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Image Segmentation based on Division and Region Fusion

Samantha Acosta-Ruiz

Benemérita Universidad Autónoma de Puebla,
Facultad de Ciencias de la Computación,
Mexico

224570157@viep.com.mx

Abstract. This article explores digital image processing with a focus on fundamental segmentation techniques. It highlights two main approaches: region division and fusion, and border-based segmentation, each suited for specific analysis objectives. Region merging and border segmentation are key for identifying areas like housing and roads in satellite images. Quantitative evaluations were performed on metrics such as mean square error, Jaccard index (IOU), and DICE coefficient. The effectiveness of methods such as Sobel, Roberts, and Laplacian over the conventional Canny edge detector in the Hough transform was noted. Techniques such as the Otsu method for thresholding, noise removal using median and Gaussian filters, and edge detection were essential. Gabor filters were crucial for highlighting textures and distinguishing features like vegetation and empty areas. Adaptability and experimentation were key, with the strategic combination of techniques, including the optimized Hough transform, proving effective in accurately delineating populated areas and roads. The study underscores the importance of selecting and combining the right techniques for optimal image processing results.

Keywords: Region fusion, Gabor filters, Hough transform, segmentation.

1 Introduction

A satellite image is not a film-based photograph, almost all commercial remote sensing satellites capture images using digital sensors based on the same principles as digital cameras. A satellite sensor has thousands of tiny detectors that measure the amount of electromagnetic radiation reflecting the Earth's surface and the objects on it. These measurements are called spectral, and each spectral reflectance value is recorded as a digital number. These numbers are transmitted back to Earth where, through a processing, they are converted into colors or shades of gray to create an image that looks like a photograph [1].

An image can be defined as a two-dimensional function of light intensity $f(x, y)$, where x and y represent the spatial coordinates and the value of f at any point (x, y) is proportional to the brightness (or gray level) of the image at

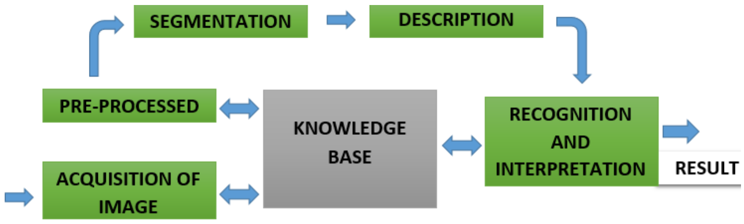

Fig. 1. Stages of image processing.

that point. A digital image is an $f(x, y)$ image that has been discretized both in terms of spatial coordinates and brightness; it can be considered as a matrix whose row and column indices identify a point of the image and the value of the corresponding element of the matrix indicates the gray level at that point. The elements of such a digital design are called picture elements or more commonly pixels, an abbreviation of their English denomination "picture elements" [5].

Figure 1 shows the necessary basic steps in image processing. The process starts with the image acquisition stage, where an image sensor produces signals that must be digitized. For example, light is used for photography; X-rays for radiography, ultrasound for sonography, etc. The nature of the sensor will depend on the type of application to study. The next stage is the preprocessing, carried out in order to detect and eliminate any flaws that may exist in the image to improve it. The most commonly used techniques at this stage are: a) contrast enhancement, b) noise removal, and c) restoration. In the following segmentation stage, the image is divided into its constituent parts or objects in order to separate the necessary processing parts from the rest of the image that are not of interest for the desired application. The basic techniques at this stage are those oriented to: a) the pixel, b) the edges, and c) the regions.

However, the techniques are not exclusive but are combined according to the type of application. The next stage is the description or extraction of features, it consists of extracting features with some quantitative information of interest or that are fundamental to differentiate one class of objects from another.

