

Mathematical Modeling and Algorithmic Optimization for Intelligent Signal and Image Processing Applications

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Abstract

The image segmentation is a very important process in computer vision and signal processing, but LiDAR-acquired height images are rather challenging because of noise, irregular signal patterns, and different object-background relationships between objects and the background. The traditional threshold-based segmentation techniques tend to be ineffective in such conditions. This study developed and evaluated an optimized segmentation framework for LiDAR-derived height images using mathematically grounded and computationally efficient image-processing techniques. A dataset of 120 annotated LiDAR height images was analyzed under three noise conditions: clean, medium, and heavy. The baseline approach applied Gaussian smoothing followed by Otsu thresholding, while the optimized pipeline incorporated image normalization, Gaussian filtering, adaptive threshold polarity selection, morphological refinement, and connected-component filtering. Segmentation performance was evaluated using the Dice similarity coefficient and Intersection over Union (IoU). The baseline method showed extremely limited performance, with mean Dice and IoU scores of 0.0173 and 0.0097, respectively. In contrast, the optimized segmentation framework achieved mean Dice and IoU values of 0.7903 and 0.6673. Strong segmentation accuracy was observed for clean and medium-noise images, while performance remained acceptable under heavy-noise conditions. These findings demonstrate that algorithmic optimization can substantially improve segmentation accuracy for LiDAR-derived height images while maintaining interpretability and computational efficiency, providing a practical alternative to more complex learning-based approaches for specialized datasets.

Keywords: image segmentation, LiDAR imaging, image processing, computer vision, signal processing

1. Introduction

Image partitioning or image segmentation is one of the core operations in computer vision and digital image analysis, which entails the division of an image into significant areas that are related to objects or structural parts. Segmentation can be used to isolate objects against the background, allowing the detection of objects, interpretation of scenes and spatial interpretation. Due to its significance, segmentation has been crucial in most of the technological applications, such as medical imaging, industrial inspection, environmental monitoring, and intelligent transportation systems. Nevertheless, reliable segmentation is difficult as noise, object complex boundaries, and image intensity variations occur. According to recent studies, the ability to create algorithms that can retain the accuracy

of segmentation under a wide range of conditions in imaging is still a major concern in the research of computer vision [1]. The development of signal and image processing has offered valuable paraphernalia in enhancing visual data analysis. Mathematical manipulations of the images, like filtering, transformation and feature extraction, are often employed to improve the quality of the image and to extract structural data prior to the image being segmented. The combination of computational algorithms and mathematical modeling has thus been significant in the process of dealing with complex visual datasets [2]. LiDAR (Light Detection and Ranging) systems are one of the emerging modern sensing technologies that have acquired much interest in capturing spacious, accurate three-dimensional information. LiDAR sensors produce elevation maps of environmental geometry; however, those images tend to be noisy and irregular in signal patterns, which makes it difficult to perform segmentation tasks and minimize algorithm performance [3].

Many forms of segmentation algorithms have been created to deal with various types of image data. Conventional methods encompass thresholding, clustering, edge detection, as well as segmentation on a region basis. The methods are also still in widespread use since they are computationally effective and relatively easy to implement. The initial studies in computer vision proved that these methods can be successfully used to recognize structural areas in the case of a high contrast between objects and the background [4]. Nevertheless, these classical methods are easy to apply, but their efficiency tends to decrease whenever the images have noise, poor edges, or complicated configurations. One of the most important parts of numerous segmentation algorithms is feature extraction, since it converts raw visual data into significant representations that outline important patterns and structures. The feature extraction methods are used to differentiate between object regions and the background through the detection of features (edges, textures, spatial relationships) that are used in separating the segmentation algorithms. In the research on computer vision, it is stressed that effective feature extraction is needed to increase the accuracy of segmentation and provide the accuracy of visual analysis in different imaging conditions [5]. Different segmentation technologies have been utilized in processing digital images to identify and separate object areas within an intricate scene. Adaptive thresholding, morphological processing, and clustering algorithms are among the techniques that have been extensively applied in a variety of applications. Whereas such techniques can perform well under controlled conditions, they can reduce their performance when images have a high level of noise or irregular structural features [6]. To overcome these shortcomings, scholars have examined computational intelligence methods that have combined optimization methods and adaptive algorithms with segmentation frameworks. The goals of these approaches are to enhance the quality of segmentation by allowing the algorithms to adjust to changes in image features [7].

