluate the segmentation results using metrics like accuracy, precision, recall, or visual inspection.

All things considered, multiple thresholding is a potent image segmentation method that can divide an image into several sections according to intensity levels, opening up a variety of applications in computer vision, object recognition, and image analysis.

### 2.4 Clustering Technique:

Based on pixel property similarities, clustering-based segmentation techniques divide a picture into discrete regions or segments. These techniques divide pixels into clusters using clustering algorithms;



pixels in a same cluster are seen as comparable to one other, while pixels in separate clusters are regarded as dissimilar.

An outline of clustering-based segmentation's basic operation is provided below:

**Feature extraction:** First, pertinent characteristics are taken out of each pixel in the image. Pixel intensities, color values in various color spaces (RGB, HSV, Lab, etc.), texture features, and other noteworthy attributes could be included in these features.

**Clustering Algorithm:** To cluster similar pixels together, a clustering algorithm is performed to the feature space. k-means clustering, hierarchical clustering, fuzzy clustering, and mean-shift clustering are popular clustering techniques used in picture segmentation.

**Cluster Assignment:** Based on the attributes that were retrieved, each pixel in the image is assigned, once the clusters have formed, to the cluster to which it most closely resembles. Distance measurements like the Mahalanobis distance, the Euclidean distance, or other similarity metrics can be used for this assignment.

**Segmentation:** Each cluster represents a segment or area in the image once pixels have been assigned to them. Assigning each pixel within a cluster to the appropriate segment yields the segmentation result.

**Post-processing (Optional):** If required, post-processing techniques including region merging, edge refining, and noise reduction can be used to enhance the segmentation outcome.

**Evaluation:** A number of criteria, including accuracy, precision, recall, and visual inspection of the segmentation output, can be used to assess the segmentation result's quality. In many different applications, including object recognition, image segmentation, medical image analysis, and remote sensing, clustering-based segmentation techniques are extensively employed. By choosing the right features and clustering techniques, they are adaptable and may be used with a variety of images and data sources.

### 3. COMPARISION TABLE

Aspect	Thresh olding	Cluster ing	Edge- Based Detecti on	Regio n- Based Detect ion
Basis	Intensit y value thresho ld	Featur e similari ty	Gradien t magnit ude	Pixel similar ity
Principl e	Discont inuity	Similari ty	Discont inuity	Similar ity
Input	Single- channel image	Multi- channe l feature space	Single- channel image	Single or multi- chann el image
Output	Binary mask	Cluster assign ments	Edge map	Segme nted region s
Sensitiv ity to Noise	Sensitiv e	Depen dent on clusteri ng algorit hm	Sensitiv e	Resilie nt
Comple xity	Low	Moder ate to High	Moder ate to High	Moder ate to High
Perfor mance	Fast	Variabl e	Variabl e	Variabl e
Applica tion Suitabil ity	Simple scenes with clear contras t	Compl ex scenes with diverse feature s	Scenes with distinct edges	Scene s with unifor m region s

Table 3.1



#### 4. Conclusion

In conclusion, sophisticated approaches like the Laplacian of Gaussian provide increased accuracy, but edge-based segmentation techniques like Sobel and Canny algorithms are essential in computer vision for identifying object boundaries through changes in intensity or color. But issues like noise sensitivity and dependence on gradient information continue to exist, which is pushing research into preprocessing and other approaches like region-based segmentation. In the meantime, research is continuously focused on improving conventional approaches and utilizing machine learning for better flexibility. Region-based segmentation techniques extract coherent sections from images. Furthermore, by transforming binary images to grayscale, thresholding techniques provide simple segmentation. Global, multiple, and variable thresholding give versatile tools for a range of applications. Clustering-based segmentation techniques provide adaptability and efficiency in a variety of applications, from object recognition to further segmenting images based on pixel attributes.

#### REFERENCES

1. Gonzalez, R. C., & Woods, R. E. [2008]. Digital image processing [3rd ed.]. Pearson.
2. Sobel, I., & Feldman, G. [1968]. A 3x3 isotropic gradient operator for image processing. Stanford Artificial Intelligence Project.
3. Canny, J. [1986]. A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, [6], 679-698.
4. Marr, D., & Hildreth, E. [1980]. Theory of edge detection. Proceedings of the Royal Society of London. Series B. Biological Sciences, 207 [1167], 187-217.
5. Haralick, R. M., & Shapiro, L. G. [1985]. Image segmentation techniques. Computer vision, graphics, and image processing, 29 [1], 100-132.
6. Jain, A. K. [1989]. Fundamentals of digital image processing [Vol. 1]. Englewood Cliffs, NJ: Prentice-Hall.
7. LeCun, Y., Bengio, Y., & Hinton, G. [2015]. Deep learning. Nature, 521 [7553], 436-444.
8. Beucher, S., & Lantuejoul, C. [1979]. Use of watersheds in contour detection. In International workshop on image processing.
9. Adams, R., & Bischof, L. [1994]. Seeded region growing. IEEE Transactions on Pattern Analysis and Machine Intelligence, 16 [6], 641-647.
10. Lu, D., & Weng, Q. [2007]. A survey of image classification methods and techniques for improving classification performance. International journal of remote sensing, 28 [5], 823-870.
11. Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. [2009]. ImageNet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition [pp. 248-255]. Ieee.
12. Ren, X., & Malik, J. [2003]. Learning a classification model for segmentation. In Proceedings Ninth IEEE International Conference on Computer Vision [pp. 10-17]. IEEE.
13. Malik, J., & Perona, P. [1990]. Preattentive texture discrimination with early vision mechanisms. Journal of the Optical Society of America A, 7 [5], 923-932.
14. Long, J., Shelhamer, E., & Darrell, T. [2015]. Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition [pp. 3431-3440].
15. Dilpreet Kaur, Yadwinder Kaur. Various image segmentation techniques: A Review.
16. T. Shraddha, K. Krishna, B.K.Singh and R. P. Singh, "Image Segmentation: A Review", International Journal of Computer Science and Management Research Vol. 1 Issue. 4 November 2012.
17. S. Angelina, L. Padma Suresh and S. H. Krishna Veni, "Image Segmentation Based On Genetic Algorithm for Region Growth and Region Merging",



International Conference on Computing, Electronics and Electrical Technologies (ICCEET), 2012.

18. H.P. Narkhede, "Review on Image Segmentation Techniques" International Journal of Science and Modern Engineering, Vol 1, Issue 8, July 2013.

20. Bhanu, Automatic Target Recognition: State of the Art Survey, IEEE Transactions on Aerospace and Electronics Systems, AES-22 (1986) 364-379.