Then, the recognition stage is the process that assigns a label to an object based on the information provided by its descriptors. Interpretation involves assigning meaning to a set of recognized objects. Finally, the Knowledge Base stage, which will store the problem domain to guide the operation of each processing module, also controls the interaction between modules [5]. We will explore fundamental methods in image processing. Therefore, the following concepts will be defined:

Thresholding: Thresholding is one of the most important methods of image segmentation. The threshold is defined as a function that converts an image with different shades to a black and white image. If the original image is $f(x, y)$, the umbralized image is $g(x, y)$ and a threshold U is set $(0 < U < 255)$, the thresholding operation is defined as:

$$g(x,y) = \begin{cases} 255, & \text{if } f(x,y) \geq \text{Threshold.} \\ 0, & \text{if } f(x,y) \leq \text{Threshold.} \end{cases} \tag{1}$$

A threshold is selected that allows the pixels of an image that belong to various objects in the same image to be grouped, differentiating them from the background. In this way, histogram-based segmentation is based on the choice of one or more thresholds. These thresholds allow the points of the image to be grouped into regions of similar characteristics based on their gray levels [5].

Gabor Filter: Noise in an image refers to unwanted and unpredictable variations in the intensity levels of pixels. Applying a filter or mask to an image is to highlight or smooth out specific features. Gabor filters are used for texture analysis and edge detection in images. They are designed to capture features at different frequencies and orientations. The Gabor function is a combination of a sine wave modulated by a Gaussian function.

Otsu Method: Is a technique used in image processing to perform automatic thresholding. An image is divided into two distinct classes ("target" pixels and "background" pixels) based on a threshold value. The objective of the Otsu method is to find the optimal value of the threshold that maximizes the variance between the two resulting classes.

Segmentation: Subdivides an image into its constituent parts or objects, in order to separate the parts of interest from the rest of the image, therefore the level at which this subdivision is carried out depends on the problem to be solved. The basic segmentation attributes of an image are: luminance in monochromatic images, color components in color images, texture, shape, etc. Monochromatic image segmentation algorithms are generally based on one of the two basic properties of gray level values: discontinuity and similarity. In discontinuity, the method consists of dividing an image on the basis of sudden changes in the gray level.

The most important issues in discontinuity are: a) detection of isolated points, b) detection of lines and c) detection of edges of an image. In the similarity, the regularity in the gray level values is presented, the main methods are based on thresholding, region growth, and division and fusion of regions [2].

Edge Detection: Although the detection of dots and lines is essential in any presentation of image segmentation, the most common technique for identifying significant discontinuities in gray levels is edge detection. This is because these discontinuities are more frequent in practical applications. The methods of extracting edges from an image are based on the differences experienced by a feature between two adjacent regions, signaling the presence of an edge. In general, different models of edges or contours are identified: line, step type, ramp type and roof type. Discontinuities are detected using first- and second-order derivatives, in the case of first-order derivatives the gradient operator is used, while in second-order derivatives the Laplacian operator is used [5]. The first derivative produces a highlight of the areas in which the intensity is not homogeneous. The second derivative causes a sign change at the edge position.

These are the most common operators to detect edges are the following: canny, roberts, sobel and laplacian.

Edge binding and boundary detection: While there are several techniques that detect intensity discontinuities, and that should result in pixels that are at the boundary between an object and its background, in practice, this set of pixels rarely characterizes a boundary completely. This is due to noise, interruptions at the boundary due to non-uniform illumination, and other effects that introduce spurious intensity discontinuities. Therefore, edge detection algorithms are followed by a union and other border detection procedures designed to gather the edge pixels into a meaningful set of object borders [2]. Below are some techniques that fit that goal:

- *Local processing*: It consists of analyzing a neighborhood environment (for example, $3x3$, $5x5$) on all the points (x, y) of an image in which an edge detection process has been carried out, so that all the points that have similar characteristics join, forming a common border. Two properties are used to determine the similarity between edge pixels: a) Magnitude of the gradient vector (threshold value to determine the edge), and b) Direction of the gradient [5]. The first property states that a coordinate pixel (x, y) is similar to another (x, y) within its neighborhood environment if the equation holds:

$$[F(x, y)] - G[F(x', y')] \leq T, \tag{2}$$

  ehere T is a non-negative threshold.The second property, i.e. the direction of the gradient (G), can be established using the angle of the gradient vector (θ) which is given by:

$$\theta = tan^{-1} \frac{G\mathbf{x}}{Gy}, \tag{3}$$

  where (θ) represents the angle with respect to the x-axis. Thus, an edge pixel located at (x, y) has an angle similar to (x, y) which is:

$$|\theta - \theta'| \leq A. \tag{4}$$

  where A is an angular threshold and (θ) is the angle of the gradient vector. A point in the predefined neighborhood of (x, y) is bound to the pixel of (x, y) if the magnitude and direction criteria are satisfied. It is repeated for each position of the image. A record should preserve the linked points as the center of the neighborhood moves from pixel to pixel.