The LiDAR imaging technologies have presented both opportunities and challenges in analyzing images in the past few years. LiDAR devices produce elevation plots which depict spatial data in three dimensions as opposed to the traditional color or texture data. Due to such a variation in data representation, the optical image segmentation techniques might not be effective when used on the LiDAR data, and it is needed that special processing approaches are needed for elevation-based signals [8]. In addition, the increasing collection of LiDAR data has also spurred studies on segmentation algorithms that can process three-dimensional spatial data, despite the difficulty of deriving meaningful structures out of height maps because of noise artefacts and disordered surface patches [9]. In signal processing terms, LiDAR height images are susceptible to spatial signals, the worth of which is equal to the elevation measures. Contemporary signal processing methods offer mathematical attributes of analyzing such signals, such as filtering and conversion procedures that boost structural data before segmentation [10].

The more recent literature has focused on algorithmic optimization methods that integrate classical signal processing principles with modern computational methods. As an example, algorithm unrolling has been proposed as a methodology that converts iterative optimization processes to structured computational models, which can be effectively implemented in complex image processing algorithms [11]. Moreover, good feature extraction is also an important element of segmentation systems since it allows algorithms to find patterns in structure to distinguish object areas and areas of a background in image and signal processing uses [12].

Despite the current major advancement in the field of segmentation, there are still issues when it comes to processing specialized image modalities like LiDAR height images. Most of the current segmentation approaches are either based on deep learning models that are computationally expensive to build or have low levels of robustness in the presence of noisy elevation maps. Moreover, deep learning methods are sometimes sensitive to large amounts of annotated data as well as high computing resources that are not necessarily available in a realistic setting. As a result, segmentation methods, which are capable of efficiently processing LiDAR-derived images without losing computational performance or noise resilience, are required.

This study aims at creating and testing an optimal segmentation scheme of height images obtained through LiDAR on the basis of algorithmic methods based on signal and image processing concepts. This new method combines adaptive thresholding, morphological refinement, and connected-component analysis to enhance the performance of segmentation and retain computational efficiency. Quantitative performance measures such as the Dice similarity coefficient and Intersection over Union are used to evaluate the efficacy of the method, and a comparative assessment of the effectiveness of the baseline and optimized segmentation strategies can be performed on images with varying noise levels.

2. Methodology

2.1 Dataset Description

The TSQ-2024 dataset [13] that was used during the experimental analysis includes height images, which are LiDAR images, and manually annotated ground-truth segmentation masks. Each picture is a two-dimensional elevation map created through LiDAR measurements, with pixel intensities being proportional to relative height values in the scanned environment. The dataset comprises 120 images, with each image having an annotation that is a polygon-shaped area that defines the spatial size of the target object. The annotation files come in the form of JSON text and contain the coordinates of the object boundaries. Such annotations of polygons were transformed to binary masks so as to facilitate quantitative assessment of the performance of segmentation. In order to explore how signal quality affects the accuracy of the segmentation, the dataset will be divided into three noise levels: clean, medium and heavy. All the categories have 40 images, which creates a balanced dataset that can be used to compare performances.

2.2 Data Preprocessing

A number of preprocessing processes were conducted prior to the use of the segmentation algorithms to create a homogeneous input representation.

2.2.1 Image normalization

LiDAR height values are not constant across images since measurements of sensors differ and environmental conditions also differ. The 8-bit grayscale range was used to normalize each image to a minmax range of pixel intensities in order to obtain a standardized range of dynamic range:

$$I_{\text{norm}}(x, y) = \frac{I(x, y) - I_{\min}}{I_{\max} - I_{\min}} \times 255$$

where $I(x, y)$ represents the original pixel value and $I_{\min}$ and $I_{\max}$ denote the minimum and maximum intensity values within the image.

2.2.2 Noise reduction

A Gaussian smoothing filter was used to reduce the high-frequency noise components without generating any loss in structural information:

$$I_{\text{smooth}} = G_{\sigma} * I_{\text{norm}}$$

where G_{σ} denotes a Gaussian kernel and $*$ represents convolution. This step reduces local intensity fluctuations that can interfere with threshold-based segmentation.

2.3 Ground-Truth Mask Generation

The annotations of the data set were in the form of polygon coordinates which indicated the boundaries of the target object. These annotations were represented as binary segmentation masks in order to be evaluated.

Given a set of polygon vertices

$$P = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$$

a filled polygon was rasterized onto the image grid to generate the ground-truth mask:

$$M_{\text{gt}}(x, y) = \begin{cases} 1 & \text{if } (x, y) \in P \\ 0 & \text{otherwise} \end{cases}$$

The resulting mask represents the reference segmentation against which predicted masks were compared.

2.4 Baseline Segmentation Method

Segmentation was conducted first by using the global thresholding algorithm of Otsu. The algorithm designed by Otsu finds an optimal threshold T which gives the maximum between-class variance of the image histogram.

Given a grayscale image I , the segmented mask is obtained as

$$M(x, y) = \begin{cases} 1 & I(x, y) \geq T \\ 0 & I(x, y) < T \end{cases}$$

It is a baseline method which offers a simple but widely used threshold-based segmentation method of grayscale images. Nevertheless, the baseline technique does not necessarily isolate the target object because LiDAR height images can have different intensities of polarity between object and background regions.

2.5 Optimized Segmentation Algorithm

To overcome the shortcoming of the baseline method, an optimal segmentation pipeline was designed. The adaptive threshold polarity selection, morphological refinement and connected-component filter are included in the proposed approach.

2.5.1 Adaptive threshold polarity

At LiDAR height images, the area of the object can either be lighter or darker as compared to the background as a result of acquisition conditions. Thus, the common Otsu thresholding and inverse thresholding were tested.

Two candidate masks were generated:

$$\begin{aligned} M_1 &= I \geq T \\ M_2 &= I < T \end{aligned}$$

The segmentation mask producing the higher overlap with the expected object structure was selected for further refinement.

2.5.2 Morphological refinement

Binary masks that are a result of thresholding can have little noise areas or empty spaces. Morphological operations were used to enhance the quality of the masks.

First, morphological opening was used to remove small noise artifacts:

$$M_{open} = (M \ominus B) \oplus B$$

where B represents the structuring element.

Next, morphological closing was performed to fill small holes and smooth object boundaries:

$$M_{close} = (M_{open} \oplus B) \ominus B$$

These operations enhance spatial coherence in the segmented mask.

2.5.3 Connected-component filtering

With the refinement of the morphology, several disconnected areas can still be left in the binary mask. A connected-component analysis has been conducted since the target object usually covers the most contiguous region.

Let C_i represent the set of connected components detected in the mask. The final segmentation mask was defined as

$$M_{final} = \arg \max_{C_i} |C_i|$$

where $|C_i|$ denotes the number of pixels in the component C_i . Selecting the largest component effectively removes residual noise regions.

2.6 Performance Evaluation Metrics

Two standard measures commonly used in image segmentation research were used to assess performance on segmentation.

2.6.1 Dice similarity coefficient

The Dice coefficient measures the overlap between the predicted mask M_p and the ground-truth mask M_{gt} :

$$Dice = \frac{2 |M_p \cap M_{gt}|}{|M_p| + |M_{gt}|}$$

Dice values range from 0 to 1, where 1 indicates perfect agreement between the predicted and reference masks.

2.6.2 Intersection over Union

The Intersection over Union (IoU) metric quantifies the ratio between the intersection and union of two masks:

$$IoU = \frac{|M_p \cap M_{gt}|}{|M_p \cup M_{gt}|}$$

IoU provides a stricter measure of segmentation accuracy and is widely used in computer vision evaluation.

3. Results

3.1 Dataset Characteristics

The data were 120 LiDAR height images, each of which had an associated ground-truth label of the target object region. The photographs had been placed uniformly in three noise conditions: clean, medium, and heavy, with 40 samples per category. This was a balanced design that made it possible to make consistent segmentation performance measurements at different noise levels. The noise categories used were roughly one-third of the data set and enabled the performance of the algorithms to be compared without bias with the various signal conditions.

3.2 Baseline Segmentation Performance

Preliminary experiments with segmentation used a base Otsu thresholding method after smooth-Gaussian-filtering. Two commonly used measures of performance in image segmentation were considered, including the Dice similarity coefficient (Dice) and the Intersection over Union (IoU). The baseline strategy had very low segmentation strength. Table 1 also demonstrates that the average Dice score of all images was 0.0173 and the average IoU was 0.0097, which means that the predicted masks were rarely overlapped with ground-truths. These very small values of overlap reflect that in the vast majority of the images, the threshold-based method failed to solve the problem of object target against background. The findings thus indicate a clear need to have a complex global thresholding approach to be used in the correct segmentation of LiDAR-generated height images, and that other sophisticated processing methods are needed to obtain credible object extraction.