- *Global processing using the Hough Transform*: Originally it was designed to detect lines and curves, using known analytical equations of object edges, however with this original method, it is not always possible to find analytical equations describing edges. The generalized Hough Transform makes this possible, i.e. to detect edges of objects even when the edge analytic expressions are not known. Intuitively, this method of edge detection consists of calculating the gradient of an image, then creating an accumulation field based on the parameters of the function being searched, and subsequently

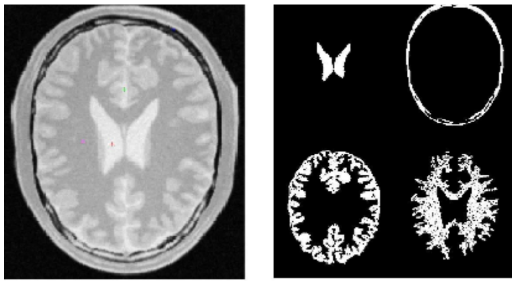

Fig. 2. Segmentation by region growth.

the maxima in the accumulation space indicate the existence of the searched objects. Previously, before applying the transform, the input image will be the binary image of the pixels that are part of the image contour. It allows to detect edges of images that are not lines, circles or ellipses. Likewise, it allows detection of objects with predetermined shapes, it is even possible to detect objects whose exact shape is not known but having or assuming prior knowledge an approximate model of the object can be formed [5].

Region-Oriented Segmentation: The spatial characteristics of an image are used to carry out its segmentation into regions. In other words, the image is divided into related regions, where each region has distinct properties that differentiate them from each other. In short, the goal is to extract the objects from an image, allowing their processing to be independently. Several techniques have been developed for this classification, and in this paper two of the most commonly used are presented: a) the growth of regions and b) division and fusion.

– *Growth of regions*: The region growth method is widely used and is based on the grouping of adjacent pixels that share similar characteristics or properties. This process starts with a set of points called "seed" and the regions are grown by incorporating neighboring points that exhibit similar properties, such as intensity, texture, color, among others. For example, if the considered property is intensity, a common criterion for including a pixel in a region might be that the absolute difference between the intensity of the pixel and the intensity of the seed is less than a predefined threshold [2, 7]. In Figure 2 the process is observed, on the left side of the image, the seed pixel labeling is found, while on the right side the region growth technique is shown using the increasing region brightness rule.

– *Division and merger of regions*: It consists of initially dividing an image into a set of arbitrary disjoint regions, for example 64 divisions, then, depending on the segmentation criterion, adjacent regions are merged if they have similar properties such as similar gray level, or are divided if they do not share the same properties, such as considerable variations of gray levels.
Finally, the image is segmented into a set of homogeneous regions [6, 9].

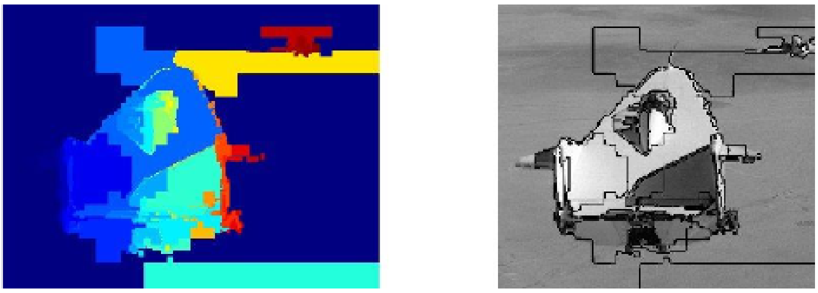

Fig. 3. Stages of image processing.