Table 1. Baseline segmentation performance (Otsu thresholding)

Metric	N	Mean	SD	Min	Median	Max
Dice	120	0.0173	0.0542	0.0000	0.0085	0.4109
IoU	120	0.0097	0.0333	0.0000	0.0043	0.2586

3.3 Performance of the Optimized Segmentation Algorithm

An optimized set of processing pipelines was applied so as to enhance the accuracy of segmentation. The improved version used adaptive polarity threshold selection, morphological refinement and connected-component filtering to separate the main object area. The refined algorithm gave a significant enhancement of the accuracy of the segmentation. As indicated in Table 2, the average Dice score was improved to 0.7903, with the average IoU being 0.6673. These findings indicate that the optimized pipeline has the ability to detect the target object in the majority of the images in the dataset. The distribution of Dice scores in Figure 1 indicates that a high percentage of images have Dice scores greater than 0.75, and a few samples are close to 0.90, which implies a high degree of agreement between the predicted and the ground-truth masks. The same trend can be noted in the distribution of IoU shown in Figure 2 because the majority of the scores lie in the range of 0.65 to 0.80.

Table 2. Optimized segmentation performance

Metric	N	Mean	SD	Min	Median	Max
Dice	120	0.7903	0.1192	0.3817	0.8502	0.8964
IoU	120	0.6673	0.1435	0.2359	0.7394	0.8123

Figure 1. Distribution of Dice scores obtained using the optimized segmentation algorithm.

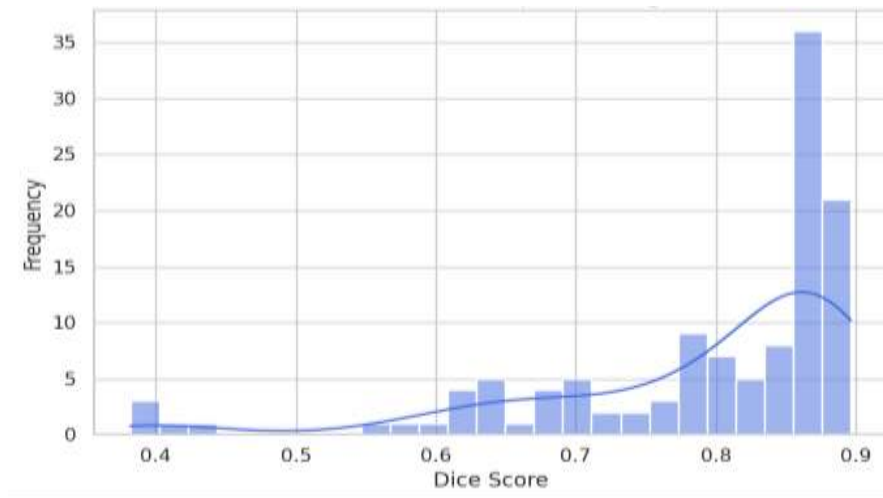
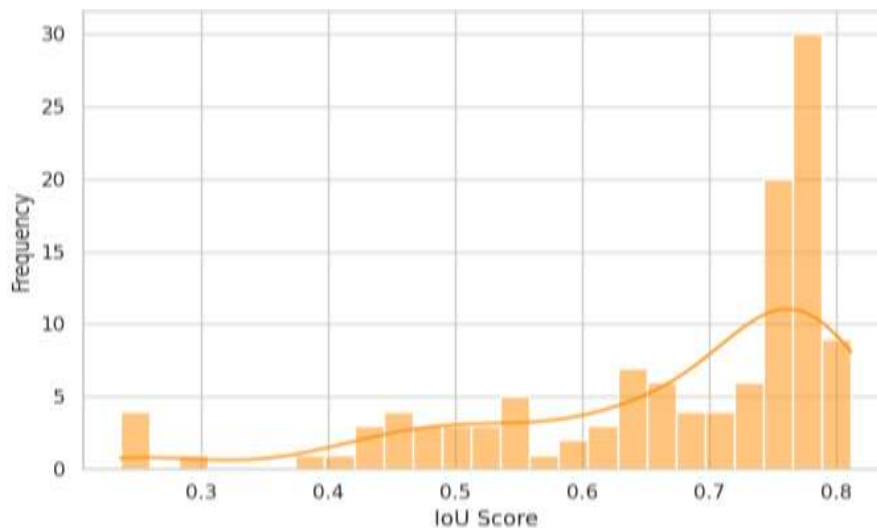
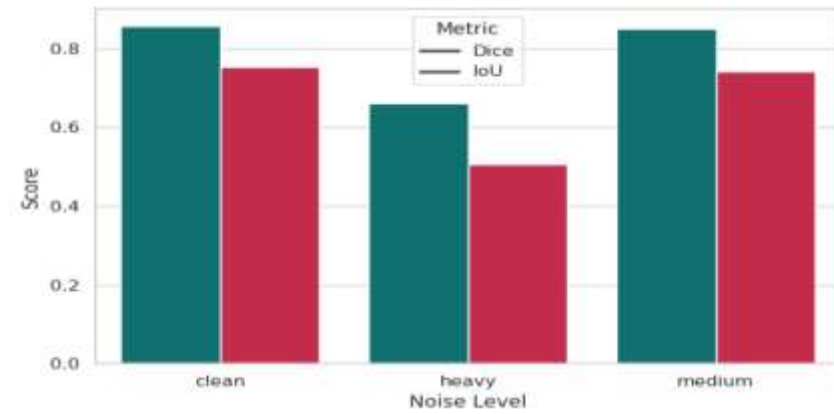


Figure 2. Distribution of Intersection over Union (IoU) scores for the optimized segmentation algorithm.



3.4 Segmentation Performance Across Noise Levels

The strength of the optimized algorithm was also tested with the three sets of noise. Table 3 reports a summary of the Dice and IoU scores of each noise condition. The accuracy of the highest segmentation was the best with clean images, with the mean Dice score of 0.8578 and the mean IoU of 0.7529. Medium-noise images' performance was also equally robust and got an average Dice score of 0.8511. On the contrary, the accuracy of the segmentation was lower in heavy noise conditions, and the Dice score dropped to 0.6621 and the IoU to 0.5069. Although these results were decreased, the algorithm still gave fairly good object masks in the face of strong noise interference. Figure 3 presents the results of the comparison of the performance of segmentation under varying noise levels, indicating the average values of Dice and IoU scores per category.

Figure 3. Segmentation performance across noise levels.**Table 3. Segmentation performance by noise level**

Method	Noise Level	Dice Mean	Dice SD	IoU Mean	IoU SD
Baseline Otsu	Clean	0.0104	0.0043	0.0052	0.0022
Baseline Otsu	Medium	0.0099	0.0033	0.0050	0.0017
Baseline Otsu	Heavy	0.0318	0.0929	0.0188	0.0570
Optimized Segmentation	Clean	0.8578	0.0397	0.7529	0.0583
Optimized Segmentation	Medium	0.8511	0.0311	0.7420	0.0451
Optimized Segmentation	Heavy	0.6621	0.1246	0.5069	0.1333

3.5 Improvement Over the Baseline Method

Table 4 compares the optimized and the baseline approaches directly. The final pipeline was optimized, which improved the score of 0.0173 to 0.7903, indicating an absolute improvement of 0.7730. Equally, the increase in the IoU was 0.0097 to 0.6673.

Table 4. Baseline and optimized segmentation performance

Metric	Baseline Mean	Optimized Mean	Absolute Improvement	Fold Improvement
Dice	0.0173	0.7903	0.7730	45.6 times
IoU	0.0097	0.6673	0.6577	69.1 times

The proposed algorithmic enhancements proved to be effective as the optimized approach worked in relative terms with improvement in Dice scores by 45.6 times and IoU values by 69.1 times.

4. Discussion

When algorithmic optimization was implemented in the processing pipeline, the performance of segmentation was improved significantly. The global thresholding-based baseline segmentation technique resulted in very low Dice and IoU scores, which implies that the predicted regions did not tend to match the ground-truth object boundaries. This

low performance indicates that a simple threshold-based type of segmentation cannot readily be applied to LiDAR-derived elevation images where object-background interactions are conditioned by irregular signal intensity and noise fluctuations. Conversely, the streamlined pipeline drastically improved the quality of segmentation as it used adaptive threshold polarity, morphological sifting and connected-component selection. The segmentation obtained with the resulting segmentation was very high in both Dice and IoU scores in most images, indicating that well-designed algorithmic refinements can enhance segmentation's large-scale performance without the need to use sophisticated learning architectures. Findings show that LiDAR height images have advantages of preprocessing procedures that consider the polarity differences of the signal and structural continuity, which enables the algorithm to be more reliable when determining the prevailing object area. The other observation of importance is that of noise affecting segmentation accuracy. There was a very similar performance in the segmentation of clean and medium-noise images, indicating that the optimized pipeline is resistant to moderate signal perturbations. But the accuracy of the segmentation was lower in the heavy-noise category, indicating it was hard to maintain structural boundaries in the case where signal distortion becomes significant. Although this deteriorated, segmentation performance under noisy conditions was not overly poor, and this shows that the proposed approach does not lose much of its robustness when the noise conditions change.