Figure 3 shows this process: on the left is the labeled image and on the right, the segmented image using this technique. One observation about this technique is that it does not preserve the actual contours in the result.

1.1 Related Works

In image processing, the continuous nature of data makes gradient-based attack approaches applicable, making it possible to create subtle and specific disturbances in images. However, the detection and classification of urban and rural areas present particular challenges due to the variability in visual and spatial characteristics. In this section, we present works related to the analysis and processing of images for the identification and characterization of urban and rural areas using different techniques and architectures:

In [8], image fusion techniques are presented to improve and calibrate meteorological information from ground-based radar images using satellite images. To calibrate the radar images, a method based on the discrete wavelet transform was implemented. A methodology is defined for the selection of global segmentation thresholds and for the calibration of radar images.

In [1], aims to show the results of the application of two cloud segmentation techniques in GOES satellite images; the first is a region-based technique, the thresholding by gray levels; and the second is a border-based technique, the Hough Transform. Finally, the results found by the two methods are compared with the segmentation obtained from a software specialized in satellite images by separating the spectral band with the information of interest.

In [3], the objective is to establish a reliable methodology of automatic detection of buildings for the automatic classification of land uses in urban environments using high resolution aerial images and LiDAR data. These data correspond to the information acquired with in the framework of the National Plan of Aerial Orthophotography (PNOA), and are available to the Spanish public administrations.

In this paper we analyze the development of an advanced satellite image segmentation system in urban and rural environments. Specialized filters are applied to eliminate noise and improve the quality of the images. The

Otsu method adjusts the threshold to improve the segmentation of regions, identifying homogeneous areas accurately. Gabor filters highlight important textural features, improving the distinction of details in complex environments. Segmentation techniques based on regions and edges are combined to obtain accurate and detailed results. The parameters of the Hough transform are optimized to reliably detect boundaries and contours, accurately representing the geospatial structure. This approach contributes to applications such as urban planning, agricultural monitoring and environmental change analysis, providing detailed information on urban and rural characteristics in complex spatial contexts.

2 Methodology

In the development of this work, satellite images covering urban areas, roads, uninhabited areas and vegetation in PNG format were used [4]. These images were subjected to segmentation methods, the first of them based on regions. Given the distinctive characteristic of vegetation, it was chosen to use the gray level thresholding method, which is equivalent to a segmentation by division and fusion of regions. On the other hand, the second selected method is based on the identification of limits, and for this the Hough transform was applied.

The edges of the images were extracted and subsequently compared with the results obtained by the aforementioned methods. To evaluate the effectiveness of the methods, metrics such as the mean square error, calculated pixel by pixel, as well as the Jaccard Index (IOU) and the Dice coefficient were used. In the initial phase, image selections were made, followed by grayscale conversion and subsequent binarization of the same. Given the observation that testing with different thresholds would take a long time, the decision was made to employ the Otsu method. This method made it possible to find the optimal threshold in an automated way in relation to the image in question, streamlining the segmentation process.

Subsequently, Gabor filters were used in order to enhance certain textures or specific characteristics. While these filters are effective at highlighting fine details, they also have the potential to introduce some level of noise into the image. To counteract this unwanted effect, noise filtering techniques were implemented, including the median filter, average filter, Gaussian filter and bilateral filter.

In this instance, the decision was made to maintain the result obtained with the bilateral filter. Although the changes were not obvious to the naked eye, a subtle alteration in the frequency histogram of the image could be perceived. This adjustment was crucial, since a slight noise had been generated in the image that, although it was not visually perceptible, was reflected in the histogram analysis.

Then, edge detection was carried out, using operators such as Canny, Laplacian, Roberts and Sobel. This procedure aimed to evaluate which of these operators could offer optimal performance. After edge detection was completed, region-oriented segmentation was performed. In this case, we chose to use the Felzenszwalb method, an algorithm designed to divide an image into homogeneous regions. This method is based on the identification of natural boundaries in the image and the grouping of nearby pixels that share similar characteristics. The following steps describe the operation of the algorithm:

– *Construction of the Graph*: The image is represented as an undirected graph, where each pixel is a node and the connection between pixels is established according to some measure of similarity, such as the difference in color or intensity.

– *Ordering of the Edges*: The edges of the graph are ordered according to the similarity measure. This is done in an ascending manner, so that the edges with the least similarity are considered first

– *Hierarchical Grouping*: The edges are traversed in ascending order and the nodes connected by each edge are grouped if they belong to different regions. Grouping is done using efficient data structures, such as union-find.

– *Binding Criterion*: The decision whether or not to join two regions is based on a threshold criterion that compares the similarity measure between the pixels connected by an edge with a predefined threshold value.

– *Adjusting Segment Size*: A parameter is entered that controls the minimum size of a segment. This parameter influences the joining decision, allowing small regions to be merged or separated according to the desired size.

– *Linear Complexity*: An outstanding feature of Felzenszwalb's method is its linear complexity. As the edges are processed in ascending order, the time complexity is proportional to the size of the graph, which makes it efficient.

The final result is a partition of the image into homogeneous regions, where the natural boundaries have been respected to the extent that the similarity between connected pixels is greater than the defined threshold. Felzenszwalb's method is effective in segmenting images with complex structures and local variations in texture and color. The variation of these parameters can have the following effects on the scale adjustment: a) Increasing, generates larger segments and less details, which can lead to a more generalized segmentation, and b) Decreasing, generates smaller segments and more details, which can result in a finer and more detailed segmentation.The parameters that were modified from this method are as follows:

– *Standard Deviation Adjustment (sigma)*: Increasing sigma, the segmentation becomes less sensitive to intensity variations, resulting in a smoother segmentation. Decreasing sigma, the segmentation becomes more sensitive to intensity variations, resulting in a finer and more detailed segmentation.

- *Minimum Size Adjustment (min-size)*: A larger value, there is a larger merging of small segments, resulting in a smaller number of segments in the output, and a smaller value, there is a smaller merging of small segments, resulting in a larger number of segments in the output.

Then, to address edge-based segmentation, the Hough Transform was implemented with the specific objective of delimiting roads or tracks. We chose to use the implementation of the probabilistic Hough Transform in the Python CV2 libraries. This variant represents an optimization of the original Hough Transform. Instead of considering all the points in the image, the probabilistic Hough Transform selects a random subset of points, which is sufficient for line detection. This strategy contributes to an improvement in computational efficiency. It is only necessary to reduce the threshold to adapt to the use of this subset of points, thus simplifying the line detection process.

Finally, the implemented methods were evaluated by applying specific metrics. Key measures such as mean square error, Jaccard index (IOU) and DICE coefficient were used. These metrics provide a quantitative evaluation of the performance of the segmentation and detection methods, allowing an objective and detailed comparison of their results. The metrics were computed as follows:

- *Mean Square Error (MSE)*: measures the average quadratic difference between the actual and predicted values. The lower the MSE, the better the agreement between the predictions and the current values:

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y-\hat{y})^2. \tag{5}$$

- *Jaccard Index (IOU)*: measures the similarity between two sets. In the context of image segmentation, A and B represent the segmented and reference areas, respectively:

$$IOU = \frac{|A \cap B|}{|A \cup B|}. \tag{6}$$

  Where $A \cap B$ it is the size of the intersection between the segmented image (A) and the reference image (B), and $A \cup B$ is the size of the junction between the segmented image (A) and the reference image (B).

- *Coefficient DICE*: Is a measure of the similarity between two sets. Similarly to the Jaccard Index, it is commonly used in image segmentation evaluation. The closer the DICE coefficient is to 1, the greater the agreement between the segmented and reference areas:

$$DICE = \frac{2 \cdot |A \cap B|}{|A + B|}. \tag{7}$$

  Where $A \cap B$ it is the size of the intersection between the segmented image (A) and the reference image (B), and $A + B$ is the sum of the size of the segmented image (A) and that of the reference image (B).