The outcomes that have been achieved in this paper are similar to what has been previously reported regarding the significance of optimization methods to enhance image processing algorithms. Research into swarm intelligence optimization techniques emphasizes the fact that adaptive optimization techniques can be very beneficial in improving segmentation performance by the ability of the algorithm to dynamically adapt to the characteristics of the complex image [14]. It has been stressed in such ways that segmentation can be refined by making the parameters of the algorithms and decision rules optimal instead of fixed. On the same note, neural network and mathematical modeling studies show that algorithmic design with mathematical analysis can be used to come up with efficient and interpretable solutions in the analysis of image data [15]. In spite of the high performance of deep learning models in most segmentation problems, they can be taxing (requiring a huge amount of training data and huge computational power). By comparison, algorithmic methods of optimization can provide competitive results, as well as be transparent and computationally efficient.

Optimized segmentation pipeline also supports the results that the computationally intelligent algorithms could be used to optimize the multimedia and image-processing performance by modifying the algorithm behavior according to the changing conditions of inputs [16]. Image processing systems are being improved using artificial intelligence methods, especially when the original algorithms do not cope with the noisy or irregular data distributions [17]. Development of the segmentation schemes based on optimization, like the multi-thresholding strategies, is also demonstrated to be more effective than the simple thresholding schemes in treating the complex intensity patterns [18]. The recent studies on nature-inspired optimization algorithms indicate further that engineering problems can be addressed with adaptive search algorithms that can be used to find optimal solutions in a complex environment [19]. In a more general sense, intelligent optimization surveys reveal that the combination of learning-based and optimization-based algorithms has emerged as a significant field of effort towards enhancing performance in signal and image processing applications [20].

The results bear some significant implications for image processing and LiDAR-based analysis. First, the findings show that the accuracy of segmentation can be much enhanced by optimization of the algorithm, even with very simple image processing methods. This

underscores the need to come up with processing pipeline designs that take into consideration the structural properties of specialized datasets like LiDAR height images. Second, the findings indicate that deterministic and efficient algorithms are still very applicable in practice. Even though deep learning algorithms prevail in most computer vision problems, optimization-based image processing techniques can be good substitutes when there is a lack of sufficient training data or when computation efficiency is needed. Lastly, the high enhancement in segmentation performance highlights the importance of combining several processing steps, including normalization, adaptive thresholding, and morphological refinement, into a well-organized system as a means of object boundary recognition and minimization of noise effects.

Although the results have shown good segmentation performance, there are a number of considerations that should be made. The experiments were carried out on a dataset entailing one object category and pre-established conditions of noise. Though this controlled arrangement facilitated systematic assessment within the noise-levels, the extension of the proposed framework to other datasets with a greater variety of scenes may provide further insight into the overall applicability. The pipeline of segmentation is based on the deterministic image processing operations, which have benefits in interpretability and computational efficiency. More complex environments, however, can be advantageous to adaptive mechanisms that can capture more complex spatial patterns. Future studies can thus examine hybrid frameworks, which combine optimization-based image processing with learning-based models. Specifically, novel model-based deep learning algorithms that integrate both optimization principles and neural network structures can further improve the performance of segmentation without requiring loss of interpretability and efficiency.

5. Conclusion

Mathematical modeling and algorithmic optimization were found to be very useful in enhancing height image segmentation based on LiDAR. Although the overlap of the baseline thresholding method with the reference masks was extremely small, the optimized pipeline achieved a significant enhancement in segmentation accuracy by integrating adaptive threshold polarity choice, morphological refinement and connected-component filtering. The good results obtained on clean and medium-noise images, as well as reasonable robustness in case of heavy-noise-based conditions, demonstrate that the suggested framework can be trusted to reliably record the target object areas in conditions of different signal qualities. The results of this study indicate that well-formulated, interpretable image-processing pipelines can still be useful in specialized image segmentation, especially in cases where the size of the dataset is small and the computational efficiency is of interest. The findings also indicate that, without necessarily having to resort to the complex deep learning architecture, it is possible to gain meaningful performance improvements. In general, the suggested framework offers a viable and computationally efficient approach to LiDAR image segmentation and a viable structure on which future research can be conducted on the hybrid optimization-driven and learning-based approaches in intelligent signal and image processing applications.

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