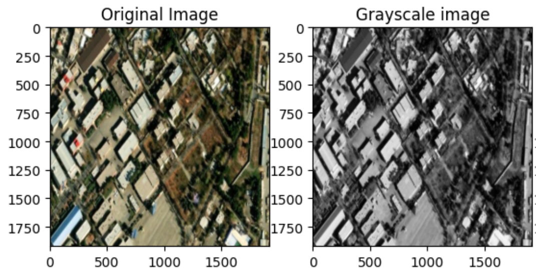

Fig. 4. Original image and with the pre-processing from color scale to grays.

The choice of these metrics is crucial to understanding the effectiveness of the methods in terms of accuracy, robustness and ability to capture the relevant information in the images. The mean square error provides a measure of the discrepancy between the segmentations and the reference images. On the other hand, the Jaccard Index and the DICE coefficient evaluate the overlap between the segmented areas and the reference areas, which are valuable indicators of the quality of the segmentation in terms of concordance with earthly truth.

3 Results

This section presents the results obtained from the various experiments carried out in this practice, along with their analysis and comparison. From the set of available images, 10 test images were selected for further analysis. The first stage of the process consisted of opening an image for manipulation, which has a size of 1920 x 1920 pixels, followed by its conversion to grayscale. A representative example of the results obtained is shown in Figure 4, corresponding to image number 4 indicated in Tables 1 and 2.

As detailed above, the next phase of the procedure involves the binarization of the image, i.e. the application of a threshold to distinguish the areas of interest. In this context, the Otsu method was implemented to optimize the assignment of this threshold automatically, using the OpenCV library. This approach seeks to improve the efficiency of the process by automatically determining the most appropriate value. Through experimentation, a significant distinction was made between manual binarization and the application of the Otsu method, which optimally determined that the most suitable threshold for the image in question is 111, as shown in Figure 5. Next, a Gabor filter was implemented with the purpose of highlighting textured areas or elements that present finer details. The hyperparameters used were: a kernel size of 31, a sigma value of 4.0, a theta value of 10 (filter orientation), a lambda value of 10 (filter wavelength), and a gamma value of 0.5 (filter aspect factor). This process is illustrated in Figure 6. Then a filtering was applied to eliminate the noise that could have been generated in the image by using the Gabor filter. Several filters were analyzed, including the median, average, Gaussian and bilateral. A 5×5 kernel was used for the Gaussian filter and a 3×3 one for the medium one.

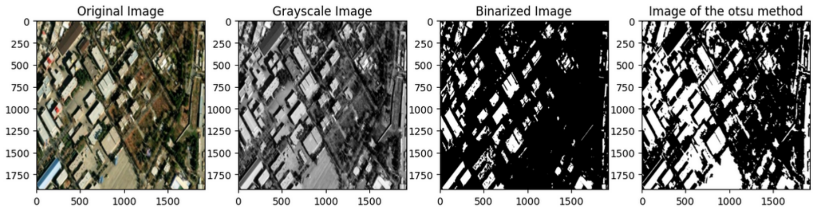

Fig. 5. Comparison with normal binarization and with the otsu method.

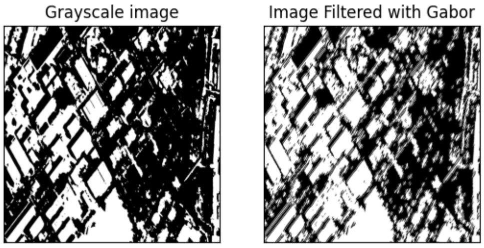

Fig. 6. Image with binarized pre-processing and with gabor filter.

At first glance, there were no significant changes in the application of the various filters. To select the filter that would be kept for further work, their histograms were plotted and the variations between them were evaluated. Although a subtle difference was observed between the filters, it was decided to work with the bilateral filter due to its ability to preserve the image characteristics while providing effective smoothing. After choosing the bilateral filter, we proceeded to extract the edges of the image by applying operators such as Canny, Sobel, Roberts and Laplacian. The results obtained with each of these operators are presented in Figure 7.

After completing this process, the analysis was initiated by region-oriented segmentation, specifically using the gray-level-based division and merging of regions approach. The algorithm mentioned above in the introduction was implemented, which is typical of the scikit-image library (skimage). This algorithm is fundamentally based on Canny's edge operator and was configured with specific parameters, including scale= 70, sigma= 0.5 and min-size=50. The result is shown in Figure 8.

This operation was performed on several images, and metrics such as the Jaccard Index (IOU) and the DICE coefficient were used to evaluate the effectiveness of the process and quantify the number of segments generated in each image. The detailed results are presented in Table 1. To analyze these metrics, ground truth (the reference image in gray scale) and image segmented by this method were used to analize the effectiveness of obtaining the correct segmentation.

As we observed in the results, images 31, 34, and 50 seem to have very good results, and the current thresholds could be considered effective. It is important to consider the specific context of your data and your goals to determine which

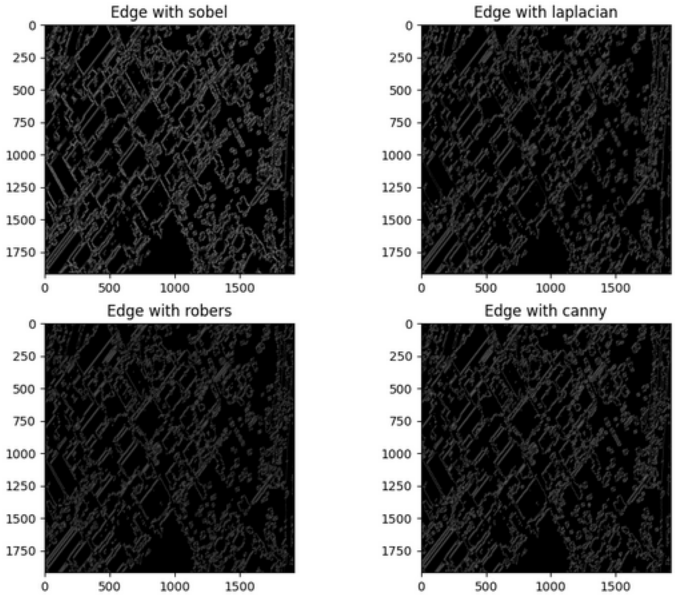

Fig. 7. Operators for edge detection.

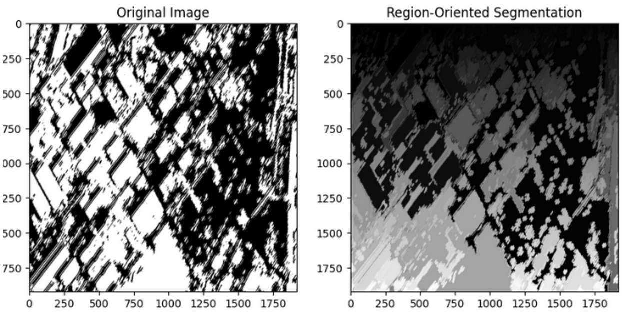

Fig. 8. Segmentation based on division fusion of regions by gray levels.

results are considered acceptable or desirable in your particular application. In addition, the interpretation of the metrics may vary depending on the specific requirements of the project.

Now we will proceed to analyze the border-based segmentation using the Hough transform that we described above. The initial parameters with which we trained was using the Canny edge operator, a threshold of 179, line of 50 and gap of 50, the results are shown in Figure 9. According to the results shown in Figure 9, it is evident that when using this operator, the image presents some distortion. The lines, which are thick, make the image choppy, mostly segmenting large areas.

Although it manages to segment some crossings, it does not do it optimally. Lowering the threshold only results in thinner lines without substantially

Table 1. Results of segmentation based on division and mergers of regions by gray levels.

ID-image	Threshold	IOU	Coefficient DICE	N-regions
4	111	0.9999	0.0018	3370
15	111	0.9957	0.0009	5354
28	114	0.9349	0.0015	3938
31	89	0.9978	0.0029	2792
34	90	0.9998	0.0030	1804
37	102	0.7417	0.0022	3581
42	103	0.8212	0.0026	2943
50	108	0.9859	0.0052	2055

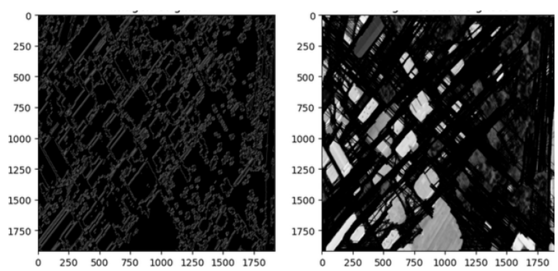

Fig. 9. Border-based segmentation using hough transform.

improving the quality of the segmentation. Therefore, the test was carried out with the Sobel, Roberts and Laplacian operators to analyze the differences. When analyzing the images, a remarkable similarity was observed between the three. The difference lies in the choice of the operator and the application of a threshold of 100, a line of 50 and a space of 50. This adjustment allowed a more effective segmentation of the edges or boundaries of the elements present, such as houses, roads and non-populated areas, while the rest corresponds to the vegetation zone, see Figure 10.

In Table 2 the mean square error of the 10 images was analyzed with each of the operators.To do this, the segmentation lines were drawn on the original grayscale image, and the error was calculated between that image and the image with the detected edges of all the elements to check the effectiveness of the segmentation.

According to the results of Table 2, the average and the standard deviation of each operator were analyzed. The results are as follows: *Sobel* (Average 77.7451, Standard Deviation 9.3545), *Canny* (Average 85.8375, Standard Deviation 23.2516), *Roberts* (Average 60.7196, Standard Deviation 18.2048), *Laplacian* (Mean 60.9174, Standard Deviation 16.3434). Observing these results, Sobel and Laplacian have lower standard deviations, indicating less variability in edge detection. Therefore, more robust options against noise could be considered.

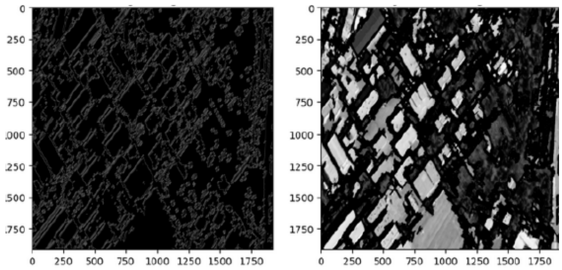

Fig. 10. Edge-based segmentation by Hough transformation using Sobel.

Table 2. Results of the mean square error of boundary-based segmentation using hough transform.

ID-image	Sobel	Canny	Roberts	Laplacian
4	73.9297	84.1937	53.6348	52.6819
15	63.707	39.0652	28.9142	35.4735
28	66.7526	63.3363	43.2689	43.2352
31	75.4467	93.9469	58.9237	58.3859
34	86.6452	106.3451	75.0496	74.0103
37	82.3606	99.3396	68.2301	67.2245
42	84.9869	98.7343	74.9895	74.3306
50	90.1322	101.7385	82.7425	81.9969

4 Conclusions

The choice between the two types of segmentation, based either on the division and merging of regions or focused on borders, significantly depends on the specific objectives of the analysis. In the case of merging regions based on gray levels, it is observed that it allows to detail areas with greater precision, which is beneficial when you want to highlight specific aspects of the image. On the other hand, border segmentation facilitates the identification of segments that act as borders, being useful, for example, to mark areas of interest in satellite images, such as populated areas, homes, roads and uninhabited regions.

It is noteworthy that, in the analysis of the Hough transform, it was evident that, unlike many works that use the Canny edge detector, in this case, methods such as Sobel, Roberts or Laplacian offered more satisfactory results by highlighting the relevant contours and features more effectively. In addition, Gabor filters were introduced to emphasize textures and differentiate features such as vegetation and empty areas. It is essential to recognize that the choice of each method and the combination of techniques will depend on the specific nature of the images and the particular objectives of the analysis. As a future work, applying deep learning methodologies would help the segmentation processes and adapt to more complex patterns in images. Consider the integration of multispectral data to take advantage of, in order to improve the accuracy of the segmentation of features such as vegetation and water. The analysis of temporal changes in images could also be addressed, allowing the identification of variations in the landscape over time.

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